

Detection and Prediction of Land Use Land Cover (LULC) Change and Ecosystem Service Due to Mega Project: A Case Study for Dhaka-Mawa Expressway

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Research Article

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Abstract

The Dhaka-Mawa Expressway, the first-ever expressway in Bangladesh, has significantly influenced land use and land cover (LULC) patterns, with major implications for the region's ecosystem services. This study investigates the LULC changes from 2000 to 2020 using Landsat satellite data and predicts future shifts up to 2040 through the CA-Markov model, focusing on the environmental impact of rapid infrastructure development. The study also evaluates the Ecosystem Service Values (ESV) by using the Ecosystem Services Valuation Database (ESVD). Nine upazilas (subdistricts) of five districts associated with the highway were chosen as the study area. Results show that from year 2000 to 2020, there was an increase in built-up areas amounting to 155.63 km². The increase of built-up areas took place at the cost of natural land covers through the loss of 92.33 km² of vegetation areas and 24.6 km² of water bodies. The study predicts that from 2020 to 2040 the urban area will increase by 67.12% and waterbodies and greeneries (vegetation + agricultural) will decrease to 16.66% and 18.97%, respectively. Between 2010–2020, among the selected areas, the most increase in urban development had happened in Zanjira (76.39%), and it also faced a major loss of agricultural land (53.88%), whereas Sreenagar had the major decrease in waterbodies (88.65%). These LULC changes have generated marked effects on ESV, which decreased by 14.96% from 2000 to 2020 and is still forecasted to further decline by 2040. Thus, the total ESV is expected to fall from \$362.18 million/year in 2000 to \$255.04 million/year by 2040, which accounts for a 29.6% reduction within the 40-year period. Water bodies, which provide the highest ecosystem services, are seen to decline by about 28.5% in ESV by 2040 due to urban encroachment. On the contrary, huge losses of ESV emanate from forested areas as a result of deforestation and expansion into agriculture. Indeed, this has pointedly called for integrated land management and policy intervention with a view to balancing infrastructural growth with environmental conservation. Predictive modeling of future LULC trends reveals further urbanization and hence sustainable urban planning is crucial for reducing negative impacts on ecosystem services.

1. Introduction

The term "land cover" refers to the material components that make up the earth's surface. These include vegetation, build-up regions, forest land, and all bodies of water [1], [2]. All these elements combinedly function the biophysical characteristics of the earth's surface and help the ecosystem to develop. Besides, any human activities on the earth's surface are referred to as 'land use'. These include agriculture activities, urban development, recreational activities, forestry, etc. [3], [4]. Both human activities and the natural environment comprehend the concept of LULC and there is also a level for the dynamics of LULC. Human activities entail infrastructure development, urbanization, deforestation, and agriculture [5], while natural processes include ecological succession, natural disasters, and climatic changes [6], [7]. These activities combinedly effect the urbanization, pattern of development, the ecosystem service, and even the microclimates. For effective urban planning and sustainable environmental management, it is essential to analyze the LULC patterns and predict them for the future.

Lambin et al. (2001) were among the first to show how changes in land cover were influenced by citizens' responses to economic expansion [8]. In recent years, developing countries have experienced an excessive quantity of development activities as well as population growth, which increased the rate and scope of LULC changes [9], [10]. The expansions lead to economic growth, which puts strain on land resources and hastens significant changes in the landscape. In Bangladesh, the significance of analyzing and managing LULC changes for sustainable development is on the rise as human populations continue to expand and the demand for land increases [11], [12], [13]. Decision-making in urban planning heavily relies on the examination of LULC changes and patterns [14].

Earth surface dynamic analysis, effective environmental monitoring, land use and land cover change analysis, and climate impact assessment have all made substantial use of remote sensing [2], [3], [11]. Recently, multiple research studies in Bangladesh have shown their interest in using geographic information systems (GIS), remote sensing, and the CA Markov model regarding land use land cover change analyses and prediction [16], [17], [18]. Islam and Ahmed (2012) [15] pioneered applying the GIS, remote sensing, and Markov Cellular Automata model to analyze and predict the land cover change in Dhaka city Bangladesh. They analyzed the trends from 1991 to 2008 and also predicted for the year 2020 and 2050. The main objective of their study was to aid the planning for a livable and habitable urban environment in Dhaka city. Another study was conducted in a lower region like Lakshmibaur-Nalair Haor by Bhattacharjee et al. (2021). By applying Landsat multispectral data and GIS tools, they found a considerable reduction in water bodies (both shallow and deep), vegetation, and cropland between 1989 and 2019 [16]. Similarly, Islam et al. (2024) used semi-automated classification in QGIS in Chittagong Metropolitan City to analyze the land use land cover change from 1990 to 2020 and ended up with the result in urban essentials and its implication [17].

The worldwide use of the CA-Markov model in LULC pattern analysis has also emerged. For instance, Radwan et al. (2019) showed the effect of urbanization on agriculture land in the Nile Delta. They found that, if the current pattern continues, it will cause a significant loss of agriculture and land by the year 2030 [18]. Another study was also done using the CA-Markov model in Jiangxi, China, to show the effective status of urban planning and resource management for the year 2036 by analysing the current land cover change pattern [19]. Besides, studies like Mehra & Swain (2024) applied artificial neural networks with cellular automation to forecast LULC and changes to find urban growth and conservation initiatives [10]. Research around the world considers Cellular Automata as a holistic and robust tool in terms of land use land cover change, and prediction analysis. It is a grid-based technique that considers a cell as a particular land use category [20], [21]. A finite number of parallelly evolving cells at discrete time steps make up cellular automata, which are discrete computing systems with finite states in both space and time. These abstract structures are called cellular automata and can serve as broad models of complexity [22], [23]. Besides, a Markov chain model is a type of stochastic process that examines the likelihood of a state changing into another; that is, it predicts a system's state at time t_2 based on its state at time t_1 [24].

Combining cellular automata and Markov chains can be a useful technique for analyzing current conditions and forecasting future events based on historical data on changes in land use and cover. By using the transition probabilities between many land use patterns throughout time, Markov Chain assists the CA model in forecasting future trends [25], [26], [27]. This local rule-based strategy is useful in complex spatial dynamics that define urban growth and landscape modification, as modifications in one place often create cascading repercussions in surrounding places [3]. As a result, multiple studies were conducted in several regions in the same context of land use land cover change around the world by using the combination of CA and Markov Chain Model [28], [29], [30],

[31]. However, the CA Markov models have some drawbacks, often implicit socio-economic and environmental factors due to their neighborhood effects. As a result, the capture of the eligibility dynamics can be limited, especially when analyzing a broader region [32]. Besides, the efficiency of LULC change models varies depending on the particular environmental circumstances of every research location [33]. Despite these setbacks, the CA model is one of the most used models to predict land use and land cover change due to its applicability in resource management, urban planning, effective simulation, and environmental conservation [21], [34]. Besides, along with the CA models, several popular techniques like the convolutional neural network model (CNN) and logistic regression (LR) model are also applied in combination with GIS and remote sensing to LULC prediction and change analysis [35], [36], [37].

The Padma multipurpose bridge and Bangladesh's first freeway, the Dhaka-Mawa freeway, are expected to increase the country's GDP by 1.23% and the southwestern region's GDP by 2.5%. [38]. To connect the Bangladesh capital Dhaka to the entire southern and southwestern part of Bangladesh (especially Barishal, Faridpur, Jashore, Khulna, and surrounding districts) [39]. According to the director of the Bangladesh Bridge Authority, more than 30,000 vehicles use this expressway every day, which has significantly reduced their travel cost and time and increased the transport ability of goods [40]. On the contrary, among the 110 billion BDT of total cost, 61.40 billion BDT was only responsible for land acquisition. As a result, they may also, nevertheless, result in the uprooting of nearby populations and modifications to the patterns of land ownership [8], [41]. Infrastructural development causes a great impact on its vicinities. Several factors, including agricultural land, forest land, built-up areas, waterbodies along the ecosystem, and microclimate, also face substantial changes Change [31], [42]. Besides, major infrastructure projects frequently lead to a substantial increase in urban area [43], [44]. This may result in the conversion of agricultural land, marshes, and forests into urban and industrial areas. Except that, changes in land use and cover can affect local and regional climatic patterns. The development of densely populated areas may lead to the formation of urban heat islands, which could potentially affect the local weather and climate. It is imperative to understand these changes in order to develop strategies for climate adaptation [45], [46], [47].

Assessing the effect of Dhaka-Mawa expressway on LULC is essential for subdivision planning, change detection of land use categories, and forecasting the future growth pattern of built-up areas.. Besides, LULC change and prediction analysis also necessitates applying environmental protection, ecosystem preservation, and environmental impact assessment for policy making [10], [47], [48]. This study consists of multiple objectives. It analyzes and explore the change dynamics of the subject area for the years 2000 to 2020. Then this study applies the CA-Markov technique with multicriteria evaluation (MCE) to predict the land use change for the years 2030 and 2040. Furthermore, this study evaluates the ecosystem service value (ESV) for the same time span.

2. Methodology

2.1 Study Area

The 55km long Dhaka-Mawa Expressway started from Jatrabari Interchange in Dhaka District (artery N8) and ends up in Bhanga Interchange in Bhanga, Faridpur District (artery N804/N805) [49]. The study covers all the 09 upazilas (subdistricts) of 05 concerned districts for this study that passed by the expressway which is expressed in Table 1. This motorway project has been completed with the construction of five flyovers, 19 underpasses, four railway overpasses, 25 bridges, four main bridges, 54 culverts, and two inter-changes [50]. This expressway has influenced several rivers like Padma, Kumar, Arial Khan, and Moynakata and a huge amount of agricultural land that could pose a change in land use ecosystem service value in the future.

Table 1
Districts and subdistricts covered by Dhaka-Mawa Expressway

Districts	Upazila/Thana	Union/Ward	Area (Sq/km)	Latitude	Longitude
Faridpur	Bhanga	12	215.30	23°23' N	89°59' E
Madaripur	Shibchar	19	332.90	23°21'N	90°10'E
Shariatpur	Zajira	12	246.21	23°16' N	90°26' E
Munshiganj	Lohajang	10	131.10	23°28'N	90°20'E
	Sreenagar	14	202.98	23°27'N	90°25'E
	Sirajdikhan	14	180.19	23°34'N	90°23'E
Dhaka	Jatrabari	5	13.19	23°42'N	90°20'E
	Keraniganj	12	166.87	23°37'N	90°13'E
	Kadamtoli	6	10.16	90°26'N	90°28'E
[49], [51], [52], [53]					

2.2 Data Used

The LULC classes of the study area were monitored and analyzed using remotely sensed data from Landsat series satellites [54], [55]. The quantification and analysis of land use and land cover changes necessitate the use of satellite images from different periods [56]. Various studies have shown substantial usage of satellite remote sensing. Landsat-5 Thematic Mapper (TM) - collection 1, level 1 image was collected for the years 2000 and 2010 [57]. Table 2 illustrates the data used in the study. The approach used in this investigation is shown in a flow chart in Fig. 2.

Table 2
Data source description

Sensor	Source	Dates	Spatial Resolution
Landsat 5 TM C1 Level-1	U.S. Geological Survey (https://earthexplorer.usgs.gov/)	December 16,2010	30
Landsat 8 OLI/TIRS C1 Level-1	U.S. Geological Survey (https://earthexplorer.usgs.gov/)	March 30, 2020	30

2.3 Classification of Land Use Land Cover (LULC)

The classification of the satellite images' land cover and land use was done using the combined image classification method. Both supervised and unsupervised methods are combined in this. The first step was unsupervised categorization, in which 50 basic classes were created using the improved satellite photos. Following the completion of this step, the composite raster bands are compared with reference data from Google Earth photos in order to identify and classify these classes. This was followed by the application of the re-code tool to manually fix the problematic locations. The entire image area is carefully examined, and any discrepancies are found by cross-referencing it with Google Earth and band combinations. When inaccurate classifications are discovered, the re-coding procedure is carried out once more, this time with accurate polygons formed around the impacted regions. This iterative approach yields a final, finely tuned categorized image once the required accuracy is attained. The approach improves classification accuracy by enabling manual involvement in situations where automated procedures are insufficient, in addition to offering flexibility.

2.4 Change Detection of Classified Image

The classified image was detected and labelled as different land use classes (Urban, Water Body, Agriculture, Forest and Bare Land). Table 3 depicts the description and appearances of these classes in satellite image.

Table 3
Classification scheme of LULC

LULC Type	Description	Appearance in Near-Infrared (NIR) Band
Urban	All man-made infrastructure- residential, industrial, commercial, road networks etc.	Light to medium gray due to lower vegetation content and more impervious surfaces.
Water Body	Rivers, lakes, ponds, reservoirs, and other standing or flowing water bodies.	Appears almost black in NIR, as water absorbs NIR light.
Agriculture	Farmlands, crop fields, etc. subject to seasonal changes.	Appears bright red in NIR, due to high reflectance of chlorophyll. Fallow or harvested fields may appear darker red or gray.
Forest	Dense areas of natural or planted trees and other vegetation.	Appears bright red in NIR, indicating healthy, dense vegetation with strong reflectance of NIR light.
Bare Land	Exposed soil, rocks, or construction sites.	Appears dark gray or black in NIR, due to low reflectance.

2.4.1 Image Processing and Improvement

In the process of composite raster formulation, all the bands of Landsat 8 imagery (1–7) were employed in several steps of enhancement. After stacking the layers, the spatial quality was enhanced by a 3x3 kernel edge enhancement convolution [58]. The black pixels, though not always visible, were removed to avoid complications. The refined image was prepared using the "Compute Pyramids and Statistics" tool, and unsupervised image classification was conducted with 100 classes [59]. After the classification, classes were identified, and colors were assigned by cross-checking band combinations with Google Earth images. Pixel numbers were re-coded to define class values, with manual adjustments for unfixed pixels. Cross-checking and corrections were repeated across the image to ensure accuracy, resulting in the final classified output [60], [61].

2.4.2 Accuracy Assessment of the Classified Image

The reference data for accuracy assessment is obtained from ground-referencing from Google Earth imagery [62]. To identify whether the product fits the needs of the intended application, accuracy assessment is a key phase for research [63]. Accuracy is measured as the user's accuracy and producer's accuracy. The user's accuracy is more of a map-based accuracy, whereas the producer's correctness is reference-based [64], [65]. Sampling strategies for accuracy testing include random, systematic, stratified, cluster, and systematic unaligned sampling, with random sampling offering precise statistical advantages.

In most cases, the stratified random sampling method is extensively used [66].

$$\text{Overall classification accuracy} = \frac{\text{Number of correctly sampled points}}{\text{Total number of points}} \dots\dots\dots (i)$$

The accuracy assessment process includes comparing class types of reference sources and class types of classified maps. The Kappa coefficient estimates the proportion of agreement from consideration after removing the chance agreement [67]. Kappa increases with the decrease of chance agreement. The kappa becomes zero when classified data and verified data are equal [68].

The formula of the kappa co-efficient of agreement is as follows (Stehman, 2010):

$$K = \frac{N \sum_{i=1}^r X_{ii} - \sum_{i=1}^r X_{i+} X_{+i}}{N^2 - \sum_{i=1}^r X_{i+} X_{+i}} \dots\dots\dots (ii)$$

Here, N = total number of observations

r = total number of rows and columns in the error matrix

X_{ij} = observation in row i and column j,

X_{i+} = marginal total of row i, and

2.4.3 Multi-criteria Evaluation with Fuzzy Operation

Multi-criteria evaluation (MCE) is a fundamental decision-support process in Geographic Information Systems (GIS) that provides valuable solutions for complex geographical decision problems [69]. MCE helps analyze trade-offs among choices (e.g., plans or sites) by considering socio-economic and environmental factors, yielding compromise alternatives, and ranking them by suitability. Decision-makers aim to identify the optimal location or solution by evaluating a limited set of alternatives based on multiple criteria and competing objectives [70]. MCE often converts criteria into Boolean statements or continuous numerical scales (e.g., 0–1, 0–100), a process known as standardization. Weighted linear combination (WLC), a common MCE method, requires weights summing to one, calculated using techniques like Saaty's principal eigenvector approach. These weights represent the relative importance of criteria in decision-making. In the TerrSet SDM interface, factors are standardized, added to the decision variable, and combined with Fuzzy operations defined by specific functions, shapes, and control points [71]. The MCE operator in TerrSet assigns weights using pairwise comparison to evaluate and prioritize alternatives effectively [72].

2.4.4 LULC Prediction Using LCM

The IDRISI Land Change Modeler (LCM) was used for change detection by analyzing two land cover maps from periods 1 and 2 [73]. The initial phase involved evaluating gains, losses, net change, persistence, and specific transitions through graphical and map-based tools [74]. The layers of roads and digital elevation model are offered as optional inputs in which the roads will be employed as a dynamic development base. Quantitative assessments of gains and losses were made by adding gains and subtracting losses from prior land cover areas [34]. Map changes and transitions were analyzed to provide spatial and quantitative insights.

A spatial trend analysis tool (3rd order) was used to interpret human-driven landscape changes. Transition potential grouped changes between the two maps into sub-models, each defined by explanatory variables and simulated using a multi-layer perceptron neural network [34]. The analysis focused on built-up areas, with explanatory variables comprising six static and five dynamic variables [34], [75]. The transition sub-model was run using these variables, and the resulting transition probability matrix informed the extent of changes. Soft prediction maps were generated to depict vulnerability to change for the identified transitions.

2.5 Ecosystem Service Value, Its Elasticity and Validation

2.5.1 Ecosystem Service Value

Ecosystem service valuation has been regarded as a globally significant tool for understanding the diverse benefits provided by natural ecosystems. Over the past few decades, extensive research has been conducted to assess the economic value of various ecosystem services, including those offered by tropical forests, endangered species conservation, and protected areas [76], [77]. These studies aim to quantify the environmental, social, and economic contributions of ecosystems to human well-being. Among the many approaches developed, the model introduced by Costanza et al. (1997) is widely recognized comprehensive and reliable method for estimating the ESV [78]. However, the method developed by Costanza et al. has received some criticism, especially for its reduced estimation of farmland unit. Nevertheless, the model remains one of the most comprehensive approaches for initial approximations of ESV.

The ecosystem service value is calculated for each land use type of the study based on the following equation as employed in earlier research [12], [79]. The calculated ESV generated the anticipation of changes in ecosystem services over the year.

$$ESV = \sum A_k \times VC_k \dots\dots\dots (iii)$$

Here, ESV = Ecosystem service value

$$A_k = A_k \text{ is the area in hectare for each LULC category 'k'}$$

$$VC_k = \text{the value coefficient (US\$ ha}^{-1} \text{ year}^{-1} \text{) for LULC type 'k'}$$

To determine the ecosystem service values for each of the five-land use and land cover (LULC) categories of the study area, these were aligned with categories with the 16 biomes identified by Costanza et al. (1997) [78]. Each LULC category was assigned the most relevant biome as a proxy for valuation purposes. For instance, the 'cropland' biome was matched with 'agricultural land,' the 'wetland' biome with 'water bodies,' 'tropical forest' with 'vegetation,' 'urban' with 'built-up areas,' and 'desert' with 'bare land.' LULC types, equivalent biome, and corresponding value coefficient are presented in Table 4.

Table 4
Biome equivalents for the five land-use categories and the corresponding ecosystem values
(US \$ ha⁻¹yr⁻¹)

Equivalent Biome	LULC Types	Ecosystem Service Value Coefficient (US \$ ha ⁻¹ yr ⁻¹)
Urban Green and Blue Infrastructure	Urban	0.00
Rivers and lakes	Water Body	14,785
Tropical forests	Vegetation	2007
Cultivated areas	Agriculture	92
Desert	Bare Land	0.00

2.5.2 Elasticity for the response of ESV of LULC change

Elasticity is originally a key economic concept used to measure the responsiveness of the changes in one variable to changes in another. This indicator is essential for understanding dynamics of dependence between variables and making informed decisions. The response of ESV with the changes in LULC was calculated in this study [80].

$$EEL = \frac{\left(\frac{ESV_{final\ year} - ESV_{initial\ year}}{ESV_{initial\ year}} \right) \times \frac{1}{T} \times 100\%}{LTP} \dots\dots (iv)$$

$$LTP = \sum \frac{\Delta LCA_i}{LCA_i} \times \frac{1}{T} \times 100\% \dots\dots (v)$$

Here, elasticity for the ESV response to LULC changes is denoted by EEL. This is calculated using the initial and final year of the economic service value. Furthermore, LTP refers to the percentage of land transition which shows the speed and degree of LULC changes. It is calculated using the converted area of each LULC category of each period.

2.5.3. Sensitivity Analysis

Initially, a similarity assessment was conducted between the five LULC categories and the 16 biomes identified by Costanza et al. [84]. Each LULC group was represented with the most similar biome. However, there are errors in the coefficient values used to compute ESV because these biomes are not exact matches for the LULC categories. Therefore, sensitivity analysis is essential to evaluate the extent to which changes in the coefficient values of specific LULC types influence the total ESV. The Coefficient of Sensitivity serves as a metric to assess the accuracy of biome representation and the reliability of the assigned value coefficients for different LULC categories.

The following standard economic concept of elasticity calculation was employed in this study (Hu, Wenjun, & Cao, 2008), (Rahman & Szabó, 2021):

$$CS = \frac{(ESV_j - ESV_i) / ESV_i}{(VC_{jk} - VC_{ik}) / VC_{ik}} \dots\dots (vi)$$

Here, *CS*= Coefficient of Sensitivity; *ESV* and *VC* stand for estimated total ecosystem service value and value coefficient, respectively; *k* denotes the specific LULC type, while *i* and *j* stand for the initial and adjusted values. To evaluate the impact of changes in value coefficients on total ESV, the value coefficient for each LULC category was adjusted by ± 50%, and the adjusted ESV and Coefficient of Sensitivity (*CS*) were calculated. *CS* quantifies the extent to which changes in a specific LULC type's value coefficient influence total ESV. If *CS* is less than 1, the estimated ESV is considered inelastic, indicating minimal sensitivity to value coefficient changes and reliable representation of proxies and estimated ESV. If *CS* exceeds 1, the *ESV* is deemed elastic and more sensitive to coefficient changes. Sensitivity analysis, as widely applied in previous studies, helps validate the reliability of *ESV* assessments by understanding the dependence of total *ESV* on value coefficient variations.

3. Results & Analysis

3.1 Change in LULC types

After conducting combined image classification, it was used to detect the change in different LULC types. Figure 3 shows the classified images of the years 2010 and 2020, indicating the five primary LULC types. Table 3–5 summarizes the LULC change statistics. Change analysis of five dominant LULC classes has been discussed in the following sections.

3.1.1 Changes in Urban Area

Tables 5, 6 and 7 represent the details of change between the time periods among the categories, while Table 8 depicts the change area-wise between 2010 and 2020. The analysis of multi-temporal Landsat images revealed a significant increase in urban areas over time. In 2000, Dhaka's urban area was 41.60 km², which increased to 50.30 km² in 2010 and further to 60.70 km² by 2020. Similarly, Bhanga saw a decrease from 43.31 km² in 2000 to 39.37 km² in 2010, followed by a sharp rise to 58.05 km² in 2020. This rise can be linked to enhanced economic opportunities driven by ongoing development projects [34]. The breakdown of changes in land use for different upazilas, as shown in Table 4 and Figure 2, highlights significant shifts in built-up areas. For example, Shib

Char experienced the most drastic increase, from 33.58 km² in 2000 to 51.15 km² in 2010, reaching 76.56 km² by 2020. This rapid urbanization is likely influenced by the proximity to the Padma Bridge project, which boosted connectivity to major urban centers. Although the Padma Bridge was under construction between 2010 and 2020, the already inaugurated Mawa-Bhanga expressway likely spurred early investments in land and infrastructure development [81]. Businesses and real estate developers anticipated future growth, leading to increased demand for housing, services, and retail spaces. Temporary settlements near the infrastructure project may have evolved into permanent urban areas as economic opportunities expanded. Smaller towns like Louhojong and Sreenagar saw moderate increases. Louhojong’s urban area grew from 17.27 km² in 2000 to 20.84 km² by 2020, while Sreenagar declined between 2000 and 2010 (from 34.40 km² to 18.46 km²) but slightly increased to 23.88 km² by 2020. These moderate changes may indicate a slower pace of urban expansion, possibly due to more rural characteristics or limited economic opportunities compared to larger areas [82].

3.1.2 Changes in Natural Area

The water body, agriculture, forest, and bare land are mentioned here as natural areas. Other than built-up/urban settlements, the natural areas have experienced extensive changes over the years. Between 2000 and 2020, water bodies decreased by 24.6 km², shrinking from 173.53 km² in 2000 to 148.93 km² in 2020, reflecting a 1.61% loss. From 2010 to 2020 alone, water bodies declined by 20.83%, from 188.12 km² to 148.93 km². This decline could be attributed to land reclamation for urban or agricultural purposes, or environmental factors such as reduced rainfall or groundwater depletion [83]. Agricultural land has seen growth over time. Between 2000 and 2020, it expanded by 76.66 km², increasing from 351.36 km² in 2000 to 428.02 km² in 2020, marking a 5% rise. During the 2010–2020 period, agricultural land grew by 16.66%, from 358.12 km² to 417.8 km². This increase likely reflects the growing demand for food production, leading to the conversion of forests or other lands into farmland [84]. It also suggests that agriculture remains a dominant activity in the region, potentially supported by government policies or improved infrastructure. However, forest cover (referred to as vegetation) has seen a substantial decrease. From 2000 to 2020, vegetation cover decreased by 92.33 km², falling from 510.13 km² to 417.8 km², representing a 6.02% loss. Between 2010 and 2020, forest cover dropped by 28.93%, declining from 602.27 km² to 428.02 km², indicating significant deforestation, possibly due to urban expansion, agricultural encroachment, and illegal logging [85]. This has severe environmental consequences, including loss of biodiversity and the degradation of ecosystem services. Finally, bare land experienced fluctuating changes. From 2000 to 2020, bare land decreased by 115.12 km², dropping from 331.77 km² to 216.65 km², a 7.51% reduction. However, between 2010 and 2020, bare land increased by 38.98%, rising from 155.89 km² to 216.65 km². This suggests temporary land use changes, such as cleared land awaiting development or agricultural use, or degradation due to deforestation and soil erosion [86].

Table 5
LULC change statistics between 2000 and 2010

	2000		2010		Change 2000–2010	
Land Use Category	Area (Km ²)	Area (%)	Area (Km ²)	Area (%)	Area (Km ²)	Area (%)
Urban	167.83	10.94	230.34	15.01	62.51	4.07
Water	173.53	11.31	188.12	12.26	14.59	0.95
Vegetation	510.13	33.24	358.12	23.33	-152.01	-9.91
Agriculture	351.36	22.89	602.27	39.24	250.91	16.35
Bare Land	331.77	21.63	155.89	10.16	-175.88	-11.47

Table 6
LULC change statistics between 2010 and 2020

	2010		2020		Change 2010–2020	
Land Use Category	Area (Km ²)	Area (%)	Area (Km ²)	Area (%)	Area (Km ²)	Area (%)
Urban	230.34	15.01	323.46	21.08	93.12	40.43
Water	188.12	12.26	148.93	9.70	-39.19	-20.83
Vegetation	358.12	23.33	417.8	27.22	59.68	16.66
Agriculture	602.27	39.24	428.02	27.89	-174.25	-28.93
Bare Land	155.89	10.16	216.65	14.12	60.76	38.98

Table 7
LULC change statistics between 2000 and 2020

Land Use Category	2000		2020		Change 2000–2020	
	Area (Km ²)	Area (%)	Area (Km ²)	Area (%)	Area (Km ²)	Area (%)
Urban	167.83	10.94	323.46	21.08	155.63	10.14
Water	173.53	11.31	148.93	9.70	-24.6	-1.61
Vegetation	510.13	33.24	417.8	27.22	-92.33	-6.02
Agriculture	351.36	22.89	428.02	27.89	76.66	5
Bare Land	331.77	21.63	216.65	14.12	-115.12	-7.51

Table 8
Area-wise Breakdown of LULC

Area	2010					2020							
	Urban	Water	Agriculture	Vegetation	Bare Land	Urban	Change	Water	Change	Vegetation	Change	Agriculture	Ch
Dhaka (portion)	50.30	11.56	47.26	77.67	29.71	60.70	20.66%	11.22	-2.94%	74.12	56.85%	42.44	-45
Bhanga	39.37	4.05	67.46	100.28	3.47	58.05	47.48%	2.25	-44.44%	74.74	10.79%	64.79	-35
Louhojong	18.51	24.25	24.26	42.70	30.08	20.84	12.60%	26.66	9.93%	34.82	43.54%	36.13	-15
Serajdikhan	22.86	8.40	55.52	66.83	20.34	28.91	26.47%	5.27	-37.26%	49.87	-10.17%	61.04	-8.1
Shib Char	51.15	26.06	77.82	144.05	33.83	76.56	49.73%	45.51	74.63%	78.08	0.33%	72.44	-49
Sreenagar	18.46	43.97	38.57	78.82	19.34	23.88	29.37%	4.99	-88.65%	47.94	24.30%	109.12	38.
Zanjira	30.91	69.56	47.17	91.21	19.40	54.52	76.39%	53.03	-23.74%	58.24	23.47%	42.06	-53

3.2 Land Use Prediction

Looking ahead, the trend of increasing urbanization is expected to continue. Based on predictions for 2030 and 2040, urban areas are projected to expand significantly [12]. By 2030, urban areas are expected to cover 414.47 km², accounting for 27.01% of the total land area. This trend is anticipated to further intensify by 2040, with urban areas potentially reaching 540.58 km², or 34.56% of the total land area. This growth can be attributed to ongoing development projects, population influx, and the increasing concentration of economic activities. Similarly, other land use categories are expected to shrink. Water bodies are projected to decrease from 148.93 km² in 2020 to 138.01 km² by 2030 (8.99%) and further down to 124.12 km² (7.93%) by 2040, likely due to continued land reclamation and environmental factors. Similarly, agricultural land is expected to decrease from 428.02 km² in 2020 to 374.11 km² in 2030 (24.38%), and eventually to 340.61 km² by 2040 (21.77%), reflecting a shift from rural to urban land uses driven by economic and infrastructural changes. Vegetation, which has already seen a decline, is also expected to continue decreasing, from 417.8 km² in 2020 to 395.21 km² in 2030 (25.75%), and to 344.71 km² by 2040 (22.04%). This reduction could be linked to deforestation for urban and agricultural expansion, further exacerbating environmental concerns such as biodiversity loss and ecosystem degradation. Bare land is projected to remain relatively stable, with a slight fluctuation between 2020 and 2040. It is expected to decrease slightly to 212.95 km² in 2030 (13.88%) and then marginally increase to 214.25 km² by 2040 (13.70%). These minor changes might reflect temporary land use transitions or the aftermath of urban and infrastructural development activities. Table 9, and Fig. 4 depicts the prediction statistics and visualization. The map in Fig. 5 is showing the transition potential from different land use to urban area.

Table 9
LULC Change Prediction

LULC Category	2030		2040	
	Area (Km ²)	Area (%)	Area (Km ²)	Area (%)
Urban	414.47	27.01	540.58	34.56
Water	138.01	8.99	124.12	7.93
Agriculture	374.11	24.38	340.61	21.77
Vegetation	395.21	25.75	344.71	22.04
Bare Land	212.95	13.88	214.25	13.70

3.3 Changes in Ecosystem Service Value

The percentage change of ESV was calculated for each land use category over the period from 2000 to 2040. The **equation (iii)** was used for the calculation of changes. Table 10, Fig. 6, and Fig. 7 provide the detailed results of the ESV for the periods and their spatial distribution, including the predicted years of

2030 and 2040. The total ecosystem service value (ESV) declined from \$362.18 million per year in 2000 to \$255.04 million per year in 2040, reducing 29.6% over the 40-year period. The changes from 2030 to 2040 are predicted based on land-use projections. Rivers and lakes, the largest contributors to ESV, initially increased in value by 8.41%, rising from \$256.56 million in 2000 to \$278.14 million in 2010. However, after 2010, a sharp decline occurred, with the ESV dropping by 20.83% to \$220.19 million by 2020. This trend is expected to continue, with projected declines of 7.33% between 2020 and 2030 and 10.07% between 2030 and 2040, leading to a predicted value of \$183.50 million in 2040. The cumulative loss of \$73.06 million (28.5%) over the study period can be attributed to the loss of waterbodies due to urban encroachment and the conversion of wetlands into other land uses.

Tropical forests also experienced significant reductions in ESV, beginning with a steep drop of 29.80% between 2000 and 2010, from \$102.38 million to \$71.87 million. Although there was a moderate recovery by 2020, with a 16.66% increase to \$83.85 million, the trend is predicted to reverse again. The ESV for tropical forests is projected to decrease by 10.46% between 2020 and 2030, followed by a further decline of 8.95% between 2030 and 2040, reaching a predicted value of \$68.36 million. This indicates that despite reforestation efforts, deforestation and land conversion may continue to negatively impact these ecosystems. Cultivated areas, while contributing a smaller portion of the overall ESV, showed substantial fluctuations. Between 2000 and 2010, the ESV for cultivated areas increased by 71.41%, from \$3.23 million to \$5.54 million, possibly reflecting an expansion in agricultural activities. However, this trend reversed after 2010, with a 28.93% reduction by 2020, bringing the ESV down to \$3.94 million. Predicted values suggest further declines of 7.66% between 2020 and 2030 and 12.78% from 2030 to 2040, resulting in a projected value of \$3.17 million in 2040, indicating a gradual shift of agricultural land to other non-ESV-contributing uses. Urban green and blue infrastructure and desert areas did not contribute to the total ESV throughout the study period. While urban areas may have expanded, they do not provide direct ecosystem services, emphasizing the cost of natural ecosystem loss. The total ESV for all land-use categories from 2000 to 2040 is projected to amount to \$1025.71 million, with rivers and lakes remaining the largest contributors despite their significant decline. The overall reduction in ESV underlines the expected future impacts of ongoing urbanization and land-use changes on natural ecosystems and the services they provide.

Table 10
Calculated ecosystem service values in US\$/ha/yr for LULC category in the study area (\$ million/yr).

Equivalent Biome	2000	2010	2020	2030	2040	Total
Urban Green and Blue Infrastructure	0	0	0	0	0	0
Rivers and lakes	256.56	278.14	220.19	204.05	183.50	754.89
Tropical forests	102.38	71.87	83.85	75.08	68.36	258.11
Cultivated areas	3.23	5.54	3.94	3.64	3.17	12.71
Desert	0.00	0.00	0.00	0.00	0.00	0.00
Total	362.18	355.55	307.98	282.77	255.04	1025.71

3.4 Sensitivity Analysis of ESV

To evaluate the reliability of the results, we performed a sensitivity analysis by calculating the Coefficient of Sensitivity (CS) using Equation (vi) with a $\pm 50\%$ adjustment to the original value coefficients proposed by Costanza et al [84]. For the Ecosystem Service Value (ESV) estimation to be reliable, CS must remain below 1. In this study, all CS values were consistently below 1, confirming that the ESV estimation was inelastic to changes in the value coefficients, demonstrating reliance and proper assignment of these coefficients.

The CS values for waterbodies ranged from 0.173 in 2000 to 0.124 in 2040, indicating a decreasing sensitivity over time despite their relatively higher coefficient. This shows that while water significantly impacts ESV, adjustments to its value coefficient have minimal effect on overall ESV. For vegetation, CS values ranged from 0.069 in 2000 to 0.046 in 2040, consistently remaining low. Agriculture showed a higher range, peaking at 0.551 in 2010 before declining to 0.292 in 2040. Though higher than water and vegetation, these values confirm that the ESV for agriculture is still inelastic to coefficient changes, ensuring the reliability of the analysis.

Table 11
Coefficients of sensitivity (CSs) from an adjustment of ecosystem valuation coefficients (VC).

	2000	2010	2020	2030	2040
Water	0.173	0.188	0.149	0.138	0.124
Vegetation	0.069	0.048	0.056	0.050	0.046
Agriculture	0.298	0.551	0.376	0.343	0.292

4. Conclusion

The study quantifies the LULC dynamics of the study area in previous years, and to predict future changes in light of a significant bridge construction, namely the Dhaka-Mawa-Bhanga Expressway. The analysis of LULC (Land Use and Land Cover) change dynamics of this study mainly finds that consistent decline of agricultural land, water bodies, and forest/vegetation cover along with bare land, while steady increase of built-up areas over time [19], [87]. The dynamic and nonlinear changes in LULC are attributed to the influence of different natural and human factors, which do not follow a consistent pattern over time. During the years 2000–2020, the built-up area significantly expanded by 155.63 Km² which is largely at the cost of agricultural land, water bodies, and

forested areas. The projection shows the amount of built-up area will be almost 34% of the total area by 2040. The research further quantifies the consequence of changes in LULC in the ecosystem by estimating the service value of the study area. The trend indicates a significant decline in the ESV during the study period, primarily due to reductions in natural areas. The ESV analysis reveals a significant decline of 14.96%, equating to a 54.20 million USD decrease from 362.18 million USD in 2000 to 307.98 million USD in 2020. The projection suggests the decrease will be 17.20% overall in the year 2040. Notably, the decrease in water bodies emerged as the predominant factor, accounting for a 12.42% change in the 2000–2020-year span, which is projected to decrease by 17.40% in 2020 years. This reduction in ESV is attributable to their high value and extensive area [88]. Additionally, the findings also suggest the built-up area in the study expanded from 10.94% to 21.08% during this period, encroaching on agricultural land, water bodies, and forest areas. Since built-up areas contribute no ecosystem service value, this development has further contributed to the overall decline in ESV, a trend echoed in other studies documenting similar conversions of land for urban development.

This study quantifies ecosystem service value (ESV) using Landsat satellite images and the benefit transfer method developed by Costanza et al. (1997) [78]. However, there are few limitations and uncertainties associated with this approach. As the estimation of ESV is contingent on accurate land cover classification, the medium resolution of Landsat images may lead to reduced classification accuracy. Although Landsat images offer higher resolution, they are only available from 2013 onward. Furthermore, benefit transfer methods assume spatial homogeneity in ecosystem service value coefficients. Besides, human-environmental systems are inherently complex and heterogeneous; thus, the same LULC type may yield varying ecosystem service values in different contexts. The generalization of value coefficients without considering local conditions can result in erroneous ESV estimates. Future research should focus on developing localized value coefficients for Bangladesh, as there is currently a lack of specific coefficients for different LULC types. Future studies should also consider adjusting the socioeconomic coefficients to reflect temporal changes of LULC accurately. The development plans of certain areas can address the greenery reduction issue and describe the adjustment policy into the subdivision, local, or master plan [31]. Laws and regulations can be imposed to maintain urban development, preserve greenery and natural resources [89]. Above all, the study appeals to preserve and enhance green spaces while managing urban expansion. It recommends the sweet spot where development and nature coexist, ensuring even as cities grow, the ecological services provided by natural landscapes are not lost but integrated into urban planning for a healthier, more sustainable future.

Declarations

Competing interest

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Author Contribution

Md Abul Hasan Shovon: Idea Development, Literature Search, Modelling, Software, Data Analysis, Draft Writing, Editing and Revision of the Writing.

Data Availability

The data supporting the findings of this research are available upon reasonable request from the author.

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Figures

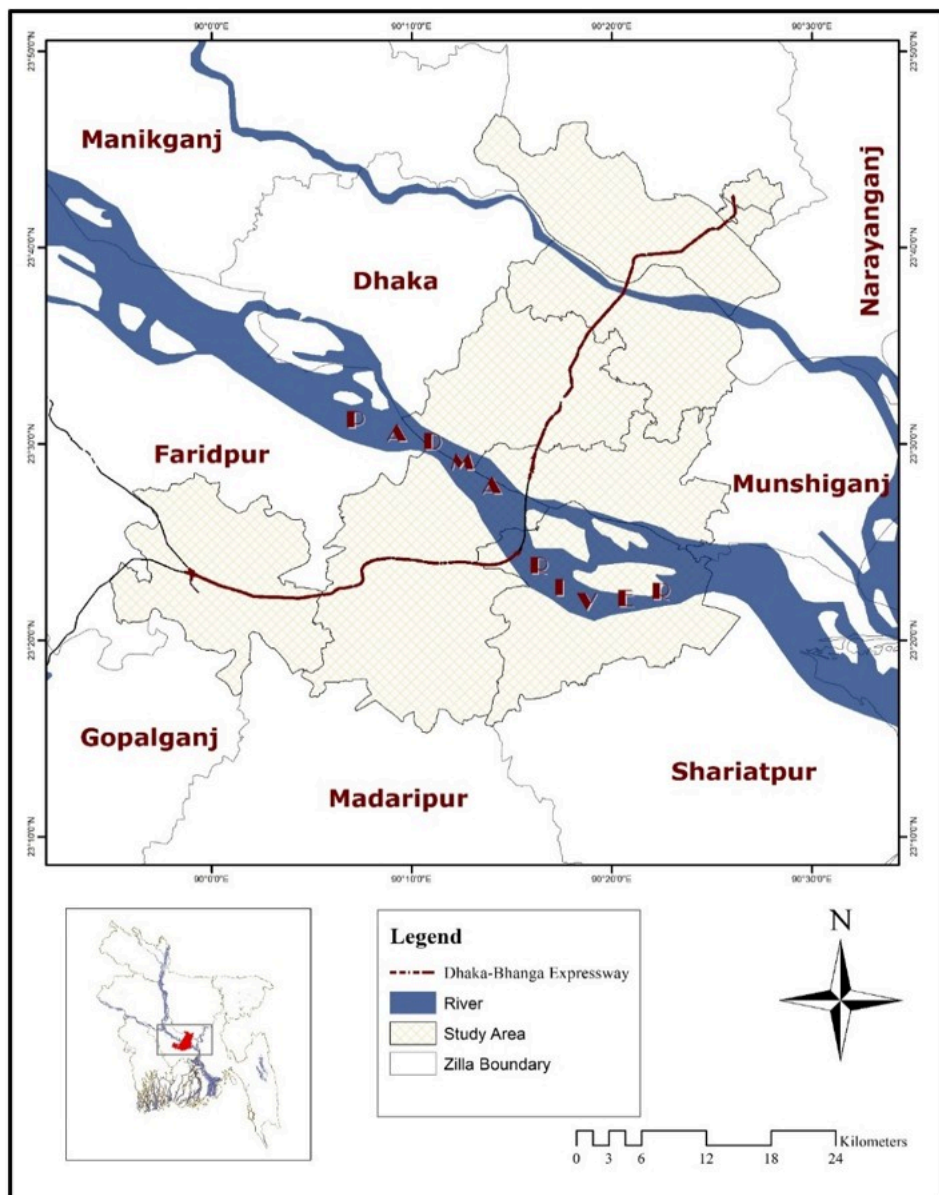


Figure 1

Location of study area

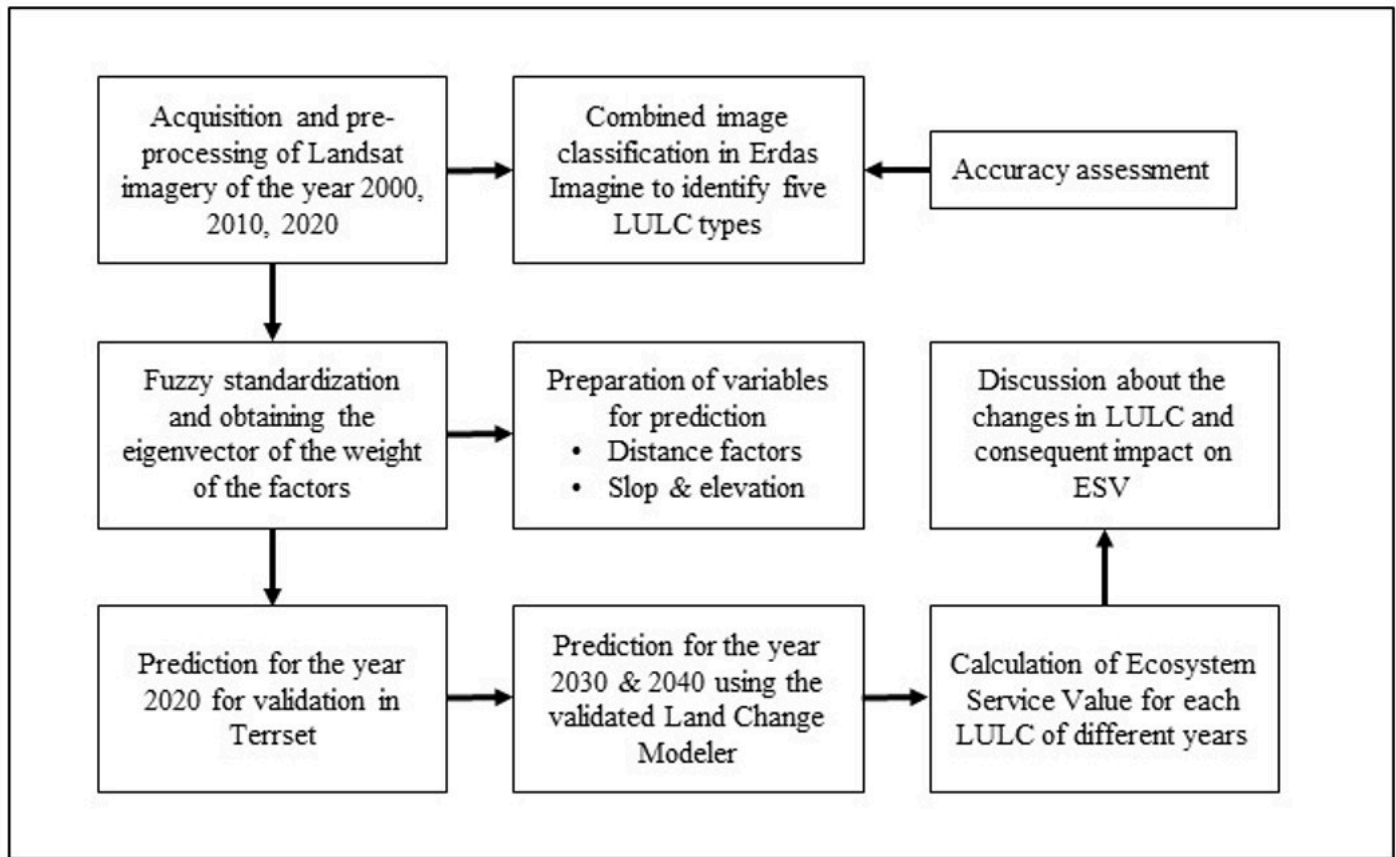


Figure 2

Methodological flowchart of the study

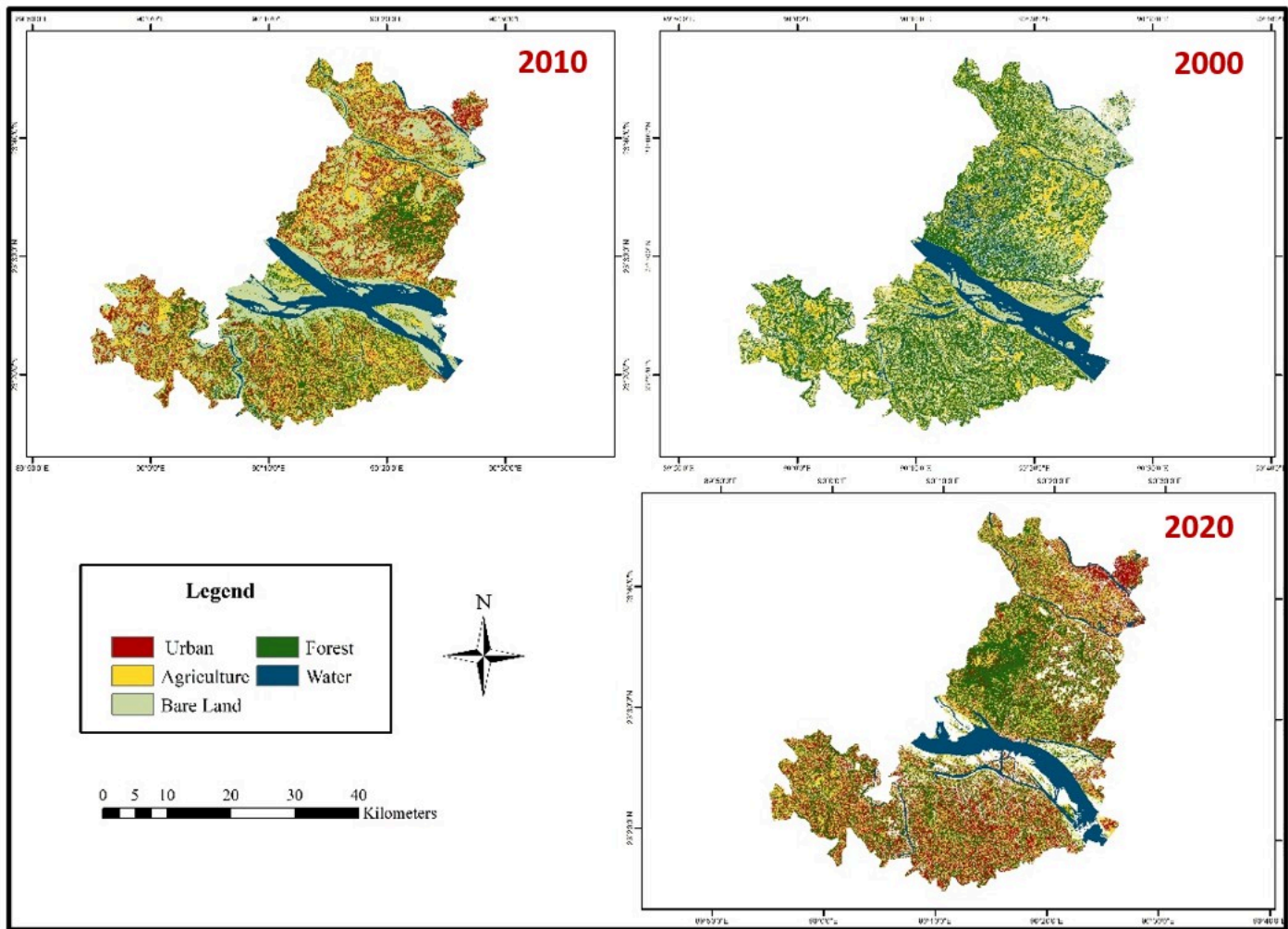


Figure 3

LULC of the Study Area in Different Years

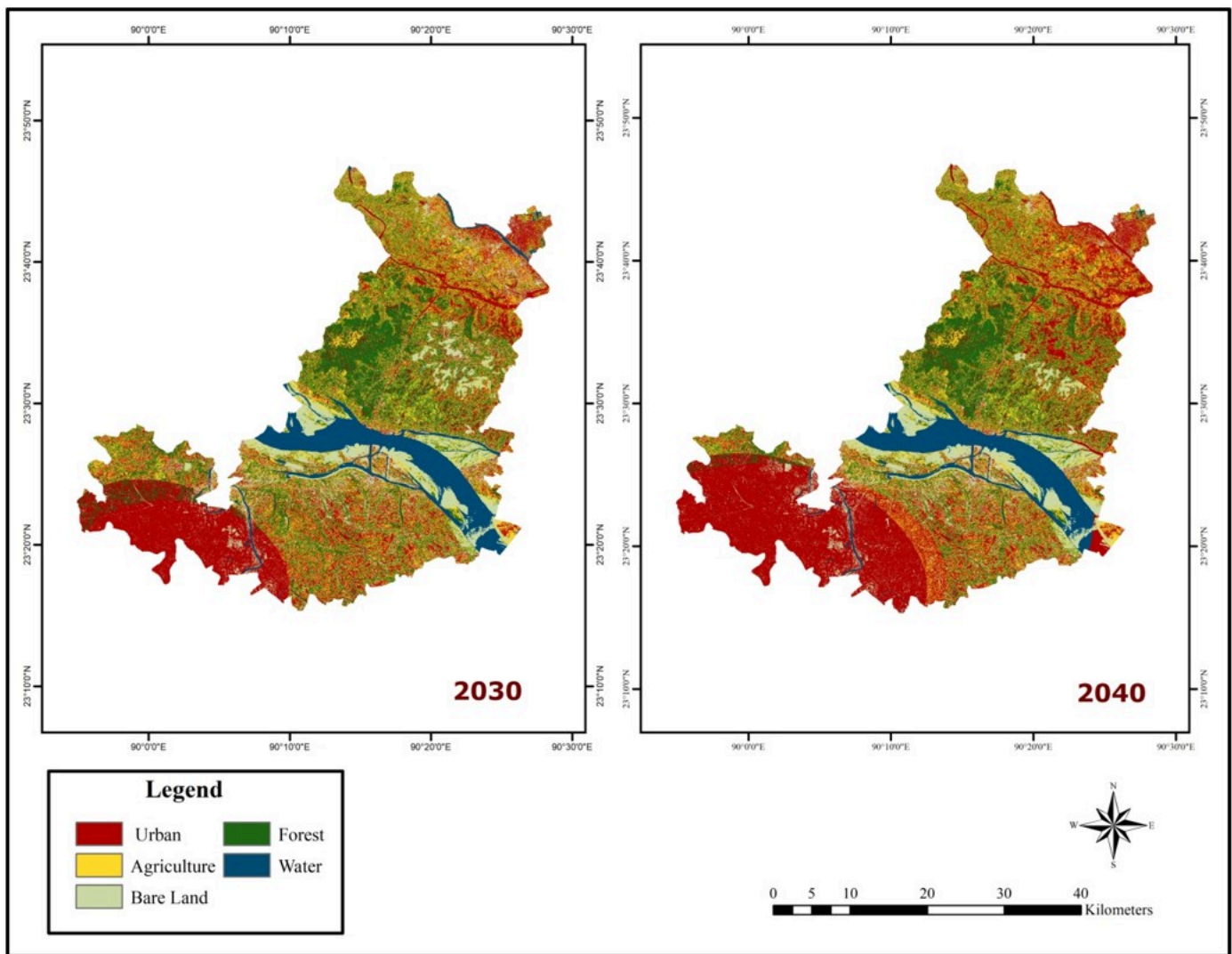


Figure 4

Predicted LULC of the Study Area in Different Years

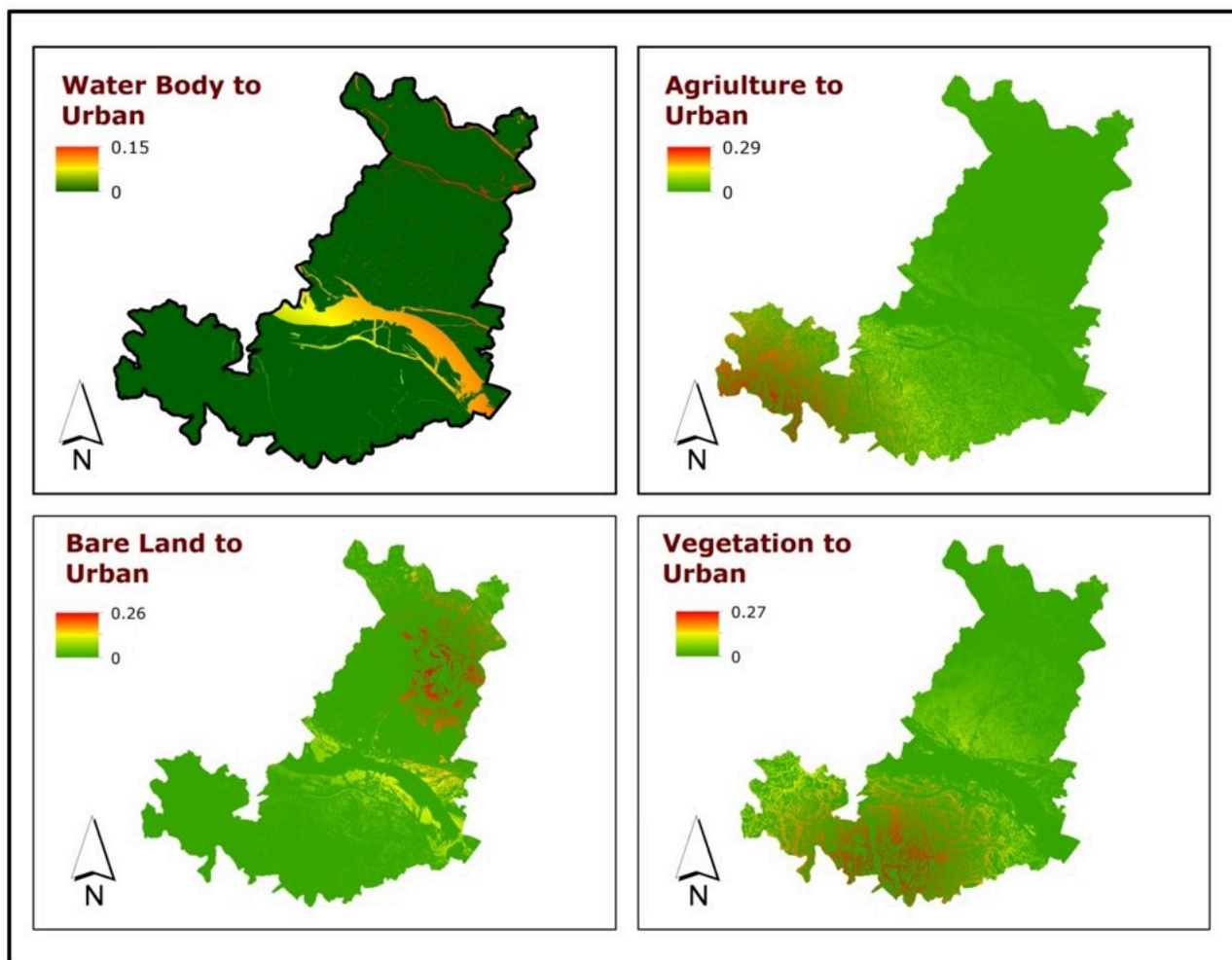


Figure 5

Transition Potential of Different Land Cover to Urban/Built-up Area

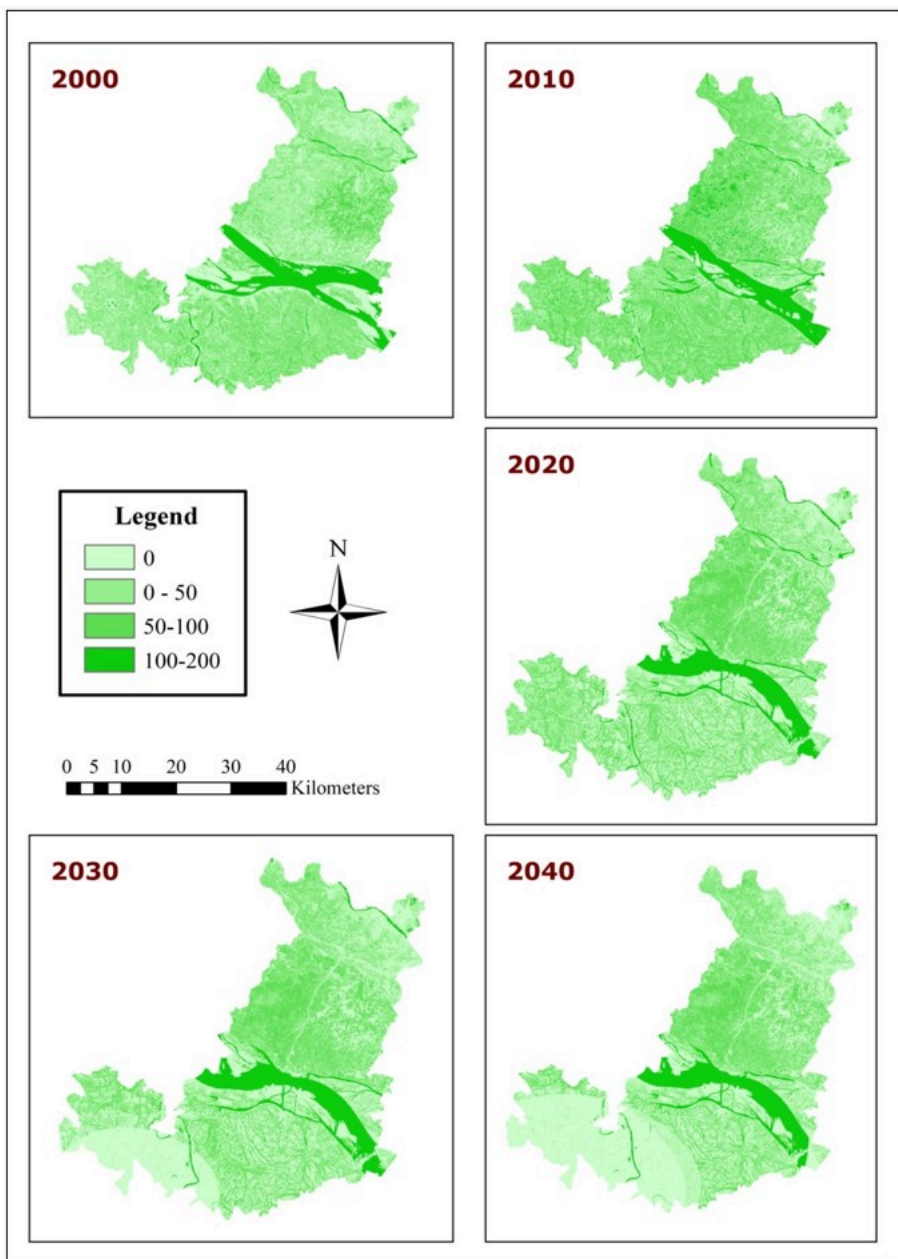


Figure 6

Spatial distribution of ecosystem service values (\$/ha/year) in the study area of different year (including predicted)

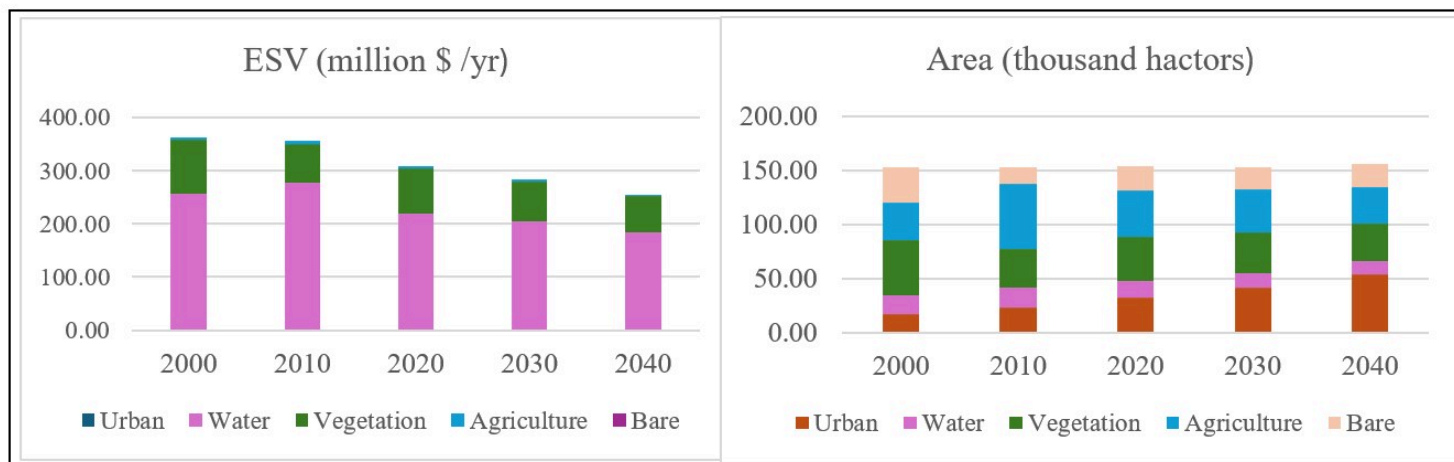


Figure 7

Area and ecosystem services value contribution of LULC types for different reference years in the study area.