Assessment of Urban Dynamics and Ecosystem Services: A Case Study in Guwahati Metropolitan Area

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Abstract. Rapid urbanization has globally altered land use and land cover (LULC) patterns, with significant impacts on ecologically sensitive zones. Perhaps, as a growing city, the Guwahati Metropolitan Area (GMA) represents the most pronounced LULC transformation in North-East India over the past few decades. Thus, this study analyzes the spatio-temporal dynamics of LULC from 1995 to 2025 using satellite data and the Random Forest algorithm in the Google Earth Engine (GEE) platform. Additionally, the paper aims to find the Ecosystem Service Value (ESV) of separate LULC classes using Constanza's valuation system for biomes. The research identifies five LULC classes: built-up, vegetation, waterbody, fallow land, and sand. The finding shows a notable expansion in builtup areas, increased by 258.27% from 1995 to 2025, reflecting significant landscape modifications. Additionally, waterbody and sand increased by 99.80% and 137.59%. Conversely, vegetation and fallow land decreased by 25.82% and 37.35% respectively. Furthermore, the Ecosystem Service Value (ESV) for vegetation declined from 35.01 million US$ to 25.97 million US$, while the value for waterbodies rose from 8.25 million US$ to 16.48 million US$. It is noteworthy that Constanza's valuation does not encompass builtup areas, fallow land, or sand. The total ecosystem service value diminished from 43.25 million US$ to 42.45 million US$. Therefore, the city has experienced a notable decline in its ecosystems, adversely affecting environmentally sensitive zones, elevating pollution levels, and ultimately impeding human well-being and sustainable development. Thus, this study emphasizes the critical importance of sustainable land management, policy development, and ecosystem conservation to mitigate the environmental impacts of urban sprawl and foster long-term ecological and socio-economic resilience within the region.

Keywords: Ecosystem Service Value (ESV), Random Forest (RF) Algorithm, Guwahati, India

1 Introduction

Nearly half of the population resides in cities. Individuals relocate to urban areas for improved opportunities in life, including access to better job opportunities, healthcare facilities, and higher education. Now, this unnecessary population growth significantly affects a city's LULC features [1] as urban land is predominantly covered by builtup structures, such as residential zones, commercial zones, roads, and other builtup features, while there are also some limited and fragmented features, including barren

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land, fallow land, urban agriculture, parks, rivers, and water bodies [1]. Additionally, hilly topography experiences fragmented builtup areas.

In 1995, the International Human Dimensions Program (IHDP) and the International Geosphere-Biosphere Program (IGBP) jointly opened a new research perspective through their scientific research plan on LULC change detection [2][3]. Following this, extensive research has been conducted on LULC change detection and prediction in many locations [4][5][6]. Therefore, LULC change modelling has become popular among scientists to understand the significant changes in surface features, which reflect the impacts of human activities on terrestrial resources, including forests, rivers, and lakes [7]. Real-time, multi-spatio-temporal data are necessary for these analyses [6].

The changing patterns of LULC in urban areas remarkably impact the surrounding ecosystem. It is essential to understand the changes that have occurred in the ecosystem and their impact on the services it provides, as these play a crucial role in enhancing the standard of living for urban residents. Moreover, the value of ecosystem services (ESVs) varies with changes in LULC classes. According to [8], the ESV for some biomes, such as deserts, tundra, ice/rock, and build-up, is almost zero; on the other hand, forests, water bodies, grasslands, and agricultural lands have significantly higher values [8]. As the population grows, LULC patterns increasingly favor infrastructure development, which in turn degrades urban ecosystem services [9]. Thus, the transformations in LULC control the supply of ecosystem services [9]. Ensuring the sustainable management of land and forest resources, promoting water conservation, and advancing food security and other socio-economic development are crucial for protecting the ecosystem, which is now a global challenge.

After reviewing the literature on LULC patterns, which shows continuous, unplanned growth of human settlements and the decline of eco-sensitive zones, this paper aims to examine LULC patterns and ESV in the Guwahati Metropolitan Area (GMA). The objectives are 1. To examine the spatial and temporal dynamics of LULC in GMA from 1995 to 2025. 2. To assess the temporal dynamics of Ecosystem Service Value (ESV) of GMA using Costanza’s valuation system of biomes. 3. To show how LULC change makes an impact on ESV over decades in GMA.

2 Study Area

Guwahati is the heart of the North-Eastern states of India; of the seven sisters, it serves six of them. The city is located between 26°5' and 26°13' N latitude and 91°35' and 91°52' E longitude, along the banks of the Brahmaputra River. This study focuses on the area covered by the Guwahati Metropolitan Development Authority (GMDA) Master Plan 2025. According to GMDA's jurisdiction, the total area of the Guwahati Metropolitan Area (GMA) is 328 sq. km. The city's topography is undulating, with elevations ranging from 49.5m to 55.5m above mean sea level [10]. A large number of scattered hills are distributed throughout the land; these are the continuous hills extending from Meghalaya. The city is home to 18 hills covering 68.81 sq. km. These hills are mostly covered by bare rocks with various forest formations, including sal forest, mixed moist deciduous forest, evergreen forest, Bamboo brakes, and secondary shrub forests [11]. There is a total of 14 reserve forests within and around the city boundary [11]. The population of GMC was approximately 1 million in 2011, which is estimated to grow to 2.8 million by 2025 [12]. That much population growth leads to a rapid escalation of anthropogenic activities and changes in the city's LULC features. The climate is subtropical and humid, with heavy rainfall from May to June, and a hot summer characterized by high humidity. The average annual rainfall is 1752 mm, and the average winter temperature is 16.5 °C, and the average summer temperature is 17 °C. (See figure 1)

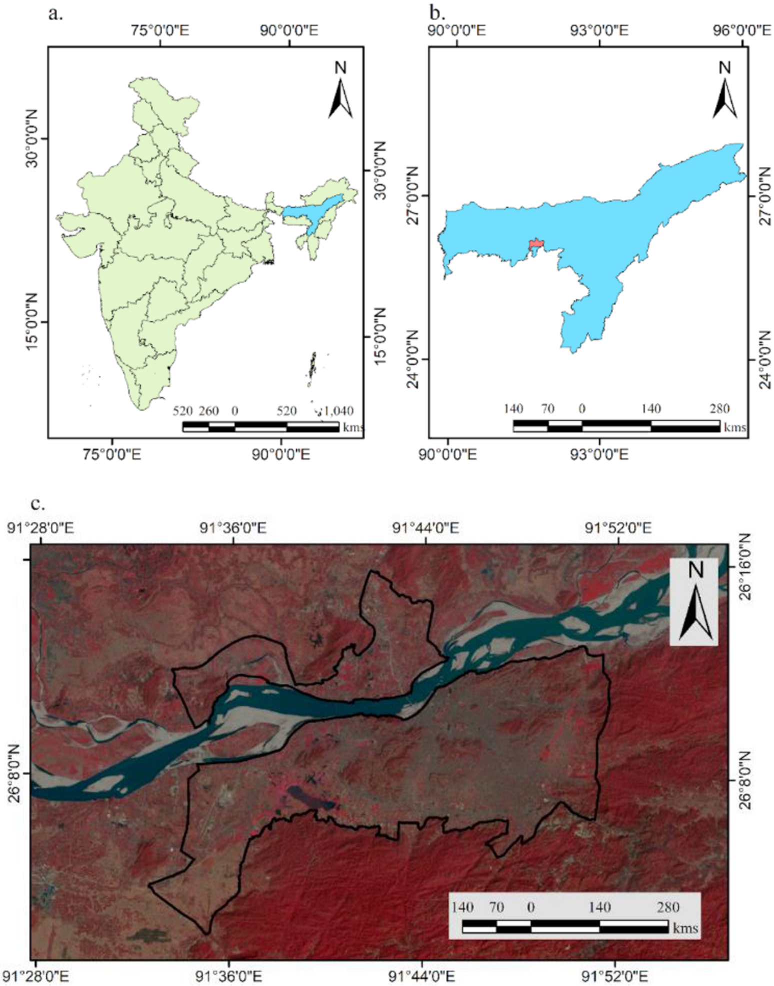

Fig.1. a. depicts India with its state boundaries, while b. illustrates the state boundary of Assam, c. delineates the boundary of the Guwahati Metropolitan Area (GMA)

3 Methodology

3.1 Database

Satellite remote sensing, when combined with GIS techniques, is a reliable and valuable tool for identifying land use classes, detecting LULC changes, and monitoring vegetation. This study utilized multi-temporal satellite data. Specifically, Landsat 5 TM data were used for the years 1995 and 2005, while Landsat 8 OLI data were used for 2015 and 2025 (Table 1). The satellite images were sourced from the GEE portal, with a preference for cloud and haze-free imagery. All images were in UTM (Universal Transverse Mercator) Zone 46N projection and WGS84 (World Geodetic System) datum. The spatial resolution of all images is 30 meters, and they consistently follow path and row coordinates 137 and 42.

Table 1. Database for the study.

Name	Data Source	Time	Spatial Resolution
Landsat TM	Google Earth Engine	1995	30 m
Landsat TM	Google Earth Engine	2005	30 m
Landsat OLI	Google Earth Engine	2015	30 m
Landsat OLI	Google Earth Engine	2025	30 m

3.2 Supervised classification

Supervised classification is a well-established technique used for classifying satellite images. Since the 1970s, several methods have been developed for LULC classification, including maximum likelihood classification [13], minimum distance classification [14], and nearest neighbor analysis [15]. However, with advancements in machine learning algorithms, a new paradigm for LULC classification has emerged. Several machine learning (ML) techniques have been developed for image classification, including artificial neural network (ANN) [16], support vector machine (SVM) [17], and random forest (RF) [18]. For LULC classification analysis, the paper uses the random forest algorithm.

The Random Forest (RF) algorithm is a supervised image classifier within the ML model. For the very first time, this model was introduced by Breiman [19]. The Google Earth Engine (GEE) platform is well known for performing the random forest (RF) algorithm. It depends on six input parameters, including number of variables and trees, random seeds, fraction of input variables, minimum leaf population, and out-of-bag mode [19]. The higher the number of trees, the greater the classification accuracy, until it reaches a point of overfitting.

3.3 Accuracy assessment

Accuracy assessment is a needful and last step in any image classification. It quantifies how accurately the classified image matches the actual classes on Earth's surface [20]. Moreover, accuracy refers to the degree of similarity between the ground truth and the produced map. Various methods have been developed for accuracy assessment. However, Overall Accuracy (OA) and Kappa Coefficient are widely accepted methods, also known for their potential in evaluating accuracy [5][21]. Hence, equation 1 represents the formula for OA, and equation 2 defines the kappa coefficient. The range of the Kappa coefficient is -1 to 1, where a value close to 1 indicates the classification is accurate, and 0 indicates it is similar to random classification. A negative value indicates worse classification performance.

$$Overall\ Accuracy\ (OA) = \frac{Total\ no.of\ correcteed\ point}{Total\ no.of\ point} \times 100 \tag{1}$$

$$Kappa\ Coefficient = \frac{\sum_{i=1}^{k} n_{ii} - \sum_{i=1}^{k} n_{ii}(GiCi)}{n^2 - \sum_{i=1}^{k} n_{ii}(GiCi)} \tag{2}$$

Where i represents the class number, while n indicates the total number of classified pixels being compared to the actual data, the term nii refers to the number of pixels that belong to the actual data class i and have been classified as class i. Additionally, Ci is the total number of classified pixels that belong to class i, and Gi is the total number of actual pixels that belong to class i.

3.4 LULC change assessment

LULC change assessment helps obtain information on the changing patterns of land-use features relative to others. The amount, degree, and direction of transformation of LULC classes are examined using this method. The area of transformation from one class to another, and vice versa, is identified through this change assessment [22]. For the present study, ArcMap 10.7.1 was used to identify the transition matrix of the study area. From 1995 to 2025, a 30-year transition was examined.

3.5 Ecosystem Service Value (ESV)

The impact of urbanization on ESV is one of the most pressing environmental concerns. Several studies have examined ES in monetary terms. In 1997, Costanza initially presented a valuation system for ecosystem services across 16 biomes and their respective functions. A later study updated the estimation of ESV by adopting a broader spatial scale [23]. However, the present study includes ESV, ESV of function (f), and the change rate of ESV for the Guwahati Metropolitan Area. The formula for ESV and ESV for function (f) is given in equations 3 and 4 [24], as follows:

$$ESV = \sum(A_k \times VC_k) \quad (3)$$

Where ESV is ecosystem service value, Ak represents area in hectares, and VCk represents the coefficient value ($ha-1year-1) of the concerning LULC type ‘k’. The coefficient value is used directly from Costanza’s valuation system.

$$ESV_f = \sum(A_k \times VC_{fk}) \quad (4)$$

Where, ESVf is ecosystem service value for the function ‘f’, Ak represents area in hectares, and VCfk represents the coefficient value for the function ‘f’ ($ha-1year-1) of the concerning LULC type ‘k’.

Following the finding of ESV with their specific function ‘f’ of each LULC class, later on, the change rate of ESV was calculated using equation 5 [25].

$$ESV_{cr} = \frac{ESV_{i2} - ESV_{i1}}{ESV_{i1}} \times \left(\frac{1}{t}\right) \times 100\% \quad (5)$$

Where, ESVcr represents changes in ESV over a specific time; ESVi1 represents ESV of the initial year for LULC class ‘i’; ESVi2 represents ESV of the later year for LULC class ‘i’; and t represents the temporal span between the initial year and the later year.

4 Results

This section will cover the final output of all the methodologies used to fulfill the objectives.

Land Use Land Cover (LULC) Maps and Accuracy Assessment

The LULC map has been prepared using a random forest algorithm over 4 decades: 1995, 2005, 2015, and 2025. These maps are classified into five LULC classes: builtup, vegetation, waterbody, fallow land, and sand. Figure 2 illustrates the LULC maps for 1995, 2005, 2015, and 2025. The comparative areas of different LULC classes are shown in Figure 3. The percentages of area and actual area of LULC classes are shown in Table 2. The accuracy (overall accuracy and kappa coefficient) of these maps is calculated using the Google Earth Engine platform (Table 3). (See figure 2)

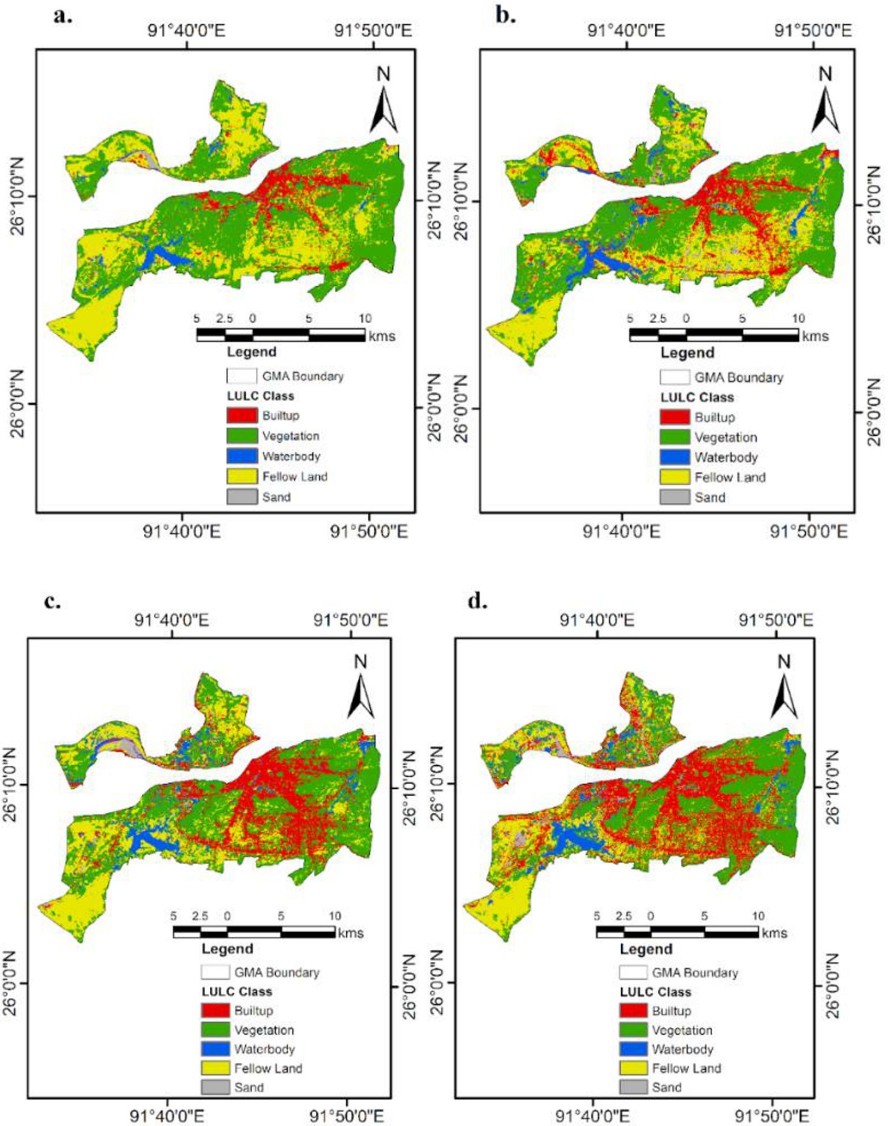

Fig. 2.a. depicts the Land use and land cover map of 1995; b. illustrates the land use and land cover map of 2005; c. presents the land use and land cover map of 2015; and d. shows the land use and land cover map of 2025 for the Guwahati Metropolitan Area.

4.1 Land Use Land Cover Map

The LULC maps of 1995, 2005, 2015, and 2025 reveal the spatial extent of different land use features (Fig. 2). The comparative bar diagram (Fig. 3) shows a moderate decline in vegetation and fallow land, while builtup areas increase rapidly, and water bodies and sand increase slowly. Furthermore, Table 2 shows that the area under builtup areas was 29.10 sq. km in 1995, 47.51 sq. km in 2005, 77.09 sq. km in 2015, and 104.25 sq. km in 2025. The vegetation zone was 174.42 sq. km in 1995, 160.43 sq. km in 2005, 146.00 sq. km in 2015, and 129.40 sq. km in 2025. The waterbody was 9.71 sq. km in 1995, 16.76 sq. km in 2005, 18.82 sq. km in 2015, and 19.39 sq. km in 2025. The fallow land was 113.58 sq. km in 1995, 100.33 sq. km in 2005, 82.99 sq. km in 2015, and 71.16 sq. km in 2025. The sand was 1.89 sq. km in 1995, 3.64 sq. km in 2005, 3.78 sq. km in 2015, and 4.49 sq. km in 2025.

Table 2 also represents the percentage of area calculated after preparing the LULC maps. In 1995, the land use distribution was as follows: the builtup area accounted for 8.85%, vegetation accounted for 53.07%, water bodies accounted for 2.95%, fallow land accounted for 34.55%, and sand accounted for 0.58%. In 2005, the builtup area increased to 14.45%, while vegetation decreased to 48.81%, water bodies rose to 5.10%, fallow land decreased to 30.53%, and sand increased slightly to 1.11%. By 2015, the builtup area had further increased to 23.45%, with vegetation accounting for 44.42%. Waterbody rose to 5.73%, fallow land was reported at 25.25%, and sand grew to 1.15%. Looking forward to 2025, 31.72% of the area is builtup, while vegetation covers 39.37%, water bodies occupy 5.90%, fallow land comprises 21.65%, and sand makes up 1.37%.

Table 2. Showing the percentage of area and the actual area for all LULC classes

LULC Classes	1995		2005		2015		2025	
	Area in sq. km	Area in %	Area in sq. km	Area in %	Area in sq. km	Area in %	Area in sq. km	Area in %
Builtup	29.10	8.85	47.51	14.45	77.09	23.45	104.25	31.72
Vegetation	174.42	53.07	160.43	48.81	146.00	44.42	129.40	39.37
Waterbody	9.71	2.95	16.76	5.10	18.82	5.73	19.39	5.90
Fallow Land	113.58	34.55	100.33	30.53	82.99	25.25	71.16	21.65
Sand	1.89	0.58	3.64	1.11	3.78	1.15	4.49	1.37

4.2 Accuracy Assessment

The overall accuracy, as shown in Table 3, is 0.99 in 1995, 0.98 in 2005, 0.98 in 2015, and 0.99 in 2025. The value indicates that the classification performs well, providing correct measurements overall. The kappa coefficient was 0.99 in 1995, 0.98 in 2005, 0.96 in 2015, and 0.98 in 2025, further demonstrating the classification's high accuracy. These values represent almost no misclassification of samples.

Table 3. Showing the findings for Overall Accuracy (OA) and Kappa Coefficient (KC)

Year	Overall Accuracy (OA)	Kappa Coefficient (KC)
1995	0.99	0.99
2005	0.98	0.98
2015	0.98	0.96
2025	0.99	0.98

4.3 Land Use Land Cover Change

Analysis of multi-temporal satellite images provides valuable insights into changes in LULC classes within the GMA from 1995 to 2025. This spatio-temporal analysis reveals significant shifts in LULC classes during this period, highlighting both increases and decreases. Drastic changes have been observed in builtup areas, vegetation, and fallow land, while only minor changes have occurred in water bodies and sand in the last few decades. The substantial rise in builtup areas has impacted vegetation, fallow land, and water bodies. Below are key points describing the patterns of LULC change over the decades (Table 4). (See figures 3 and 4)

Table 4. Decadal temporal changes across all LULC classes in the GMA

LULC Classes	1995-2005 change in %	2005-2015 change in %	2015-2025 change in %	1995-2025 change in %
Builtup	63.28	62.26	35.23	258.27
Vegetation	-8.02	-8.99	-11.37	-25.82
Waterbody	72.71	12.26	3.05	99.80
Fallow Land	-11.66	-17.29	-14.26	-37.35

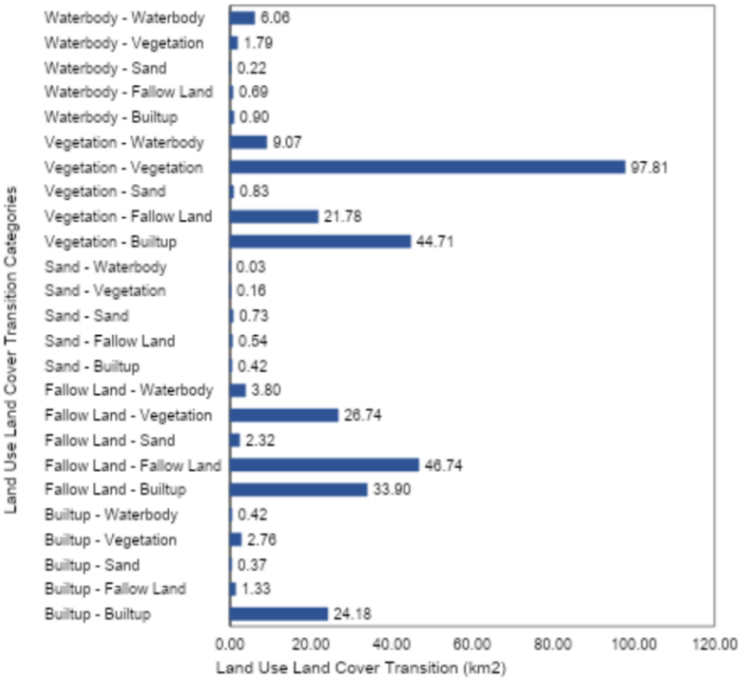

Fig. 3. Bar diaram illustrating Land Use and Land Cover Transitions (km^2) from 1995 to 2025

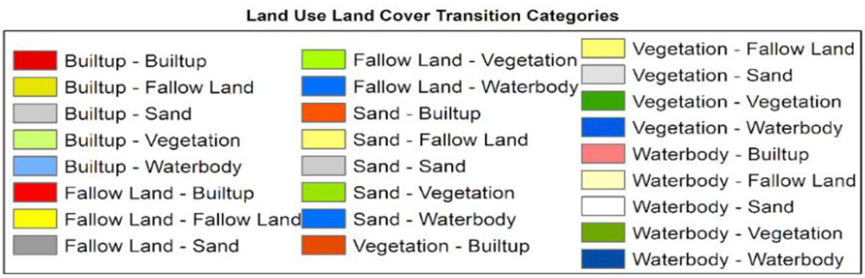

Fig. 4. Land use land cover transition map of the Guwahati Metropolitan Area (GMA)from 1995 to 2025

4.4 Changes in Builtup

The study indicates a significant increase in builtup areas over the decades, as shown in Table 04. From 1995 to 2005, the builtup area rose by 63.28%. This was followed by a 62.26% increase from 2005 to 2015 and a 35.23% increase from 2015 to 2025. Overall, the total area has increased by 258.27% from 1995 to 2025. Change detection analysis (Fig. 4 and 5) shows that 24.18 sq. km of land remained unchanged as builtup area, 33.90 sq. km of fallow land in 1995 was converted to builtup area by 2025, 44.71 sq. km of vegetation was also transformed into builtup area during the same period, 0.90 sq. km of waterbody in 1995 was changed to builtup area by 2025, and 0.42 sq. km of sandy land was similarly transformed to builtup area within the same timeframe.

4.5 Changes in Vegetation

The study analyses significant changes in vegetation zones within the area, as shown in Table 4. From 1995 to 2005, vegetation area decreased by 8.02%; from 2005 to 2015, by 8.99%; and from 2015 to 2025, by 11.37%. Overall, the vegetation area decreased by 25.82% between 1995 and 2025. The change detection analysis (Figs. 4 and 5) indicates that 97.81 sq. km of the area showed no change and remained vegetated. Additionally, 26.74 sq. km of fallow land from 1995 transitioned into vegetation by 2025. Furthermore, 2.76 sq. km of builtup areas in 1995 changed to vegetation, along with 1.79 sq. km of water bodies and 0.16 sq. km of sand, which also transitioned to vegetation by 2025.

4.6 Changes in Fallow Land

The study examines a notable decline in fallow land from 1995 to 2025. (see Table 4). The findings indicate that the area of fallow land diminished by 11.66% from 1995 to 2005, by 17.29% from 2005 to 2015, and by 14.26% from 2015 to 2025. Overall, the total area of fallow land has decreased by 37.35% from 1995 to 2025. The change detection analysis (see Figs. 4 and 5) reveals that 46.74 sq. km of land remained unchanged and was classified as fallow land from 1995 to 2025. Additionally, 21.78 sq. km of vegetation classified in 1995 has been converted to fallow land by 2025. There have also been transitions from builtup areas, with 1.33 sq. km changing to fallow land, and 0.69 sq. km of waterbody also converting to fallow land. Finally, 0.54 sq. km of sandy areas have been transformed into fallow land during this period.

4.7 Change in Waterbody

The study analyses trends in water bodies over the past few decades, as illustrated in Table 4. The area covered by the waterbody increased by 72.71% from 1995 to 2005, by 12.26% from 2005 to 2015, and by 3.05% from 2015 to 2025. Overall, the total area of water bodies rose by 99.80% from 1995 to 2025. The change detection analysis depicted in Figures 4 and 5 shows that an area of 6.06 sq. km remained unchanged as a waterbody from 1995 to 2025. Additionally, 9.07 sq. km of land classified as vegetation in 1995 transitioned to a waterbody by 2025. Furthermore, 0.42 sq. km of builtup area in 1995 was converted to a waterbody, along with 3.80 sq. km of fallow land and 0.03 sq. km of sandy area, which were also converted to waterbodies by 2025.

4.8 Change in Sand

The study analyses the linear relationship and a slight increase in sand over the decades, as shown in Table 4. From 1995 to 2005, the area covered by sand increased by 92.74%. This growth continued with a modest 3.86% increase from 2005 to 2015, followed by an 18.68% increase from 2015 to 2025. Overall, the total area of sand expanded by 137.59% from 1995 to 2025. The change detection analysis, illustrated in Figures 4 and 5, indicates that an area of 0.73 sq. km has remained unchanged as sand from 1995 to 2025. Additionally, 0.83 sq. km of land that was classified as vegetation in 1995 transitioned to sand by 2025. Furthermore, 0.37 sq. km of builtup areas were converted to sand, along with 2.32 sq. km of fallow land and 0.22 sq. km of water bodies that changed to sand during the same period.

4.9 Ecosystem Service Value (ESV)

This study examines the pattern of ESV for these three decades. These LULC classes are treated as individual biomes (Table 5), and Costanza's (1997) valuation system is used to analyze ESV. Thereafter, the result shows a declining trend in the overall ES values of GMA. Among the five LULC classes, only two have ES value: vegetation and waterbody. The remaining three (builtup, fallow, and sand) do not have ES value. As the spatial extension of vegetation declined due to the expansion of builtup infrastructure, the ES value also reduced.

Table 5. Ecosystem Service Value (ESV) for all LULC classes in Million US$

LULC Classes	Respective Biomes	ESV (Million US$)			
		1995	2005	2015	2025
Builtup	Urban	0.00	0.00	0.00	0.00
Vegetation	Tropical Forest	35.01	32.20	29.30	25.97
Waterbody	Lakes/Rivers	8.25	14.25	15.99	16.48
Fallow Land	Bare Land	0.00	0.00	0.00	0.00
Sand	Dessert	0.00	0.00	0.00	0.00
Total		43.25	46.44	45.29	42.45

4.10 Analysis of ESV

The LULC classes are represented as their respective biomes, like builtup as urban, vegetation as tropical forest, waterbody as lakes/rivers, fallow land as bare land, and sand as desert. Table 5 shows that the ES value for vegetation decreased from 35.01 million US$ in 1995 to 32.20 million US$ in 2005, 29.30 million US$ in 2015, and 25.97 million US$ in 2025. On the other hand, the ES value for waterbody is slightly increasing, 8.25 million US$ in 1995, 14.25 million US$ in 2005, 15.99 million US$ in 2015, and 16.48 million US$ in 2025. The overall ES value of GMA decreased over time, from 43.25 million US$ in 1995 to 46.44 million US$ in 2005, 45.29 million US$ in 2015, and 42.45 million US$ in 2025. Of the 17 ES subtypes, four (gas regulation, pollination, biological control, and habitat/refugia) have no value to vegetation or water bodies (Table 6). The maximum ESVs obtained from nutrient cycling (from vegetation) and water regulation (from waterbody), respectively, are 16.08 and 10.64 (million US$). The minimum ESVs obtained from culture and disturbance regulation, respectively, are 0.03 and 0.06 (million US$).

Table 6. Ecosystem Service Value of function f (ESVf) in Million US$ for all LULC classes

Ecosystem Services	Sub-types	ESV_f (Million US$)				ESV_f Change			
		1995	2005	2015	2025	1995-2005	2005-2015	2015-2025	1995-2025
Provisioning Service	Food Production	0.60	0.58	0.54	0.49	-0.02	-0.04	-0.05	-0.10
	Raw Materials	5.49	5.05	4.60	4.08	-0.44	-0.45	-0.52	-1.42
Regulating Service	Gas Regulation	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Climate Regulation	3.89	3.58	3.26	2.89	-0.31	-0.32	-0.37	-1.00
	Disturbance Regulation	0.09	0.08	0.07	0.06	-0.01	-0.01	-0.01	-0.02
	Water Regulation	5.39	9.22	10.33	10.64	3.83	1.11	0.30	5.25
	Water Supply	2.19	3.68	4.10	4.21	1.48	0.42	0.11	2.01
	Waste Treatment	2.16	2.51	2.52	2.42	0.35	0.01	-0.11	0.25

Supporting Service	Erosion Control	4.27	3.93	3.58	3.17	-0.34	-0.35	-0.41	-1.10
	Soil Formation	0.17	0.16	0.15	0.13	-0.01	-0.01	-0.02	-0.05
	Nutrient Cycling	16.08	14.79	13.46	11.93	-1.29	-1.33	-1.53	-4.15
	Pollination	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Biological Control	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Habitat/ Refugia	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Genetic Resources	0.72	0.66	0.60	0.53	-0.06	-0.06	-0.07	-0.18
Cultural Service	Recreation	2.18	2.18	2.07	1.90	0.01	-0.11	-0.17	-0.28
	Culture	0.03	0.03	0.03	0.03	0.00	0.00	0.00	-0.01

4.11 Changing Pattern of ESV

The decadal change in ESV showed a positive trend of 3.19 million US$ from 1995 to 2005; thereafter, declines were observed from 2005 to 2015 and from 2015 to 2025, amounting to -1.15 and -2.84, respectively. The total temporal decline of ESV was -0.81 million US$ from 1995 to 2025 (Table 7). After the analysis, almost 0.19 million US$ in ES has been degraded each year from 1995 to 2025. The annual change of ES value is 0.74 million US$ from 1995 to 2005, -0.25 million US$ from 2005 to 2005 2015, and -0.63 million US$ from 2015 to 2025. Additionally, Figure 6 represents the location-wise ESV for the Guwahati Metropolitan Area. (See figures 5 and 6)

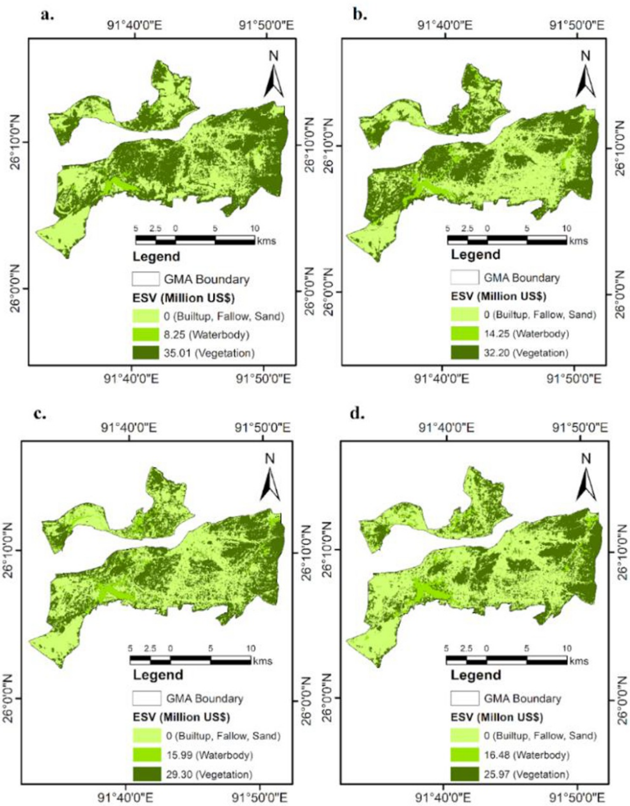

Fig. 5. a. Ecosystem service valuation (million US$) map of 1995; b. Ecosystem service valuation (million US$) map of 2005; c. Ecosystem service valuation (million US$) map of 2015; d. Ecosystem service valuation (million US$) map of 2025 for the Guwahati Metropolitan Area.

Table 7. Temporal Decadal Change and Annual Change Rate of Ecosystem Service Value in the Guwahati Metropolitan Area

Year	Total ESV (Million US$)	Decadal Change in ESV	Annual Change Rate of ESV (ESVcr)
1995	43.25		
2005	46.44	3.19	0.74
2015	45.29	-1.15	-0.25
2025	42.45	-2.84	-0.63
Total		-0.81	-0.19

5 Discussion

The sustainability of the future for the upcoming generation depends on how we exploit natural capital. Natural capital and man-made capital are both essential to make a sustainable world. As of now, we are readily dependent on comfort, so directly or indirectly, we hamper our natural capital. Infrastructure is built in non-beneficial places (such as fallow land, waste land, and degraded land), which are less likely to affect natural capital. Perhaps, if development directly affects our vegetation, soil, water, and air, then it should be the reason for unsustainable management. In today's world, rapid population growth leads to a rapid increase in built infrastructure. The transformation in land use and land cover (LULC) from the past to the future is trending towards a more urban landscape. A study conducted on the Asansol Municipal Corporation found that the area under vegetation transformed to built-up land was 1.31 km2 from 2000 to 2010 and 4.06 km2 from 2010 to 2020. Additionally, the built-up infrastructure area increased by almost 19.08 km2 from 1991 to 2021 [26]. Along with this trend, this study also finds a sharp decline of 44.71 km2 of vegetation area, which has been converted into built-up area from 1995 to 2025. Additionally, a 258.26% increase in built-up area was observed over the same period. Therefore, the growth of artificial infrastructure reduces the availability of natural resources. Now, assessing natural capital in terms of ecosystem services is easier after Costanza's biome-based valuation system. Because LULC classes are represented as individual biomes for ESV evaluation, the total ESV of an area depends on those classes. As a built-up area does not enhance any value coefficient, its increasing expansion will lead to a decline in the total ESV. The present study found that the total ESV for 1995 was 43.25 million US$, which decreased to 42.49 million US$ by 2025. The most significant reduction occurred in vegetation, dropping from 35.01 million US$ to 25.97 million US$. As a result, the study area is losing its ecological benefits by 0.186 million US$ every year.

6 Conclusion

Maintaining ecosystem services, conserving natural resources, and promoting sustainable development are interconnected endeavors, all essential for human well-being. To enhance a city's sustainability, it is imperative to analyze population growth patterns, potential future urban sprawl, land use and land cover (LULC) transitions, and rates of change in ecosystem service values (ESV). The ESV threshold signifies the minimum level required to support the city's sustainability. Urban ecosystem resilience planning is essential to safeguard natural capital. The significant expansion of built-up areas has resulted in a decline in vegetation and fallow land, as well as a decrease in ecosystem service values. Consequently, insights into ecosystem service valuation and change rates can assist urban planners and policymakers in formulating a comprehensive development agenda. For the sustainable development of Guwahati, it is vital to protect sensitive zones such as forests and lakes from urban expansion. Moreover, preventing degradation of the city's ecosystems is critically important for fostering sustainable growth. Instead of horizontal expansion, vertical growth may be an effective strategy to reduce urban sprawl. Wasteland and fallow land should be converted into agricultural zones or infrastructure to support urban needs. Policymakers should prioritize stopping deforestation and desertification. These recommendations aim to enhance Guwahati's sustainability in the future.

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