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Case Report

Assessment of land use transition and crop intensification using geospatial technology in Bangladesh

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ABSTRACT

Despite dealing with numerous challenges, the agricultural sector in Bangladesh is consistently growing every year because of the crop intensification efforts in many areas to ensure food security. However, the effect of intensive cropping on land use changes remains unclear due to the lack of systematic monitoring. This study assesses Land Use Land Cover (LULC) dynamics, particularly in Bhanga Upazila (a subdistrict), Bangladesh, using remote sensing and GIS technologies. Landsat 5 and 8 satellite imagery to understand the impact of agricultural intensification from 1988 to 2023. This study showed that agricultural land utilization was increased by more than five times (551.8%) and the built-up area was expanded by 155.6% during the study period. This substantial land conversion was expected due to the significant decrease of barren and waterbodies by 63.1% and 72.4% at the same time respectively. Despite the fact that Bhanga was a typical rural place where agriculture had only a 5% (1012 ha) share of its total land (20,309 ha) back in 1988, Bhanga experienced a notable surge in agricultural land utilization over the past three decades from 5.0% in 1988 to 32.5% by 2023, with a temporary dip to 2.4% post a devastating flood in 1999. The Normalized Difference Vegetation Index (NDVI) and Normalized Difference Water Index (NDWI) analyses justify the increase of agricultural and built-up zones, contrasting significant decrease in waterbodies and barren areas as detected by RF (Random Forest) machine learning algorithm. These findings reveal that crop intensification initiatives convert waterbodies and barren lands into croplands. Government policies and supports such as various agriculture extension activities, availability of irrigation facilities, adaptation of technologies, and improved regional connectivity likely contributed to this positive transformation. This study offers crucial insights for policymakers to take region-specific customized agricultural strategies to ensure food security and sustainability.

1. Introduction

Transformation of land use is a global concern with far-reaching implications for food security and ensuring sustainability [1]. In Bangladesh, Land Use Land Cover (LULC) dynamics are impacted by a complex interplay among agricultural intensification, urbanization, environmental vulnerabilities, and socioeconomic factors [2]. The country is densely populated with a land-scarce landscape. In addition, the escalating population and rapid urbanization have led to substantial changes in land utilization patterns. The transition from rural to urban areas, coupled with rapid industrialization put pressure upon agricultural lands [3]. To meet the high demand of food for its large population, the Government of Bangladesh has taken a series of policy measures and provided numerous financial incentives for agricultural intensification. Conversion of agricultural land to non-agricultural is common, but in many places, positive transformation is also taking place. For instance, due to the inadequate rainfall during the monsoon, many waterbodies are coming under agriculture especially in the dry seasons [4]. In addition, a large area of barren lands is also transformed into crop land by utilizing government incentivized technologies and resources such as

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irrigation pumps, fertilizers, high yielding, climate resilient varieties, trainings, and demonstration [5,6]. However, to ensure food security with sustainable land utilization, proper land management is crucial [7].

Bangladesh, historically an agrarian society, relies heavily on agriculture which is also the backbone of its economy [8]. The situation is particularly acute due to its limited land availability compared to a densely populated landscape. Agricultural activities have traditionally occupied around 60% of the total land area [9]. The rich deltaic plains and fertile soil provide an ideal environment for rice and other crops cultivation [10]. Additionally, this agricultural landscape undergoes continuous evolution due to various factors, including technological advancements, changing market demands, and improved transportation systems [11].

Adding to the complexity, Bangladesh is susceptible to climate change influence, contributing to annual conversions of nearly 1% of agricultural lands to non-agricultural uses [9]. This transformation is a direct threat to the nation's food production objectives. On the contrary, agricultural land has increased in certain areas in Bangladesh due to multiple factors [12]. For instance, one study reported that 73% of fallow land was transformed into agriculture, and waterbodies were severely impacted by gradual sand deposition and soil erosion [5]. However, population growth remains a primary driver that increases the demand for food, prompting the expansion of cultivable lands by converting forests, wetlands, and marginal areas into agricultural lands. Technological advancements have also played a crucial role, empowering farmers to utilize fallow lands by adopting improved irrigation, resilient crop varieties, and better farming practices [13]. Furthermore, government policies encouraging agricultural development, including land reclamation initiatives, dissemination of advanced agricultural technologies, development and distribution of climate-resilient varieties, and subsidies, also contribute to this agricultural expansion [14]. Market demands for specific crops often lead to the conversion of non-agricultural land to meet these needs. Infrastructure development, such as new roads, facilitates access to remote areas and encourages agricultural farming [15].

Climate change-induced events like riverbank erosion or salinity intrusion decrease arability and sometimes force populations to abandon affected areas [16]. Livelihood diversification among rural communities also drives the conversion of non-agricultural land to cropped land to generate supplementary incomes [17]. Nonetheless, crop intensification meets immediate food demand, and it poses some environmental risks like deforestation, biodiversity loss, and soil degradation [18]. Sustainable land management policies and practices are crucial to mitigate these risks and ensure food security while preserving environmental sustainability [19]. Thus, proper monitoring of land use transition and impact of crop intensification is essential.

Regular monitoring of land use and change detection of LULC is foremost for analyzing the dynamics of land use change over time and understanding the socio-economic and environmental consequences [20]. Land use denotes anthropogenic land utilization and land cover represents the bio-physical infrastructures or settings on the earth surface which includes the distribution of vegetation, croplands, soil, waterbodies, and any other physical features [21–23]. LULC maps facilitate to ensure proper spatial planning, management, and monitoring of natural resources at local, national, and regional levels [12,24,25].

Remote sensing together with GIS are effective tools to produce detailed land cover maps [26]. In addition, remote sensing applications have been recognized for land monitoring, especially for monitoring of agricultural land use change [27]. In contrast, field-level data collection is expensive and time-consuming and there is a possibility of erroneous visual interpretations on collected information [27–30]. Studies on assessing land use transition using GIS and remote sensing technology are still limited in Bangladesh [31]. Previous land use transition studies mostly evaluated the impact of climate change in coastal areas [32,33], salinity-induced change [34], land use change on the ecosystem [35,36], flooding [5,37], urbanization and industrialization [38] monitoring of reserve forests including mangrove forests [39–41], and dynamics of land surface temperature (LST) [42,43]. These studies represented land use change in the classified hot-spot areas and/or on specific man-made or natural events. To the best of our knowledge, no study has been conducted to assess the impact of crop intensification on land use change dynamics in the non-classified areas which represent significant lands in Bangladesh. Therefore, undermining this vast area with the underlying change in land use remains unclear for the policymakers to take appropriate policy measures. To bridge this knowledge gap, we assessed the impact of agricultural intensification on land use change in Bhanga Upazila (a subdistrict), Faridpur, Bangladesh over the past three decades by using advanced geospatial technology. It is the first study of the detection of spatiotemporal change of different LULCs for the low-lying heterogeneous south-central region of Bangladesh.

In this regard, remote sensing data provide accurate and reliable information in a short interval with low cost [44]. The freely available and processed remote sensing data play a key role in assessing, mapping, identifying, and monitoring the geospatial and temporal change of different surface features over a short and long period [45,46]. For instance, the Landsat imagery is a freely available online-based remote sensing dataset which is continuously monitored the global land use change since 1972 [30]. Landsat-5 Thematic Mapper (TM) and Landsat-8 Operational Land Imager (OLI) provide satellite data for detecting changes in LULC, NDVI, and NDWI [44].

Google Earth Engine is a big geodata processing platform that has better computational capacities and is used for geospatial data processing over a wide area [47]. In addition, Random Forest (RF) is one of the renowned classification algorithms applied in remote sensing for multispectral and hyperspectral image classification. RF classification has higher accuracy and shows its strength against the overfitting training data [12]. GIS is an integrated approach to collecting, storing, analyzing, and finally presenting geographically referenced information for decision-making purposes [24]. NDVI and NDWI indices are also used to verify the accuracy of LULC classification [48].

The specific objectives of the study were:

1) To identify how different types of land use changes happened over the specified period.
2) To determine the spatial and temporal changes in agricultural landscapes over the past three decades.

1.1. Study area

Bhanga Upazila, a sub-district of Faridpur district, Bangladesh, was selected for this study due to due to its unique combination of rural landscapes and robust agricultural settings. Bhanga serves as a representative sample of the broader regions of Bangladesh. Bhanga is located in the south-central of Bangladesh with an area of approximately 216.34 km^2 between 23°17′ and 23°28′ north latitudes and 89°55′ and 90°06′ east longitudes, approximately (Fig. 1).

Bhanga is surrounded by the river Padma on its north and east sides. This region experienced extensive infrastructure developments such as the six-lane Dhaka-Bhanga Expressway and the construction Padma Multipurpose Bridge (length 6.15km) [49]. These mega infrastructures facilitate substantial agriculture development aimed at better communication and nationwide marketing opportunities [49]. Especially, Bhanga is a highly agriculture-friendly area due to its clay loam soils. It is located in the Arial Khan River floodplain which causes silt or alluvial deposition and makes the low-lying areas fertile [50,51]. The annual average rainfall is 1546 mm, the maximum temperature is 35.8 °C in May and the minimum temperature is 12.6 °C [52]. Agriculture contributes 48% of the income source, with rice as the primary crop, followed by onion, vegetables, fruits, mustard, jute, and sugarcane [53].

Through the adoption of new crop varieties and technologies,

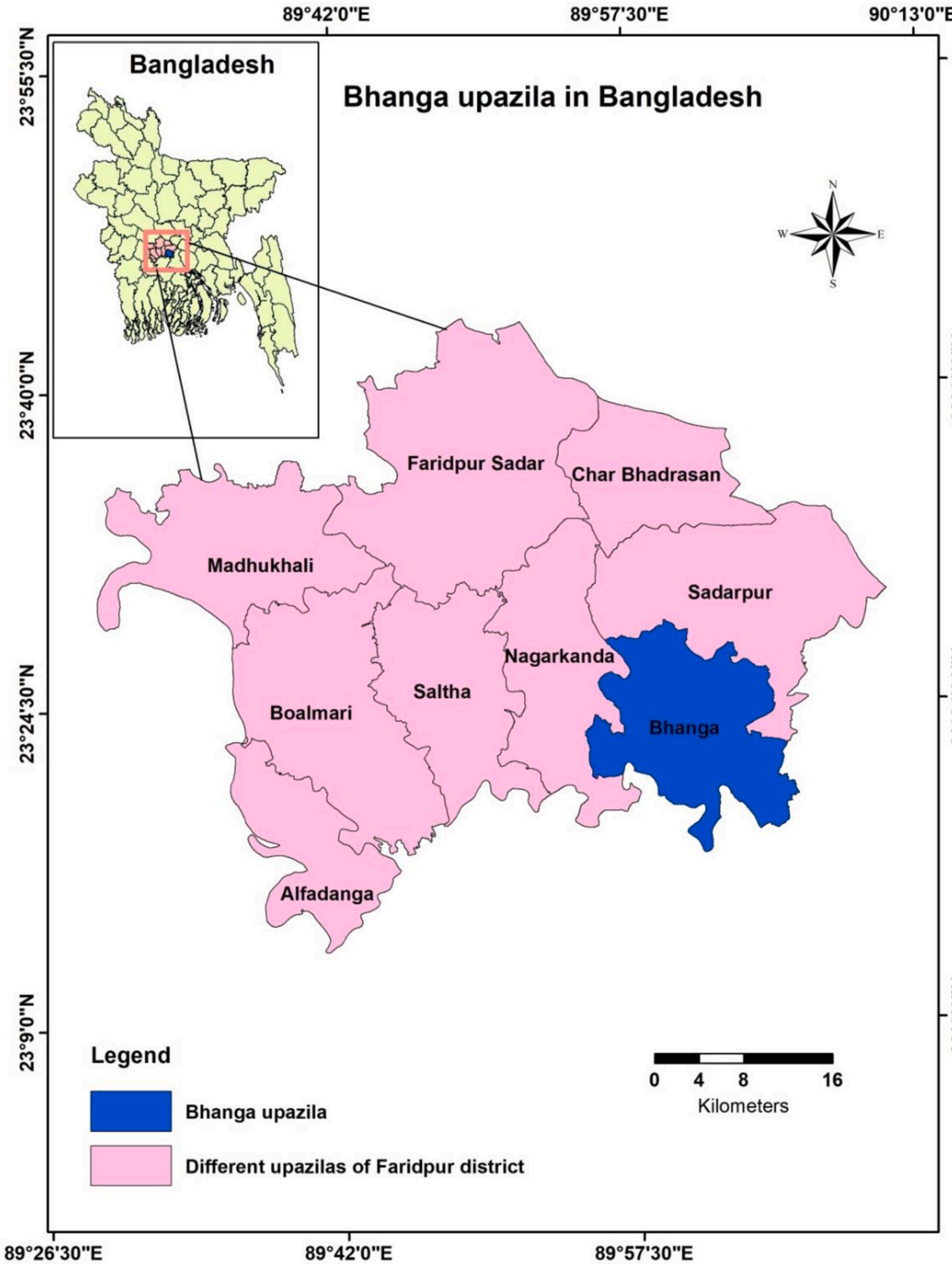

Fig. 1. Location map of the study area (Bhanga subdistrict, Faridpur district, Bangladesh).

farmers in Bhanga have aimed for higher productivity, especially in Boro and Aman modern rice varieties [54,55]. This intensified cropping system has increased multiple cropped areas, agricultural productivity, strengthening food security and economic development in the community [56]. Therefore, the findings derived from this study can contribute significantly by providing informed land-use policies, agricultural strategies, and sustainable development initiatives not only for Bhanga but also for similar regions facing comparable challenges.

2. Materials and methods

2.1. Satellite data source, data acquisition, and time selection

Landsat offers extensive, continuous, and high-resolution (30 m) data capturing the Earth surface over 40 years [27]. For this study, we utilized satellite imagery including Landsat-5 Thematic Mapper (TM) and Landsat-8 (Operational Land Imager (OLI) reflectance multispectral temporal images in Google Earth Engine (GEE) through USGS Earth Explorer (https://earthexplorer.usgs.gov/).

During winter, submerged low-lying regions are utilized for agriculture, and thereby Bangladesh experiences the highest cropping intensity for diverse crop cultivation [57]. Additionally, favorable weather conditions and technological advancements facilitated extensive crop production during this period. To mitigate the impact of seasonal variations, February was specifically chosen for this study. Additionally, February offers the advantages of diverse crop coverage across fields and a relatively cloud-free sky, enhancing the suitability of imagery for analysis. Table 1 provides a detailed description of the data as well as the acquisition dates. We analyzed the data over thirty-five years (from 1988 to 2023) to understand the land use transition.

2.2. Methods

We extracted LULC classification using the information from collected satellite imagery. Fig. 2 depicts the methodological framework for this study. The collected Landsat images were divided into five LULC classes, such as i) Agriculture, ii) Vegetation, iii) Built-up, iv) Waterbodies, and v) Barren lands. Detailed descriptions of each class are shown in Fig. 3.

2.3. Image processing and detection of LULC classification

2.3.1. Google Earth Engine (GEE) platform

The research took advantage of the GEE platform's amazing capabilities for satellite imagery collecting and processing to facilitate a comprehensive understanding of geospatial analyses. Landsat 5 TM and the Landsat 8 OLI reflectance images were collected from the GEE platform for 1988, 1999, 2011, and 2023. In the beginning, the filter date and study area (region of interest) were set with cloud cover <3% to remove cloud interference (shadow) on the images. The imageries were collected from February 2023 with the path 137 and row 044. The band combinations (B1, B2, B3, B4, B5 and B7) were selected for Landsat-5 imagery and the band combinations (B2, B3, B4, B5, B6 and B7) were selected for Landsat 8 imagery collection. Then the collected imageries were stacked using a mosaic of collected imagery and clipping of roi (region of interest). High-resolution satellite imagery were used for generating 500 training data in the form of points collection for the five different classes. We acquired training samples (random 75%) and validation samples (random 25%). The training points were collected from the whole area for each study period. Then the points were overlayed to obtain training samples. For overall accuracy assessment, confusion matrix, kappa coefficient, consumer accuracy, and producer accuracy were used for 1988, 1999, 2011, and 2023.

2.3.2. Random Forest (RF) machine learning

The RF machine learning algorithm is one of the most common techniques to enhance the precision and accuracy of satellite image classification for land cover analysis [58]. This method utilizes bagging, producing multiple predictors that collaboratively reach a final decision by aggregating votes of predictors. A random selection of training datasets and variables was used for generating multiple decision trees by RF. To establish a proper split for building a tree, RF selects variables at random from training samples at each node [59]. A simplified structure of an RF tree is shown in Fig. 4.

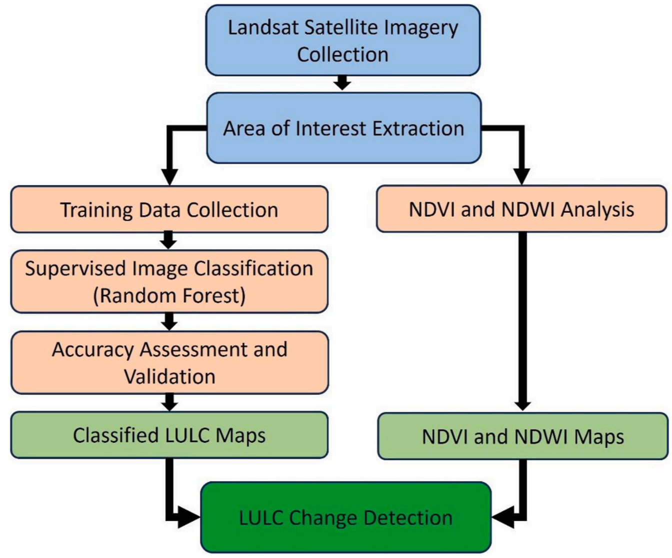

Fig. 2. Flow chart for the adopted methodology of LULC change detection.

We used the "smileRandomForest" as RF classifier machine learning algorithm for supervised image classification. Supervised classification utilizes the spectral signatures that are labelled training data which were obtained from training samples for classifying an image. The supervised learning model produces more accurate results than the unsupervised classification [60]. Here we used "ee.Classifier.smileRandomForest (numberOfTrees, variablesPerSplit" algorithm for classifier model building. We performed supervised classification and data validation using 70% of training data and 30% of testing data, respectively. We used different coloured palettes such as yellow for agriculture, green for vegetation, red for built-up, blue for waterbodies, and grey for barren lands. Subsequently, LULC classified maps were prepared for the years 1988, 1999, 2011, and 2023 from GEE with distinct five classes.

2.4. Accuracy assessment of LULC maps

Accuracy assessment involves verifying classified images to determine the quality, precision, and suitability of the produced maps [48]. Most common metrics like training error matrix, overall accuracy, Kappa coefficient, producers accuracy, consumers accuracy, validation accuracy, and validation error, are employed to assess the accuracy of the classified images [27]. For example, the Kappa coefficient determines the classification quality by comparing it against a randomly generated image. Kappa coefficient value ranges from 0 to 1, where 0.61–0.80 refer to significantly accurate, while values from 0.81 to 1 indicate nearly perfect [21]. Meanwhile, the error matrix provides

Table 1
Acquired satellite data properties.

Satellite	Date of Image Acquisition (dd/mm/yy)	Name of Sensor	Spatial Resolution (m)	Temporal Resolution (Days)	% Cloud coverage	Selected Parth/Row
Landsat 5	19/02/1988	TM	30	16	3	137/ 044
	17/02/1999	TM	30	16	3	137/ 044
	02/02/2011	TM	30	16	3	137/ 044
Landsat 8	03/02/2023	OLI/TIRS	30	16	3	137/ 044

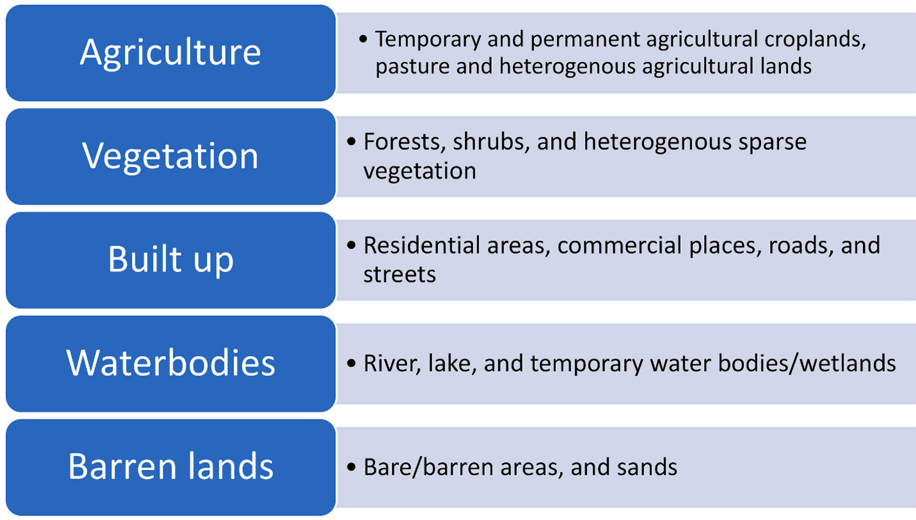

Fig. 3. Description of LULC categories used in the classification.

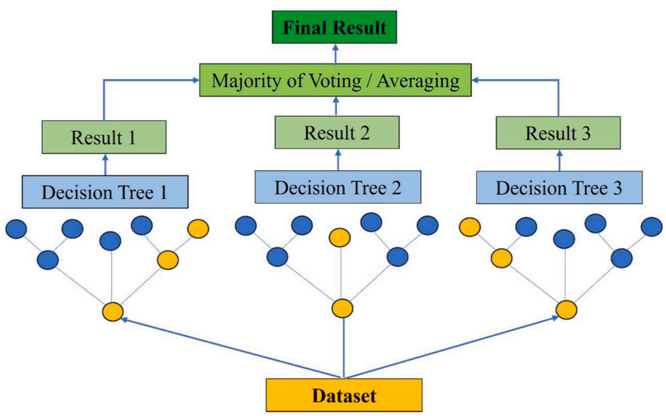

Fig. 4. Structure of an RF Tree adopted from [63].

insight into whether the sample classification for each LULC class is performed correctly or incorrectly.

2.5. LULC map generation using ArcGIS

We utilized ArcGIS 10.8 software for image processing to produce geo-referenced maps for this study. At first, we imported the LULC classified tiff images into the ArcGIS catalogue. Then we changed the symbology from stretched to unique values to get five distinct classes such as agriculture, vegetation, built-up, waterbodies, and barren lands, and to obtain LULC maps for 1988, 1999, 2011, and 2023. Then we convert the raster image into a vector (polygon) using the conversion tool 'Raster to Polygon' tool. We projected the dissolved feature in the coordinate system (WGS 1984 UTM Zone 45 N) to produce the LULC maps. Finally, we calculated the area of five classes in the attribute table. Finally, we changed the colour ramp in the tiff images to produce NDVI and NDWI maps with the desired colours for the same period.

2.6. NDVI and NDWI analysis

The NDVI which is a globally recognized tool, has been extensively utilized in previous studies to monitor seasonal and inter-annual fluctuations of crop growth [27,61]. On the other hand, the NDWI is a remote sensing-based indicator that can determine vegetation water content. It is particularly useful to identify open water sources [27]. NDWI also provides valuable indices for monitoring drought, water stress, and land degradation [62]. Both NDVI and NDWI are dimensionless, with values ranging between −1 and + 1 [48]. Higher NDVI values denote robust vegetation coverage, while negative values indicate the presence of water. Elevated NDWI refers to high water content in the soil, whereas lower values suggest reduced moisture content in the soil. NDVI and NDWI are calculated from the following equations (1) and (2) [63]:

$$\mathrm{NDVI} = \frac{(NIR - RED)}{(NIR + RED)} \tag{1}$$

$$\mathrm{NDWI} = \frac{(GREEN - NIR)}{(GREEN + NIR)} \tag{2}$$

In the case of NDVI, NIR is the reflection in the near-infrared, and RED is the red region of the electromagnetic spectrum (EMS). On the other hand, for NDWI, NIR and GREEN are the reflections in the near-infrared and GREEN range of EMS. NDVI predominantly maps vegetation, whereas NDWI maps the water content of vegetation [27]. Specific bands from the images were utilized to derive NDVI and NDWI as described in Table 2.

3. Results

3.1. LULC change detection

The LULC maps were produced from the Landsat satellite imagery using the RF algorithm for the years 1988 (Fig. 5a), 1999 (Figs. 5b), 2011 (Fig. 5c), and 2023 (Fig. 5d). The results revealed significant changes in LULC transformation as recorded in Table S1 (Supplementary materials) and presented in Fig. 6.

During the study period, the agriculture area substantially changed from 1012 ha to 6594 ha, indicating an incredible increase of 551.8% over 35 years. This huge growth of agricultural area shifts from 5.0% in 1988 to 32.5% of the total land in 2023. In addition, the built-up area also increased by 155.6%. However, the rate of change was not always linear for all types of lands. In 1988, the agricultural area was 1012 ha which constituted 5.0% of the total land. From 1988 to 1999, the agriculture area decreased to 492 ha which was reasonable due to the devastating flood in 1998 [66]. However, from 1999 to 2011, there was a drastic increase from 492 ha to 6197 ha and a 6.4% increase in the following interval 2011–2023 to make it five times than the initial agriculture area that constituted 32.5% of the total land. This remarkable increase in the agriculture area was expected due to the numerous policy measures, technological supports, and economic incentives to

Table 2
Specific bands used in NDVI and NDWI equations.

Indices	Landsat 5 images	Landsat 8 images	Reference
NDVI	$\frac{NIR\ (Band\ 4) - Red\ (Band\ 3)}{NIR\ (Band\ 4) + Red\ (Band\ 3)}$	$\frac{NIR\ (Band\ 5) - Red\ (Band\ 4)}{NIR\ (Band\ 5) + Red\ (Band\ 4)}$	[64]
NDWI	$\frac{Green\ (Band\ 2) - NIR\ (Band\ 4)}{Green\ (Band\ 2) + NIR\ (Band\ 4)}$	$\frac{Green\ (Band\ 3) - NIR\ (Band\ 5)}{Green\ (Band\ 3) + NIR\ (Band\ 5)}$	[65]

expand crop intensification in the region [67]. On the other hand, the built-up area increased by 57.6%, 26.7%, and 28.0% for the period of 1988–1999, 1999–2011, 2011–2023 respectively. This steady increase in the built-up area is attributed to recent infrastructure development in that region, notably the impact of the new mega infrastructures such as the six-lane Dhaka-Bhanga Expressway and Padma Multipurpose Bridge [68,69].

Meanwhile, vegetation, waterbodies, and barren lands decrease significantly to transform into agricultural lands. For instance, during the study period, waterbodies went through substantial changes that showed a reduction from 2441 ha in 1988 to 675 ha in 2023, reporting a 72.4% decline. In addition, barren lands were recorded at 7753 ha (in 1988) which reduced to 2864 ha in 2023, reflecting a 63.1% decrease over 35 years. Similarly, vegetation area slightly decreased from 1988 to 2023 and was recorded as 8334 ha, and 8209 ha, indicating a reduction of 1.5%. A similar decrease pattern was reported in a previous study for the period of 1990–2017 [12]. This change in waterbodies can be ascribed to landfilling of waterbodies, sand deposition in the rivers, low annual rainfall, rapid population growth, and other anthropogenic factors [70,71]. Hence, even though notable agricultural land was converted into the built-up area in many places, a substantial surge in agriculture was achieved due to the gain from large fallow and waterbodies [20].

3.2. Accuracy assessment of LULC maps

Several metrics, such as training error matrix, Kappa coefficient, overall accuracy, producer accuracy, consumer accuracy, validation accuracy, and validation error were used to assess the accuracy level of the classified images in 1988, 1999, 2011, and 2023. 30% of validation reference points were randomly selected from the total samples for the assessment. The accuracy of the classified LULC maps was evaluated using Kappa statistics and overall accuracy, as described in Table 3. Notably, the overall classification accuracy was verified at 99% for each of the years: 1988, 1999, 2011, and 2023. The overall accuracy above 85% indicates excellent precision in the LULC classification [72].

3.3. Trend analysis of LULC categories

Linear regression analysis is an effective tool to understand the correlation between dependent and independent variables [44]. Fig. 7 indicates that independent variables such as waterbodies, barren lands, and built-up areas collectively account for around two-thirds of the variation in the dependent variable, agriculture.

To evaluate the relationships with agriculture versus barren lands, waterbodies, and built-up, correlation coefficient, R^2 values were derived from the linear equations, resulting 0.82, 0.64, and 0.74 respectively. In general, regression analysis confirms that the decrease in barren lands and waterbodies facilitates agriculture to flourish.

3.4. Spatial distribution of NDVI

Two indices, NDVI and NDWI, were used to enhance LULC identification and improve the accuracy of the classification. These indices effectively distinguished the selected five land cover features. NDVI is widely used for monitoring vegetation health [41]. Fig. 8 showcased the spatial distribution of NDVI values for four specified years, ranging from −0.36 to 0.73. Particularly, forest, shrubs, and agriculture areas were visible in the NDVI map, characterized by dark and light green hues, with values hovering around 0.4 or higher. In contrast, permanent waterbodies and temporary waterbodies appeared as light red to dark red with values below zero, while built-up areas appeared whitish to light red, indicating values slightly above zero.

Fig. 8a depicted lower NDVI values across most of the study area, indicating the LULC in 1988, while random higher values denote winter crops. Fig. 8b revealed increased areas with sparse vegetation of light green colour, alongside pockets of dark green indicating crops, possibly affected by the devastating flood in 1998. Fig. 8c and d illustrate expanded agriculture zones, with minor barren lands in the central and western sectors of the study area. The NDVI analysis highlighted a significant increase in agriculture and built-up areas over time. Similar findings were reported from another study utilizing the NDVI index [73]. Table 4 outlines the highest and lowest NDVI values recorded annually.

3.5. Spatial distribution of NDWI

NDWI serves as a significant indicator to represent crop water stress and helps to specify wetland change [41]. The study area was also assessed with the NDWI and found similar to those from NDVI. Fig. 9 illustrates the spatial distribution of NDWI values across four specified years, ranging from −0.61 to 0.51. These values indicated the presence of agricultural areas, vegetation coverage, barren lands, and areas with shallow or deep water.

Agriculture areas and vegetation appeared in white to light blue hues, indicating values from −0.61 to just below zero. Meanwhile, waterbodies were shown in dark blue, with values above zero, and built-up areas occurred in white to blue, with values slightly above zero. The spatial variability of NDWI values exhibited distinct fluctuations across different years.

In 1988, NDWI values were lower across most areas, except in the center and southeastern parts of the study area. By 1999, widespread areas were identified with sparse vegetation, reflected in lower values represented by light blue shades. In 2011 and 2023, NDWI values were consistently aligned with the LULC maps, showcasing transformations from barren lands and vegetation to agriculture.

4. Discussion

GEE is the most powerful freely accessible tool to acquire, process, and analyze geospatial data for the study area. To categorize LULC maps accurately, various machine learning algorithms such as Random Forest (RF), Support Vector Machine (SVM), and Classification and Regression Trees (CART) are used. In this study, RF efficiently classified different land use land cover types with >99% accuracy. RF showed a similar highest accuracy in previous investigations [74,75]. In addition, previous studies reported that the SVM and CART erroneously categorized forests, waterbodies, and barren lands as vegetation and built-up areas [58,59]. To validate RF outputs, NDVI and NDWI were also utilized in this study to accurately classify the land types [76]. NDVI and NDWI involved the creation of training points and polygons for each class. Each pixel within the polygon serves as a training sample, with a known assigned value. This allows for a comparison with classified pixels, enabling the assessment of errors and precision [77]. Although the

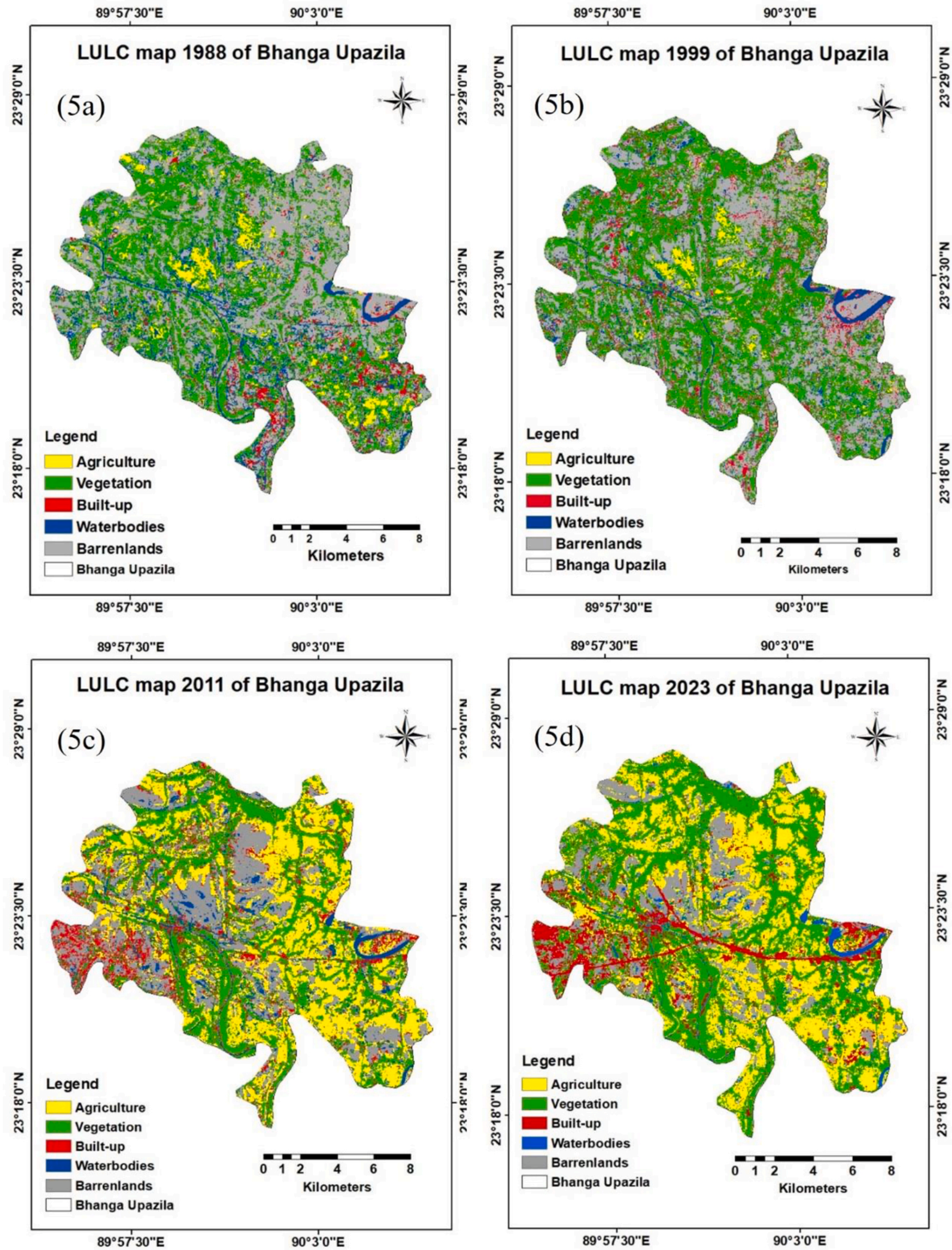

Fig. 5. Year-wise LULC classification maps in 1988 (4a), 1999 (4b), 2011 (4c) and 2023 (4d).

accuracy level was high, the agriculture land surge was compared with the historical field data to rationale the findings especially the increase of agricultural lands.

Historical ground data support this significant land transformation. For instance, irrigated Boro rice cultivation has been increasing enormously since the independence of Bangladesh in 1971 [53,56]. In the last few decades, huge areas were brought under agriculture due to the wide access to shallow and deep tube wells for proper irrigation [78] which boosted crop production in 2020–2021 compared to 2010–2011 as shown in Fig. 10. In addition, the introduction of new and sustainable stress-tolerant crop varieties (rice, mustard, wheat onion, etc.), crop diversification, modern machinery availability, and government

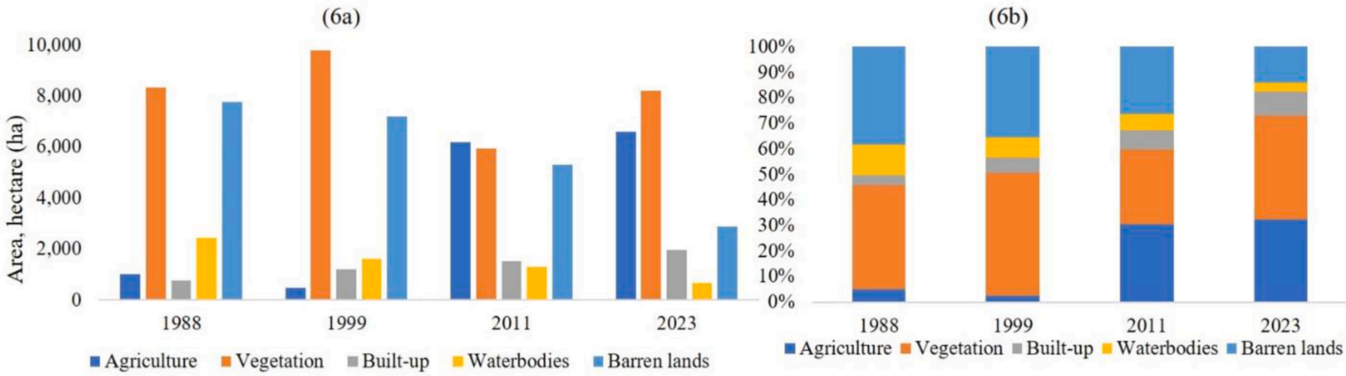

Fig. 6. LULC classes change over time (in 1988, 1999, 2011, and 2023) a) change in hectares; b) transformation in percentage.

Table 3
Overall accuracy and Kappa coefficient for year-wise training samples.

Year	Overall accuracy	Kappa Coefficient
1987	99%	0.99
1999	99%	0.99
2011	99%	0.99
2023	99%	0.99

subsidies and support for fertilizers and seeds availability have a substantial impact on crop intensification [56,79]. Despite the lack of historical data for the whole study period, Bangladesh experienced 3% growth in cropped land and 23.4% increase in selected crop production from 2010-2011 to 2020–2021 (Table S2 and Table S3), while Bhanga showed 6.4% increase in agriculture land from 2011-2023 (Table S1).

Another significant change has been recorded in the built-up areas, which increased by around 155.6% from 1988 to 2023. Almost at the same time, from 1991 to 2022, population growth in Bhanga was recorded by 36.4% as the population census reports [81–83]. Therefore, crop intensification was obvious to ensure the food security of the growing population, and the expansion of built-up areas indicated the livelihood pattern change among the inhabitants in the study area. Although built-up areas improve local livelihoods, ongoing land monitoring is essential for sustainable land usage and to mitigate any potential adverse impact of rapid urbanization. Hence, it is imperative to implement appropriate policies that ensure effective land use, thereby ensuring food security and fostering the economic development of the community.

5. Conclusion

The study employed GIS and spatiotemporal Landsat satellite imagery, along with NDVI and NDWI indices to analyze the land use and land cover dynamics in the Bhanga subdistrict, Bangladesh, spanning from 1988 to 2023. The quantitative assessment revealed an upward trajectory in agricultural lands and built-up areas, contrasted with a declining

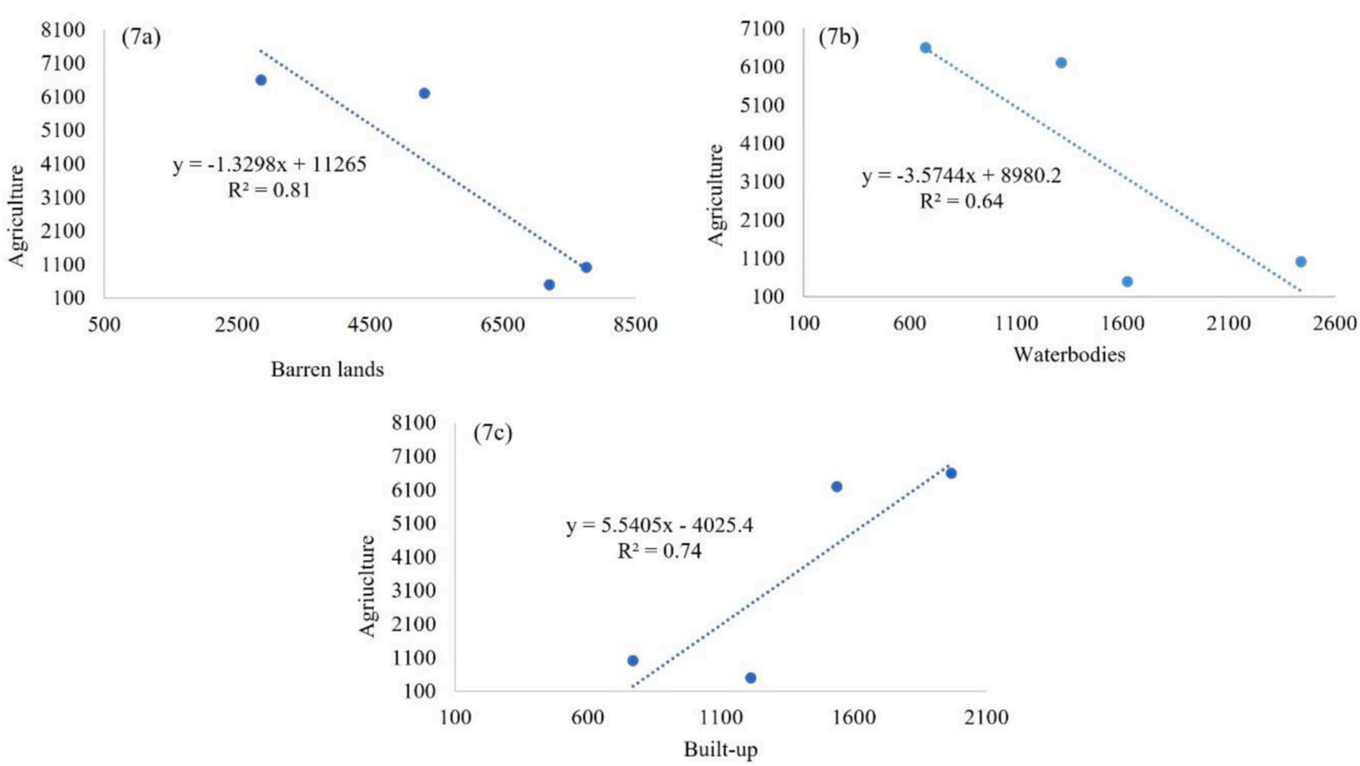

Fig. 7. a) Correlation between barren lands and agriculture; b) Correlation between waterbodies and agriculture; c) Correlation between built-up and agriculture Additionally, low R^2 values indicate the nonlinear LULC change during the study period.

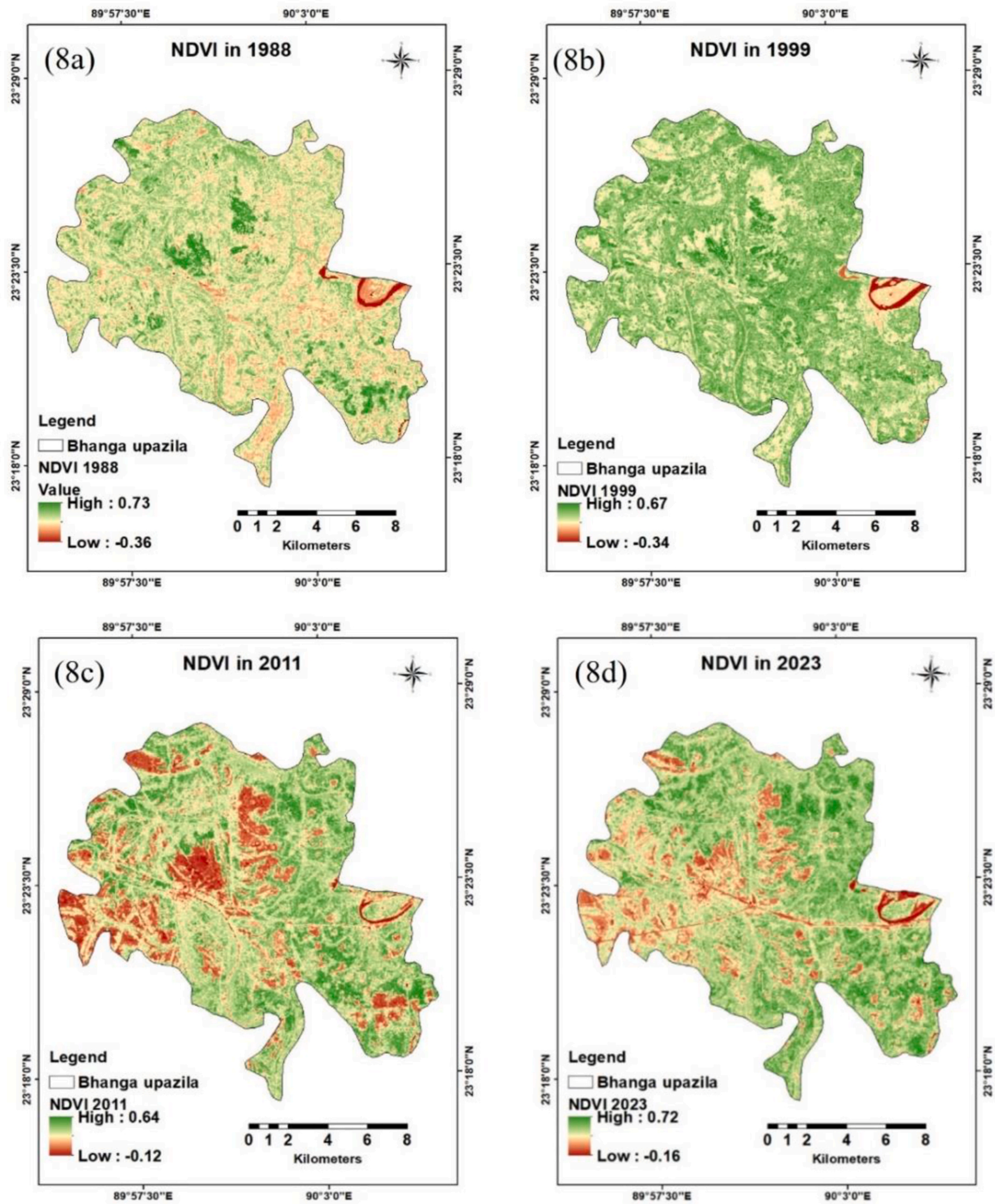

Fig. 8. Spatial distribution of NDVI for 1988 (8a). 1991 (8b), 2011 (8c) and 2023 (8d).

Table 4
Year-wise highest value and lowest value of NDVI and NDWI.

Year	NDVI		NDWI	
	Highest	Lowest	Highest	Lowest
1988	0.73	−0.36	0.51	−0.61
1999	0.67	−0.34	0.49	−0.56
2011	0.64	−0.12	0.22	−0.55
2023	0.72	−0.16	0.28	−0.61

trend in vegetation, waterbodies, and barren lands. This transformation indicates the direct impact of agricultural intensification in the study. The large expansion of agricultural lands owes credit to government support, and the introduction of high-yielding and climate-resilient new crop varieties and technologies disseminated by the Department of Agricultural Extension (DAE). This crop intensification significantly boosted crop production, ensuring greater food self-sufficiency. In contrast, more than half of the waterbodies were disappeared, which could be alarming for biodiversity and the ecosystem. It could also be noted that remaining barren land utilization might be a way forward to

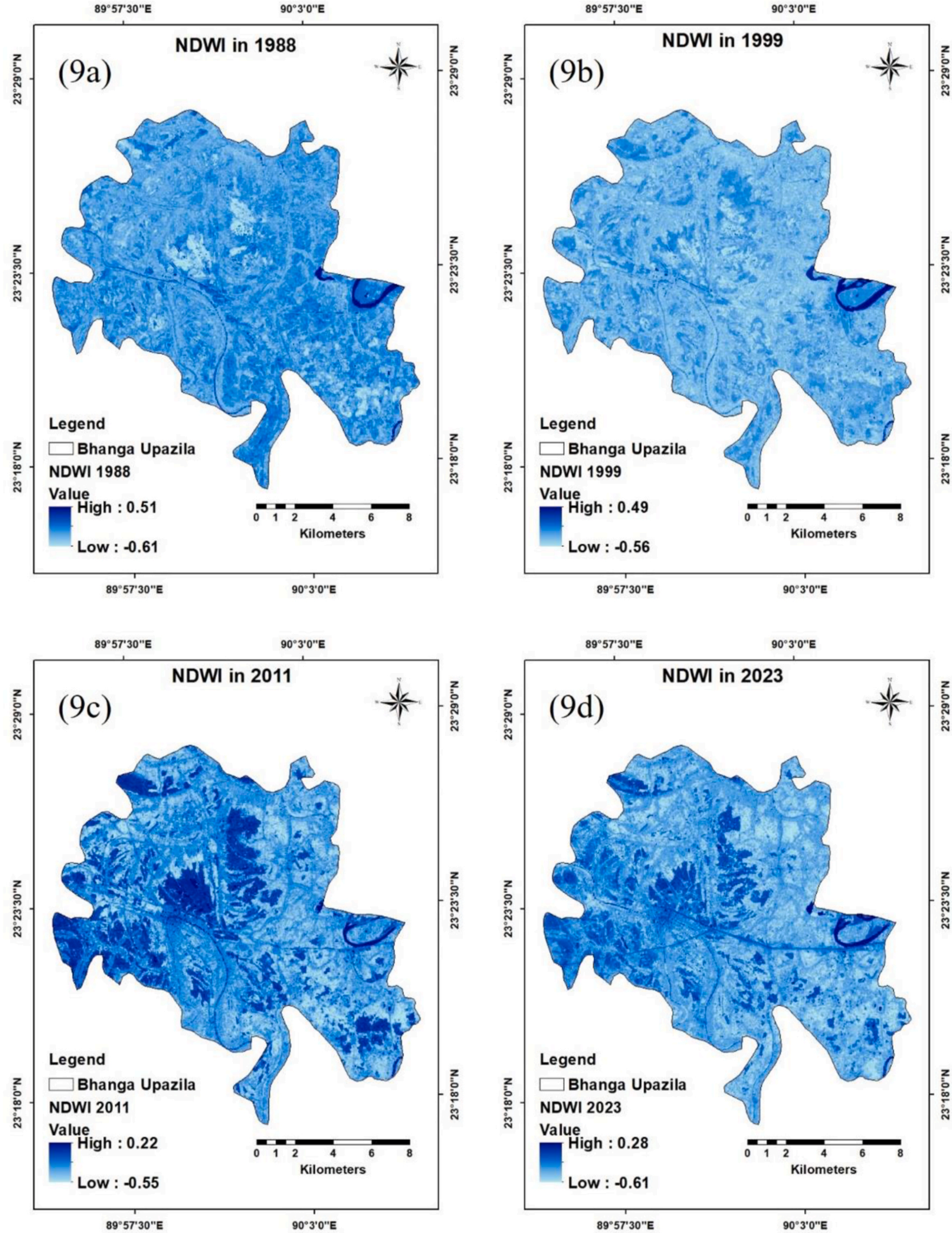

Fig. 9. Spatial distribution of NDWI for 1988 (9a), 1999 (9b), 2011 (9c) and 2023 (9d).

reduce future load on waterbodies and vegetation area coverages. This research highlights the crucial role of ongoing GIS and remote sensing-based monitoring to understand the land use change over the time to facilitate informed policymaking decisions for sustainable agricultural planning.

Most past studies were focused on climate-vulnerable regions, where agricultural land predominantly experienced a significant decline. That trend, however, does not represent the entire landscape of the country. Hence, the current study reports an opposite but positive trend, emphasizing the need for continuous monitoring of land use change to tailor region-specific initiatives instead of adopting generalized strategies to ensure food security and sustainability.

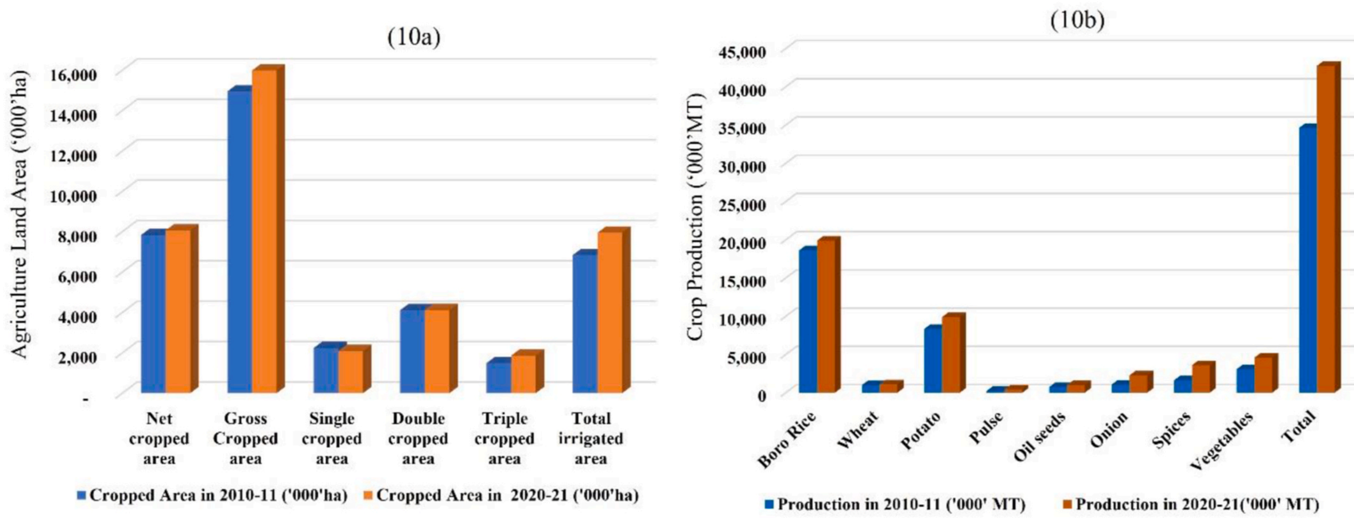

Fig. 10. a) Actual cropped area change (national) and b) Actual production increase statistics (national) for 2010-11 Vs 2020–21 [56,80].

By offering valuable insights, this study proposes actionable recommendations for policymakers. This finding can pave the way for sustainable agricultural development in Bangladesh. It is also imperative to adopt proper policies that account for region-specific variations in land use to ensure resilience and sustainable growth in the face of evolving environmental consequences.

Although there are many other methods to determine the LULC change, our methods have been demonstrated to produce comparable results with minimum efforts that can be adopted for a similar scope around the world. Nevertheless, we acknowledge the importance of utilizing other methods with onsite validation. To prepare a more realistic decision-making inputs, continuous LULC change monitoring using geospatial technologies needs to continue with bigger samples including severely climate-vulnerable and less vulnerable regions.

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CRediT authorship contribution statement

Mst Irin Parvin: Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Md Anwarul Islam:** Writing – review & editing, Project administration, Conceptualization. **Mst Farida Perveen:** Writing – review & editing, Supervision, Resources. **Md. Roushon Jamal:** Writing – review & editing. **Md. Jamal Faruque:** Writing – review & editing. **Billal Hossen:** Writing – review & editing, Methodology, Data curation. **Khayrul Islam:** Writing – review & editing, Visualization, Validation, Software, Formal analysis. **Md. Manik Sarker:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cscee.2024.100660.

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