Urban green and blue space changes: a spatiotemporal evaluation of impacts on ecosystem service value in Bangladesh

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Abstract

The rapid decline in urban green (UGS) and blue space (UBS) in developing countries has led to a widespread degradation of available ecosystem services (ES). However, impacts of UGS and UBS changes on ES tend to vary over space and time, and to date these impacts have not been studied in sufficient detail in emerging economies. By comparing UGS and UBS change patterns with multitemporal Landsat data recorded during the past 30 years (1991–2021), this study has examined the impact of several factors on ES in some of the world's climate hotspots. Although obtaining relevant and accurate information on ES is difficult in many parts of the developing world, this work has developed baseline data suitable for assessing ES loss over five densely populated cities in Bangladesh – Dhaka, Chattogram, Khulna, Rajshahi, and

Sylhet. ES loss was quantified in monetary terms using adjusted value coefficients. The topographic and anthropogenic factors driving spatial differences in ES degradation in these cities were analyzed with a geographical detector. The results indicated that the cities experienced a combined monetary loss of USD 628.58 million as a result of specific ES degradation, primarily due to the decline of UGS and UBS. The value of ES loss was notably higher in Dhaka and Chattogram than in the other cities due to marked differences in anthropogenic activities. Population growth, extensive urban sprawl, and the development of dense road networks were identified as the major causes of urban green and blue space loss and consequent reduction of ES. The findings of this study provide important insights which can be used to support the formulation of public policies and management plans aimed at restoring and maintaining sustainable urban ecosystems.

Keywords: Ecosystem services, green and blue space, spatial heterogeneity, Ecosystem services value (ESV), Cross-city comparison, spatiotemporal analysis

1. Introduction

An ecosystem is a community or region where energy and materials are transferred between organisms and their physical environment (Chapin et al., 2002). The public benefits provided by an ecosystem were first discussed in the 1970s when the concept of ecosystem services (ES) emerged (Nahlik et al., 2012). While there are different types of ES – e.g. regulatory, supporting, provisioning, and cultural (De Groot et al., 2002; MEA, 2005)) – they all contribute to the wellbeing of people and society (Vargas et al., 2019). The need to quantify ES has been recognized by various international organizations, including the Millennium Ecosystem Assessment Board (MEAB) (MEA, 2005), and in policy documents like The Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) (Díaz et al., 2015), and The Economics of Ecosystems and Biodiversity (TEEB) (Russi et al., 2013).

Excessive use of natural resources in recent decades has resulted in a rapid decline in ES (Adegboyega et al., 2019). The MEAB (MEA, 2005) has reported that different types of wetland ecosystems (e.g. lakes, rivers, marshlands), have been destroyed/degraded during the twentieth century, with a resulting alteration of the Earth's energy balance (Song et al., 2018) and biogeochemical cycles (Kaushal et al., 2014). The resulting damage to ecosystem service values (ESV[1]) is now being more broadly recognized (Costanza et al., 1998).

An ever-increasing world population (Berihun et al., 2021), overexploitation of natural resources (Dong et al., 2014), rapid urbanization (Xiao et al., 2020), and industrialization (Sanchez-Porras et al., 2018) have resulted in a serious decline in ES across the world, most pronounced in developing countries like Bangladesh where land is scarce and the pattern of land use change is complex (Crespin and Simonetti, 2016; Hoque et al., 2022). In the context of highly urbanized countries, the quantification of ESV could inform conservation efforts and the sustainable use of natural capital (Jin et al., 2021).

Intense anthropogenic activities in urban settings have major impacts on the natural environment, including a marked deterioration in vegetated and waterbody areas. This is especially common in developing countries. It has been noted that the pattern of urban land use change is strongly associated with ES in space and time (Kain et al., 2016). Different types of urban green space (UGS) such as parks or urban forests (Tian et al., 2020), and blue space (UBS) like lakes, ponds, and rivers (Dou et al., 2017) provide defined ES in urban areas (Amini Parsa et al., 2019). UGS and UBS offer a range of environmental benefits for urban dwellers, including local climate regulation (Adnan et al., 2022; Gunawardena et al., 2017) and air purification (Matos et al., 2019).

[1] Ecosystem service value (ESV) refers to the monetary values assigned to an ecosystem (Sannigrahi, et al., 2019)

The presence of UBS, for example, can reduce the ambient air temperature by 1–3 °C within 30 meters (m) of the waterbody (Kleerekoper et al., 2012). UGS and UBS also play an important role in water storage and can be used to control the release of urban water flows (Bellezoni et al., 2021), reduce energy consumption (Bellezoni et al., 2021), reduce noise (Koprowska et al., 2018), and enhance carbon sequestration (Wang et al., 2021). They also provide suitable habitats for a range of bird and aquatic species (Kowarik et al., 2019), counteract biodiversity loss, and support pollination (Threlfall et al., 2015). From a public health point of view, UGS and UBS contribute positively to mental and physical health as well as some social interaction (Labib et al., 2020). In summary, protecting UGS and UBS is essential for achieving overall environmental sustainability.

Advances in geospatial technology have enabled researchers to use geographical information systems (GIS) and remotely sensed data to evaluate the spatiotemporal pattern of geographic phenomena such as ES (Vargas et al., 2019). Land cover data derived from satellite images is now routinely used in ESV estimation (Hoque et al., 2022; Mallick et al., 2022). Various econometric, physical, and energy models are also available (Zhang et al., 2020). Econometric techniques such as market price method, benefit/value transfer method (B/VTM), contingent valuation, hedonic pricing, conjoint analysis, replacement cost, and spatially explicit biophysical models are among the various ES quantification approaches now widely used (Costanza et al., 1998; Costanza et al., 2014; De Groot et al., 2012; Sannigrahi et al., 2019). Due to continual inflation and associated price hikes, however, methods like BTM do not accurately reflect the actual loss of ES, so reliable information is difficult to obtain. To overcome this problem, coefficient values of ES were used and adjusted to minimize the sensitivity of the covariates (e.g. land use types) (Sannigrahi et al., 2019).

Estimating ES is a challenging task due to the complex interactions between various landscape elements (Braun et al., 2019; Islam et al., 2018) which play a critical role in modifying features like UGS and UBS. Different drivers need to be considered when investigating the responses of ES to landscape change caused by human activities. By detailing the changing patterns of UGS and UBS, appropriate strategies can be developed to minimize possible negative impacts on these valuable natural features. Although changes in ESV are driven by different factors (MEA, 2005), such as climate change (Sannigrahi et al., 2020), land use changes (Lin et al., 2018), and urbanization (Fei et al., 2016), most studies to date have quantified ESV by considering only a single driver (Runting et al., 2017; Zhang et al., 2020).

Quantifying ESV using multiple factors is a complex process because of the dynamic nature of the variables used and their different scales. The non-availability of data at the local scale sometimes prompts researchers to quantify bivariate associations between ESV and particular influencing factors (Li and Song, 2021). Challenges can be overcome by using credible global datasets and the establishment of applications such as the geographical detector model (GDM) (Fang et al., 2021; He et al., 2021). These provide a comprehensive explanation of interdependency and a determination of the influence of various drivers. Most existing studies have used only a single city when estimating ES loss. Rahman and Szabó (2021) investigated the spatiotemporal ES loss in Dhaka city between 1990 and 2020. Similar studies were also conducted in Taiyuan (Liu et al., 2012), New York (Miller and Montalto, 2019), Delhi (Morya and Punia, 2022), and Barcelona (Langemeyer et al., 2020). Since population growth dynamics and anthropogenic activities differ significantly between cities, it is expected that ES loss should also vary.

This study aims to: (i) investigate spatiotemporal patterns of urban green and blue spaces in five large cities of Bangladesh (Dhaka, Chattogram, Khulna, Rajshahi, and Sylhet); (ii) develop baseline information on ES loss due to anthropogenic activities at the metropolitan scale; and (iii) determine factors driving the loss of these spaces. Baseline information on ES loss is essential for the formulation of conservation and restoration strategies, but such information does not currently exist for large Bangladeshi cities. This study not only allows comparisons between cities, but also provides important insights into the wise use of the natural capital of a city.

2. Materials and methods

2.1. Study area

This study examines five of the major cities of Bangladesh – Dhaka, Chattogram, Rajshahi, Khulna, and Sylhet (Fig. 1). All these cities are located adjacent to major rivers: the Buriganga (Dhaka); Karnafuli (Chattogram); Ganges (Rajshahi); Rupsha (Khulna); and Surma (Sylhet). Dhaka has the largest area (1488.4 km^2), followed by Chattogram (729.9 km^2), Rajshahi (366.6 km^2), Khulna (233.3 km^2), and Sylhet (82.5 km^2). Dhaka also has the highest population, approximately 23 million (m) people, while Rajshahi has 9.5m, Chattogram 9m, Khulna 3m, and Sylhet 0.95m (Bondarenko et al., 2020). All five cities have experienced rapid urbanization in the recent past, with the associated conversion of extensive vegetated and waterbody areas into built-up urban areas (Abdullah et al., 2022; Moniruzzaman et al., 2020). The current annual rate of spatial growth of Dhaka is 11.5% (Moniruzzaman et al., 2020), while for Rajshahi it is 5.0% (Faridatul, 2017), and for Chattogram 3.75% (Abdullah et al., 2022). Urbanization contributes significantly to increasing Gross Domestic Product (GDP), but unplanned growth can be detrimental to both physical and social environments.

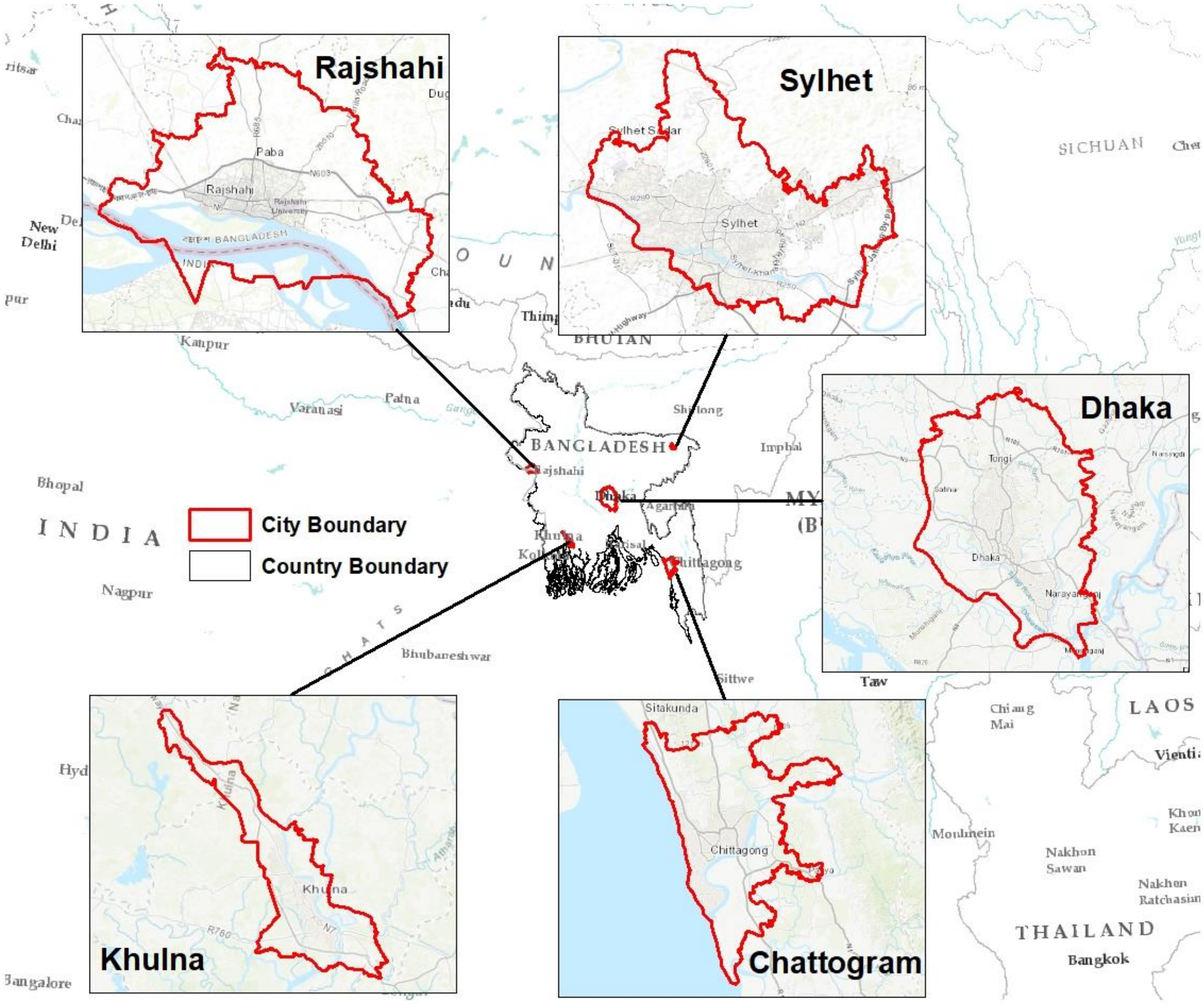


Fig. 1 Location of five cities in Bangladesh

2.2. Data collection and image preprocessing

The current study has employed multi-date Landsat images to investigate the spatiotemporal pattern of UGS and UBS during the period 1991 to 2021. A total of 49 Landsat 5 and 8 images were acquired from EarthExplorer (https://earthexplorer.usgs.gov/) for the following years – 1991, 1996, 2001, 2006, 2011, 2016, and 2021. All images used in this work were taken in the pre-monsoon month of March because the cloud cover at other times of the year was a significant problem. The images have undergone various preprocessing steps, including radiometric correction.

2.3. UGS and UBS extraction

This study has employed a normalized difference vegetation index (NDVI) (Rouse Jr et al., 1974) and a modified normalized difference water index (MNDWI) (Xu, 2006) to identify and extract UGS and UBS in the five cities. The following equations were used to compute NDVI and MNDWI from the Landsat images:

$$NDVI = (B_{NIR} - B_R)/(B_{NIR} + B_R) \quad (1)$$

$$MNDWI = (B_G - B_{MIR})/(B_G + B_{MIR}) \quad (2)$$

where B_{NIR} is near-infrared, B_R is red, B_G is green, and B_{MIR} is mid-infrared band.

NDVI values range from -1 to +1, with negative values indicating no vegetation, values 0-0.2 indicating unhealthy vegetation, 0.2-0.5 indicating moderately healthy vegetation, and >0.5 indicating healthy vegetation (Hashim et al., 2019). According to the World Health Organization (WHO), the area of an ideal UGS should be at least 0.5 ha (WHO, 2017), so locations with NDVI values ≥0.2 and area ≥0.5 ha were classified as UGS for this work. MNDWI also ranges from -1 to +1, with positive values indicating waterbodies. Locations with MNDWI ≥ 0.2 and area ≥0.5 ha were defined as UBS in a similar manner to UGS (WHO, 2017; Wu et al., 2020). The accuracy of NDVI and MNDWI for 1991, 1996, 2001, 2006, 2011, 2016, and 2021 was assessed by estimating overall accuracy and kappa statistics, and comparing with reference data collected from Google Earth. Overall accuracy illustrates the percentage of correctly classified pixels (Congalton, 1991). The kappa statistics range between 0 and 1, with 0 indicating poor agreement and 1 indicating nearly perfect agreement (Cohen, 1960).

2.4. Estimating ecosystem services values (ESV)

The benefit transfer method (BTM) (Costanza et al., 1998) was used to estimate ESV. This method is particularly useful for a quick assessment of ESV in large areas with typically large datasets (Emerton, 2014; Estoque et al., 2018). Costanza et al. (1998) proposed this method and subsequently estimated worldwide equivalent values for different biomes which were adopted by various other countries (Hoque et al., 2022; Khan et al., 2019; Liu et al., 2010; Rahman and Szabó, 2021; Sharma et al., 2020; Zhou et al., 2020). ESV is divided into four categories – provisioning, regulating, supporting, and cultural, and also includes several sub-classes (Table 1). A detailed ESV dataset for Bangladesh was not available, so the study adopted value coefficients (VC) from previous studies of the same biome (Costanza et al., 1998; De Groot et al., 2012). Most of the VC were outdated and not representative of current values, so the present BTM values were adjusted as explained in the next section.

2.4.1. Modifying the ESV

The current ES values of UGS and UBS were estimated by adjusting for the inflation rate, using a Consumer Price Index (CPI) method (Equation 3) (BLS, 2022):

$$CPI = \frac{C_t}{C_o} \times 100 \tag{3}$$

where CPI is the consumer price index at present (2022), C_t is the cost of a market basket in the current period, and C_o is the cost of a market basket in the base period.

2.4.2. Calculating ESV

Using the adjusted values (Table 1), ESV of UGS and UBS for all five cities were estimated with the following equation (Costanza et al., 1998):

$$ESV_t = \sum (A_k \times VC_k) \tag{4}$$

where ESV_t is the total estimated ecosystem services value, A_k is area (ha), and VC_k is value coefficient (USD ha^{-1}year^{-1}) for land feature k.

The following equation (Song and Deng, 2017) was subsequently employed to estimate long-term and short-term changes in ESV:

$$ESV_c = \frac{ESV_f - ESV_i}{ESV_i} \times 100 \tag{5}$$

where ESV_c is the change in ecosystem service and ESV_i and ESV_f are ecosystem values for the base and final years, respectively.

2.5. Estimating coefficients of sensitivity and elasticity

Surrogate values were used to estimate ESV, so the potential for uncertainties was large. A sensitivity test was also conducted to understand this possible issue. The response of ESV to the changes in VC (Kindu et al., 2016) was estimated using a well-known coefficient of sensitivity (CS) test (Sannigrahi et al., 2019). The CS is based on a standard economic concept of elasticity, which was measured as:

$$CS = \frac{(ESV_j - ESV_i)/ESV_i}{(VC_{jk} - VC_{ik})/VC_{ik}} \tag{6}$$

where ESV is ecosystem services value, VC is value coefficient, *i* and *j* represent initial (modified values from Table 1) and adjusted values (±50% adjusted values), and *k* is ecosystem type. ESV was measured for each ecosystem type. Services can be elastic (less reliable) when CS exceeds a threshold value of >1 or can be inelastic (reliable) when CS is <1. In addition, CS values of 1 and 0 indicate complete elasticity and inelasticity, respectively. The larger the CS value, the more critical (less reliable) the accuracy of an ESV index and vice versa.

Table 1 Old and modified ESV values of UGS and UBS

Indicators	UGS		UBS		Reference(s)
	Old values	Converted values	Old values	Converted values	
Provisioning					
Food production	200	253.2	106	134.2	(Costanza et al., 2014)
Raw materials	84	106.34			’’
Medicinal resources	1504	2,071.57			(De Groot et al., 2012)
Water supply	27	34.18	1808	2,288.93	(Costanza et al., 2014)
Genetic resources	1517	1,920.52			’’
Regulating					
Gas regulation	12	15.19			(Costanza et al., 2014)
Climate regulation	2044	2,587.70			’’
Disturbance regulation	66	83.56			’’
Water regulation	8	10.13	7514.1	9,512.84	’’
Waste treatment	120.06	152	917.7	1,161.81	’’
Pollination	30	37.98			’’
Biological control	11	13.93			’’
Erosion control	337.45	427.21			’’
Moderating extreme events	66	90.91			(De Groot et al., 2012)
Carbon sequestration	141	161.88	160.6	184.38	(Kibria et al., 2017)
Air purification	1010	1,159.57	1150.37	1,320.73	’’
Supporting					
Habitat/refugia	374.5	417.9	200.57	223.81	(Lin et al., 2018)
Soil formation	333.81	372.49	23.98	26.76	’’
Nutrient cycling	3	3.8			(Costanza et al., 2014)
Cultural					

Recreation	867	1,097.62	2166	2,742.15	(Costanza et al., 2014)
Cultural	2.0727	2.62			”
Total	**8757.9**	**11020.3**	**14047.32**	**17595.61**	

2.6. Transition of UGS and UBS to different land covers

The transition of UGS and UBS to other land covers, such as built-up or bare land, cannot be determined only with NDVI and MNDWI statistics. This study also conducted a land use and land cover (LULC) classification for the year 2021 in the five cities to examine in more detail transitions of UGS and UBS into other LULC categories. A pixel-based classification using a Random Forest (RF) classifier was implemented because this method is regarded as superior to other methods (Abdullah et al., 2019; Adam et al., 2014). The RF algorithm is based on classification and regression trees (CART), which use a recursive binary split technique to produce the final nodes in a tree structure (Breiman, 2001). RF was implemented using the random forest package (https://www.r-project.org/) in R. All parameters (except for the number of trees) were accepted as default values. To understand more fully the transition of UGS and UBS into other land cover types, the 1991 UGS and UBS boundaries were used to extract 2021 LULC data for each city.

2.7. Investigating forces driving UGS and UBS change

Spatiotemporal variations in ESV are driven by many factors (He et al., 2021; Yang et al., 2022). A geographical detector model (GDM), based on spatial variation theory, was designed to measure the spatially stratified heterogeneity of a response variable and the impacts of various driving factors (Wang et al., 2010). The GDM operates on the assumption that if an environmental factor (X) contributes to a response variable (Y), their spatial distribution should be similar. Such similarities or spatial associations can be measured via q-statistics (Fig. 2) (Wang et al., 2016). By overlaying the distribution of independent and dependent variables, variance σ_i^2 of ESV for each sub-region and σ^2 for the whole study area can be calculated. The larger the value of q, the stronger the explanatory power of an independent variable X for the dependent variable of Y, or vice versa. The GDM included a differentiation and factor detector, and interaction, ecological, and risk detectors. Interaction detectors, which compare the contributions of two attributes individually versus their combined contribution, were selected.

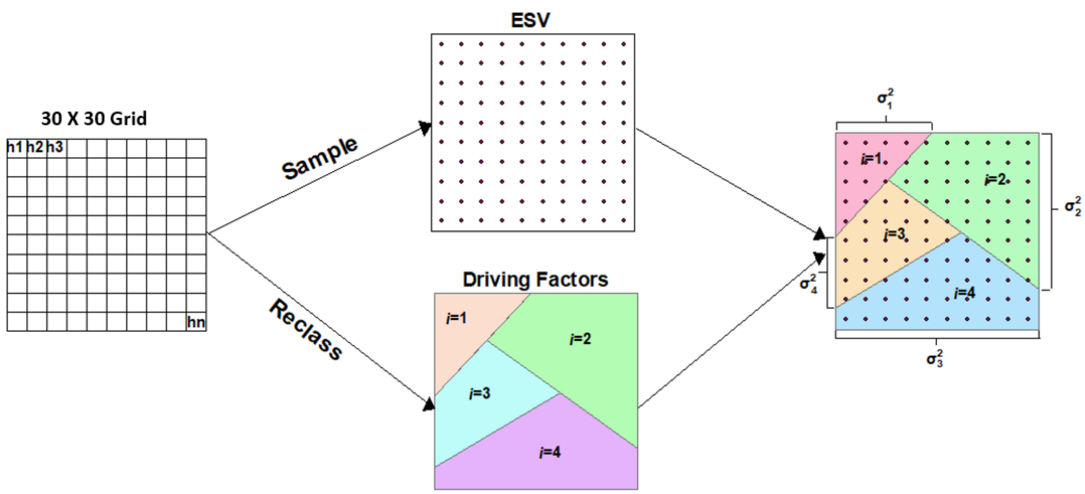


Fig. 2 Principles of the geographical detector model (GDM)

A differentiation and factor detector can be used to detect spatial differentiation of ESV and the extent to which factor X explains the spatial variation in ESV. Measured with the q value, the expression is as follows (Wang et al. 2010):

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2} \tag{7}$$

where h = 1, 2, …, L is stratification of ESV or factor X, N is the number of samples, σ^2 is the variance in ESV, and q is the degree of explanation of ESV by factor X. The value of q ranges from 0 to 1. When q = 1, factor X completely controls the spatial distribution of ESV; q = 0 indicates that there is no association between X and ESV. The interaction detector is defined to identify interaction between various factors by comparing q (X1 ∩ X2) with q (X1) and q (X2).

Five factors were selected to investigate spatial variability of ESV in five cities. They were elevation (E), slope (S), population (P), proximity to roads (R), and proximity to built-up areas (B) (Table 2). The degree of association between each factor and ESV differentiation was then estimated. The results can be used to understand whether the changes in UGS and UBS are systematic or random. In this work, a nominal grid size of 30 m was used.

Table 2 Data sources and resolution levels of factors

Data	Resolution	Source
Elevation	30 m	NASA Shuttle Radar Topography Mission (SRTM) Version 3.0 (https://earthdata.nasa.gov)
Slope	30 m	Derived from DEM
Population	100 m	WorldPop (https://www.worldpop.org)
Road	30 m	OpenStreetMap (https://www.openstreetmap.org)
Built-up area	30 m	Derived from Landsat 8, USGS (https://www.usgs.gov)

3. Results

3.1. Ecosystem valuation of UGS and UBS

The results indicated a trend of decreasing UGS in all five cities (Table 3). From 1991 to 2021, Dhaka experienced a decline in UGS from 27.46% in 1991 to 10.14% in 2021, with Sylhet going from 49.43 to 20.13%, Rajshahi from 35.6% to 21.7%, Chattogram from 27.79% to 18.1%, and Khulna from 40.1% to 32.17% (Fig. 3). These cities also experienced a significant loss of UBS during the study period (1991–2021). The greatest loss of UBS was observed in Sylhet, declining from 3.42% to 2.23%, while Chattogram had the least decline. Loss of UGS and UBS resulted in significant loss of ESV (Table 4). For instance, ESV associated with UGS in Dhaka was USD 244m in 1991, but decreased to USD 90.22m by 2021. Likewise, ESV of UBS reduced from USD 20.32m in 1991 to USD 13.44m in 2021. Fig. 4 shows the gains and losses of UGS and UBS in the five cities analyzed. Stable green and blue spaces in Dhaka appeared to diminish more rapidly than in the other four cities.

Table 3 Temporal variations in UGS and UBS in five cities, 1991-2021

Year	Area (ha)									
	Dhaka		Chattogram		Khulna		Rajshahi		Sylhet	
	USG	UBS	UGS	UBS	UGS	UBS	UGS	UBS	UGS	UBS
1991	40866.84	6788.79	41358.24	5975.64	9376.56	9376.56	13058.28	5756.13	4077.99	282.24
	(27.46%)	(4.56%)	(27.79%)	(4.01%)	(40.1%)	(10.78%)	(35.6%)	(15.69%)	(49.43%)	(3.42%)
1996	28576.80	6700.95	38843.1	5004.45	9195.57	9195.57	9299.52	3163.68	3028.23	232.56
	(19.2%)	(4.5%)	(26.1%)	(3.36%)	(39.33%)	(9.95%)	(25.35%)	(8.69%)	(36.71%)	(2.82%)
2001	27498.24	7997.31	32542.2	5291.28	8300.61	8300.61	9903.33	1278.09	2968.11	164.34
	(18.48%)	(5.37%)	(21.86%)	(3.56%)	(35.5%)	(6.74%)	(27%)	(3.48%)	(35.98%)	(1.99%)
2006	27810.90	3529.35	34212.33	5720.94	8307.99	8307.99	8346.06	3653.37	2439.72	231.93
	(18.69%)	(2.37%)	(22.99%)	(3.84%)	(35.53%)	(5.96%)	(22.75%)	(9.96%)	(29.57%)	(2.81%)
2011	23369.22	4639.50	32715.36	5421.87	8338.41	8338.41	8277.66	3380.22	1995.93	232.38
	(15.7%)	(3.12%)	(21.98%)	(3.64%)	(35.66%)	(5.9%)	(22.57%)	(9.22%)	(24.19%)	(2.82%)
2016	19143.09	4126.77	27933.03	6383.79	7987.95	7987.95	9577.08	3752.19	2169.36	181.98
	(12.86%)	(2.77%)	(18.77%)	(4.29%)	(34.17%)	(5.5%)	(26.11%)	(10.23%)	(26.3%)	(2.21%)
2021	15098.85	4491.72	26941.14	5644.62	7662.15	7662.15	7958.25	4605.48	1660.32	184.32
	(10.14%)	(3.02%)	(18.1%)	(3.79%)	(32.17%)	(6.95%)	(21.7%)	(12.56%)	(20.13%)	(2.23%)

Table 4 Temporal changes in ESV over five cities, 1991–2021

Year	ESV (million USD)									
	Dhaka		Chattogram		Khulna		Rajshahi		Sylhet	
	UGS	UBS	UGS	UBS	UGS	UBS	UGS	UBS	UGS	UBS
1991	244.19	20.32	455.78	105.15	103.33	44.35	143.91	101.28	44.94	4.97
1996	170.76	20.06	428.06	88.06	101.34	40.95	102.48	55.67	33.37	4.09
2001	164.31	23.94	358.62	93.1	91.48	27.71	109.14	22.49	32.71	2.89
2006	166.18	10.56	377.03	100.66	91.56	24.5	91.98	64.28	26.89	4.08
2011	139.64	13.89	360.53	95.4	91.89	24.26	91.22	59.48	22	4.09
2016	114.39	12.35	307.83	112.33	88.03	22.64	105.54	66.02	23.91	3.2
2021	90.22	13.44	296.9	99.32	84.44	28.58	87.7	81.04	18.3	3.24

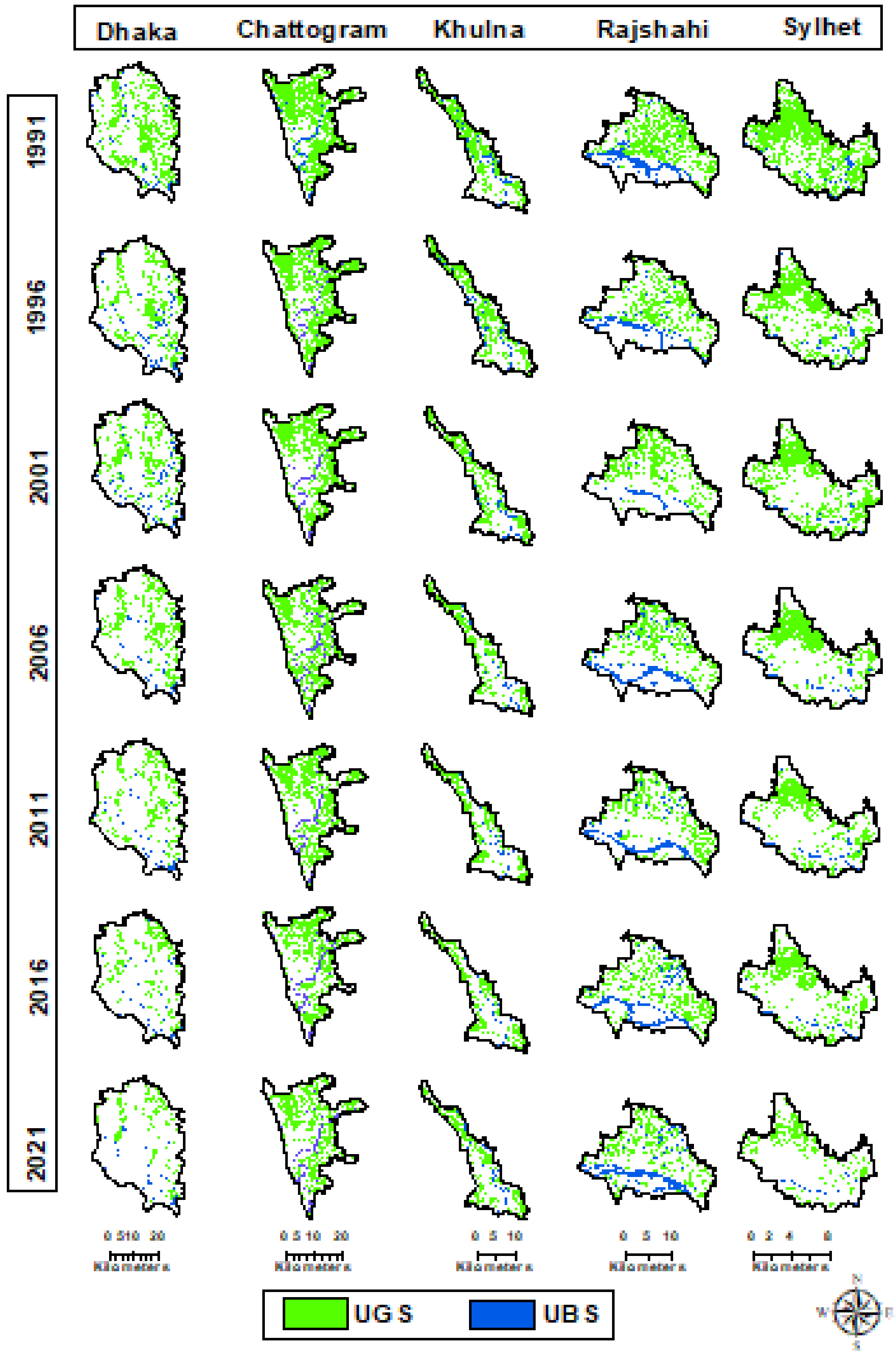


Fig. 3 Spatial distributions of UGS and UBS in five cities, 1991–2021

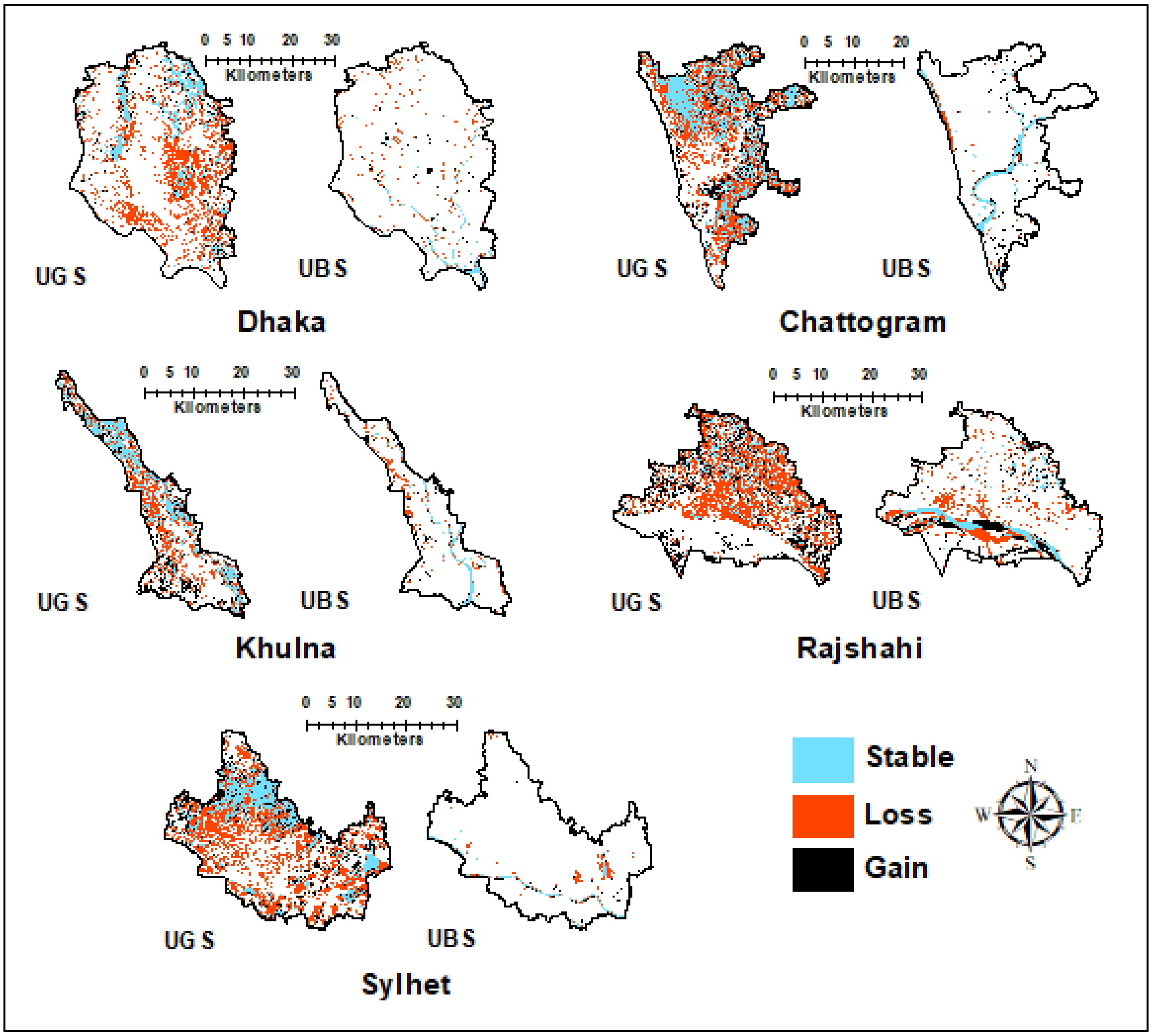


Fig. 4 Gains and losses of UGS and UBS in five cities, 1991–2021

Fig 5 shows the distribution of ESV loss for UGS and UBS between 1991 and 2021. The highest ESV loss (per km^2) was found in Rajshahi (USD 2.09m), followed by Dhaka (USD 1.94m), Khulna (USD 1.25m), Chattogram (USD 0.99m), and Sylhet (USD 0.56m). In Dhaka, Khulna, and Rajshahi, ESV declined most around the city center, while in Chattogram and Sylhet the losses were predominantly on the outskirts of the city.

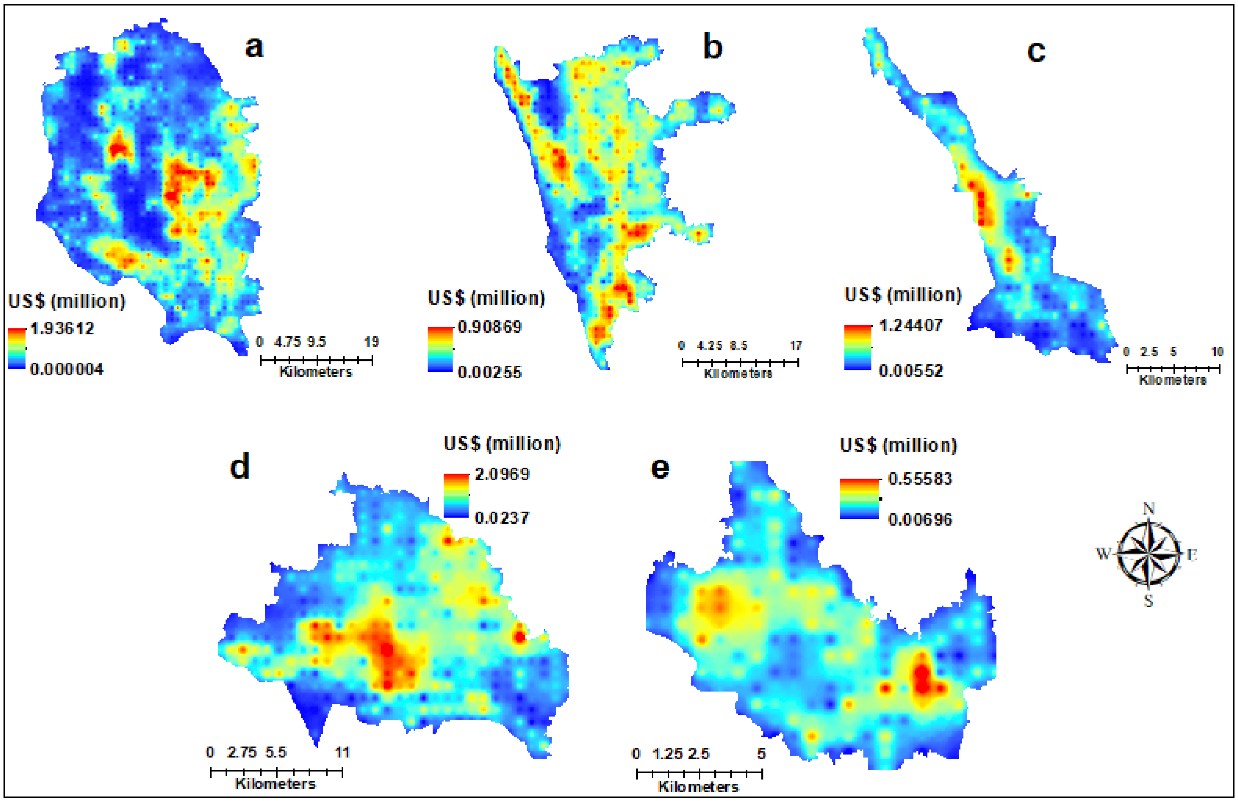


Fig. 5 Combined loss of ESV resulting from UGS and UBS degradation, 1991–2021: (a) Dhaka; (b) Chattogram; (c) Khulna; (d) Rajshahi; (f) Sylhet.

Index-based UGS and UBS accuracy was checked by computing overall accuracy and kappa statistics. The overall accuracy for UGS and UBS was 86.52%, 86.93%, 87.74 %, 86.85%, 89.21%, 89.37%, and 92.56% for the years 1991, 1996, 2001, 2006, 2011, 2016, and 2021, respectively. The corresponding kappa coefficients were 0.836, 0.839, 0.842, 0.835, 0.863, 0.872, and 0.896. Both accuracy indices indicated satisfactory results.

3.2. Transition of UGS and UBS to other land covers

This study established that a significant proportion of UGS and UBS in all five cities was transformed into bare land and land for agricultural use (Fig. 6). In Dhaka, for example, approximately 29% of UGS and 21% of UBS have been transformed into bare land over the last 30 years, with the bare land further converted into settlement or agricultural areas. Overall, around

17% of UGS and 20% of UBS was converted into agricultural land. The study also noted that a substantial portion of UGS in Dhaka (16%) was converted into built-up areas. A significant proportion of agricultural land adjacent to the city center was also converted into built-up land.

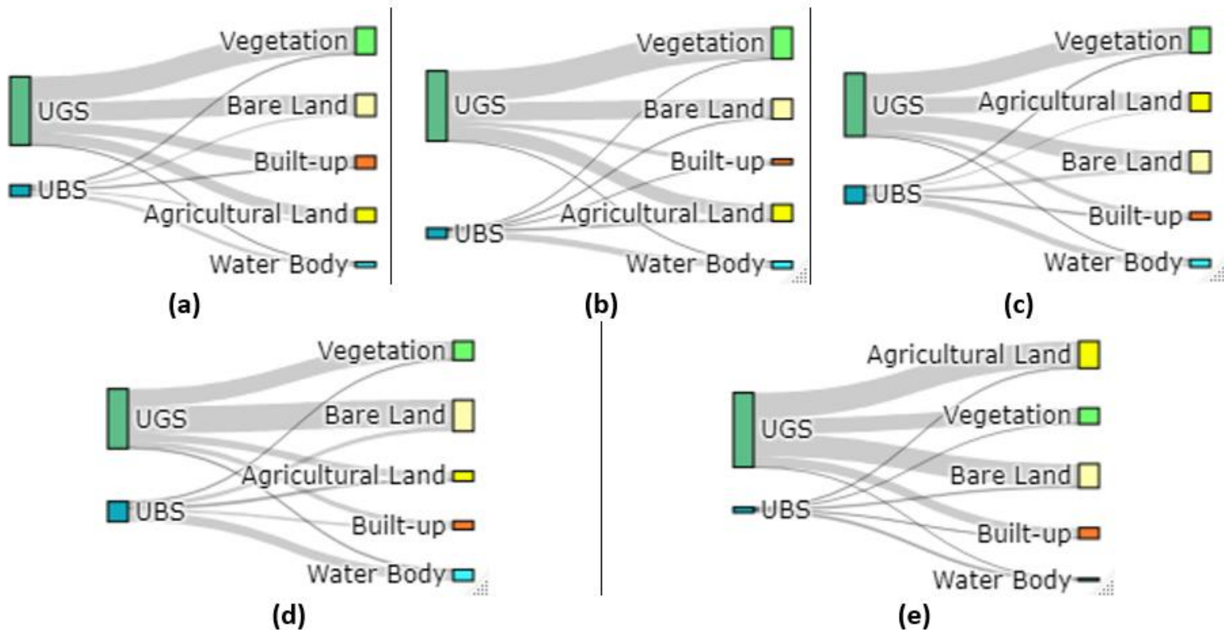


Fig. 6 Transition of UGS and UBS to different LULC types between 1991 and 2021: (a) Dhaka; (b) Chattogram; (c) Khulna; (d) Rajshahi; (e) Sylhet.

3.3. Sensitivity and elasticity of ESV

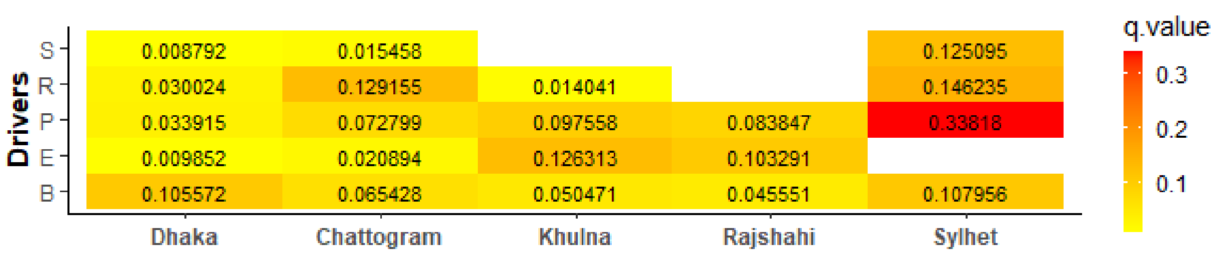
To test the reliability of the ESV loss results, CS was calculated by adjusting VC by ±50%. The results for the five cities are shown in Table 5. The annual CS values of UGS and UBS in the five cities were <1, indicating that the results are inelastic and reliable. The highest CS value of 0.6937 was for Sylhet UGS in 2021, indicating that a 1% increase in UGS is likely to increase ESV by 0.6937%. The CS values for UBS are generally lower than for UGS, suggesting that ESV is more sensitive to UGS.

Table 5 CS values of UGS and UBS for the five cities

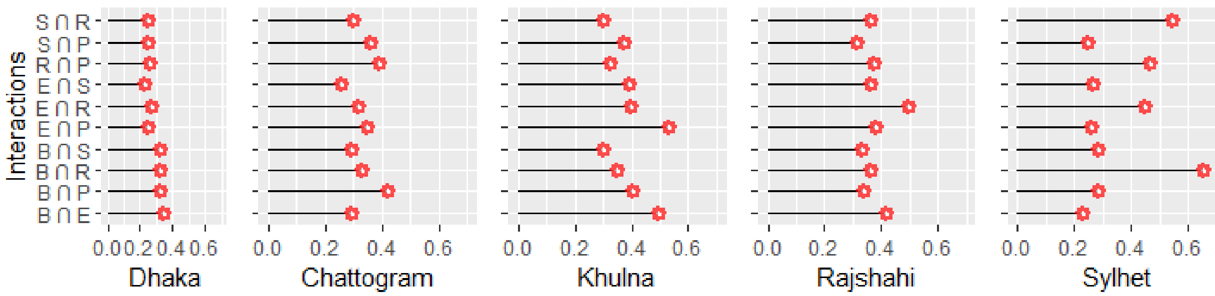
Year	Dhaka		Chattogram		Khulna		Rajshahi		Sylhet	
	UGS	UBS	UGS	UBS	UGS	UBS	UGS	UBS	UGS	UBS
1991	0.5877	0.4663	0.6579	0.4772	0.5702	0.4823	0.6693	0.4849	0.619	0.4516
1996	0.5696	0.2299	0.6296	0.3815	0.4092	0.451	0.6183	0.4284	0.6187	0.2329
2001	0.5285	0.4142	0.5575	0.4005	0.5224	0.3536	0.6075	0.2936	0.5369	0.3413
2006	0.476	0.355	0.5129	0.337	0.5184	0.3074	0.6014	0.3281	0.5114	0.3118
2011	0.4364	0.4526	0.4282	0.3653	0.4832	0.2921	0.5086	0.325	0.4707	0.2411
2016	0.4019	0.3028	0.3926	0.4508	0.5401	0.2581	0.4631	0.26	0.4404	0.4365
2021	0.3872	0.3432	0.3384	0.2381	0.3496	0.2537	0.4321	0.2303	0.3331	0.2053

3.4. Factors driving spatial heterogeneity in ESV and patterns of UGS and UBS change

Multiple factors influence the ESV of UGS (*p*-value <0.05). Elevation appears to be the most important factor for Khulna (q = 0.126) and Rajshahi (q = 0.103), suggesting elevation is significantly associated with ESV loss in these cities. Road density, extent of built-up areas, and population were significant factors for Chattogram (q = 0.129), Dhaka (q = 0.105), and Sylhet (q = 0.338), respectively (Fig. 7a). For UBS, elevation was found to be the most influential factor affecting spatial heterogeneity of ESV in all five cities (Fig. 8a).



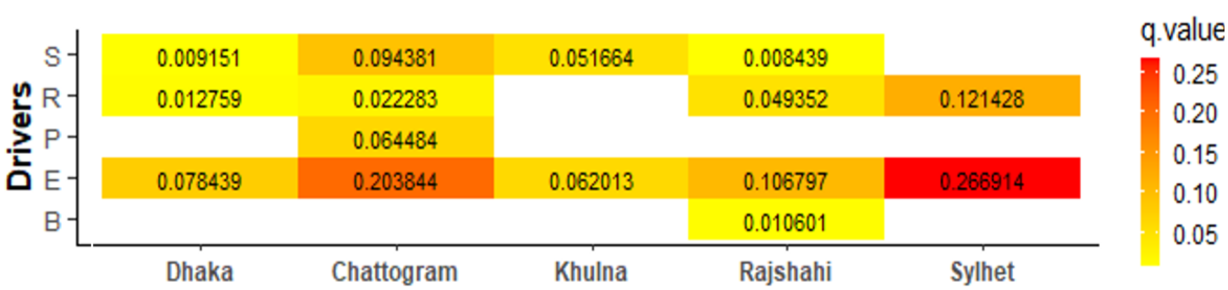
(a)



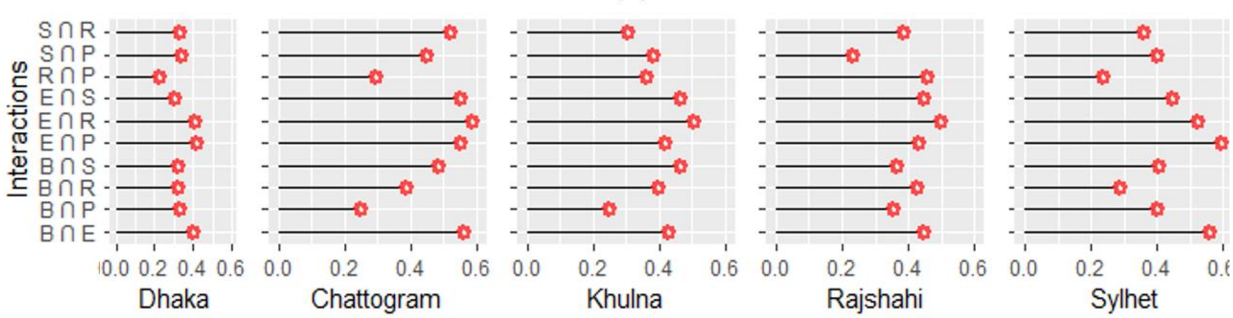
(b)

Fig. 7 Factors affecting UGS loss: (a) influence of individual factors (p value < 0.05 is shown only); (b) Combined influence of factors (B = built-up, E = elevation P = population, R = road, S = slope).

Fig. 7b and Fig. 8b show the influence of pairwise indicators on ESV loss. For instance, the extent of built-up area and population combined influenced ESV for UGS the most in Chattogram (Fig. 7b), where a combination of elevation and road density had the greatest influence on ESV loss due to UBS degradation (Fig. 8b).



(a)



(b)

Fig. 8 Factors affecting loss of UBS: (a) influence of individual factors (p value < 0.05 is shown only); (b) combined influence (B = built-up, E= elevation, P = population, R = road, S = slope).

4. Discussion

An extensive review of the available literature on the study topic has been undertaken and it appears that this is possibly the first research using geospatial data to estimate the loss of ecosystem services in several cities of a developing country. Even though the concept of ecosystem services (ES) gained popularity in the 1970s (Costanza et al., 2017), very little attention has been paid to these services in Bangladesh (Zinia and McShane, 2018), in large part due to the lack of dependable data. This lack of scientific data also means that policymakers have difficulty devising effective conservation strategies or detailed plans for ecosystem restoration (Biao et al., 2022).

The study analysis indicated that all five cities experienced a gradual, yet substantial, loss of ESV between 1991 and 2021. Cities in developing countries lack the resources to deal with the rapid urbanization resulting from population growth (Moretti, 2014), so ongoing reduction in areas of green and blue spaces tends to be widespread (Table 3). The decline observed is in large part because these lands are relatively cheap and are therefore often targeted for urban development (Yang et al., 2017), especially in Bangladesh (Dewan and Corner, 2013; Jaman et al., 2020). There are no studies showing the degree of loss of ES in other cities, though previous smaller-scale studies focusing on Dhaka (Rahman and Szabó, 2021; Zinia and McShane, 2018) indicated that ES are being depleted at a great rate due to the pressure of human activity. Rahman and Szabó (2021), using the Dhaka metropolitan area (DMA) boundary, showed that built-up land had increased by 188.35% from 1990 to 2020, thereby causing a decline in ESV from USD 142.72m in 1990 to USD 57.72m in 2020. The ability of ESV to regulate factors like air pollution means that negative impacts on microclimatic conditions are increasingly becoming a matter of grave concern. Dewan et al. (2021) showed that the differences between day and night temperatures have decreased in the five cities studied due to the massive loss of vegetated areas to urbanization. This has resulted in increased energy consumption and air pollution in the cities has become chronic, severely affecting public health (Dewan et al., 2022) and overwhelming the ability to effectively remove these pollutants in a timely manner (Fletcher et al., 2021). As greenspaces are declining at a great rate in Bangladeshi cities like Dhaka, cultural ecosystem services are reduced considerably, affecting the wellbeing of urban dwellers (Sultana and Selim, 2021).

Large and densely populated megacities exert significant pressure on the natural capital of a region. The way cities are planned, however, also plays a critical role in influencing development patterns and the resulting impacts on the existing environment. While sprawling cities can produce more greenhouse gas emissions due to high dependence on motor vehicles, unplanned urban growth and density can also contribute significantly to ongoing environmental problems. Urban expansion has been shown to increase overall water yield and thus increase flood risk (Delphin et al., 2016). Bangladesh is situated on a deltaic floodplain, so most of its cities are well endowed with waterbodies that provide various provisioning, cultural, and regulation services. Flooding of existing waterbodies and waterlogging of low-lying areas are very common during the monsoon season in almost all the large cities, but the process of urbanization can reduce the associated supporting services. A study in the Pearl River Delta (PRD), for example, observed a 50% decline in habitat quality caused by urban land expansion (Wang et al., 2022). In the case of Bangladesh, a large decline in the extent and quality of fish habitat has been reported, causing a significant degradation of the aquaculture industry (Islam et al., 2004).

Climate change and land use/land cover changes are the two main factors affecting ecosystem services (Biao et al., 2022). Although this study did not consider the role of climate change in ecosystem service changes, it can be strongly suggested that rapid land use/land cover changes, responding to the various demands of ever-increasing populations, are mainly accountable for the deterioration of ES in the five cities studied. Land use/land cover changes bring significant changes to ecosystems at all levels, from local to global scale. As demonstrated by Costanza et al. (2014), the value of ecosystem services lost due to land use/land cover changes between 1997 and 2011 ranged from USD 4.3 to 20.2 trillion per annum. Land use composition and configuration can also affect the proper functioning of an ecosystem (Guo et al., 2021), which inevitably reduces ES supply (Eigenbrod et al., 2011). Ma et al. (2022) showed that, between 2000 and 2020, deforestation and urbanization in Zhejiang province resulted in net primary productivity (NPP) loss of 192 gC/m^2 and 115.75 gC/m^2, respectively.

The interaction of different factors affecting UBS and UGS loss were examined. Variables such as elevation and slope were strongly associated with spatial heterogeneity of ESV, particularly in Khulna, which has the lowest mean elevation and slope of all the cities examined. Results from previous studies have indicated that elevation is positively associated with greater vegetation cover, as built-up areas are usually concentrated in areas of low elevation (Liu et al., 2019; Wang et al., 2018). This observation appears to be true in our cases too, meaning that urban expansion is both directly and indirectly linked with loss of UGS and UBS. Population growth and proportion of built-up areas drove loss of UGS in Khulna, Rajshahi, and Sylhet, but in Dhaka and Chattogram all five factors (elevation, slope, population, road, and built-up area) were associated with the degradation of UGS.

This study investigated the spatiotemporal degradation of urban green-blue spaces and the resultant ES loss. The work is, however, not entirely free of limitations and there is scope for improvement. Surrogate VC values were used in this work for the whole biome, not specifically for Bangladesh, so there could be some deviation in the VC of the same ES for different regions, which has the potential to produce some uncertainty in the results. This method is also unable to calculate ESV for some abstract ES services, such as aesthetic beauty and cooling effects. Future studies could address these limitations. This study tested five drivers to explain the causes of changes in UGS and UBS. Inclusion of other variables, such as public policy, could also improve the research results. Despite these limitations, this study does provide useful baseline information which can be used to inform policies for saving the valuable natural capital of Bangladesh.

5. Conclusion

This study mapped spatiotemporal patterns of urban green and blue spaces in five major cities (Dhaka, Chattogram, Khulna, Rajshahi, and Sylhet) of Bangladesh using multitemporal Landsat data. The benefit transfer method (BTM), adjusted for present-day values, was used to understand the impacts of rapid urban growth on ecosystem service values (ESV). Finally, drivers of urban green and blue space loss were determined. The results revealed a significant loss in UGS and UBS in all five cities during the past 30 years, with Dhaka experiencing the greatest decline in both types of space, followed by Chattogram, Rajshahi, Sylhet, and Khulna, respectively. Rapid, unplanned urbanization associated with population growth has led to substantial increases in the proportion of built-up areas and is the predominant cause of green and blue space loss. Elevation, slope, and road density were factors which also had a significant influence on the depletion of UGS. An estimated total ESV loss of USD 628.6m was calculated for the five cities.

A detailed understanding of the spatiotemporal patterns of UGS and UBS is essential when developing plans to protect these areas. The findings of this study can be used to inform planning, both high-level policy development and detailed planning work aimed at protecting the environments of these rapidly growing cities. The results could also help to improve city land use structure. This study was conducted in five cities of Bangladesh, but the results could have wider applicability, e.g., in enhancing ecosystem-based climate adaptation, providing efficient governance of urban ecosystems, and promoting sustainable urban development. The framework of this work could be transferred to other areas experiencing similar growth patterns.

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