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Vulnerability Assessment of Urban and Peri-Urban Areas in Dhaka: Exploring Ecosystem Service Loss

Rapid unplanned development, a primary cause of urban change, endangers ecosystems greatly. Quantifying ecosystem services helps portray the declining ecological functions caused by the urban land cover change. Dhaka, one of the most densely populated cities in the world, exerts little effort toward sustainability; affecting both the inner city and the outer periphery (peri-urban area) called extend Dhaka (5 km buffer from the city's border). This study examines Dhaka's urban growth impact on ecosystem service values (ESV) from 2004-2020 and projects these impacts to 2050, considering three scenarios: business as usual (BAU), conservation, and development. We employed Landsat images, different image classification techniques, the CA-Markov model for future simulation, and the global value coefficient for ESV. The research shows water bodies and tree covering change forecasting up to 2050. Due to fast urban growth in the expanding Dhaka city during 2004-2020, the total ESV declined (a decrease ESV of 211.92 million US dollars). If this pattern continues, the ESV will further drop $ 156 million by 2050. Consequently, ESV loss will be severe in outlying extended Dhaka city, and among the three forecasted scenarios, the development will lose most of its ESV. This study also suggests that for every one percent increase in total GDP, approximately 2 million dollars of ecosystem service loss results. In addition, significant changes in ecological functions, such as waste treatment, raw materials, habitat/ refugia, and water supply, caused the ESV to decline most. This concludes that appropriate planning and regulations to safeguard natural ecosystems will avoid future deterioration.

Keywords

Geographic Information Systems (GIS), Remote Sensing (RS), Gross Domestic Product (GDP), Urban expansion, CA-Markov model, Ecosystem service value (ESV)

INTRODUCTION

The loss of ecosystem services has an adverse effect on the environment, interrupting critical ecological processes and contributing to a decline in biodiversity, ecosystem stability, and overall natural system health. The term "Ecosystem services" denotes the commodities and services continuously given by ecosystems and their activities. These services cover and preserve people's environmental needs and material demands (Lin et al. 2021). Moreover, urban ecosystem services describe the benefits of a city's ecological environment inside the city's physical limits (Das and Das 2019). Urban land alteration, a significant driver for global shifts in environmental conditions and ecosystem services, alters ecosystem services by reshaping the structure and functionality of the ecosystem (Yueriguli et al. 2019; Hecht et al. 2020). The progression of urbanization results in changes in land use types, which results in changes in ESV that affect the urban ecological structure and indirectly governs the types of ecological services (Chen et al. 2021; Feng et al. 2022).

As a global phenomenon with a plethora of perspectives, urbanization has become a metaphor for modernity, socializing, economic advancement, and political power (Nagendra et al. 2018; Asma et al. 2017). With the global urban population anticipated to grow by 68% by the year 2050, 90% of that estimated increase will occur in Asia and Africa. Annual urban growth in Asia and the Pacific was 2.3%, compared to the world average of 2.0%, with the most rapid rates of urbanization occurring in countries with less developed economies (UNESCAP 2015). As a result of global urbanization activities, major metropolitan cities and regions across nations are increasingly expanding their physical development boundaries into nearby peri-urban areas (Mortoja et al. 2003; Roy et al. 2021; SHLC 2020). Thus, peri-urbanization has become the most common kind of urbanization globally, with rapid urbanization in the periphery (Mortoja and Yigitcanlar 2020).

In recent years, Bangladesh has seen dramatic growth in both the rate of urbanization and total urbanized area, with Dhaka at the core of this development. In a sense of urbanization, a study conducted in 2018 revealed the city has seen an addition of 234 m^2 of built-up area in its periphery since 1991 (Roy et al. 2021). Dhaka's population has risen from 3 million in the 1980s to over 23 million in 2023 (Macrotrends 2023); an uncontrolled and uneven development has made it one of the world's most densely populated cities. A side effect of this growth produced an undesirable urban shape, riverbank constriction, and the loss of vegetation (Alam 2019).

An in-depth investigation of the causes and patterns of land-use dynamics and urbanization is necessary for modeling Urban land cover change across time and space and conveying long-term development by imposing urban economic, demographic, and environmental strategies and policies (Keshtkar and Voigt 2015; Feng et al. 2017; Islam et al. 2018; Abdullah et al. 2019b). In such cases, Geographic Information Systems (GIS) and remote sensing (RS) are prominent and convenient tools for evaluating the spatial and temporal dynamics of urban areas (Zhang et al. 2022; Abdullah et al. 2021; Miah et al. 2023; Ahmed et al. 2023). Data from RS provides critical multi-temporal information on the processes and patterns of land cover change, and GIS may be utilized to map and study these patterns (Moazzam et al. 2022; Alam et al. 2017). Through excellent planning, management, and strategy, which can be achieved through dynamic simulations that assess the future portrait of metropolitan regions dependent on various driving forces, it is possible to mitigate unplanned urban sprawl and development (Getu et al. 2022).

Previous research on megacity Dhaka mostly includes loss of wetland (Abdullah et al. 2021), forest cover change (Kafy et al. 2022; Abdullah et al. 2019a; Islam et al. 2022), urban heat island (Kafy et al. 2022; Rahaman et al. 2022), Land surface temperature (Imran et al. 2021; Kafy et al. 2021), flooding (Subah 2021), traffic congestion (Islam et al. 2021), urban migration (Sowgat and Roy 2022; Al-Maruf et al. 2022). Despite the need and importance of urban prediction and quantification of ecosystem services, none of the studies address the quantification of ecosystem goods and services and their partitioning based on the updated value coefficient proposed by (Costanza et al. 2014). Moreover, there is a definite lack of information on how Dhaka city will influence the ecosystem service of extended Dhaka city (periphery) in the year 2050.

This paper addresses two major questions; first, how has Dhaka's urban land coverage and its extended area has/ will be changed over the past 16 years (2020) and beyond (2050)? Furthermore, how much impacts of ecosystem services would take place due to Urban land pattern shifts? To address the questions mentioned above, the study was designed based on these two objectives: i) To understand the changes in ecosystem goods and services in Dhaka and its extended area during 2004-2020, and ii) To predict and quantify the future land conversion dynamics and value of ecosystem services of the study sites during 2020 - 2050.

MATERIALS AND METHODS

Study Area

Dhaka is Bangladesh's most established, historically largest, and midway-located city (Hasan and Southworth 2017). It is one of the most densely populated areas and one of the fastest-growing megacities in the world, with a population density of 23,000 per square kilometer (Opu 2022). This research separates the study area into two distinct areas: Dhaka City and Extended Dhaka City. Dhaka City can be defined as an area that encompasses the Dhaka Metropolitan jurisdiction, which is bounded by four major river systems: The Buriganga, Turag, Tongi, and Balu, which flow toward the south, west, north, and east, respectively (Dewan and Yamaguchi 2009) and has an area of 305.85 km^2. On the other hand, extended Dhaka city can be defined as an area that excludes actual Dhaka city, which consists of five kilometers buffers zone from the periphery of the Dhaka city boundary and has an area of 481.35 km^2. Figure (1) depicts the study area of Dhaka city and the extended Dhaka city, which is located between 90.28 E and 90.56 E longitudes and 23.59 N and 23.95 N latitudes. The study area is according to geomorphic classifications; the largest area comprises a relatively young floodplain, followed by higher terraces from the Pleistocene period. Compared to other cities in Bangladesh, the city's built-up area expanded dramatically over the previous 30 years, resulting in a significant decline in vegetation and water bodies. Hence, special attention should be paid to the vulnerability assessment of Dhaka associated with ecosystem service loss.

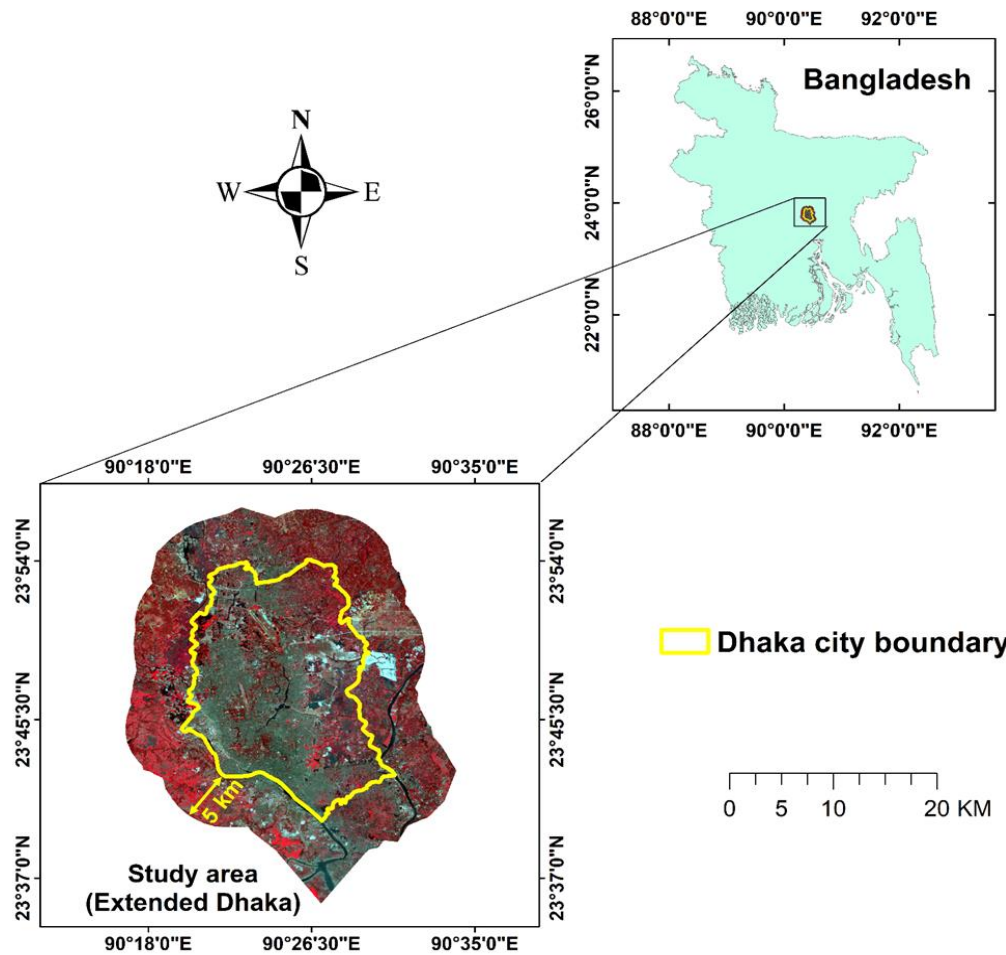

Figure 1: The study area map of megacity Dhaka and extended area. Here, yellow boarder line indicates the main city boundary and 5 km periphery is taken as extended area of Dhaka

Data Acquisition:

Remote sensing is beneficial because of its synoptic perspective, repeated coverage, and legitimate data acquisition (Shaw and Das 2017). Figure 2 shows the overall flowchart of this study in this study.

To monitor the fluctuations of spatiotemporal trends of land use land cover (LULC) change in extended Dhaka city, multitemporal Landsat-5 Thematic Mapper (TM) and Landsat-8 Operational Land Imager (OLI) satellite images (path/row: 137/44 & 137/43) composed of 30m resolution were attained for the years 2004, 2010, 2015, and 2020 were ordered from United States Geological Survey. It was decided to use images obtained during the dry season (December and January) since there was less cloud cover at that time, the shift in surface reflectance was negligible, and the image quality was much finer.

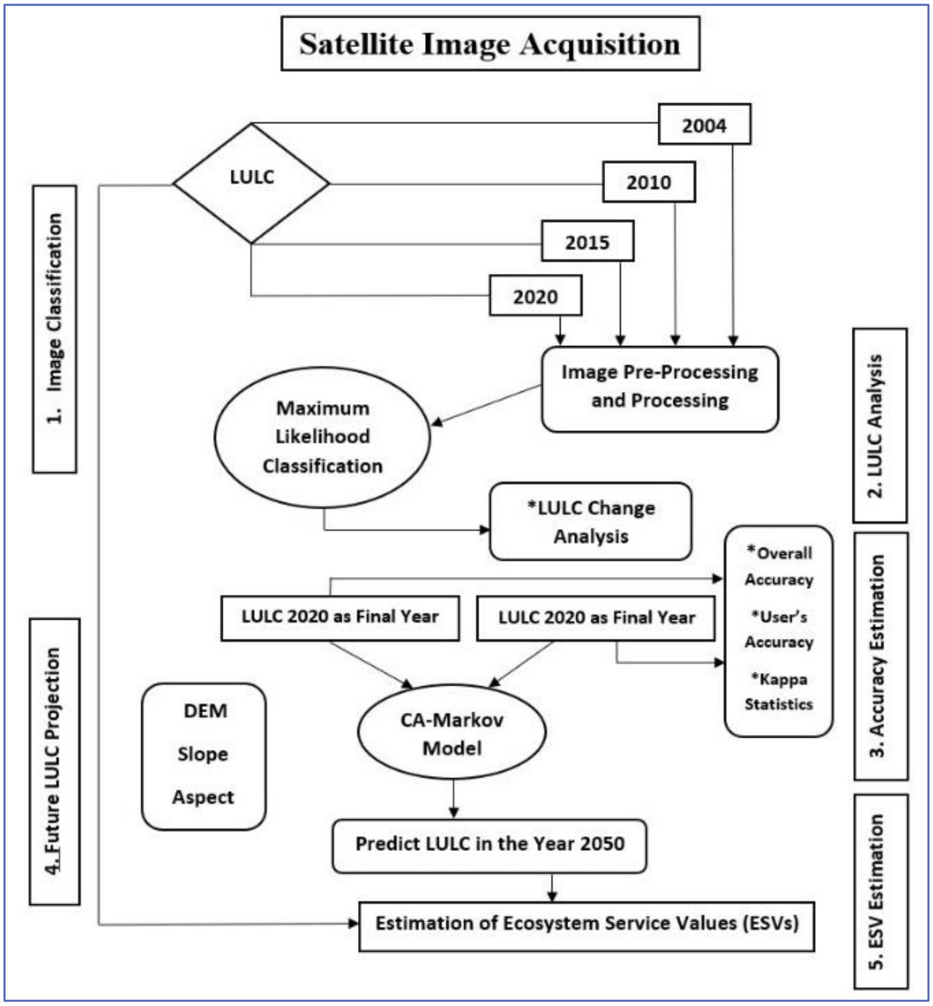

Figure 2. Flowchart of the total procedure of the study

Data Processing and Image Classification

Remotely sensed data are susceptible to radiance, geometric, and atmospheric distortions due to acquisition systems and platform movements. One major function of pre-processing is to remove such distortions, especially when optical sensor data is used. After acquiring all the required datasets, the following image pre-processing techniques were performed in ERDAS Imagine Professional, ENVI 5.3, and ArcGIS software. The techniques include (i) re-projecting the images into Universal Traverse Mercator (UTM) Zone 46 N with World Geodetic System 1984 (WGS84) datum, (ii) removing haze and correct topographic normalization using ATCOR (Atmospheric and Topographic Correction) (iii) image enhancement (iv) mosaicing the image scenes (v) imagery clipping.

Spatial-temporal land cover map helps to detect the changes in the area of different land use by highlighting the trend and pattern of land cover change of a particular place. Recently, researchers have developed many methods to classify the satellite image, including the maximum likelihood (ML), random forest (RF), support vector machine (SVM), etc. (Rahman et al. 2020; Mohajane et al. 2018; Noi and Kappas, 2018; Raczko and Zagajewski 2017; Saharan et al. 2019).

This study has been conducted by applying all three methods (ML, RF, SVM), which are mentioned above individually, to classify the satellite image of the study area for the years 2004, 2010, 2015, and 2020. In this regard, 85 sample signatures for each land cover changes were collected separately for each satellite image in ArcGIS 10.5. Five land cover categories were identified in the land cover map of the study area. These are water bodies, agri/grassland, landfill, built-up, and tree cover. The classification schematic is represented in Table 1. Finally, the maximum likelihood method of image classification was performed in TerrSet, spectral angle mapping in QGIS, and image classification through RF and SVM was executed using the R statistical software.

The resulting categorized imagery was subjected to accuracy validation using the error matrix and kappa index (Keshtkar and Voigt 2017) to evaluate the effectiveness and quality of imagery by comparing it to actual field points and high-resolution Google Earth data. The following shows the formula by which the Kappa coefficient was calculated (Congalton and Green 2019).

$$Kappa\ coefficient = \frac{\sum_{i=1}^{k} nii - \sum_{i=1}^{k} nii(GiCi)}{n^2 - \sum_{i=1}^{k} nii\ (GiCi)}$$

Where i is named class number, n is the total number of classified pixels which are compared to actual data, nii is the number of pixels linking to the actual data class i, that were classified with a class i, Ci is the total number of classified pixels associated to class i and Gi is the total number of actual data pixels affiliated to class i.

Accuracy was measured by a confusion matrix based on 60 points for each land cover class executed from high-resolution images. Using reference data and classified images, an error matrix was then produced from which accuracy matrices (e. g., overall, user's accuracy, and kappa statistics) are calculated (Table 1). This study adopted the output of a maximum likelihood image classifier for further analysis due to its better accuracy than others.

Table 1. Accuracy assessment for the classified images

Reference Year	Classified image	matrix value		
		Maximum likelihood	RF	SVM
2004	Landsat 4-5 TM	0.92	0.89	0.88
2010	Landsat 4-5 TM	0.89	0.87	0.87
2015	Landsat 8 OLI	0.92	0.85	0.89
2020	Landsat 8 OLI	0.91	0.88	0.85

Prediction of Land Cover Change Using the CA-Markov Model

Based on classified maps of 2015 and 2020, the study focused on predicting urban land cover change of Dhaka city and its extended area up to 2050. As the CA-Markov model is considered a widely used modeling tool and technique in detecting and predicting urban land cover changes, therefore we applied the CA–Markov model to quantify the extent and magnitude of land use and land cover transition, the rate of change, and changed detection matrices for each land use and land cover types (Sohl and Claggett 2013).

The Markov model is only appropriate for land use modeling when land use data are spatially dependent and suitable for short-term projections because of not being spatially explicit (Overmars et al. 2003; Sinha and Kumar 2013). Moreover, the Markov model does not consider spatial information allocation within each class and the probabilities of change between landscape states that are not constant. However, it can offer the proper magnitude, unable to address the direction of change. To eliminate this limitation, Cellular Automata (CA) model can be combined with the Markov model because the bottom-up dynamics model, CA can add modeling direction that can demonstrate spatial and dynamic processes in simulation (Subedi et al. 2013). A combination of both models can stimulate spatial variation in complex systems and the transition probability matrix generated by the cross-tabulation of two different images. Thus, the CA–Markov model can predict two-way transitions among the available land use types and has the ability to outperform regression-based models in predicting land-use changes (Wang et al. 2021).

To implement the process of the CA–Markov model, we have followed (1) the preparation of land cover maps of 2015 and 2020; (2) the calculation of transition area matrices based on classified maps; (3) the generation of transition potential maps using driving factors; (4) evaluating the model's ability to simulate future changes based on kappa indices; and (5) simulating the land cover maps for the coming years (2050).

Based on the selective drivers, transition probability matrix, and spatial trend, this study attempted the prediction of urban land cover using the CA-Markov model in the year 2050 (Figure 4). Accuracy and validation of classification models is an important pre-requisite step in classifying, detecting, and predicting land cover change studies. Therefore, we predicted 2020 land cover map based on 2010 and 2015 land cover map using CA-Markov to compare with actual 2020 land cover map (Figure 3). The comparative analysis of observed versus forecasted land cover for the year 2020 is depicted in Figure 5, providing a detailed juxtaposition. In a "business as usual" scenario, the land cover remains unchanged with no substantial efforts to prevent land conversion, while a conservation scenario actively adopts methods for preserving natural habitats and prioritizes the conservation of green spaces, and finally, a development scenario entails indiscriminate infrastructure construction solely focused on increasing infrastructure quantity. In the first scenario, the BAU scenario, we explored the future of Dhaka city by considering the current transition matrix of 2015-2020. In the second future scenario, we applied conservation approaches by limiting the rate of expansion of built-up areas to protect the natural ecosystems such as waterbodies, tree cover, agri/grassland from further deterioration. However, in the third scenario, we considered different planning of the city authority of Dhaka city and if the city authority prioritizes development initiatives over conserving natural ecosystems by building more infrastructures to boost the economy, which will favor aggressive urban growth.

Ecosystem Service Valuation

The term ecosystem services refer to all the material and non-material benefits living organisms enjoy from a particular environmental unit (Costanza 1997). To show the impact of urban growth on the ecosystem, calculating the ecosystem service value of each land cover was necessary (Das and Das 2019). To calculate the total ecosystem produced per year by the megacity Dhaka and its extended areas, we used the value coefficient proposed by Costanza (2014). The five land cover categories used to classify satellite imagery were compared to the 16 biomes described by Costanza et al. (2014) in their ecosystem service valuation model to generate ecosystem service values for diverse ground cover types (Table 2). Although in 2014 Costanza modified the value of the built-up area from 0 to 6661$/ha/yr, we are still considering it as a null value since megacity Dhaka fails to complete the essential requirement of greenery and service value of habitability. Another important fact is that Dhaka, located in a tropical region, is naturally surrounded by ecosystems that are characteristic of such climatic zones. Tropical forests, with their diverse tree species, closely represent the native vegetation and ecological processes of the area. Hence, they serve as a fitting proxy for the broader LULC class.

Table 2: Costanza et al. (2014) biome equivalents for land categories and corresponding ecosystem values.

LULC categories	Equivalent Biome	Ecosystem service coefficient
Water bodies	Wetlands	140174
Agri/Grassland	Cropland	5567
Landfill	Bare land/Desert	0
Built-up	Urban	0
Tree cover	Forest	5382

Each land cover category was represented as a proxy of Costanza's most representative biome, and they are i) Water for Wetland ii) Agriculture for cropland iii) Landfill for bare land/ desert iv) Built-up for urban v) Tree for the tropical forest.

The overall value of ecosystem services in the selected region was calculated using the formula:

$$ESV=\sum(Ak \times VCk)$$

where ESV is the estimated ecosystem service value, A_k is the area (ha), and VC_k is the value coefficient (US \$ ha^{-1} yr^{-1}) for land cover category k.

The changes in ecosystem service value were calculated by calculating the difference between the ESV of each year. The percentage change in ESV is calculated as follows:

$Percentage\ change\ of\ ESV = ((ESV_{final\ year} \times ESV_{initial\ year})/ESV_{final\ year}) \times 100$

Here, a positive percentage indicates increased value, and a negative percentage indicates a decrease in ecosystem service value.

Sensitivity Analysis

To evaluate the reliability and robustness of our results, the coefficient of sensitivity (CS) analysis was also conducted to check whether any uncertainties existed in the value coefficient. In this research value coefficient of LULC corresponding to water, agriculture, and tree were adjusted by 50%, and the corresponding coefficient of sensitivity (CS) was calculated using the below equation as in Kreuter et al. (2001), which is similar to the standard concept of elasticity in economics.

$$CS = \frac{\frac{ESVj - ESVi}{ESVi}}{\frac{VCjk - VCik}{VCik}}$$

Where ESV_i and ESV_j = initial and adjusted total estimated ecosystem service values, respectively, and VC_{ik} and VC_{jk} = initial and adjusted value coefficients (US\$ ha^{-1} $year^{-1}$) for LULC type 'k'. If CS is more than one, the projected ecosystem value is said to be elastic, and the results will not be that reliable, but if CS is less than one, then the estimated ecosystem value is considered to be inelastic, and the result will be reliable even if the value coefficient has relatively low accuracy. The greater the proportional change in the ecosystem service value relative to the proportional change in the valuation coefficient, the more critical is the use of an accurate ecosystem value coefficient (Li et al. 2013).

RESULTS

Urban Dynamics from 2004 to 2020

The land cover change detection is a compelling analysis for understanding biophysical changes such as: loss of productive ecosystems/biodiversity, deterioration of environmental quality, and loss of forest and agricultural lands, which are considered important parameters for planning sustainable cities (Islam et al. 2022).

Land cover changes during 2004 -2020 periods and their corresponding area are shown in (Figure 3). From 2004 to 2020, In the past 16 years, the land cover types that changed most dramatically were in water bodies, tree cover, and built-up areas.

In 2004, 2010, 2015, and 2020 respectively, the total built-up area in Dhaka City were 4847 ha, 8494 ha, 10729 ha, and 14327 ha, while the total built-up area in Extended Dhaka city area were 1262 ha, 2544 ha, 6800 ha, and 7720 ha (Table 3). In 2004, most of the construction of

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infrastructure was limited within Dhaka city's boundary (Figure 3). Because there was minimal capacity for the increased built-up area within Dhaka city, rapid urban expansion of extended Dhaka city began after 2010. We found that landfill and Agri/grassland areas were the major contributors to the built-up areas as most areas of these land cover types were already pre-phase of built-up areas.

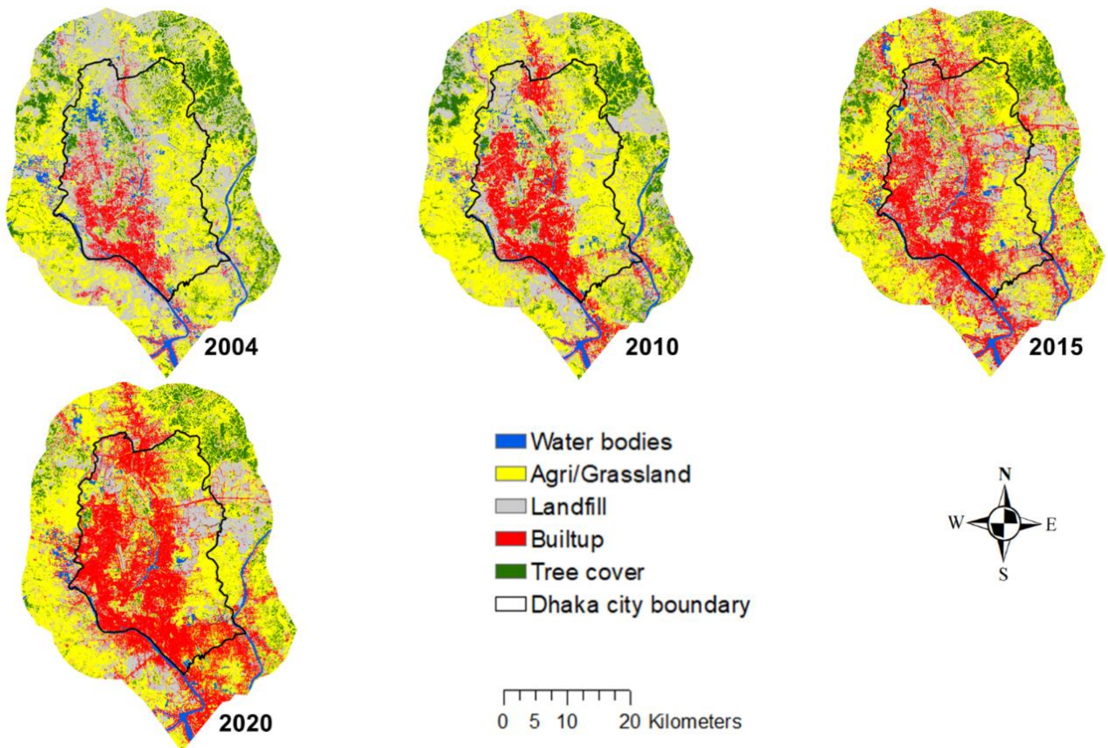

Figure 3. The map showing the land cover change from 2004-2020

Natural ecosystems within Dhaka city have undergone significant modification in the past 16 years. In 2004, the total wetlands area was 1945 ha which was 2.47% of Dhaka City, but in 2020, bodies were reduced to 1068 ha (1.36%) (Table 3). Similarly, during the same period, the wetland area was reduced from 2509 ha (3.19%) to 1974 ha (2.51%) in the Extended Area.

Another crucial natural environment resource is tree cover, which has faced the same trend as waterbodies from 2004-2020. In 2004, 2010, 2015, and 2020, respectively, the total tree-covered area in Dhaka City was 1746 ha (2.22%), 982 ha (1.25%), 867 ha (1.10%), and 855 ha (1.09%) while the total tree-covered area in extended area was 6771 ha (8.60%), 6403 ha (8.13%), 4712 ha (5.99%) and 3985 ha (5.06%).

The total area under agri/grassland was estimated at 10219 ha (12.98%), 10598 ha (13.46%), 8272 ha (10.51%), and 8699 ha (11.05%) in Dhaka City and 21893 ha (27.81%), 25093 ha (31.88%), 23669 ha (30.07%), and 24455 ha (31.19%) in the Extended Area in 2004, 2010, 2015, and 2020, respectively. During the same period, landfill was estimated at 11828 ha (15.03%), 8975 ha (11.40%), 9213 ha (11.70%), and 5636 ha (7.16%) in Dhaka City and 15700 ha (19.94%), 11751 ha (14.93%), 10791 ha (13.71%), and 10003 ha (12.71%) in the extended Area.

Land cover change maps created from Landsat and IRS-1D data have an overall accuracy of 85% to 90 %. According to the classification accuracy test results, the overall Kappa statistics for the years 2004, 2010, 2015, and 2020 were 94%, 89%, 91%, and 87%, respectively, and overall classification accuracy for the years 2004, 2010, 2015, and 2020 were 95%, 91%, 92%, and 88% respectively (table 3). These estimates indicate that the classification accuracies were of substantial agreement.

Table 3: Area with percentage of land use and land cover types of Dhaka city and its extended area of 2004, 2010, 2015 and 2020

LULC	2004		2010		2015		2020	
	Dhaka city (%)	Extended Area (%)	Dhaka city (%)	Extended Area (%)	Dhaka city (%)	Extended Area (%)	Dhaka city (%)	Extended Area (%)
Water bodies	1945 (2.47)	2509 (3.19)	1536 (1.95)	2347 (2.98)	1504 (1.91)	2165 (2.75)	1068 (1.36)	1974 (2.51)
Agri/Grassland	10219 (12.98)	21893 (27.810)	10598 (13.46)	25093 (31.88)	8272 (10.51)	23669 (30.07)	8699 (11.05)	24455 (31.19)
Landfill	11828 (15.03)	15700 (19.94)	8975 (11.40)	11751 (14.93)	9213 (11.70)	10791 (13.71)	5636 (7.16)	10003 (12.71)
Built-up	4847 (6.16)	1262 (1.60)	8494 (10.79)	2544 (3.23)	10729 (13.63)	6800 (8.64)	14327 (18.20)	7720 (9.81)
Tree cover	1746 (2.22)	6771 (8.60)	982 (1.25)	6403 (8.13)	867 (1.10)	4712 (5.99)	855 (1.09)	3985 (5.06)

Future of Land Cover Change Dynamics of Urban and Peri-urban from 2020 to 2050

The accuracy of the simulated 2020 land cover map is 89% (Table 1) compared with the actual 2020 land cover map, which is satisfactory. In this research, we proposed three scenarios to exhibit future aspects of urban growth of Dhaka city and extended area (Figure 4). In the first scenario, which is BAU scenario, we explored the future of Dhaka city by considering the current transition matrix of 2015-2020 and found that if Dhaka city's future growth rate of the last five years remains persistent then after 30 years, the built-up areas of Dhaka city and extended area will be increased to 6120 ha and 11762 ha. These are 42.72% and 152.36% increase in built-up area in Dhaka city and extended area, respectively, which will significantly affect other land cover types because, at present, there is very little space for the extension of urban growth within Dhaka city. In 2050, the built-up area of Dhaka city will be 20447 ha, while in extended Dhaka city will be 19482 ha (Table 4). As a result, both Dhaka city and the extended portion of Dhaka city's ecosystem will be affected significantly.

In the second future scenario or conservative scenario, government policy can slow down urban growth, then Dhaka city and its surrounding built-up area can be limited to 17838 ha and 13335 ha, respectively (Table 4). On the other hand, if the city authority imposes strict laws and policies to protect remaining natural ecosystems, then the total area of wetlands (1018 ha and 1818 ha) and tree covers (809 ha and 3459 ha) for the Dhaka city and the extended area will less likely to lose its area to built-up area, and will be more suitable for habitat.

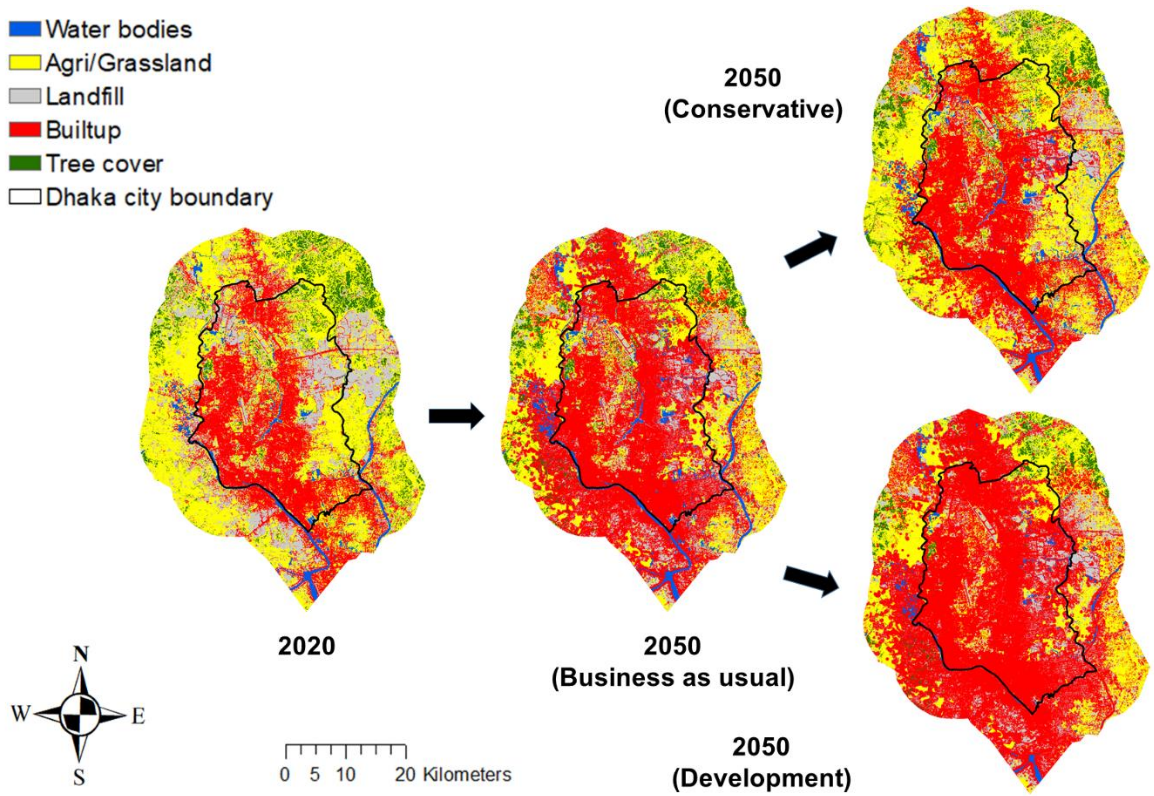

Figure 4: Showing the simulated (2050) land use and land cover map of Dhaka city considering conservative and development.

Table 4: Area with percentage of simulated (2050) land use and land cover map of extended Dhaka city considering BAU, conservative and development.

LULC	2050 (BAU)		2050 (Conservative)		2050 (Development)	
	Dhaka city (%)	Extended Area (%)	Dhaka city (%)	Extended Area (%)	Dhaka city (%)	Extended Area (%)
Water bodies	872 (1.11)	1595 (2.03)	1018 (1.29)	1818 (2.30)	468 (0.59)	1000 (1.27)
Agri/Grassland	4267 (5.42)	16351 (20.77)	7627 (9.69)	22717 (28.86)	2731 (3.47)	13239 (16.82)
Landfill	4326 (5.5)	7653 (9.72)	3264 (4.15)	6838 (8.69)	3214 (4.08)	6788 (8.62)
Built-up	20447 (25.97)	19482 (24.75)	17838 (22.66)	13335 (16.94)	23929 (30.40)	25121 (31.91)
Tree cover	673 (0.85)	3057 (3.88)	809 (1.03)	3459 (4.40)	243 (0.31)	1989 (2.53)

In the development scenario, the projected urban growth within Dhaka and the extended area will significantly increase. Among the total area (30585 ha) of Dhaka city, 23929 ha area will be converted into built-up area. Similarly, 25121 ha of the extended area will become built-up area. This scenario will severely damage the ecosystem's cycle. Dhaka city's wetlands and tree cover will be 468 ha and 243 ha, respectively, whereas the waterbodies and tree cover of the extended area will end up at 1000 ha and 1989 ha, respectively (Table 4).

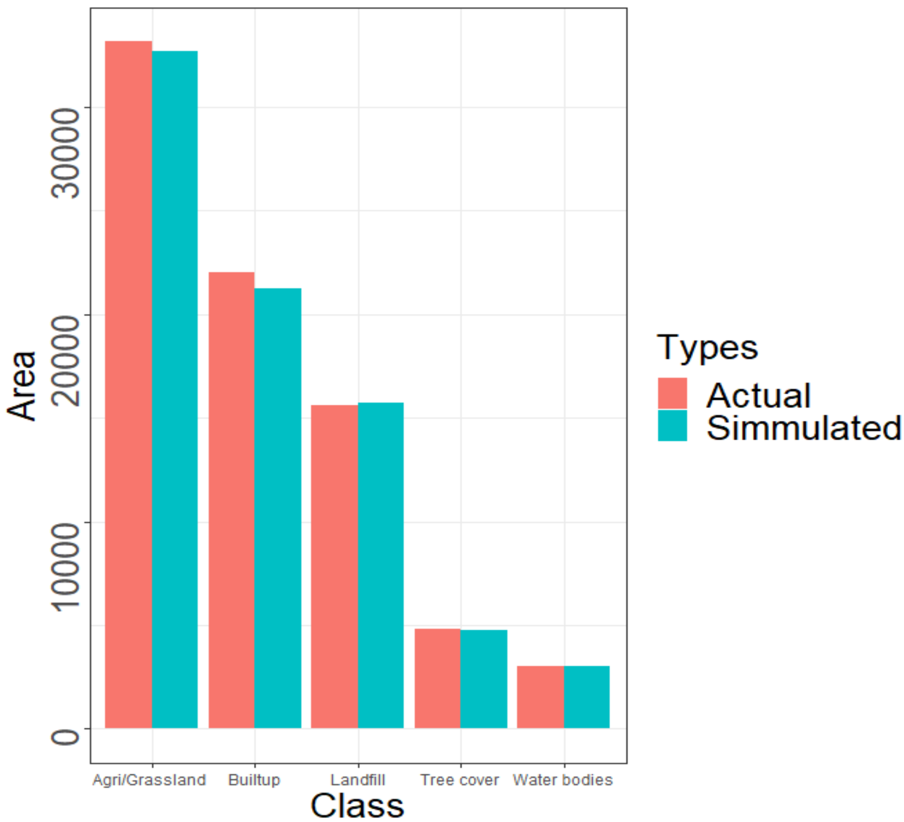

Figure 5. Comparison of actual (2020) and simulated (2020) area of study site.

Quantification of Ecological Services

After the ecosystem service valuation with the adjusted ecosystem service value coefficient by Costanza et al. (2014), we can see a significant change in total ecosystem value (Figure 6) in extended Dhaka city from 2004 to 2020, revealing a downward trend in total ecosystem value. During the last 16 years, the ecosystem has lost about 25% of its entire value, which is equivalent to 211 million dollars. If this trend continues, ecosystem services will lose an additional 156.36 million USD in 2050. Also, we compare the total ecosystem service value for both Dhaka city and the extended Dhaka City area. From 2004 to 2020, Dhaka City lost almost 40 percent of its total value worth 136.19 million Dollars, whereas Extended Dhaka City lost almost 15 percent of its total value worth 75.72 million Dollars. However, in our forecast of overall ecosystem service value, extended Dhaka city will lose the majority of the total ecosystem service value (for each of the three scenarios, namely, BAU, conservative, and development) compared to Dhaka city.

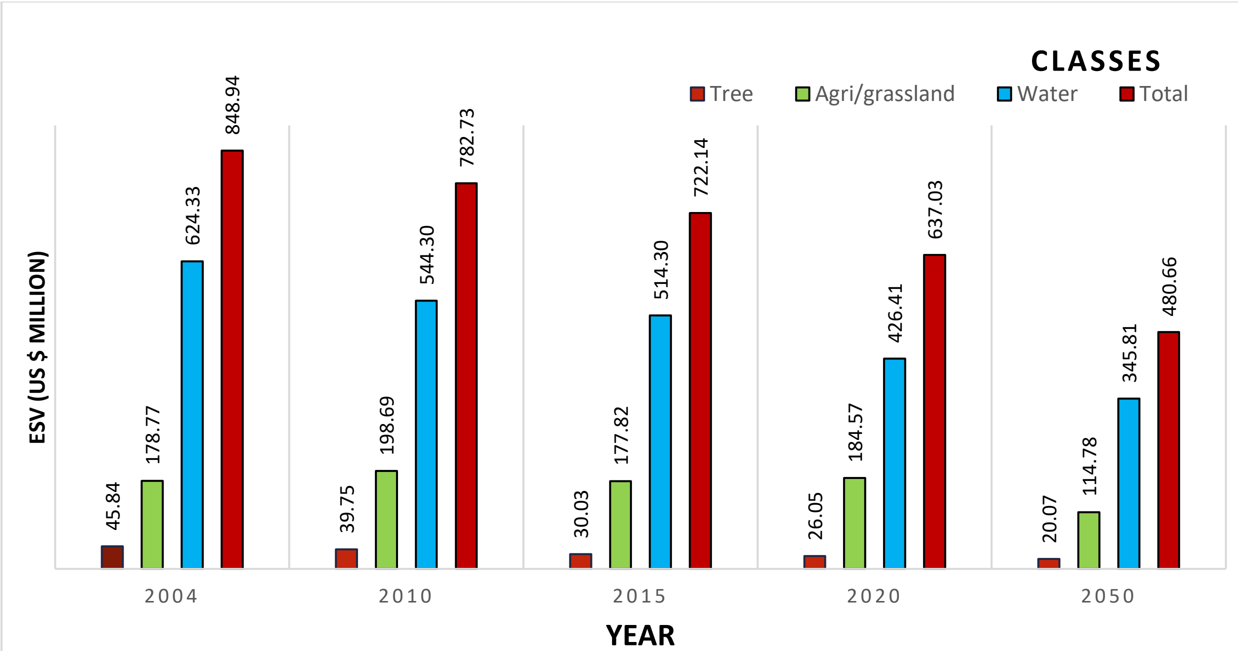

Figure 6. Estimated ecosystem service value (in millions) for different classes over the years

Further analysis revealed that from 2020 to 2050, Extended Dhaka city will lose 103.34(24% loss), 34.37(8% loss), and 209.71 (48% loss) million dollars for each of the three predictions, namely BAU, Conservative, and Development scenarios (Figure 7). On the contrary, Dhaka city will lose 53.13(26% loss), 13.22(6.5% loss), and 120.62 (60% loss) million dollars, respectively, under the same three alternative scenarios (BAU, conservative, and development) from 2020 to 2050. In summary, for each of the three scenarios, the tendency of ecosystem service loss will shift towards the extended Dhaka city from the mainland of Dhaka as the majority of the city areas will be occupied with built-up regions in the future, and most people will relocate out of the city area to nearby places.

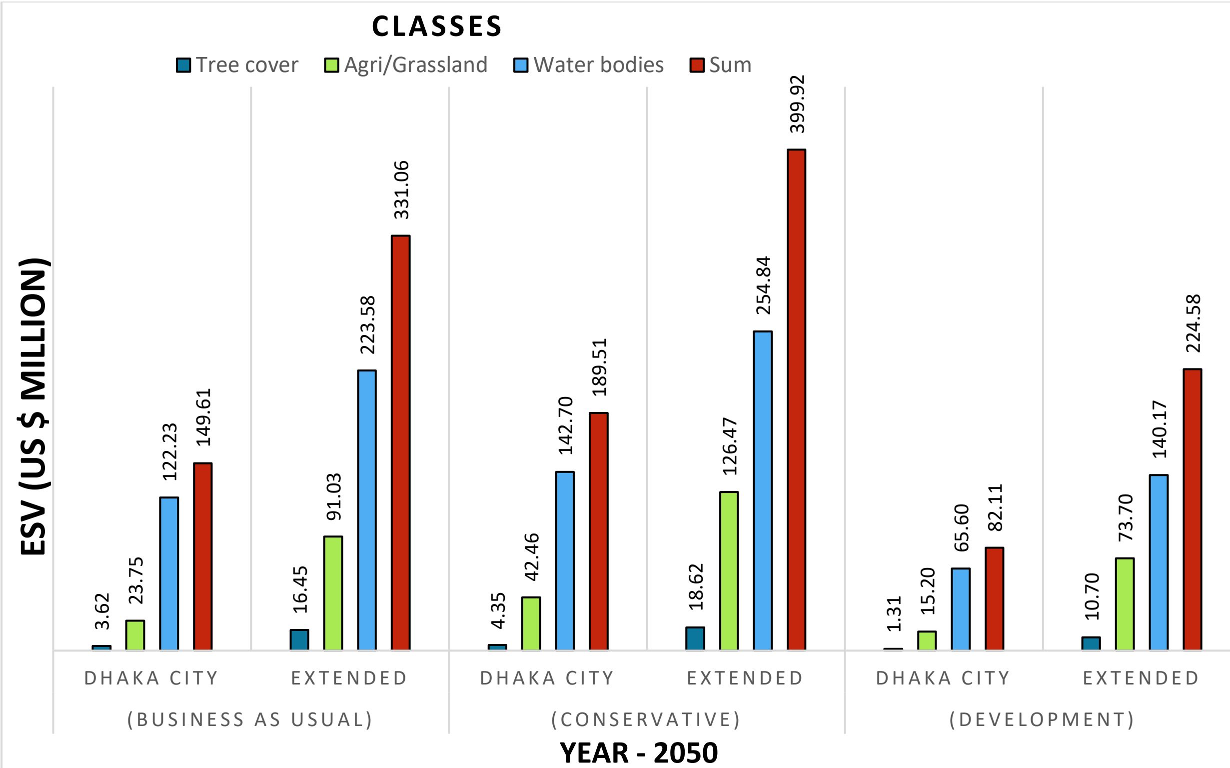

Figure 7. Comparison of the total ecosystem service value (in millions) of Dhaka city and extended Dhaka city in three different cases.

Tables 5 and 6 show the individual value of service function for Dhaka and Extended Dhaka city in 2004, 2020, and 2050. For 2004 and 2020, waste treatment, raw materials, habitat/refugia, and water supply contributed the most to the total service value for Dhaka city and extended Dhaka city. However, in 2050, for all three scenarios, food production, genetic resource, waste treatment, and habitat/refugia contributed the most to the total service value both for Dhaka city and extended Dhaka city. These four service functions are the most susceptible service functions in our study area.

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Table 5. The estimated value (million USD) of individual ecosystem service functions for Dhaka City and Extended Dhaka City during the period 2004 and 2020

Individual ESV Function		2004 Dhaka City	2004 Extended	2020 Dhaka City	2020 Extended
Provisioning	Food Production	6.00	11.35	4.53	11.78
	Raw Materials	25.94	54.60	21.40	59.49
	Genetic Resources	3.19	6.41	2.42	6.51
	Water Supply	13.77	33.69	10.62	32.01
Regulating	Gas Regulation	0.02	0.08	0.01	0.05
	Climate Regulation	8.16	23.34	5.54	18.59
	Disturbance Regulation	9.05	11.98	4.96	9.34
	Water Regulation	3.49	4.54	1.92	3.56
	Erosion Control	8.50	13.42	4.96	10.88
	Waste Treatment	220.83	288.87	122.47	229.98
	Biological Control	1.00	1.63	0.65	1.51
Supporting	Soil Formation	5.46	11.74	4.64	13.07
	Nutrient Cycling	1.13	1.47	0.62	1.15
	Pollination	0.28	0.68	0.22	0.66
	Habitat/Refugia	24.29	31.51	13.33	24.74
Cultural	Recreation	6.63	13.18	3.80	9.80
	Cultural	1.24	1.61	0.68	1.26
	Total	338.99	510.11	202.77	434.37

To evaluate the robustness of our ecosystem service value estimate, we performed a sensitivity analysis by adjusting the coefficients of the ecosystem services offered by main land cover categories. The effects of the adjusted coefficient in extended Dhaka city are shown in Table 7.

After adjusting the value coefficient (VC) for 2004, 2020, and 2050, we found that the coefficient of sensibility was highest for water compared to Agri/grassland and forest. From the sensibility analysis, we can conclude that, by the 50% increase or decrease of the coefficient of water bodies, Agri/grassland, and tree cover, the total value of ecosystem services of our study areas changed negligibly, and the value of the coefficient of sensitivity is less than one and near to zero. So, this indicates that the total ecosystem value estimated for the study area is relatively inelastic with respect to the ecosystem service coefficients. Since all the values were below 1 for all the years, we can conclude that our assumption for value coefficients was justifiable.

Table 6. The predicted value (million USD) of individual ecosystem service functions in three different scenarios (BAU, Conservative, and Development) for Dhaka City and Extended Dhaka City in 2050.

Individual ESV Function		BAU		Conservative		Development	
		Dhaka City	Extended	Dhaka City	Extended	Dhaka City	Extended
Provisioning	Food Production	10.88	40.11	18.85	55.19	6.84	32.10
	Raw Materials	1.35	4.50	2.16	6.02	0.81	3.48
	Genetic Resources	5.68	22.06	9.42	29.36	3.33	17.06
	Water Supply	2.56	8.15	4.05	10.92	1.55	6.31
Regulating	Gas Regulation	0.01	0.04	0.01	0.04	0.00	0.02
	Climate Regulation	3.30	13.29	4.99	16.77	1.71	9.71
	Disturbance Regulation	4.05	7.53	4.73	8.58	2.17	4.73
	Water Regulation	1.57	2.88	1.83	3.28	0.84	1.80
	Erosion Control	3.74	8.37	4.66	9.97	2.02	5.59
	Waste Treatment	98.87	184.45	116.47	211.86	53.22	116.84
	Biological Control	0.44	1.10	0.60	1.39	0.25	0.79
Supporting	Soil Formation	2.28	8.74	4.07	12.13	1.46	7.07
	Nutrient Cycling	0.51	0.93	0.59	1.06	0.27	0.58
	Pollination	0.11	0.45	0.19	0.60	0.07	0.35
	Habitat/Refugia	10.88	19.98	12.71	22.77	5.84	12.53
Cultural	Recreation	2.85	7.50	3.57	8.86	1.46	5.01
	Cultural	0.56	1.02	0.65	1.16	0.30	0.64
	Total	149.64	331.12	189.55	399.99	82.13	224.62

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Table 7. Ecosystem service value after adjusting ecosystem service value coefficient (VC) and coefficient of sensitivity (CS)

Change in valuation coefficient (VC)	ESV (US $ Million)			Effect of Changing CV from the original value		
	2004	2020	2050	2004	2020	2050
				Coefficient of Sensitivity		
Water VC +50%	1161.11	850.23	653.57	0.74	0.72	0.67
Water VC -50%	536.77	423.82	307.76	0.74	0.72	0.67
Agri/Grassland VC +50%	938.32	729.31	538.05	0.21	0.24	0.29
Agri/Grassland VC -50%	759.56	544.74	423.27	0.21	0.24	0.29
Forest VC +50%	871.86	650.05	490.70	0.05	0.04	0.04
Forest VC -50%	826.02	624.00	470.63	0.05	0.04	0.04

DISCUSSION

The change in land cover plays a significant role in changing the ecosystem's structure and function, leading to change in the ESV (Kindu 2016). Therefore, in this study, we investigated the influence of land use change for Dhaka City and the extended Dhaka City on the basics of ESV from 2004 to 2020 and beyond (2050). From 2004 to 2020, the built-up area increased by 260 percent, and this area gain was possible due to 31%, 43%, and 43% area loss from water bodies, tree cover, and landfill, respectively. Without proper plans or policies and effective public administrations, urbanization generally results in unmanaged urban growth (Rimal et al. 2018).

Dhaka is regarded as Bangladesh's revenue creation center due to the presence of several industries, business prospects, and commercial activities. Also, many people migrate towards Dhaka because of its better health and education facilities. To accommodate this large population, Dhaka city has no choice but to build houses and infrastructure for its people, which often leads to converting wetlands, agricultural/grassland, and tree coverage areas to bulitup areas, which can often lead to unplanned urbanization. Dhaka city has nearly reached its full in terms of built-up area capacity, and there would be very few places left for the development of buildings and infrastructure. People will be forced to relocate to the nearest available habitat near Dhaka city, also known as extended Dhaka city, because they will have no other choice, and extended Dhaka will suffer the same fate as Dhaka city if proper planning measures for building a sustainable city are not implemented.

Despite the fact that Dhaka city's GDP earning capacity has expanded significantly over the previous two decades and overall GDP has increased by 108 billion USD, resulting in a 107% percent growth, there have been severe repercussions associated with this GDP expansion (Murad et al. 2021). The Dhaka city's GDP tends to show inverse relation with total ecosystem service value. According to the findings of this study, over the last two decades (precisely 16 years), every one percent increase in total GDP has contributed to approximately 2 million dollars of ecosystem service loss.

According to World Bank forecasts and reports, the northeast side of Dhaka will be influenced more in case of urbanization, and there will be significant growth on that side of Dhaka city since there is an ongoing mega project ("Purbachal New Town") (World Bank, 2007). However, our forecast paints a somewhat different narrative, indicating that both the south and north sides will undergo significant urbanization in the future. Moreover, In the southern-west areas, the roads and bridges built over the rivers will create a massive opportunity for development and commercial success. Additionally, the waterways built in Jinjira and Keraniganj have also helped in small-scale industrialization and urban expansion. Due to the connection with the Chittagong port, the development of industrial setup and transportation facilities are expected to be witnessed in the southeastern part of Dhaka city.

Another crucial factor is that Dhaka is a low-lying, flood-prone region. Even a few millimeters of rain can cause water to become logged and drown certain parts of Dhaka as the drainage system of Dhaka is poor. Impervious areas block the majority of water-flowing regions inside Dhaka, and if, in the future the extended Dhaka city follows the same pattern and proliferates in an unexpected way, the whole city's drainage system will be hampered tremendously. The city Dhaka will be an inhospitable place to live due to toxic air, unsafe water for drinking, unprecedented population density, inadequate road and vehicle facilities resulting traffic gridlocks, waterlogging and mosquito infestation problem eventually there will be no choice but to proclaim it as a dead city (Bay 2022). If we can somehow contain the total value of the extended Dhaka city, there will still be some hope for the main Dhaka city. Sustainably planning the extended Dhaka city will not only help the periphery area but also it will help to dissuade specific problems of existing Dhaka city.

CHALLENGES AND LIMITATIONS OF THE STUDY

This research undertook a comprehensive analysis of the historical, current, and projected future value of ecosystem services in Dhaka city. However, the study encountered numerous challenges and limitations in its execution. Firstly, we employed the 2014 biome valuation framework by following Constanza et al. (2014) as a benchmark for assessing the value of ecosystem services across past, present, and future scenarios. However, a more precise estimation would be achievable by utilizing current biome values for ecosystem services as the value coefficient of ESV changes over time (Zank et al. 2016). Secondarily, for the acquisition of extended sequential satellite imagery, the Landsat satellite imagery was utilized, notwithstanding its relatively coarse resolution. The foundation of the Ecosystem Service Value (ESV) estimation in this study is intricately linked to various land cover types. Consequently, the precision of the estimated ESV is intrinsically tied to the accuracy of land cover classification, which, in turn, is contingent upon the resolution of the satellite imagery**.** Access to high-resolution imagery, although available, is often limited by its lack of long-term series and considerable associated costs. Finally, methods that transfer benefits often think every area's ecosystem service value is the same, but this isn't true because human-environment systems are complex and vary a lot as same type of land might have different ecosystem service values in different countries because of differences in society, nature, and the economy (Song and Deng 2017). For the future studies creating a value that considers the unique conditions of each local area is suggested as using one general value for all areas can lead to wrong estimates of ESV.

CONCLUSIONS

This study investigated the past, present, and future urban and peri-urban changes in Dhaka city alongside the extended area, its impact on the ESV utilizing the spatial information system, and the global value coefficient. The study showed that due to rapid urbanization from 2004 to 2020, the urban area coverage of Dhaka city and its extended area has changed significantly, and if preventative measures are not implemented, it will continue to do so in the future. Dhaka being the center of development, a lot of infrastructure and built-up areas had been established, which in turn caused severe pressure on the unprotected areas (waterbodies and tree covers). Over the last 16 years, the total increase in built-up area was 260 percent, whereas due to this rapid increase in built-up area, the unprotected water bodies and tree cover decreased by 31 and 43 percent, respectively. Based on these trends, we explored Dhaka's future urban change dynamics and its extended areas utilizing the CA-Markov model. The predicted urban land utilization pattern revealed that if the current trend of turning vast waterbodies and tree areas into urban structures of Dhaka remains unchecked, then in the next three decades' built-up areas will be increased by 81%, 42%, and 122% for BAU, development, and conservative respectively.

On the other hand, the upsurge of the built-up area will create disturbance in the ecosystems and biodiversity of the peri-urban area of Dhaka city. This will cause a decrease of waterbodies up to 19%, 7%, and 52%, alongside tree cover at 23%, 12%, and 54% for BAU, development, and conservative, respectively. As waterbodies and tree cover are the main contributors to ESV, changes in urban expansion will also affect the ESV. This study revealed that within the next 30 years, the expected overall ESV will decrease by 24 percent, and in terms of monetary value, it is almost 156 million dollars. In addition, substantial alterations in ecological functions, such as waste treatment, raw materials, habitat/refugia, and water supply, were primarily responsible for the ESV's decline. This study also suggests that ecosystem services decline by approximately two million dollars for every one percent increase in total GDP. All of the above statistics indicate that the natural ecology is increasingly affected by anthropogenic activities. Hence, it is needless to say that forests, cropland, rivers, and lakes must be protected. It is also possible to slow down land change and retain the local ecosystem through effective land development and utilization.

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