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Geospatial Measurement of Urban Landscape Dynamics and Urban Sprawl Using Multi Temporal Datasets (1991-2021): Case Study of English Bazar Urban Agglomeration, West Bengal

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Abstract : *The second-largest urban agglomeration in North Bengal, the English Bazar Urban Agglomeration (EBUA), is considered a magnet because it is the central urban hub of Malda district and attracts people from surrounding districts and neighbouring states to access various urban amenities. This study primarily focused on the spatiotemporal dynamics of urban expansion and the underlying facilities that govern urban growth. Additionally, Shannon's entropy (H_n), relative Shannon's entropy (H'_n), and the Urban Expansion Intensity Index (UEII) have been used to illustrate urban sprawl. The integrated CA-Markov model has been used to predict future LULC scenarios using several driving variables. Results revealed that the urban built-up area increased progressively by approximately 19.97 km² (339.63%) between 1991 and 2021, primarily at the expense of agricultural and vegetated land. Correspondingly, Shannon's entropy values rose from 1.210 to 2.262, while relative entropy increased from 0.525 to 0.982, indicating a transition from a compact urban form toward more dispersed, fragmented spatial growth. Furthermore, the UEII values increased steadily from 0.272 in 2001 to 0.502 in 2021, confirming that the intensity of urban expansion has progressively strengthened over time. The northern (N), north-eastern (NE), and eastern (E) sectors remain the primary growth corridors, while the western (W) and south-western (SW) sectors have experienced more recent urban expansion. Influential urban facilities such as administrative offices, educational centres, healthcare services, transport, and markets act as important drivers of the uneven, uncontrolled urban expansion. The predicted analysis confirms the ongoing process of urbanization and spatial expansion in the region. The findings of this study can assist local authorities in developing environmentally sustainable and orderly urban expansion strategies.*

Key words: *Urban growth dynamics; Urban sprawl; Shannon's entropy; Urban Expansion Intensity Index; CA-Markov model*

Introduction

Global urbanization has accelerated rapidly in recent decades. According to the United Nations (World Urbanization Prospects: 2018 Revision), about 55% of the world's population currently lives in urban areas, a proportion projected to rise to nearly 68% by 2050. In recent

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decades, developing countries such as China, India, and Nigeria have experienced rapid urbanization and development, leading to an unexpected rise in the number of people living in cities (Sun et al. 2020; Pande et al. 2023). India, recognized as one of the world's rapidly urbanizing nations, has experienced parallel rapid urban population growth (Tumbe 2016). According to the Census of India, the share of the urban population in India increased from 23.3% in 1981 to 31.2% in 2011. According to the United Nations (UN DESA, *World Urbanization Prospects: The 2018 Revision*), India had approximately 460 million urban residents in 2018, accounting for about 34% of its total population. This proportion is expected to increase steadily, with the urban share projected to rise to nearly 52–53% of the population by 2050. Evidence of this urban transformation is visible in the growth of large cities, as the number of urban agglomerations with populations exceeding one million increased from 35 in 2001 to 53 in 2011 (Chandramouli & General 2011). India's economic liberalization in 1991 accelerated urban growth by stimulating economic expansion and developmental activities (Rahaman et al., 2018). However, this rapid post-liberalization urbanization has also exerted significant pressure on regional ecology, land-cover patterns, and water resources (Sarkar, 2019).

The term "urban landscape dynamics" refers to the rapid, often non-linear transformation of urban environments, marked by the expansion of built-up areas, rising population density, and infrastructure growth, often at the expense of natural, agricultural, or open land. These changes reflect the combined influence of demographic pressure, economic development, and planning processes shaping cities' spatial structures over time. Urban landscapes are not static; they evolve through interactions between human activities and natural systems. Rapid urbanization often results in phenomena such as densification, fragmentation of green spaces, and environmental stress, including pollution, biodiversity loss, and urban sprawl (Azad et al., 2026).

The term "urban sprawl" has long been a subject of research in the developed world and has recently gained increasing attention in developing countries like China and India, where rapid urbanization is reshaping urban landscapes (Jha et al., 2025). Urban sprawl is typically associated with urban peripheral areas that are experiencing rapid growth (Mahata et al. 2024).

English Bazar UA has emerged as one of the most urbanized zones in Malda district, where rapid industrial growth, expanding socio-economic activities, and changing agricultural patterns have collectively accelerated urban sprawl (Dutta & Das, 2019). Urbanization in this town has accelerated since its recognition as an urban agglomeration in 2011. In particular, a strong administrative setup, diverse service facilities, migration from remote regions, and increased employment opportunities due to the establishment of various institutional facilities have further contributed to urbanization.

Objectives:

Numerous empirical investigations have focused on urban growth and land-use/land-cover scenarios in the region. For example, Dutta & Das (2019) assessed the extent and scale of urban sprawl using Shannon's entropy index and landscape metrics within remote sensing and GIS frameworks. (Bindajam et al. 2023) assessing landscape fragmentation due to urbanization in English Bazar Municipality. (Shaw & Das, 2018), identifying peri-urban growth in small and medium towns using GIS and remote sensing techniques. (Pal & Ziaul, 2017) detected the relation between LULC change and LST. After reviewing the literature, we found that this research has mainly focused on urban expansion without integrating spatial pattern analysis, driving factors of urbanization, environmental consequences, and planning implications into a single analytical framework. Additionally, there has been less focus on future urban land dynamics.

Keeping the above in mind, the present study attempts to address this gap by combining long-term spatiotemporal land-use analysis, entropy-based assessment of urban form, identification of the underlying influential facilities that govern urban growth, and predictive modelling within a unified framework. By linking historical urban growth patterns with future projections and sustainability concerns, this research provides a more comprehensive understanding of urban transformation, which could guide future structural, industrial, and policy development. Specifically, the objectives of this study are:

1. To detect and quantify the spatiotemporal dynamics in LULC in EBUA over the last 30 years (1991-2021) using remote sensing data.
2. To analyse the spatial pattern and degree of urban dispersion using Shannon's entropy and related spatial metrics.
3. To identify the major drivers of urban expansion and examine their environmental implications in the study area.
4. To forecast LULC variability for the year 2031 using the CA-Markov model.

This study makes three distinct contributions compared with previous studies on urban growth—first, long-term spatiotemporal analysis of land-use dynamics in English Bazar UA. Second, the study combined a remote sensing-based land-use map, entropy-based spatial analysis, driving forces governing urban expansion, and CA–Markov predictive modelling within a single analytical framework, thereby offering a more comprehensive methodological approach to understanding urban landscape dynamics. Third, by linking future growth projections and spatial expansion patterns with environmental implications, the study provides local governing authorities with critical insights for sustainable planning and management decisions.

Justification for the selection of the study area

English Bazar Urban Agglomeration serves as the main urban centre of Malda District and is linked between north and south Bengal. Geographically, it is situated between 24°592 N and 25°042 N latitudes and 88°062 E and 88°102 E longitudes, covering an area of approximately 28 km^2. English Bazar was officially recognised as an Urban Agglomeration in the 2011 Census, comprising two statutory towns, i.e., English Bazar Municipality (EBM) and Old Malda Municipality

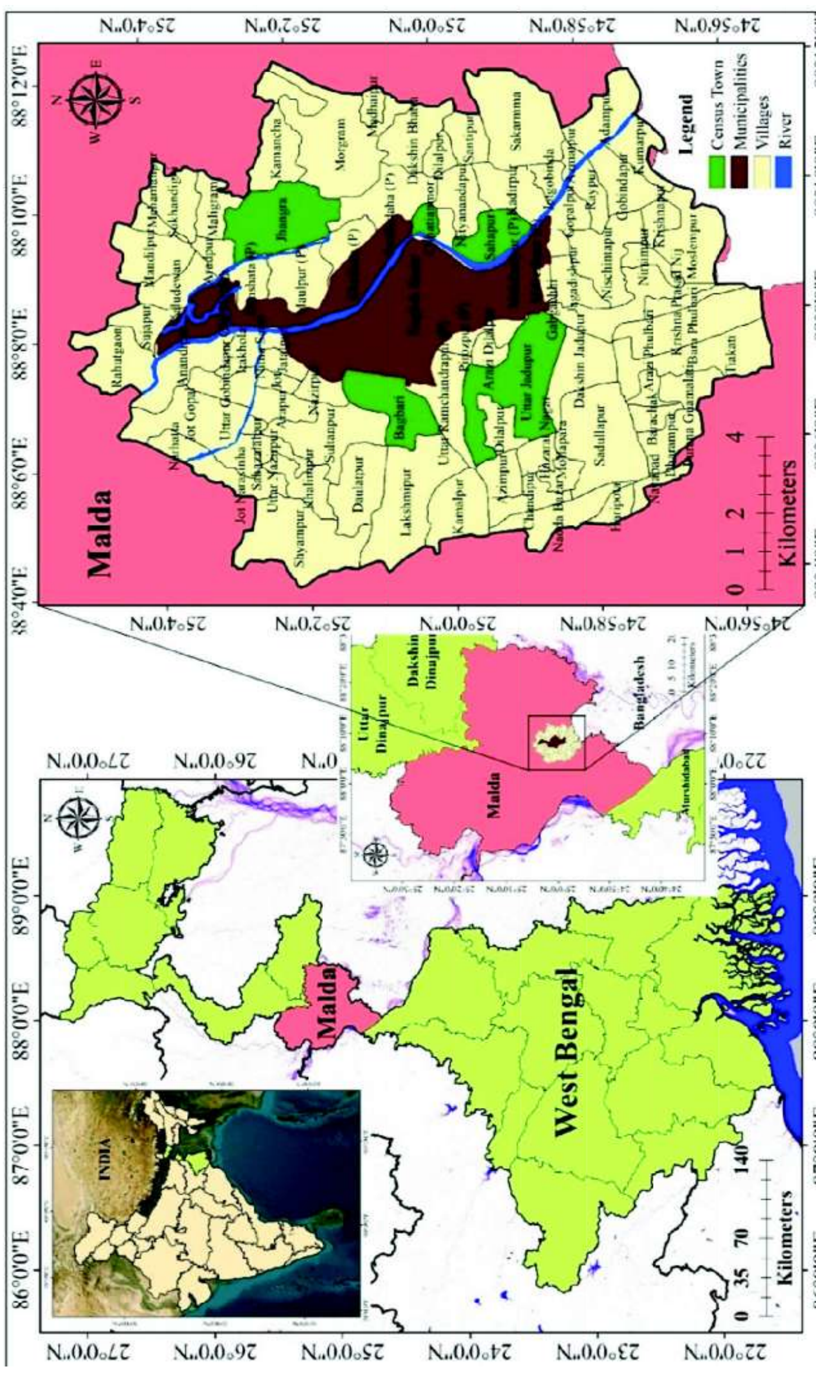


Fig. 1: Location map of English Bazar Urban Agglomeration

(OLM), and three census towns, i.e., Bagbari, Chattianmore, and Sahapur. Old Malda Municipality recorded a very sharp increase in population from 13,024 in 1991 to 62,959 in 2001, followed by a more moderate rise to 84,012 in 2011. English Bazar Municipality, in contrast, exhibited steady and continuous urban expansion. Its population increased from 139,204 in 1991 to 161,456 in 2001, and further to 205,521 in 2011. According to the Census of India (2011), Malda recorded the highest rate of urban population growth (124.81 %) among the remaining districts of West Bengal. A combination of geographical, economic, and administrative factors has contributed to the rapid urbanisation of the study area. One of the most significant factors is the district's strategic location in West Bengal's central region, which has enabled it to serve as a node connecting North Bengal with the state's southern region and with adjacent Bihar and Jharkhand. This locational advantage has facilitated the growth of transportation networks, regional trade, and market connectivity. In addition, as the district headquarters, English Bazaar concentrates administrative functions, educational institutions, healthcare facilities, and commercial services, thereby attracting continuous migration from rural to urban areas. Together, these factors have transformed English Bazar UA into the principal urban growth pole of Malda district and one of the emerging urban centres of North Bengal.

Materials and methods

Data acquisition

Remote sensing data have emerged as a highly accurate, time-efficient, and reliable approach for analysing LULC change. In this study, Landsat imagery was used to delineate LULC categories and quantify temporal changes. Landsat 5 TM data were acquired for 1991, 2001, and 2011, while Landsat 8 OLI-TIRS imagery was used for 2021 (Table 1). All images have a spatial resolution of 30 m and were selected from cloud-free dry-season scenes corresponding to path/row 139/43. The boundary map of the study area was obtained from the English Bazar Municipality administration.

Table 1: Details Characteristics of Landsat satellite imagery used in this study

Satellite Images	Path /Row	Acquisition Data	Resolution	Projection	Source
Landsat-5 TM	139/43	17-03-1991 21-03-2001 17-03-2011	30m	WGS1984 & UTM 45°N	https://earthexplorer.usgs.gov/
Landsat-8 OLI	139/43	19-03-2021	30m	WGS1984 & UTM 45°N	https://earthexplorer.usgs.gov/

Source: USGS Earth Explorer

Image pre-processing and Supervised classification

Satellite image pre-processing is essential to ensure accuracy and reliability in remote sensing analysis. In this study, Landsat 5 TM and Landsat 8 OLI imagery were geometrically corrected, radiometrically calibrated, atmospherically corrected, and subset using ArcGIS 10.4. Band compositing and histogram equalization were also performed to enhance image quality and improve classification accuracy. All datasets were projected to the UTM Zone 45N coordinate system with the WGS 1984 datum. LULC maps for 1991, 2001, 2011, and 2021 were then generated using supervised classification with the Maximum Likelihood Classifier (MLC). The authors selected training samples to categorize pixels into five LULC classes: built-up area, water bodies, vegetation, agricultural land, and fallow land. The classified outputs were subsequently analysed using ArcGIS statistical tools to quantify the spatial distribution and temporal changes in land-use and land-cover patterns.

Accuracy assessment

Accuracy assessment refers to classification accuracy measured against actual ground observations. Google Earth Pro was used to verify ground observations, with 100 points randomly collected for each class in 1991, 2001, 2011, and 2021. To compute user, producer, and overall accuracy, and the kappa coefficient, a User Error Matrix was used. A standard measurement of the Kappa coefficient was retained. In addition, reasonable accuracy was indicated when the Kappa coefficient was greater than 0.75 (Kafy et al., 2020; Rahman et al., 2012). Hence, we found a Kappa value of more than 0.80, which validates vital accuracy for the study area.

Land use and cover change detection

Change detection analysis delineates and quantifies disparities between images of the same area acquired at different times. For this research, the researchers employed a post-classification change-detection method in ArcGIS 10.4 to identify discrepancies across four LULC map pairs (1991/2001, 2001/2011, 2011/2021, and 1991/2021). The post-classification technique, widely recognised as the most accurate change-detection method, identifies changes in LULC by analysing images from different time points and classifying them accordingly. The spatial distribution of different LULC classes and their changes was subsequently analyzed using cross-tabulation.

Measuring urban sprawl

Assessing land use and land cover is insufficient to capture the dynamics of urban growth; therefore, it is necessary to examine the intensity and magnitude of changes within the urban fabric. In studies on urban sprawl, Shannon entropy is a popular evaluation method for assessing the distribution of urban expansion. (Sudhira et al., 2004; Yeh & Li, 2001) This tool is essential for recognizing urban sprawl because it quantifies the degree of urban expansion or dispersion among ‘n’ zones (Sun et al., 2007; Deka et al., 2011; Bhatta et al., 2010). In this study, we used

Shannon entropy to identify and quantify the sprawling urban landscape in the EBUA. Shannon entropy (Hn) is computed using the formula as expressed below:

$$H_n = -\sum_{i=1}^{n} P_i \log_e (P_i)$$

Where *Pi* represents the proportion of the built-up area in the i[th] zone, and *n* is the total number of zones.

Entropy ranges from 0 to log‘ (n); a value close to 0 indicates compact growth, while higher values signify dispersed development and greater urban sprawl.

The Shannon Entropy approach indicates compactness or dispersion. In contrast, relative Shannon entropy provides a sense of sprawl and a quantifiable measure of growth over a given time period. Relative Shannon’s entropy is used to normalise entropy values on a scale ranging from 0 to 1 (Patra et al., 2022). The relative entropy for *n* spatial zones is computed as follows (Punia & Singh, 2012):

$$H'_n = \frac{\sum_i^n P_i \log_e \left(\frac{1}{P_i} \right)}{\log (n)}$$

In which,

$$P_i = \frac{X_i}{\sum_i^n X_i}$$

Where,

where *Xi* is the density of land development in the i[th] Zone, and *Pi* represents the proportion of the built-up area in the i[th] Zone. n is the total number of zones. H'_n is the relative entropy. Relative entropy ranges from 0 to 1; values above 0.5 denote sprawl, while values below 0.5 indicate compact growth.

Urban Expansion Intensity Index (UEII):

The Urban Expansion Intensity Index (UEII) is a valuable tool for identifying urban growth trends over time and indicating the potential direction and extent of urban expansion across regions or quadrants. In this study, the UEII is used to measure Shannon entropy spread across each quadrant and to verify the results.

$$UEII = \frac{BLA^{t_2} - BLA^{t_1}}{TLA \times \Delta t} \times 100$$

Where, BLA = built-up land area; t_1 = base year; t_2 = ending year; $\Delta t = t_2 - t_1$, TLA = Total land area of the study area.

The Urban Expansion Intensity Index (UEII) values are classified into five categories to represent different rates of urban growth: values below 0.28 indicate very slow expansion, 0.28–0.59 represent slow expansion, 0.59–1.05 denote medium-speed expansion, 1.05–1.92 indicate high-speed expansion, and values above 1.92 reflect very high-speed urban expansion.

CA–Markov Modelling for LULC Projection

CA-Markov Chain analysis is a useful method for modelling land-use change, especially when landscape changes are complex and constantly evolving. This model was used to predict the expansion of urban land use and land cover. It has a significant impact on predicting the dynamics of land-use and land-cover change. Recent studies have used the CA-Markov model to simulate land-use changes because it effectively combines the strengths of the Cellular Automata (CA) and Markov models (Sarkar & Chouhan, 2019).

In this study, ArcGIS 10.8.1, ERDAS 2014, QGIS 3.16.3, and TerrSet software were employed to predict the future LULC map. To predict future land-use/land-cover change, the study considered several factors, including Digital Elevation Model (DEM), slope, road density, distance to roads, rivers, and urban areas, and Topographic Position Index (TPI) (Singh & Singh, 2024). These factors are commonly used in LULC studies and prediction because they help explain how both human activities and natural factors influence land-use change.

In this study, the CA–Markov model was implemented through several steps. First, LULC maps were prepared at equal time intervals for the years 1991, 2001, 2011, and 2021. Transition probability and area matrices were then generated from these maps using the Markov chain analysis module in TerrSet. These matrices describe the likelihood of land-use transitions and help predict future changes. Next, transition potential maps were produced by incorporating various driving factors, including DEM, slope, and distance to urban areas and rivers (Fig. 2). Based on the transition probabilities, the extent of land-class conversions was estimated. The simulated LULC map for 2021 was validated against the actual 2021 map to assess model accuracy. Finally, the validated model was used to predict the LULC pattern for the year 2031.

Results & Discussion

Accuracy assessment

In LULC change detection research, it is essential to assess accuracy (Rwanga & Ndambuki, 2017). The error matrix for each categorized dataset was used to assess accuracy, including the

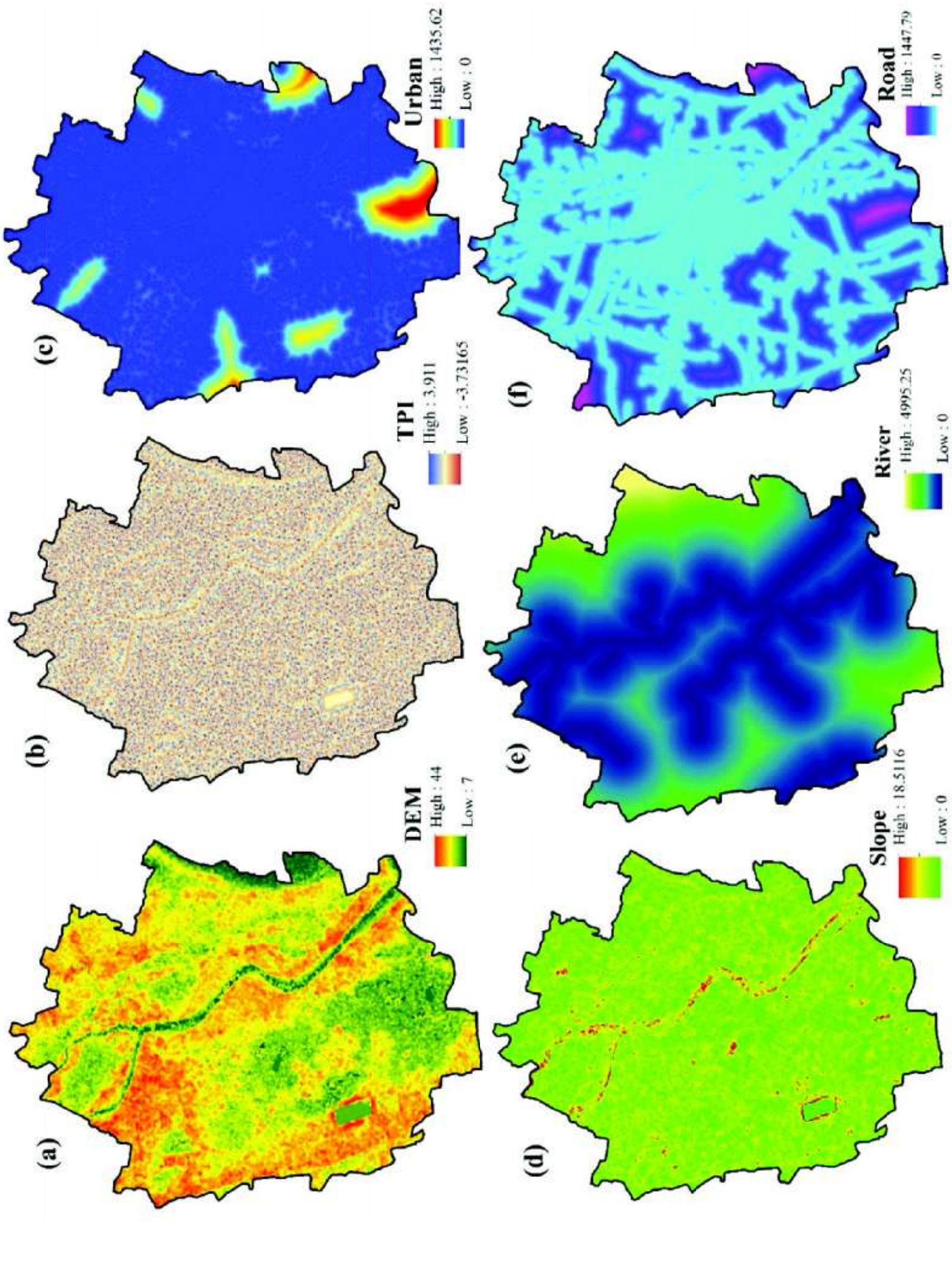


Fig. 2: Driving factors used in CA–Markov-based LULC prediction.

kappa coefficient, user's accuracy, and producer's accuracy. The result reveals that the overall accuracy was 0.97 in 1991, 0.98 in 2001, 0.97 in 2011, and 0.96 in 2021. Furthermore, the overall Kappa values for 1991, 2001, 2011, and 2021 are 0.0.96, 0.98, 0.96, and 0.95, respectively. The accuracy percentage and Kappa coefficient indicate strong agreement between the classified image and the ground-truth points (Das & Angadi, 2020).

The changing scenario of land use/land cover (LULC) in EBUA

The LULC classification results from multi-temporal remote sensing data using a supervised classification technique for four time periods (1991, 2001, 2010, and 2021) within the study area are presented in Table 2 and Fig. 2a-d. The data for 1991, 2001, 2011, and 2021 were classified into five categories: Built-up, water bodies, vegetation cover, agricultural land, and barren land (Roy & Kasemi, 2021)

The LULC distribution presented in Table 2 and Figure 2a-d illustrates the temporal areal expansion of LULC categories in the English Bazar UA between 1991 and 2021. In 1991, built-up land covered 5.88 km² (3.66%), increasing steadily to 10.25 km² (6.38%) in 2001, 17.77 km² (11.05%) in 2011, and 25.85 km² (16.07%) in 2021, indicating rapid and sustained urban growth. In contrast, both vegetation and agricultural land exhibited a declining trend. Vegetation cover decreased from 75.78 km² (47.13%) to 67.72 km² (42.11%), while agricultural land declined from 69.70 km² (43.35%) to 59.42 km² (36.95%), suggesting that urban expansion has largely occurred at the expense of productive and green landscapes. Water bodies showed minor fluctuations, increasing slightly in 2001 before declining to 8.30 km² (5.16%) in 2021. Meanwhile, fallow land steadily reduced from 2.13 km² (1.32%) to 0.53 km² (0.33%), indicating its gradual conversion into built-up or cultivated land. Overall, the results highlight a significant transformation of the landscape, from predominantly agricultural and vegetated land to a progressive increase in urban land.

Table 2: Distribution of LULC area from 1991 to 2021

LULC	1991		2001		2011		2021	
	Area in km²	Area in %	Area in km²	Area in %	Area in km²	Area in %	Area in km²	Area in %
Built Up	5.88	3.66	10.25	6.38	17.77	11.05	25.85	16.07
Water Body	7.32	4.55	9.10	5.66	8.56	5.32	8.30	5.16
Vegetation	75.78	47.13	71.76	44.62	68.50	42.60	67.72	42.11
Agricultural	69.70	43.35	68.22	42.42	64.95	40.39	59.42	36.95
Fallow Land	2.13	1.32	1.48	0.92	1.04	0.65	0.53	0.33

Source: Computed by authors based on satellite data

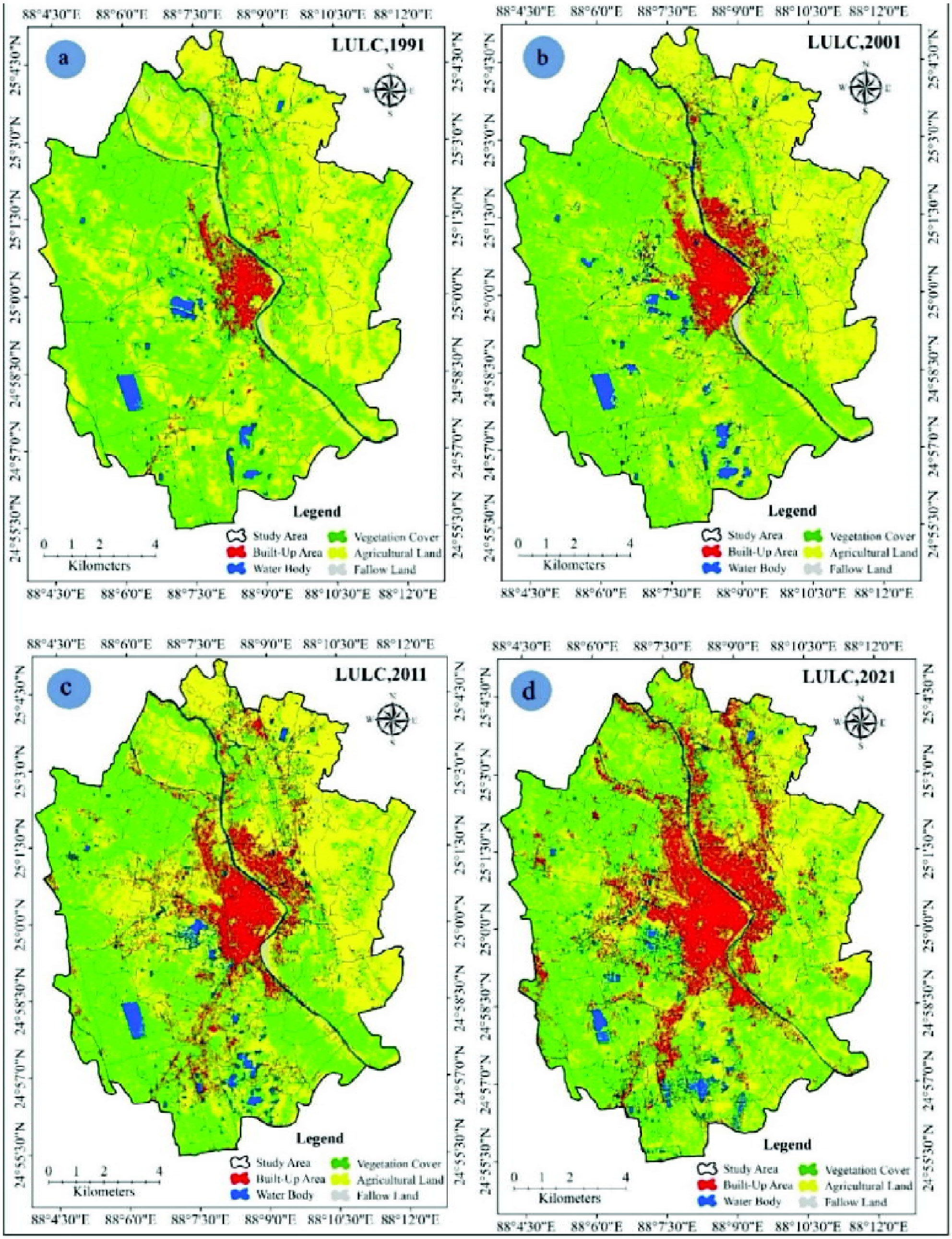


Fig. 3: Spatio-Temporal Changes in Land Use/Land Cover (LULC) in the Study Area, a. 1991; b. 2001; c. 2011; d. 2021

Land transformation during the period of 1991-2021

The built-up area shows a continuous and substantial increase across all decades, expanding by 4.38 km² between 1991 and 2001, 7.51 km² between 2001 and 2011, and 8.08 km² between 2011 and 2021, for a total of 19.97 km² (12.42%). In contrast, vegetation cover consistently declined throughout the study period, resulting in a total loss of 8.06 km² (“5.01%), indicating a gradual depletion of green spaces due to anthropogenic pressures. Agricultural land also experienced a notable reduction of 10.29 km² (“6.40%) between 1991 and 2021, suggesting that urban growth has largely taken place through the conversion of productive agricultural land. Fallow land followed a similar downward trend, shrinking by 1.60 km² (“0.99%), reflecting its gradual transformation into built-up or cultivated land. Water bodies increased during 1991–2001 but subsequently declined in later decades, with a modest net gain of 0.98 km² (0.61%) over the entire period. Overall, the table clearly demonstrates that urban expansion has been the dominant landscape process over the past four decades, primarily occurring at the expense of agricultural and vegetated land, thereby reinforcing the trend of increasing urbanization and declining natural and productive land resources in the study area.

Table 3: Resultant LULC changes from the past four decades (1991-2021)

LULC	Changes from 1991 to 2001		Changes from 2001 to 2011		Changes from 2011 to 2021		Changes from 1991 to 2021	
	Area in km²	Area in %	Area in km²	Area in %	Area in km²	Area in %	Area in km²	Area in %
Built Up	4.38	2.72	7.51	4.67	8.08	5.02	19.97	12.42
Water Body	1.78	1.11	-0.54	-0.34	-0.26	-0.16	0.98	0.61
Vegetation	-4.03	-2.50	-3.26	-2.03	-0.78	-0.48	-8.06	-5.01
Agricultural	-1.49	-0.93	-3.27	-2.03	-5.53	-3.44	-10.29	-6.40
Fallow Land	-0.64	-0.40	-0.44	-0.27	-0.52	-0.32	-1.60	-0.99

Source: Computed by authors

Urban growth measure based on direction and distance

English Bazar UA, the principal administrative and functional centre of Malda District, exhibits a pattern of urban expansion strongly influenced by the location of key factors, including education, markets, administrative services, health care services, and transportation networks. The spatial growth of built-up areas in the region is largely guided by road corridors and roadside development, with national and regional highways shaping the directional spread of urbanization. The rapid increase in urban sprawl in the study area is driven by unregulated development in the built-up area. In this analysis, the study area was divided into eight quadrants and ten multiring

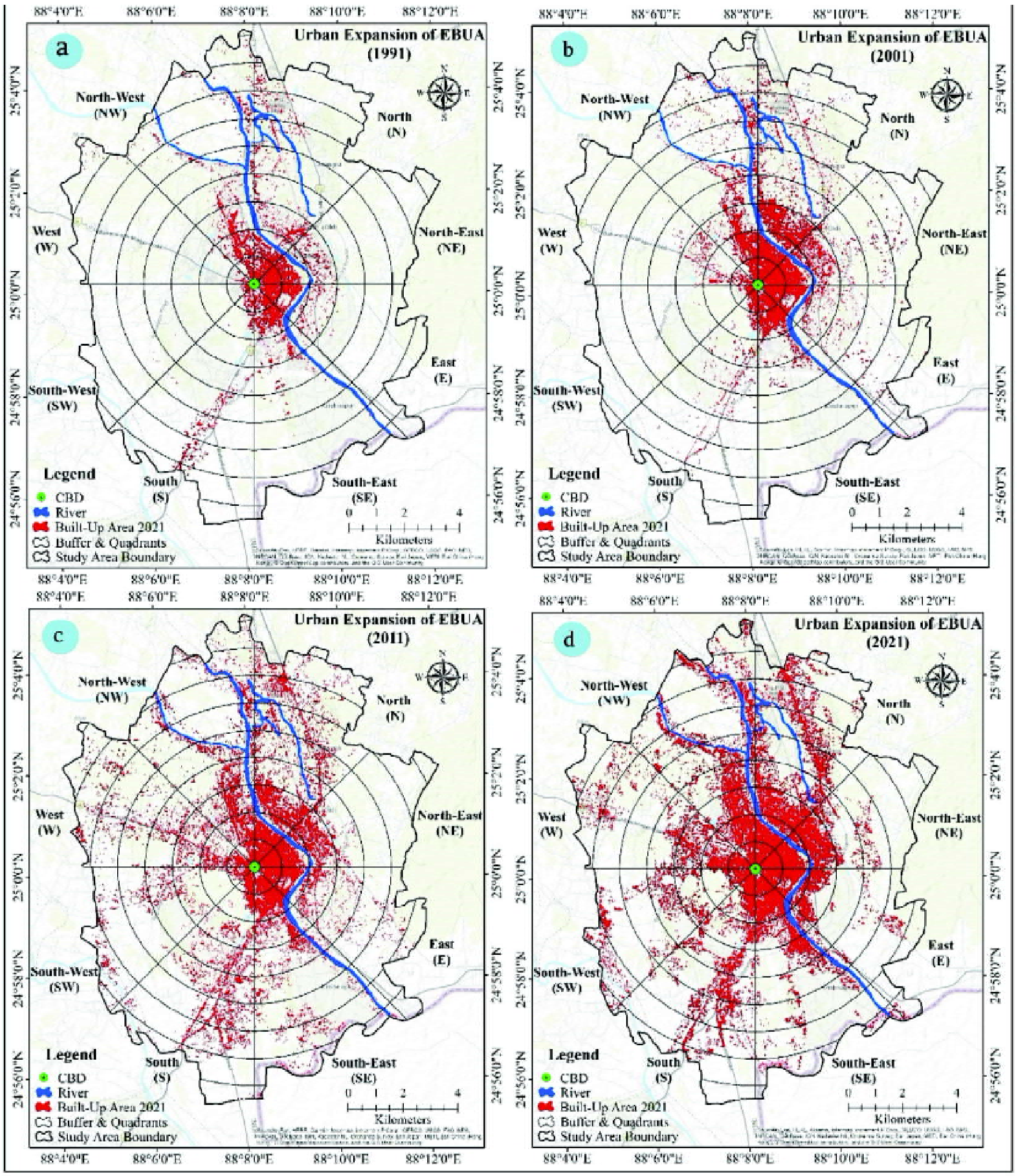


Fig. 4: Directional and distance-based urban expansion in the study area, a. 1991 b. 2001 c. 2011 and d. 2021

buffers to examine how built-up areas have evolved in terms of direction and distance between 1991 and 2021 (Fig. 4a-d).

Figs. 4a-d & 5 show the direction-wise growth of urban areas within the study region between 1991 and 2021, along with the total land available in each direction. It helps identify which sectors experienced stronger urban expansion. The directional analysis of urban expansion from 1991 to 2021 reveals a substantial increase in built-up area across most sectors of the study region, indicating a clear outward growth of the urban landscape. The most pronounced urban expansion occurred in the north-east (NE) quadrant, where built-up area increased from 0.97 sq.km to 3.67 sq.km, representing nearly 278% growth over the study period. The southern (S) quadrant also experienced rapid expansion, rising from 0.59 to 2.93 sq km, an increase of about 397%. Substantial growth is also observed in the south-east (SE) and western (W) quadrants, which expanded by approximately 240% and 407%, respectively, highlighting these directions as major corridors of urban expansion.

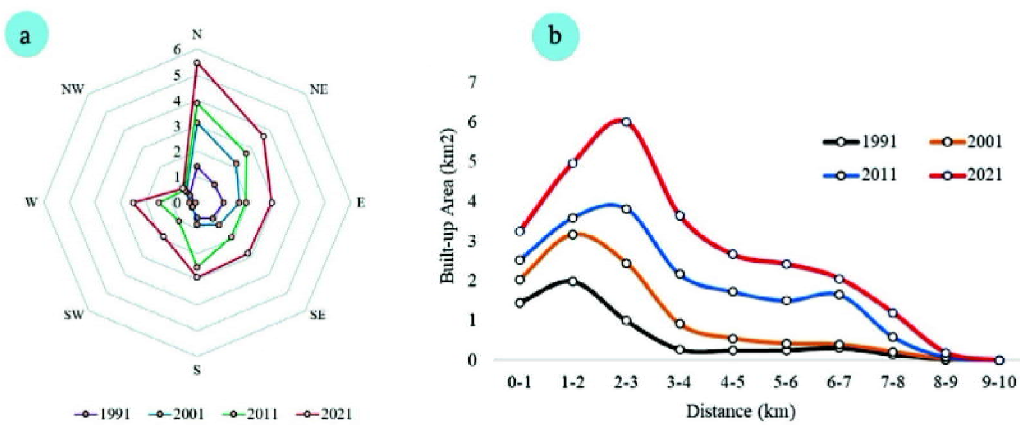


Fig. 5: Direction and distance-wise growth of built-up area (1991-2021)

The buffer-wise analysis of built-up expansion between 1991 and 2021 reveals a clear outward diffusion of urban growth from the city core. The highest concentration of built-up area is observed within the 0–1 km buffer, where urban land increased from 1.46 km² in 1991 to 3.25 km² in 2021, indicating continued densification of the central zone. However, the most rapid expansion is visible in the 1–3 km and 2–4 km buffer ranges, particularly the 2–3 km zone, where built-up area rose sharply from 1.00 km² to 6.00 km², reflecting strong peri-urban growth. Beyond 4 km, urban expansion continues but at a gradually declining intensity, suggesting that new development is occurring mainly along roads and highways. Beyond 7 km, urban growth is limited, with most development concentrated in the inner and intermediate zones. This indicates that the city is not expanding uniformly in all directions. Overall, the results demonstrate that urban growth in EBUA follows a pattern of core densification accompanied by rapid peri-urban expansion, highlighting the emergence of transitional growth zones surrounding the city.

Quantification of Urban Sprawl

The visual representation (Figs. 4a-d & 5) clearly delineates the spatial pattern of urban growth and how its progressive expansion has gradually encroached on adjacent areas within the study region over the study period. Shannon entropy and UEII have been used to measure urban expansion and urban sprawl. Both absolute and relative Shannon's entropy were computed for each quadrant. Additionally, UEII has been used to quantify the rate of built-up growth in different quadrants.

Table 4: Temporal changes in Built-up, Shannon's Entropy, and UEII (1991-2021)

Year	Built-up & change			Entropy & change			UEII
	Built-up (km²)	Built-up Change (km²)	Built-up Change (%)	Shannon's entropy (Hn)	Relative Shannon's entropy (H2 n)	Change in Relative Shannon's entropy	Urban expansion intensity index (UEII)
1991	5.880			1.210	0.525		
2001	10.250	4.370	74.320	1.392	0.604	0.079	0.272
2011	17.766	7.516	73.327	2.031	0.882	0.278	0.468
2021	25.850	8.084	45.503	2.262	0.982	0.100	0.502

Source: Computed by authors

Table 4 presents a temporal analysis of built-up expansion, Shannon entropy, and the Urban Expansion Intensity Index (UEII), which expresses a consistent pattern of urban growth and increasing spatial dispersion within the study area between 1991 and 2021. The built-up area expanded markedly from 5.880 km² in 1991 to 25.850 km² in 2021, indicating sustained urban development over three decades. The highest decadal growth occurred during 2001–2011, when built-up land increased by 7.516 km², reflecting accelerated urbanization possibly driven by infrastructure improvements and demographic pressure. Correspondingly, Shannon's entropy values rose from 1.210 to 2.262, while relative entropy increased from 0.525 to 0.982, indicating a transition from a compact urban form toward more dispersed, fragmented spatial growth. The change in relative entropy peaked during 2001–2011, suggesting that this period experienced the most pronounced spatial restructuring. Furthermore, the UEII values increased steadily from 0.272 in 2001 to 0.502 in 2021, confirming that the intensity of urban expansion has progressively strengthened over time. Collectively, these indicators demonstrate that urban growth in the study area has not only intensified but also become increasingly spatially extensive and less compact.

Directional analysis of urban sprawl

Table 5: Directional analysis of Shannon's Entropy, Relative Entropy, and Urban Expansion Intensity Index (UEII) in the Study Area (1991–2021)

Year	Spatial Measures	Direction							
		N	NE	E	SE	S	SW	W	NW
1991	S.E.(Hn)	0.160	0.167	0.152	0.130	0.078	0.020	0.024	0.153
	Rel. SE (H2 n)	0.077	0.080	0.073	0.062	0.037	0.010	0.011	0.074
	Change (%) in Rel. SE.	-	-	-	-	-	-	-	-
	UEII	-	-	-	-	-	-	-	-
2001	S.E.(Hn)	0.265	0.247	0.194	0.156	0.086	0.033	0.083	0.211
	Rel. SE (H2 n)	0.128	0.119	0.093	0.075	0.041	0.016	0.040	0.102
	Change (%) in Rel. SE.	5.05	3.88	2.05	1.25	0.40	0.61	2.85	2.81
	UEII	0.75	0.55	0.24	0.13	0.03	0.03	0.17	0.35
2011	S.E.(Hn)	0.307	0.262	0.230	0.245	0.230	0.155	0.197	0.237
	Rel. SE (H2 n)	0.148	0.126	0.110	0.118	0.111	0.075	0.095	0.114
	Change (%) in Rel. SE.	2.03	0.70	1.70	4.26	6.92	5.90	5.49	1.25
	UEII	0.48	0.13	0.24	0.58	0.77	0.46	0.55	0.19
2021	S.E.(Hn)	0.363	0.349	0.338	0.309	0.298	0.222	0.272	0.311
	Rel. SE (H2 n)	0.175	0.168	0.163	0.149	0.143	0.107	0.131	0.150
	Change (%) in Rel. SE.	2.67	4.20	5.23	3.12	3.28	3.21	3.62	3.54
	UEII	1.31	1.30	1.31	0.70	0.66	0.41	0.60	0.78

Source: Computed by authors

The directional analyses of Shannon's entropy, relative entropy, and the Urban Expansion Intensity Index (UEII) are presented in Table 5, which suggests pronounced spatial asymmetry in the pattern of urban growth within the study area over the three-decade period. In 1991, entropy values were relatively high in northern (N), north-eastern (NE), and eastern (E) directions and low in the southern (S) and south-western (SW) directions. By 2001, rising entropy and UEII values in most directions suggest the emergence of multidirectional urban expansion, with pronounced growth toward the north (N) and north-east (NE). The 2011 results indicate further intensification, with significant increases in entropy in the southern and south-eastern directions, suggesting that urban development had begun to extend into previously less developed zones. By 2021, entropy values rose substantially in all directions, indicating the city has become more dispersed and less dense, showing characteristics of urban sprawl rather than compact growth. The highest UEII values recorded in the northern (N), north-eastern (NE), and eastern (E) sectors confirm that these directions remain the dominant growth corridors. In contrast, the western (W) and south-western (SW) sectors, despite showing recent increases, still exhibit comparatively lower expansion intensity. However, the northern and eastern sectors continue to serve as the principal axes of urban expansion, and recently, the western and south-western directions have experienced the most urban growth.

Concentric zone-wise analysis of urban sprawl

To understand the sprawling phenomenon at the micro-level, the city has been divided into 10 concentric rings, each 1 km from the centre, to analyze the nature of sprawling. Fig. 6 shows the relative Shannon's entropy for every concentric ring. It is evident that in core areas, entropy values decrease continuously in the inner zones (0–1 km), indicating a compact urban core with concentrated development and limited outward expansion. But later, the entropy peak shifted slightly outward, reflecting the beginning of suburban growth and the gradual diffusion of built-up areas beyond the core. The 2011 pattern shows a more balanced entropy distribution across the middle zones (2–6 km), suggesting transitional growth in which development spread into intermediate areas, reducing the dominance of the central core. In comparison, the 2021 curve shows higher entropy values across a wider area, especially in the outer rings (8–10 km), suggesting that urban growth has become more dispersed. This outward rise in entropy indicates a transition from a compact city structure to a more sprawled urban form, confirming that recent

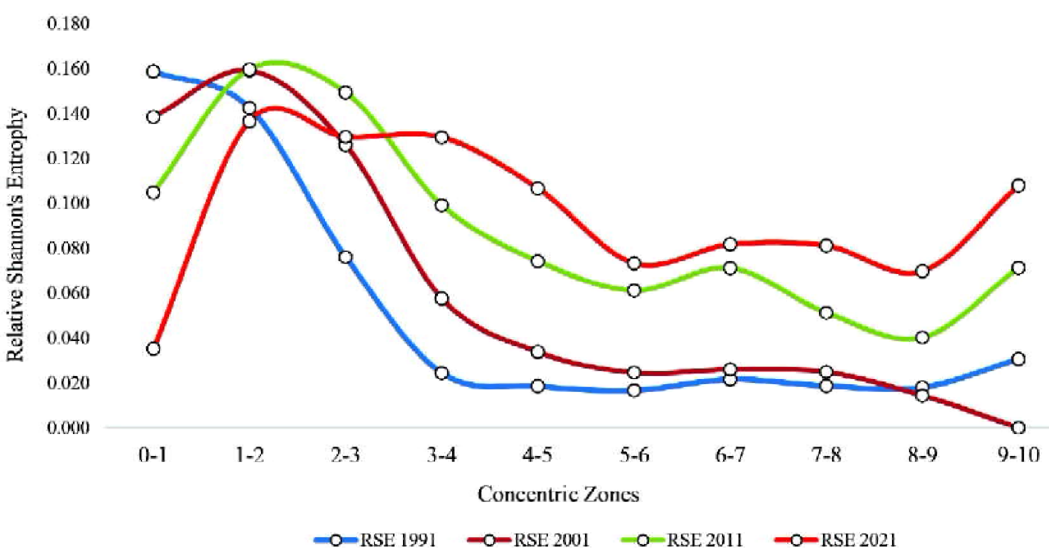


Fig. 6: Temporal variation of Relative Shannon's Entropy across concentric buffer zones (1991–2021)

growth has been driven primarily by peripheral development rather than core densification. Overall, the concentric entropy trends clearly illustrate the progressive decentralisation of urban growth and the emergence of spatially extensive expansion in the study area.

Major drivers influence the urban growth in the study area

Driving forces of urbanisation are the factors that attract population, activities, and infrastructure to urban areas, leading to city expansion and transformation. In this study, we have considered the influential urban facilities shown in Fig. 7 & Table 6 as driving forces of urbanisation. Urban institutional facilities such as administrative offices, educational centres, healthcare services, transport, and markets act as important drivers of urbanization, attracting population, generating employment, stimulating service activities, and promoting infrastructure development in surrounding areas. Most institutional facilities are concentrated near the CBD, showing that the city centre plays a major role in service access and urban development. Most administrative services, including the Malda district court, collectorate office, DM office, and police station, are located within approximately 1–1.2 km of the CBD, predominantly toward the east

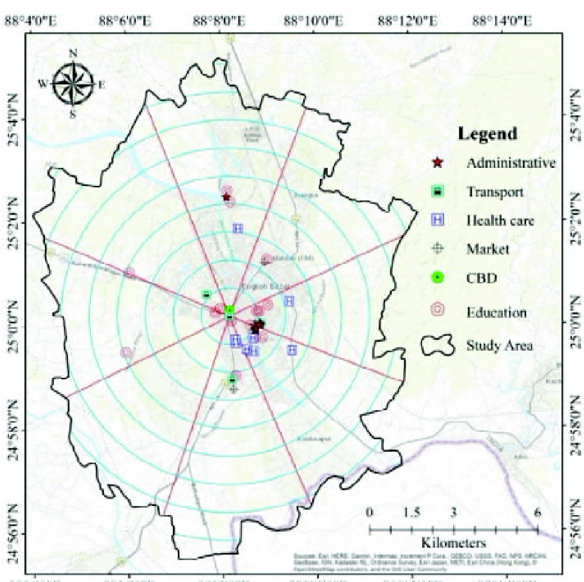


Table 6: Distance and directional distribution of urban facilities from the CBD

Institutional facilities		Distance from CBD (km.)	Direction from CBD
Administrative Service	E.B.M.	1.19	E
	Malda district court	1.12	E
	District collectorate office	1.08	E
	Malda head post office	0.96	SE
	English Bazaar P.S.	1.07	SE
	DM office	1.05	E
Health care facilities	Malda medical college	0.8	S
	Dishari Nursing Home	1.13	SE
	Sonoscan	1.42	SE
	MMC	1.13	SE
Market	Rathbari market	0.1	
	Mangalbari Market	2.26	NE
	DCR market	0.92	E
	Mokdumpur Market	1.08	SE
	English bazar regulated Market	2.56	S
Educational facilities	Malda College	0.27	SE
	ITI College	0.49	W
	Holly Child	2	W
	North point	3.47	N
	KVS	3.67	W
	Polytecnic	4.06	W
	Womens College	0.6	S
	UGB	2.11	S
	Gour College	2.5	NE

Fig. 7: Spatial distribution of urban facilities influencing urban growth

Source: Computed by authors

and south-east. Healthcare facilities also show a similar spatial tendency. The Malda Sadar hospital & medical college, nursing homes (Dishari, MMC), diagnostic centres (Sonoscan), and other medical facilities are situated largely within 0.8–1.4 km of the CBD, mainly in the southern and south-eastern directions. Rathbari Market is located extremely close to the CBD (0.1 km). Other markets, including Mangalbari and the regulated market (Aam Bazar), are situated 2–2.5 km from the CBD, mainly toward the north-east and south, suggesting a gradual outward spread of commercial activities toward the periphery. Educational institutions such as Malda College and Malda Women's College lie within the inner buffer zone, and other institutions such as North Point School, Polytechnic, and Gour College are located beyond 2–4 km from the CBD, extending mainly toward the northern, western, and north-eastern directions. Moreover, the transport network connecting these facilities to the surrounding areas is well-developed, ensuring easy accessibility. NH 31 passes through the middle of this city and connects Siliguri and Kolkata. NH 10 runs north-south through the main city, connecting Bagbari and Milki (both census towns) with the urban core. The communication network in this area has improved after the construction of the Malda Bypass (NH-12) to the south. Recently the southern and south-western directionof the study area have recorded the more developed due to establishment the University of Gour Banga (UGB), Malda regulated market (Amm Bazar), private and government bus stands, shopping malls, and many private nursing homes that employ the people across the district, leading to the development of new roads, shops, and housing colonies.

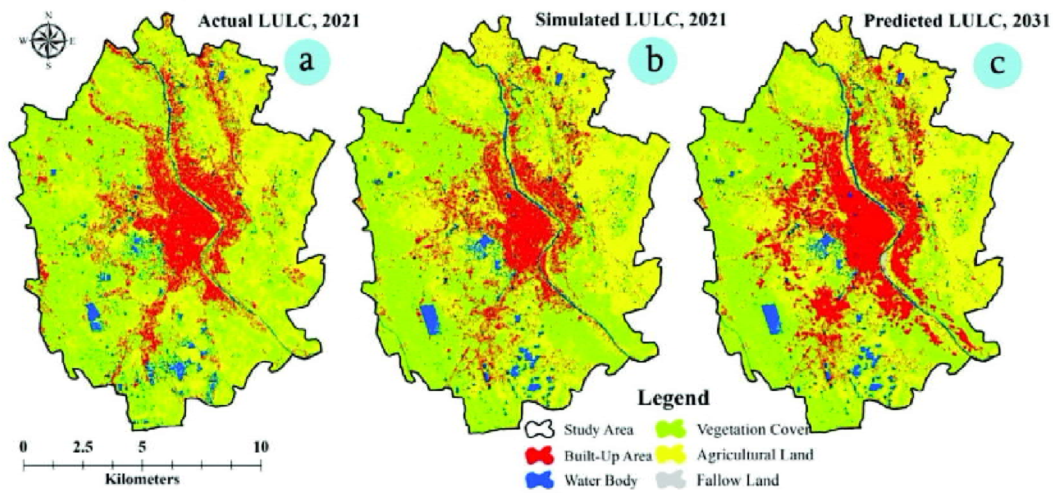
Environmental and Ecological Implications of Urban Expansion

The rapid expansion of built-up land within the EBUA region between 1991 and 2021 has created significant environmental and ecological impacts. The land-use change analysis (Tables 2 & 3) clearly demonstrates that built-up expansion has primarily occurred at the expense of agricultural land, vegetation, and water bodies. From the study, we observed that 8.87 km^2 (12.76%) of agricultural land, 11.83 km^2 (15.45%) of vegetation, 0.56 km^2 (7.94%) of water bodies, and 0.19 km^2 (10.62%) of fallow land converted into impervious surfaces in the study period indicates a decline in groundwater recharge potential (Nath et al., 2021), an increase in surface runoff (Astuti et al., 2019) and flood risk (Singh & Singh, 2011). Rapid built-up expansion of 19.97 km^2 (339.67%) has contributed to rising land surface temperatures (Pal & Ziaul 2017) and the development of localized urban heat-island effects. The reduction of open land and vegetation cover is closely associated with growing ecological stress. Ecologically, these changes indicate habitat shrinkage, increased pressure on biodiversity, and urban landscape fragmentation (Nagendra et al., 2014). Additionally, the decline of water bodies (ponds and wetlands) suggests a weakening urban hydrological balance, a loss of aquatic ecological functions, reduced aquatic habitat, and increased drainage congestion. These changes imply a gradual reduction in ecosystem services such as micro-climatic regulation, water retention, and soil stability. Therefore, the built-up expansion intensity, as reflected by UEII and Shannon's entropy values, indicates growing environmental pressure in the study area. Higher UEII values suggest increased land sealing and associated environmental stress, while rising entropy values point to dispersed urban growth and increasing ecosystem fragmentation.

Fig. 9: Newspaper and field-based evidence supporting the LULC transformation and environmental implications of urban expansion in the EBUA

Future prediction of LULC in English Bazar UA

The study applied the CA–Markov model using TerrSet software to predict the urban spatial growth of English Bazar UA for the next period of 10 years between 2021 and 2031, represented by Fig. 8. The LULC comparison between actual (2021), simulated (2021), and predicted (2031) results shows a continuing trend of urban expansion in the study area. According to predictions using the CA-Markov model, the built-up area is projected to increase substantially from 25.85 km² (15.97%) in 2021 to 32.04 km² (19.80%) by 2031, indicating rapid urban growth and land conversion. In contrast, vegetation cover is expected to decline from 41.85% to 37.90%, indicating pressure on natural land from expanding settlements and infrastructure. Agricultural land also shows a slight reduction, reflecting gradual transformation into urban uses. Water bodies remain almost unchanged, while barren land shows a small increase. It means the land looks empty now, but it may actually be under preparation for urban growth. Overall, the predicted pattern indicates a shift from natural and agricultural landscapes toward built-up surfaces, confirming the ongoing process of urbanization and spatial expansion in the region.



LULC Types	Actual LULC for 2021		Simulated LULC for 2021		Predicted LULC for 2031	
	Area (km²)	Area (%)	Area (km²)	Area (%)	Area (km²)	Area (%)
Built-up	25.85	15.97	23.44	14.49	32.04	19.80
Water Body	8.30	5.13	8.56	5.29	8.56	5.29
Vegetation Cover	67.72	41.85	68.40	42.27	61.32	37.90
Agricultural Land	59.42	36.72	60.34	37.29	57.94	35.81
Barren Land	0.53	0.33	0.07	0.04	0.95	0.59
	161.81	100.00	161.81	100.00	161.81	100.00

Fig. 8: Validation and Prediction of LULC Using CA–Markov Model (2021–2031)

Source: Computed by authors

Conclusion

This study used a combination of GIS spatial analysis and multitemporal remote sensing image interpretation to quantitatively depict the dynamics of LULC change and urban sprawl from

1991 to 2021. The study examined the characteristics of different LULC and urban growth dynamics over the last 30 years. Over the past 30 years, urbanization has led to the degradation of four LULC types: water bodies, vegetation, agricultural land, and fallow land due to rapidly expanding built-up areas.

The main issue in the EBUA region is that development has occurred in an uncontrolled, unplanned manner. As a result, urban sprawl has expanded in many directions across the study area. The findings of this study show that the relative Shannon's entropy value steadily increased from 1991 to 2021, rising from 0.525 in 1991 to 0.604 in 2001, 0.882 in 2011, and 0.982 in 2021. This rising trend indicates that urban growth has become more dispersed over time. The high entropy value in 2021 clearly shows that urban expansion has spread much farther from the city centre compared to 1991. The rising UEII values from 0.272 in 2001 to 0.502 in 2021 further confirm that urban growth intensified and became moderately rapid in recent decades. The northern (N), north-eastern (NE), and eastern (E) sectors confirm that these directions remain the dominant growth corridors. In contrast, the western (W) and south-western (SW) sectors have begun to show emerging expansion in recent years.

This study found that many factors drive the expansion of built-up areas. The spatial concentration and outward diffusion of institutional facilities have played a crucial role in shaping urban sprawl, as these service nodes attract population, infrastructure, and economic activities, thereby directing the expansion of the built-up area. The simulated results suggest that, by 2031, there will be a significant decline in agricultural and vegetation cover due to rapid urban growth in parts of the English Market UA. If this trend continues, it could increase environmental pressures, strain infrastructure, and create spatial imbalances in the region. Therefore, there is a need not only for a master plan but also for a forward-looking development strategy that includes clear land-use zoning, protection of agricultural land and water bodies, and control of construction along major roads. The plan should include appropriate "land-use zoning" to prevent haphazard construction and to ensure balanced, planned urban growth. This zoning planning method will help authorities control how land is used, ensuring development occurs in an organised way. The authorities should decide to protect the agricultural land around EBUA, which has been converted into built-up areas. During the field visit, it was observed that many houses are being constructed by filling waterbodies (ponds & wetlands), which is environmentally harmful. Therefore, the concerned authorities should take immediate steps to address this issue. Construction along the highway should be planned, not allowed to grow randomly. It should encourage compact development and, as planned, improve infrastructure to reduce unplanned sprawl. Continuous monitoring using remote sensing and GIS will help authorities track changes and make informed planning decisions in a timely manner. Through a combination of regulation, environmental protection, and continuous monitoring, urban growth in EBUA can move toward a more balanced, sustainable future.

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