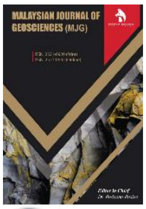
ZIBELINE INTERNATIONAL™ PUBLISHING

ISSN: 2521-0920 (Print)
ISSN: 2521-0602 (Online)
CODEN: MJGAAN

Malaysian Journal of Geosciences (MJG)

DOI: http://doi.org/10.26480/mjg.02.2024.163.172



RESEARCH ARTICLE

ASSESSMENT OF THE ALTERATION IN LANDUSE LANDCOVER DYNAMICS USING GIS APPROACH IN A REMOTE DISTRICT IN BANGLADESH: A CASE STUDY IN KURIGRAM DISTRICT, BANGLADESH

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ARTICLE DETAILS

Article History:

Received 23 June 2024
Revised 18 July 2024
Accepted 29 August 2024
Available online 11 September 2024

ABSTRACT

Land use and land cover alterations have profound implications for environmental sustainability and socio-economic development, particularly in regions experiencing rapid urbanization and population growth. This research investigates the dynamics of land use and land cover (LULC) in Kurigram District, Bangladesh, over a period of three decades from 1994 to 2024. The objective of this research is to assess changes in land use land cover patterns, with a particular emphasis on urbanization, agricultural practices, forest cover, and water bodies, and their implications for environmental management and regional development. Utilizing four sets of Landsat satellite imagery from 1994, 2004, 2014, and 2024, the research employs a combination of unsupervised classification, NDVI, and MNDWI techniques to map as well as analyze LULC dynamics. Findings indicate significant modifications in LULC dynamics between 1994 to 2024. Water bodies experienced a gradual decline, losing approximately 8,198.66 hectares over the study period, yet maintaining a consistent percentage of total land cover. Forest area fluctuated, peaking in 2014 before declining in 2024, while agricultural land showed notable variations, ranging from 39.69% in 1994 to 68.77% in 2024. NDVI and MNDWI analyses show declining water bodies (10.72% to 7.81% by 2024), fluctuating mixed land cover (30.32% to 26.27%), and dynamic agricultural land changes (39.69% to 68.77%). MNDWI reveals stable water areas (7.50% to 10.57%) and minor land fluctuations (89.43% to 92.50%), indicating terrestrial dominance over time. For accuracy assessment, the study compared a 2024 classified image with 40 ground truth data points, achieving a 90% overall classification accuracy. Utilizing Kappa Coefficient, the study found a substantial agreement (0.8703) between classified and referenced data, affirming 64% to 81% accuracy in the unsupervised classification, ensuring reliable LULC mapping results. The findings emphasize the importance of monitoring and addressing LULC changes to ensure environmental sustainability and socio-economic resilience, environmental management, urban planning in rapidly developing areas like Kurigram District.

KEYWORDS

Land cover dynamics, Satellite Images, Unsupervised Classification, NDVI, MNDWI, Accuracy assessment, Kurigram.

1. INTRODUCTION

Land use and land cover alteration plays a pivotal role in influencing climate systems, ecosystem functions, biogeochemical cycles, biodiversity, and various human activities around the globe (Agarwal, 2002; López et al., 2001). Recently, research on land use and land cover change has become integral to global change and global warming studies, examining diverse spatial and temporal scales (Aguilar et al., 2003; Lambin, 1997). This heightened focus is due to the profound impacts of human activities, such as urbanization, and natural disasters like cyclones and floods, on ecosystems within land use areas, which directly affect the life and livelihood of common people around the world (Stow and Chen, 2002). Changes in land cover impact the distribution of energy, water, activities concerning agriculture, and geochemical exchange at different scales from local to global, thereby influencing the sustainability of natural resources and socioeconomic events (Vescovi et al., 2002).

The various factors contributing to land use and land cover alterations have been thoroughly researched and analyzed by scientists and researchers around the globe (Zeng et al., 2008; Geist, 2005; Agarwal et al., 2009; Lambin et al., 2001; Veldkamp and Lambin, 2001; Lambin, 1997). A group of scientists highlighted tropical deforestation, different types of land alterations, increased agricultural activities, urban growth, and the effects of globalization as the main drivers behind changes in land utilization and surface characteristics on both globally and regionally (Lambin et al., 2001). Additionally, economic and environmental factors significantly contribute to this notable transformation in land surface characteristics (Zeng et al., 2008; Aspinall, 2004). Recognizing that shifts in land cover are major environmental concerns worldwide, these transformations have far-reaching consequences for the future of our environment and how land will be used (Agarwal et al., 2002). Continuous and extensive research on land use and land cover classification patterns, and the consequent their socioeconomic and biophysical impacts across different geographic and temporal levels, is crucial due to the dynamic and ongoing nature of this process (Lopez et al., 2001; Mondal et al., 2016).

Quick Response Code	Access this article online	
	Website: www.myjgeosc.com	**DOI:** 10.26480/mjg.02.2024.163.172

Cite The Article: Md. Fazle Rabbi Joy, Md. Bodruddoza Mia, Md. Abdur Rahim (2024). Assessment of The Alteration in Landuse Landcover Dynamics Using Gis Approach in A Remote District in Bangladesh: A Case Study in Kurigram District, Bangladesh. *Malaysian Journal of Geosciences, 8(2): 163-172.*

Satellite imagery has been extensively utilized by environmentalist and earth scientists to qualitatively and quantitatively assess terrestrial land use and land cover changes (Gopal et al., 1996; Collins and Woodcock, 1996; Coppin and Bauer, 1994). Remote sensing has proven effective in observing variability in land use and land cover, with particular emphasis on monitoring changes in vegetation and forest cover (MacLeod and Congalton, 1998). Research focusing on the alteration in different land cover types is vital for forest monitoring and comprehensive environmental oversight (Lal and Anouncia, 2015). The increasing focus on LULC classification research is driven by its ability to significantly influence large-scale environmental changes and its essential role in the effective and sustainable management of natural resources (Iqbal and Khan, 2014; Kantakumar and Neelamsetti, 2015; Lin et al., 2015).

The swift increase in Bangladesh's population has resulted in adverse impacts, including inadequate urban infrastructure, riverbank contraction, and loss of vegetated areas (Xu et al., 2020). This increase has happened without sufficient and sustainable planning, exacerbating environmental challenges. The uncontrolled expansion of urban slums, widespread poverty, waterlogging, traffic congestion, environmental degradation, and other socio-economic challenges stem from rapid population growth (Islam and Ahmed, 1970). It's crucial to assess the conversion of agricultural land to urban areas, along with changes in vegetation, water bodies, and wetlands to understand the nature and extent of these transformations. While many developing countries possess comprehensive and latest information on LULC changes, this is less common in underdeveloped nations such as Bangladesh. Remote sensing and GIS technologies are considered as a potential tools for assessing and comprehending the patterns of LULC changes in Bangladesh (Mamun et al., 2013).

Researchers in Bangladesh have extensively employed Geographic Information Systems (GIS) and remote sensing techniques to monitor land use and land cover (LULC) changes across various regions. A synthesis of previous studies reveals a diverse array of methodologies and considerations. For instance, a group researcher performed LULCC detection in Bangladesh between 2000 to 2010, utilizing Landsat TM imagery and applying object-based image analysis (GEOBIA), achieving an accuracy ranging from 89.70% to 96.14% (Xu et al., 2020). Similarly, a few researcher focused on Rajshahi, Bangladesh, from 1997 to 2017, utilizing Landsat TM and OLI/TIR data along with Maximum Likelihood Classification (MLC) method, obtaining an 87% accuracy (Kafy et al., 2019). In the Chunati wildlife sanctuary, utilized Landsat TM and OLI/TIR data from 2005 to 2015 and employed Maximum Likelihood Classification (MLC), yielding an accuracy range of 83.96% to 92.16% (Islam et al., 2018). A group researcher utilized Landsat and IRS satellite data from 1976 to 2010 for knowledge-based classification but did not specify accuracy (Rai et al., 2017).

Dewan and Yamaguchi conducted LULCC detection in Dhaka, Bangladesh, for different periods using Landsat MSS, TM, and ETM+ data, achieving accuracies between 85% to 90% and 85.20% to 91.60% respectively with MLC and Fisher Classifier methods (Dewan and Yamaguchi, 2009). Change detection studies were also prevalent, such as who applied Markov Cellular Automata to Landsat TM data from 1991 to 2008 in Dhaka, obtaining an accuracy of 49% to 61% (Islam and Ahmed, 2011). Hassan, examined multiple regions from 1973 to 2014 using various classifiers like Support Vector Machine (SVM), Artificial Neural Network (ANN), and Decision Tree (DT), with an accuracy ranging from 62% to 79% (Hassan, 2017). Ahmed, focused on Khulna from 1989 to 2019 using Landsat data and Fisher Classifier, achieving an accuracy between 85.89% to 92.78% (Ahmed, 2011). Furthermore, some researchers conducted change detection in Sunamganj from 1980 to 2010 using Landsat data and MLC method, with an accuracy ranging from 73.91% to 91.30% (Haque and Basak, 2017). A group researcher explored change detection in Dhaka from 1990 to 2010 with Landsat TM and ETM+ data using supervised classification, although accuracy was not provided (Mamun et al., 2013). These studies collectively demonstrate the diverse applications of remote sensing techniques in monitoring LULC changes across Bangladesh's landscapes (Xu et al., 2020; Kafy et al., 2019; Islam et al., 2018; Rai et al., 2017; Dewan and Yamaguchi, 2009; Islam and Ahmed, 2011; Hassan, 2017; Ahmed, 2011; Haque and Basak, 2017; Mamun et al., 2013).

The Kurigram district, the focus of this study, is pivotal in promoting agricultural diversification, significantly influencing the financial, societal, and cultural landscape of northwestern Bangladesh. This district contributes significantly to the national GDP, primarily from agricultural sector (UPPR, 2018; NEB, 2019). Additionally, Kurigram serves as a hub for various sectors, including culture, industry, education, and politics (Roy and Sarker, 2016). However, the region faces challenges such as agricultural degradation, rapid urbanization, and anthropogenic activities, placing immense pressure on local resources and leading to problems like land loss, scarcity of irrigation water during dry season, severe flooding during monsoon, lowering of groundwater level, internal migration due to riverbank erosion, pollution of biophysical ecosystem (Haque et al., 2019). Thereby, most of the researches conducted here mainly focused on flood zonation mapping, demarcation of groundwater, arsenic contamination, impact of climate change on agriculture, drought assessment (Roy and Sarker, 2016; Rana et al., 2022; Moni et al., 2019; Haque et al., 2019; Sultana et al., 2021; Kamruzzaman et al., 2018). Instead of these, being a Manga affected region, this area is far behind in terms of employment, education, and various social amenities. Therefore, several research works have also been done in this area focusing on food and nutrition security, internal-out migration of people, child marriage and other social factors (Ria et al., 2019; Guha et al.,2023; Islam et al., 2015; Hossain and Hossain, 2019; Faruque, 2021). However, there has been no research conducted to date on the long-term changes in land cover dynamics, distribution and mutual interactions of water bodies and landforms, and vegetation index.

Various methods are available for identifying and evaluating LULC types, with remote sensing and GIS methods being commonly employed by prominent researchers around the world (Dewan and Yamaguchi, 2009; Mallick et al., 2008; Mamun et al., 2013; Nemani and Running, 1997; Wang et al., 2009; Zhan et al., 2002). This study employs unsupervised classification and index-based methods (NDVI and MNDWI) to map land use and land cover changes in the Kurigram district using Landsat images over a period of three decades (1994-2024). This may represent a greater precision in depicting the land cover dynamics of the district. By generating NDVI and spatio-temporal change maps, the study aims to facilitate the analysis of vegetation cover changes and by MNDWI map may provide insights into the land-water dynamics within the investigated district from 1994 to 2024. Thereby, this investigation underscores the importance of systematically monitoring and understanding the dynamics of land cover change and its impacts on land and vegetation cover over time. It focuses on the period from 1994 to 2024 to capture recent changes, particularly significant urbanization and vegetation destruction. This timeframe was chosen due to the substantial scale of changes observed during this period compared to previous years.

Urban planners, stakeholders, and policymakers face resource shortages and limited access to timely urban information, leading to challenges in managing urban development (Hassan and Nazem, 2016). Empirical research shows increasing agricultural degradation and urbanization, resulting in diverse and fragmented land cover patterns, which negatively impact both living organisms and non-living environmental components (Qi et al., 2014; Wu et al., 2011; Hass et al., 2015). Therefore, this research can serve as a model for regional land cover dynamic studies in other parts of the country. The findings may help mitigate the risks of uncontrolled urban growth, which poses a threat to ecological balance at both community and regional scales.

2. Datasets and Methods

2.1 Study area

Kurigram District, located in the Rangpur Division of Bangladesh, spans an area of approximately 2296.10 km^2 including total land covers is about 276.45 km^2 between approximately 25° 45'N to 26° 40'N and 89° 40'E to 89° 53'E coordinates (Figure 1) (Roy and Sarkar, 2016; BBS). Known for its serene landscapes and fertile agricultural lands, Kurigram District is a vital agricultural hub and famous for its picturesque scenery, marked by lush fields and winding rivers, contributes to its natural beauty and economic significance. Within the study area, approximately 162,334.28 hectares of land are deemed cultivable, with a notable portion of 19,312.22 hectares designated as fallow. About 30% of the cultivable land sustains single crop cultivation, while 50% supports double crop cultivation, and the remaining 20% accommodates treble crop cultivation practices (Roy and Sarker, 2016).

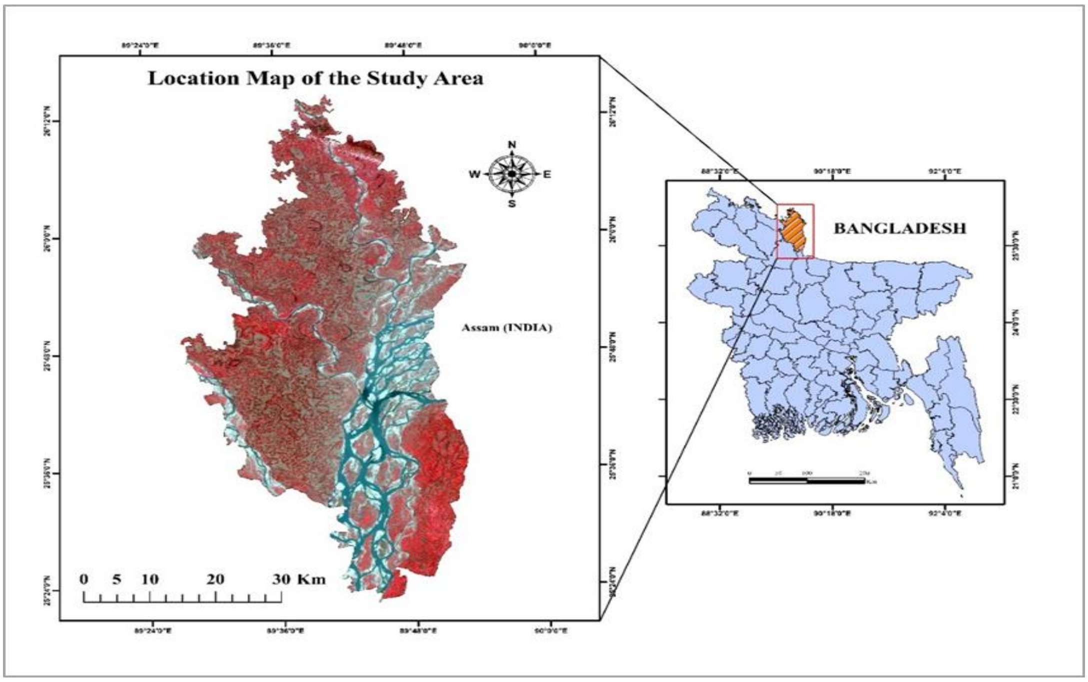

Figure 1: Multispectral satellite imagery of the study area, highlighting geographical features and water bodies. The backdrop utilizes a 2024 Landsat 8 OLI image, rendered with 5:4:3 RGB band combination. An inset map of Bangladesh indicates the location and extent of the study area.

The hydrological network of this district crisscrossed by a substantial array of rivers including Brahmaputra, Dharla, Tista, Dudhkumar, Phulkumar, Gangadhar, and Jinjiram, among others that are crucial in influencing the socio-economic fabric of the region contributing on agricultural production and often responsible for devastating floods (Roy and Sarkar, 2016). The district maintains an average elevation of 13 meters above MSL, experiencing a temperate climate throughout the year, with annual maximum temperatures reaching 90.14˚F and minimums of 52.16˚F, along with an annual precipitation total of 115.39 inches (National Encyclopedia of Bangladesh, 2020).

2.2 Data selection and acquisition

Due to minimal or low cloud coverage only, daytime images were selected for this study. Four sets of Landsat Satellite images (1994, 2004, 2014, and 2024) of the investigated region were obtained in GeoTIFF format from the USGS database (https://earthexplorer.usgs.gov/) (Table 1 were reprojected to Universal Transverse Mercator (UTM) zone 45N based on the World Geodetic System (WGS) 1984 datum. The limited availability of satellite images having a cloud coverage of less than 10% within defined path and rows hindered the collection of Landsat images at consistent time intervals. Both ERDAS Imagine 2015 and ArcGIS 10.8 software were utilized to perform image preprocessing and further analysis.

Table 1: Details of Landsat satellite Images acquired for the investigation

Year of Acquisition	Satellite Platform	Date of Acquisition	WRS Path and Row	Spatial Resolution
1994	Landsat-5 (TM)	15th April, 1994	138,42	30 m
2004	Landsat-5 (TM)	09th March, 2004	138,42	30 m
2014	Landsat-8 (OLI/TIRS)	21st March, 2014	138,42	30 m
2024	Landsat-8 (OLI/TIRS)	08th March, 2024	138,42	30 m

2.3 Methodology

2.3.1 Image pre-processing

The interpretation of satellite image is significant for having a precise, reliable picture and understanding of various properties depicted in the images. Thus, both radiometric and geometric corrections were done for the adjustment and enhancement of these images. Radiometric errors of satellite images result from atmospheric conditions, changes in solar radiation, and limitations in the precision of the scanning instruments. Hence, satellite images utilized in this study are radiometrically corrected for better visibility and representation of the original scene. Since, these acquired satellite images belong to Level 1 data, they have already undergone correction and orthorectification.

To implement layer stacking process, the bands must have identical spatial resolution. For this study, bands 1,2,3,4,5 and 6 of Landsat 5 along with bands 1,2,3,4,5,6 and 7 of Landsat 8 are stacked into a single image in ArcMap 10.8. The study area falls under a single image of different WRS path and row. Subsequently, the study area is chosen using the "extract by mask" tool. Subsequently the composite image sis beset into the study area utilizing the “extract by mask” tool to improve the motion of processing and analysis.

2.3.2 Unsupervised Classification Based LULC Mapping

The Unsupervised classification approach have applied in the following study to generate LULC maps for the years 1994, 2004, 2014 as well as 2024. This method is suitable as field information are limited which constraint the creation of individual class signatures. The ISODATA algorithm in ArcGIS 10.8 is highly regarded as an exceptional tool for exploratory pattern investigation, particularly in unsupervised classification, owing to its substantial flexibility and adaptability (Venkateshwarly and Raju, 1992). The ISODATA clustering algorithm was used to classify the image into 50 spectral classes, with a convergence threshold of 0.975 and a maximum of 30 iterations. Out of these, five spectral classes were chosen as the final information classes. (Table 2).

Table 2: Classification and description of LULC types in unsupervised classification

Classes (LULC categories)	Description
Water body	Encompasses both seasonal and permanent water bodies, including marshy areas and other wetlands.
Forest	Comprises tropical moist deciduous forests, and small orchards.
Agricultural Land	Land designated for cultivation, including areas that are plowed and seeded.
Bare Land	Consists of uncultivated, unstructured land and river char areas.
Settlement	Covers both urban and village residential areas.

2.3.3 Indices Based LULC Mapping

The Normalized Difference Vegetation Index (NDVI) and Modified Normalized Difference Water Index (MNDWI) indices are employed to assess biomass and vegetation health within a particular area (Alphan and Derse, 2013; Tan et al., 2012). NDVI and MNDWI values (between -1 to +1), are crucial for accurately classifying satellite images. Ensuring the accuracy of classification requires testing different threshold values and conducting a visual inspection of the satellite images (Jawak and Luis 2013). Thereby, for indices based Landuse-landcover mapping the NDVI and MNDWI were utilized to assess the vegetation and water cover features of Kurigram District.

NDVI quantifies vegetation by measuring the disparity between near IR light strongly reflected by vegetation, and red light, which is absorbed by vegetation. The calculation of NDVI follows the equation outlined (Rouse, 1974).

$$\text{NDVI} = \frac{NIR-RED}{NIR+RED} \tag{1}$$

For Landsat 5 (TM) and Landsat 7 (ETM+), band 4 and band 3 represents NIR and RED region respectively. While, band 5 and band 4 represents NIR and RED region respectively for Landsat 8.

Conversely, MNDWI proves to be a more appropriate index for improving and extracting data from water surfaces that are intertwined with built-up area and vegetation cover. (Singh et al. 2015; Xu 2006). It is determined by,

$$\text{MNDWI} = \frac{GREEN-SWIR}{GREEN+SWIR} \tag{2}$$

2.4 Accuracy assessment Calculation

Accuracy assessment is crucial for validating image classification authenticity. This involves ground-truthing in the study area. For LULC mapping, the unsupervised classified image of 2024 was compared with 40 randomly selected ground truth data points representing different LULC types. This comparison evaluated accuracy by matching the classified image's LULC types with the ground data. The reference data was obtained from field investigations and high-resolution images from Google Earth Pro. Additionally, for the 2024 classified image, an error matrix and kappa statistics were manually created where the error matrix allows for the determination of classification accuracy. In this matrix, columns represent the reference value classes ('user value'), and rows represent the classified image classes ('producer value'). The diagonal cells indicate correctly classified points for each class, while off-diagonal cells show misidentified pixels, indicating discrepancies between the reference and classified data.

In this investigation, the following formulas are used to compute the user, producer, overall accuracy, and Kappa coefficient:

$$\text{Producer's accuracy (\%)} = \frac{X_{kk}}{X_{tk}} \times 100 \tag{3}$$

$$\text{User's accuracy (\%)} = \frac{X_{kk}}{X_{kt}} \times 100 \tag{4}$$

$$\text{Overall accuracy (OA)} = \frac{1}{N} \sum_{K=1}^{r} n_i \tag{5}$$

$$\text{Kappa coefficient (k)} = \frac{N \sum_{K-1}^{r} x_{kk} - \sum_{K-1}^{r}(x_{kt}+x_{tk})}{N^2 - \sum_{K-1}^{r}(x_{kt}+x_{tk})} \tag{6}$$

The terms N, r, and x_{kk} in this formula denote the total number of pixels, the number of classes, and the sum of the pixels in rows "k" and columns "k," respectively. The subscription X_{tk} represents the total samples in column "k" of the error matrix, whereas X_{kt} represents the total samples in row "k".

3. Results

3.1 Identification and assessment of landcover dynamics from 1994-2024 using LULC mapping

LULC dynamics within the have undergone significant changes over the years, reflecting the interplay of natural phenomena, anthropogenic activities, and urbanization trends. The area covered by water bodies has experienced a gradual decline from 1994 to 2024, indicating a reduction of approximately 8,198.66 hectares over the study period (Table 3). Despite the decrease in absolute area, water bodies have maintained a relatively consistent percentage of the total land cover, ranging from 5.55% in 2014 to 10.86% in 1994 (Table 3 and Figure 3). Forest area has exhibited fluctuations, with an increase observed from 1994 to 2014 followed by a decline by in 2024. The forest area peaked at 53,799.84 hectares in 2014 before decreasing to 31,827.42 hectares in 2024 (Table 3). The percentage of forest cover is also varied, ranging from 12.94% in 2004, surging up to 15.60% in 2014 and then again witnessed a reduction to 11.84% in 2024 (Table 3 and Figure 3). Agricultural land has shown variations in area, with a notable decrease from 1994 to 2004 followed by a steady increase in the next 20 years. Despite the fluctuations, agricultural land remains a dominant land cover type, ranging from 46.44% in 1994 to 35.86% in 2024 (Table 3 and Figure 3). The area designated for settlement has consistently expanded over the years, indicating significant urbanization and population growth within the study area. The proportion of land designated for settlement has progressively risen over the years from 1.97% in 1994 to 5.37% in 2024 of the total land covers (Figure 3). The extent of bare land has fluctuated over the years, with a notable increase from 1994 to 2004 followed by a slow decrease in subsequent years. The area of bare land peaked at 62,228.66 hectares in 2004 before declining to 44,389.33 hectares by 2024 (Table 3 and Figure 3). The percentage of bare land has also varied, ranging from 46.42% in 2004 to 41.26% in 2024 (Table 3 and Figure 3).

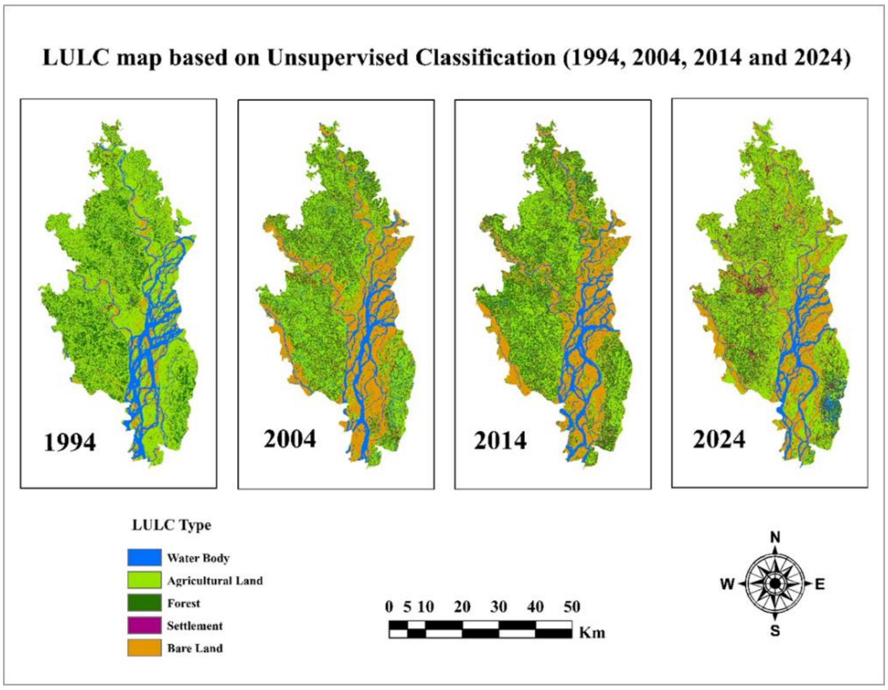

Figure 2: Land Use and Land Cover (LULC) maps for the years 1994, 2004, 2014, and 2024 illustrate the spatial distribution and changes in various LULC types over three decades within the study area.

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Table 3: Summary of LULC changes between 1994 to 2024 showing areas (in hectares) and percentages of various LULC types, along with the percentage changes between consecutive years. A positive (+) sign denotes an increase in land area, while a negative (−) sign indicates a decrease.

LULC Type	1994		2004		2014		2024		% Change (1994-2004)	% Change (2004-2014)	% Change (2014-2024)
	(ha)	**(%)**	**(ha)**	**(%)**	**(ha)**	**(%)**	**(ha)**	**(%)**			
Water Body	30,393.08	13.39	25,376.95	10.06	24,204.68	10.67	22,194.42	9.78	-3.33	0.61	-0.89
Forest	44,698.87	19.72	44,029.29	11.26	53,799.84	23.7	31,827.42	14.02	-8.46	12.44	-9.68
Agricultural Land	129,722.48	57.18	86,816.12	29.59	81,298.57	35.97	111,480.19	49.14	-27.59	6.38	13.17
Settlement	5,472.72	2.41	8,346.42	3.88	11,277.56	5.01	16,822.08	7.42	1.47	1.13	2.41
Bare Land	16,595.29	7.31	62,228.66	45.2	56,127.79	25.65	44,389.33	19.64	37.89	-19.55	-6.01

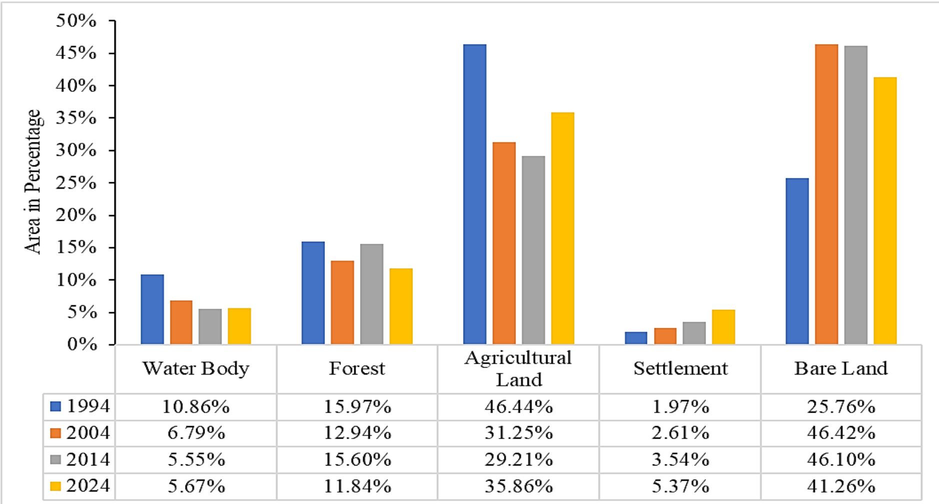

Figure 3: Bar diagram illustrating the percentage distribution of Land Use and Land Cover (LULC) types within the study area for the years 1994, 2004, 2014, and 2024 includes categories such as Water Body, Forest, Agricultural Land, Settlement, and Bare Land, highlighting the changes over time.

3.2 Evaluating Changes in LULC Patterns and Dynamics based on NDVI

The area covered by water bodies has experienced a gradual decline from 22,916.61 hectares in 1994 to 15,679.98 hectares in 2024, reflecting a reduction of approximately 7,236.63 hectares over the study period (Table 4). In relation to this, the overall area occupied by water bodies has declined from 10.72% in 1994 to 7.81% in 2024, indicating a diminishing proportion of water bodies within the landscape (Figure 5). Mixed land cover, characterized by a combination of different land cover types, has shown fluctuations in absolute area, ranging from 64,735.02 hectares in 1994 to 52,710.30 hectares in 2024 (Table 4). In terms of percentage, mixed land has ranged from 30.32% to 26.27% over the same period, suggesting a gradual decrease in the diversity of land cover types (Figure 5). Likewise, the agricultural land has exhibited dynamic changes, ranging from 84,687.03 hectares in 1994 to 138,043.71 hectares in 2024, indicating significant fluctuations in agricultural practices and land use patterns over the study period (Table 4). Percentage-wise, agricultural land has ranged from 39.69% in 1994 to 68.77% in 2024, highlighting its dominance as a primary land use activity within the study area (Figure 5). The area covered by vegetation, including forests and other green spaces, has also fluctuated significantly over the years, ranging from 54,444.78 hectares in 1994 to 20,349.45 hectares in 2024 (Table 4). Correspondingly, the percentage of vegetation has ranged from 19.27% to 9.15% during the same period, underscores changes in forest cover and vegetation density influenced by factors such as deforestation, urbanization, and climate variability.

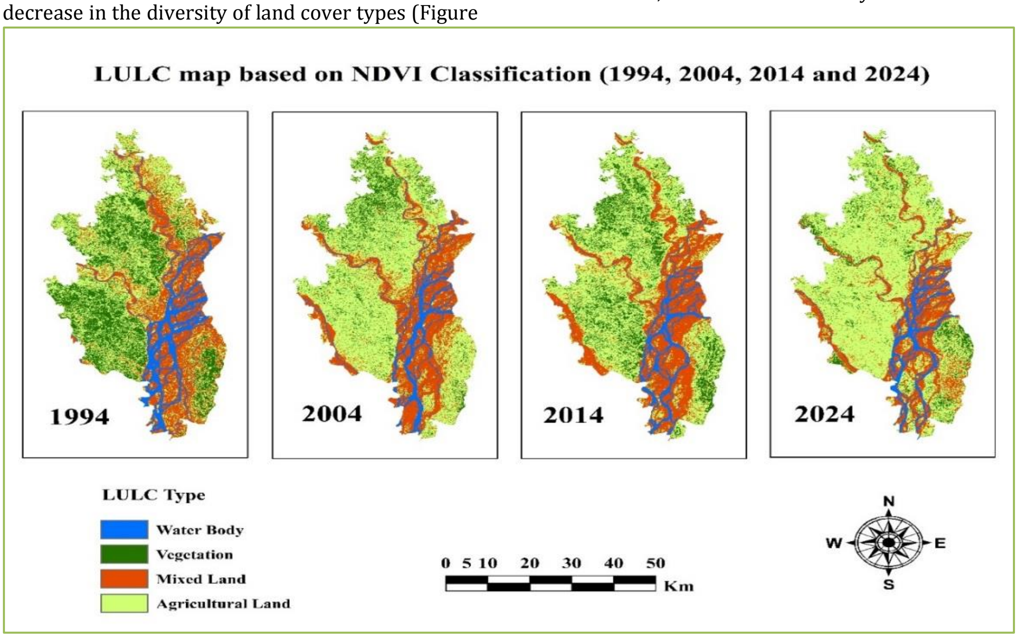

Figure 4: Land Use Land Cover maps of the study area for the years 1994, 2004, 2014, and 2024 produced using the Normalized Difference Vegetation Index (NDVI). The maps display changes in water bodies (blue), vegetation (green), mixed land (orange), and agricultural land (yellow) over time within the study area.

Table 4: Area distribution (in hectares) of different NDVI types within the investigated region for the years 1994, 2004, 2014, and 2024.

Year	Water Body	Mixed Land	Agricultural Land	Vegetation
1994	22,916.61	64,735.02	84,687.03	54,444.78
2004	16,930.08	68,005.89	118,015.11	23,832.36
2014	15,187.32	69,029.46	104,848.02	37,718.64
2024	15,679.98	52,710.30	138,043.71	20,349.45

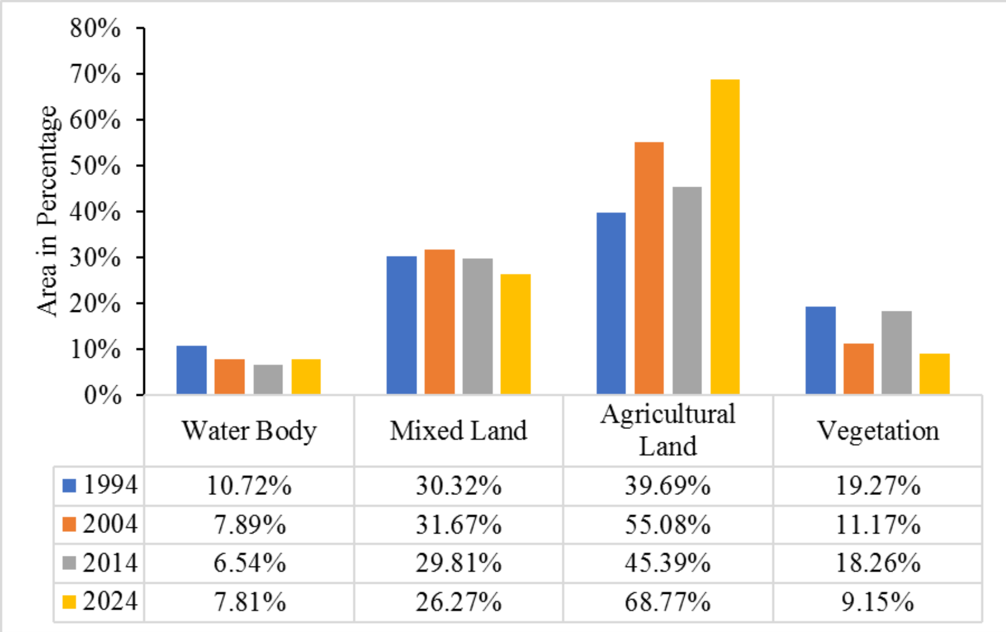

Figure 5: Bar diagram illustrating the percentage distribution of NDVI classes for the years 1994, 2004, 2014, and 2024, including categories Water Body, Mixed Land, Agricultural Land, and Vegetation, highlighting the changes over time.

3.3 Evaluating Changes in LULC Patterns and Dynamics based on MNDWI

The combined MNDWI table provides insights into the land-water dynamics within the study area. In terms of absolute area, the land area exhibited minor fluctuations with a slight increase from approximately 202,866 hectares in 1994 to 209,768 hectares in 2014 before decreasing slightly to 205,604 hectares in 2024 (Table 5). Conversely, the water area remained relatively stable, ranging from 23,917 hectares in 1994 to 21,179 hectares in 2024 with minor variations observed in between (Table 5).

Thereby, it is evident from MNDWI the land cover is dominant constituting approximately 89.43% to 92.50% of the total area (Figure 7). While, water cover representing a smaller proportion from 7.50 to 10.57% suggesting the predominance of terrestrial landscapes over the years (Figure 7).

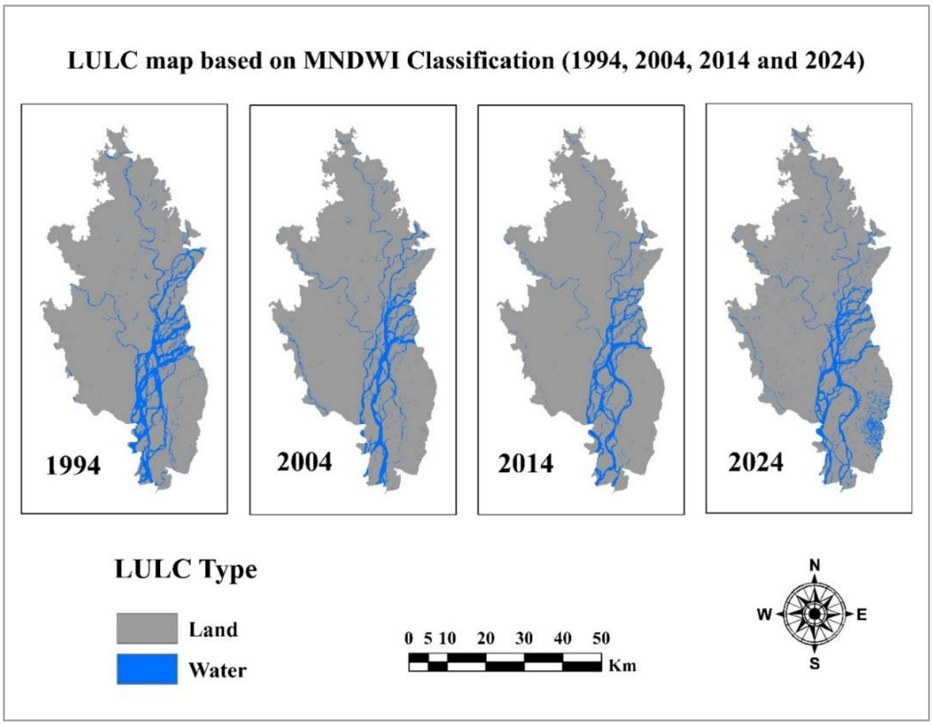

Figure 6: LULC map based on MNDWI Classification (1994, 2004, 2014, and 2024), illustrating the distribution of water bodies and land over time within Kurigram district. The blue areas represent water bodies, while the grey areas represent land. This classification highlights the changes in water coverage over the years.

Table 5: Area distribution (in hectares) of MNDWI types within the investigated region for the years 1994, 2004, 2014, and 2024.

Year	MNDWI (Hectares)		MNDWI (%)	
	Land	**Water**	**Land**	**Water**
1994	202,866.03	23,917.41	89.43%	10.57%
2004	209,233.80	17,549.64	92.26%	7.74%
2014	209,767.68	17,015.76	92.50%	7.50%
2024	205,604.28	21,179.16	90.66%	9.34%

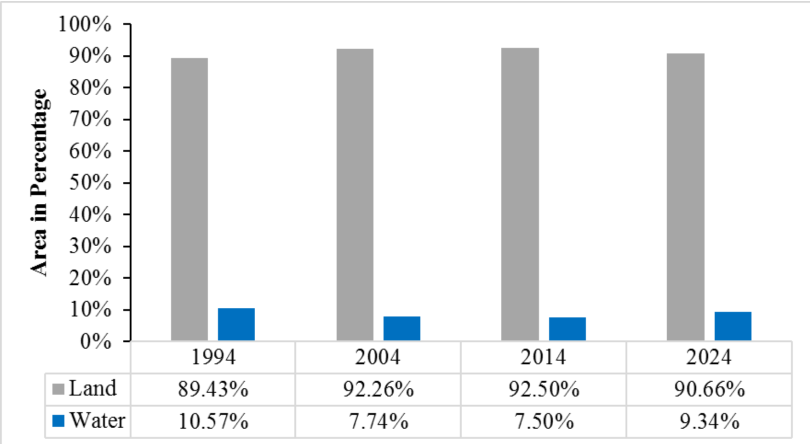

Figure 7: Bar diagram illustrating the percentage distribution of water bodies and land over time (1994, 2004, 2014, and 2024) within Kurigram district.

4. Discussion

The study conducted through LULC mapping revealed notable shifts in land cover types over the years. Water bodies experienced a gradual decline in absolute area, yet their percentage of total land cover remained relatively consistent, suggesting a steady presence within the landscape. Conversely, forest areas exhibited fluctuations, with peaks observed in 2014 followed by declines in 2024, indicating dynamic changes in forest cover. Agricultural land showed variations in area, with fluctuations observed over the study period, highlighting the dynamic nature of agricultural practices. The expansion of settlement areas over time indicates significant urbanization trends and population growth within the study area. Additionally, fluctuations in bare land area suggest changing patterns of land use and potential environmental impacts. Further analysis using NDVI and MNDWI allowed for a more comprehensive understanding of land cover patterns and dynamics. NDVI analysis revealed fluctuations in vegetation cover, influenced by factors such as deforestation, urbanization, and climate variability. Meanwhile, MNDWI analysis provided insights into land-water dynamics, with minor fluctuations observed in land and water areas over the study period. Overall, the integrated analysis of unsupervised classification, NDVI, and MNDWI data provided a comprehensive understanding of LULC dynamics from 1994 to 2024. The combined findings from unsupervised classification, NDVI, and MNDWI analyses suggest a complex interplay of natural processes, human activities, and environmental changes shaping the land cover dynamics of the investigated Kurigram district. To evaluate the accuracy of LULC mapping, the 2024 unsupervised classified image was validated against 40 randomly selected ground truth points of various land cover types (Figure 8). This comparison, which involved matching the classified image with the ground data, revealed an overall classification accuracy of 90%, demonstrating high precision in the satellite imagery-based LULC mapping.

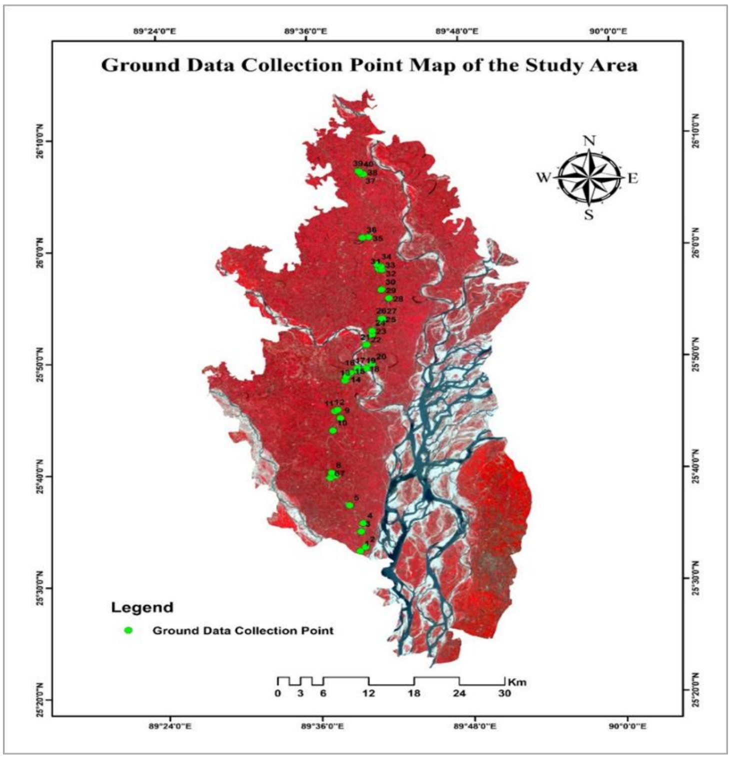

Figure 8: Map depicting the validation process of the 2024 unsupervised classified image against 40 randomly selected ground truth points of various land cover types for the LULC mapping accuracy assessment.

In this following investigation, the accuracy of the unsupervised classified image for the time frame of 2024 has calculated utilizing Kappa Co-efficient. Kappa statistics is a widely used method for assessing the accuracy of classified data by comparing it with reference data, taking into account the likelihood of agreement occurring by chance (Cohen, 1968). McHuhg, has interpreted the strength of agreement between referenced and user observed classified data based on the Cohen's Kappa Value (Table 6) (McHuhg, 2012). A Kappa value of "1" signifies nearly perfect agreement, reflecting the highest achievable accuracy and reliability. Conversely, a Kappa value of "0" indicates no agreement, representing the lowest level of reliability. Kappa values falling between these extremes denote varying degrees of agreement and reliability based on their numerical values.

Table 6: Logical interpretation of Kappa (McHugh, 2012)

Class	Referenced Total	Classified Total	Correctly Identified	Producer Accuracy	User Accuracy	Kappa Value
Water Body	4	4	4	100%	100%	1.00
Forest	8	8	7	87.50%	87.50%	0.84
Agricultural Land	12	13	12	92.30%	100%	0.94
Settlement	6	5	4	80%	66.67%	0.68
Bare Land	10	10	9	90%	90%	0.87
Total	***40***	***40***	***36***	***Overall Accuracy = 90%***		***0.8703***

The observed Kappa value is 0.8703 (Table 7) for the unsupervised classified image of 2024, which indicate substantial level of agreement between the classified and referenced data and signifies minimum 64% up to 81% (Table 6) of accuracy of the unsupervised classified image and further affirming the reliability of the LULC mapping results.

Table 7: Overall classification accuracy and overall kappa statistics of unsupervised classification of 2024 satellite image.

Kappa Value Range	Degree of Agreement	Data Reliability Percentage
0.0-0.20	No agreement	0-4%
0.21-0.39	Slight agreement	4-15%
0.40-0.59	Fair agreement	15-35%
0.60-0.79	Moderate agreement	35-63%
0.80-0.90	Substantial agreement	64-81%
Above 0.90	Almost perfect agreement	82-100%

5. Conclusion

The comprehensive analysis of land cover dynamics in the Kurigram District between 1994 to 2024 provides valuable insights into the changing landscape. The methodology employed, including image pre-processing, unsupervised classification, and indices-based mapping, facilitated a thorough examination of LULC patterns over time. The derived results reveal significant shifts in various land cover types, such as water bodies, forests, agricultural land, settlements, and bare land. Despite a gradual decline in the absolute area of water bodies, their proportion of total land cover remained relatively stable, suggesting a consistent presence within the landscape. Conversely, forest areas exhibited fluctuations, with peaks observed in 2014 followed by declines in 2024, indicating dynamic changes in forest cover. Agricultural land showed variations in area, highlighting the dynamic nature of agricultural practices. The expansion of settlement areas over time indicates significant urbanization trends and population growth within the study area. Fluctuations in bare land area suggest changing patterns of land use and potential environmental impacts. Further analysis using NDVI and MNDWI provided additional insights into vegetation cover and land-water dynamics, respectively. NDVI analysis revealed fluctuations in vegetation cover influenced by factors such as deforestation, urbanization, and climate variability. Meanwhile, MNDWI analysis indicated minor fluctuations in land and water areas over the study period, with the predominance of terrestrial landscapes. Accuracy assessment of the LULC mapping results, revealed a high level of accuracy, with an overall classification accuracy of 90% and a substantial level of agreement (Kappa value of 0.8703) between the classified and referenced data. Overall, the integrated approach of image analysis and classification techniques, combined with accuracy assessment, provided a comprehensive understanding of LULC dynamics in the Kurigram District over the past three decades. These findings are valuable for informing land management strategies, environmental conservation efforts, and sustainable development planning in the region.

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