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Article

Application of geo-spatial indices for detection of growth dynamics and forms of expansion in English Bazar Urban Agglomeration, West Bengal

Journal of Urban Management

Provided in Cooperation with:

Chinese Association of Urban Management (CAUM), Taipei

Suggested Citation: Dutta, Ipsita; Das, Arijit (2019) : Application of geo-spatial indices for detection of growth dynamics and forms of expansion in English Bazar Urban Agglomeration, West Bengal, Journal of Urban Management, ISSN 2226-5856, Elsevier, Amsterdam, Vol. 8, Iss. 2, pp. 288-302, <https://doi.org/10.1016/j.jum.2019.03.007>

This Version is available at:

<https://hdl.handle.net/10419/271354>

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Journal of Urban Management

journal homepage: www.elsevier.com/locate/jum

Application of geo-spatial indices for detection of growth dynamics and forms of expansion in English Bazar Urban Agglomeration, West Bengal



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ARTICLE INFO

Keywords:

Peri-urban
Urban sprawl
Land use/ land cover
Spatial metrics
Remote sensing

ABSTRACT

In India, urban sprawl of metropolitan cities and other large cities is a widespread concern for planners and policy makers. Modeling urban sprawl of small and medium size towns is completely bypassed urban research of India. This study attempted to fill-up the gap by addressing the three urban growth types of infilling growth, outlying growth and edge-expansion growth of EBM which is a medium size town of West Bengal. In this study, an integrated approach of remote sensing and GIS along with spatial landscape matrices have employed to identify and distinguish between three urban growth types of EBM which helps planners to better identify, understand and address the sprawl of small and medium size towns of developing countries. Result shows that the proposed methods successfully identifies and visualize different urban growth types of EBM. Infilling growth is the dominant expansion type. Edge-expansion is concentrated at sub-urban areas. Outlying growth mainly occurs relatively far from the urban core. The analysis shows that initially the urban area expands mainly as edge-expanding growth during the different temporal periods. Next, growth shows gradual increasing of the area under outlying growth from phase 1 (1991–2001) to phase 3 (2011–2016) with area cover of 2.04 km²–3.25 km². Growth filled in vacant non-urban area inwards, resulting into a more compact and aggregated urban pattern. The study shows an improved understanding of urban growth, and helps to provide an effective way for urban planning.

1. Introduction

The small and medium size towns in India represent a very dynamic process of urbanization resulting fundamental changes on the spatial structure and dynamics of growth. The accelerated speed of lateral expansion of small and medium size towns in India has emerged as a major challenge of urban planning India (Denis et al., 2012; Shaw, 2005). Small and medium size towns in India are expanding outward into rural/peri-urban zones in an unplanned manner and results in development of sprawl. According to Census of India (2011) at present India have 3894 number of small and medium size towns and are growing at faster pace compared to large and metro cities both in terms of population and spatial spread (Pradhan, 2013; Samanta, 2012; 2017). Despite these concerns, study on urban sprawl of small and medium size towns is very limited. In the absence of a universal definition, it is very difficult to determine urban sprawl. Recent research employed classification of urban growth types as an effective means for identification of urban sprawl. The typological classification of urban growth for the first time was made by Wilson, Hurd, Civco, Prisloe, and Arnold

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<https://doi.org/10.1016/j.jum.2019.03.007>

Received 7 September 2018; Received in revised form 19 February 2019; Accepted 25 March 2019

Available online 01 April 2019

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(2003) and on the basis of analysis from remote sensing imageries three types of urban growth pattern had been identified by them: Infilling, Edge-expansion, and Outlying. Each urban growth pattern represents a special form of geometric and spatial features of built-up areas. Infilling type of urban growth occurs through conversion of non-urban areas surrounded by urban into urban built-up. Edge pattern of urban expansion refers to the newly developed urban built-up which expands outward from the fringe of existing urban patches. The outlying growth occurs away from existing urban built-up areas. The Outlying growth pattern is further classified into isolated, linear and clustered type of growth. Research on urban growth types employed varied methodology to identify and distinguish infilling, edge and outlying growth. In the opinion of Xu, Liu, Zhang, An, and Chen (2007) the ratio between the length of common edge and patch perimeter can be used to identify and distinguish between infilling, edge-expansion, and outlying growth, while Pham and Yamaguchi (2011) used a percentage of a like adjacency metric; Shi et al. (2014) apply object-based backdating approach to detect and differentiate the three urban growth types.

Contemporary studies on analysis of urban growth types have employed multi-stage images along with spatial landscape metrics to quantify the urban growth pattern and spatial temporal trends of urban growth (Choudhury, Das, & Das, 2018; Ghosh & Das, 2017). Shi et al. (2014) have carried out object-based backdating approach to examine the pattern of urban growth for Lianyungang City of China and found that edge expansion was dominant in the city during entire study period. Yu and Zhou (2017) in their study on three largest urban mega-regions of China found all three types of urban growth (infill, edge and outlying) occurred with varying size and intensity. This trend is also visible in large Indian cities. Sharma and Joshi (2013) with the help of landscape metrics examined the urban growth pattern of Delhi city and introduced the theoretical conception about ribbon development. Kantakumar, Kumar, and Schneider (2016) put forwarded the notion of ribbon development and employing proximity analysis tool on pixel-based maximum likelihood supervised classification technique explored the dynamics of three type of urban growth of Pune city.

Sprawls are associated with several adverse environmental impacts and hence quantifying and modeling different types of urban growth is useful and meaningful to help planners for better understanding and to address the issues attributed to growth of in small and medium size towns of India. In India, urban sprawl mapping has been performed either for metropolitan cities or for other large cities (Allen, 2003; Das, Chatterjee, & Khan, 2015; Mohammady & Delavar, 2015; Nkeki, 2016; Ramachandra & Bharath, 2013a, 2013b; Ramachandra, Bharath, & Sowmyashree, 2014; Sudhira et al., 2004, 2007) but identification of urban growth types to detect typology of urban sprawl from remote sensing data has not been exercised at the scale of small and medium size towns till date. Therefore, EBM (English Bazar Municipality) a vibrant and dynamic variant of medium size town of West Bengal has chosen as the study area for an understanding of the urban growth model in small and medium size towns of developing countries (Shaw & Das, 2017; Dutta & Das, 2018a, 2018b). This study analyzes the urban growth by providing a topological classification and representation of infill, ribbon, edge and leapfrog development of EBM. Urban growth analysis of medium size town like EBM is urgently required for describing the urban expansion process and the type of urban growth occurring in small and medium size towns of developing countries. Thus, a precise analysis of the urban growth type by combining multi-stage images along with spatial landscape metrics at the micro-level for EBM is required.

This study will not only provide an ideal platform to urban planners for planning of EBM but also offered detailed analysis of sprawl within the city. It is also indicative for policymakers to design appropriate policy and implement to ensure sustainable urban growth process in EBM. The objective of the paper is to (1) quantify the urban expansions trajectory to analyze dominant urban growth pattern (2) to analyze the urban expansion in terms of pattern and aerial extent of each type of urban growth (3) and finally, developing a comprehensive urban trajectory map for EBM which incorporates infilling, edge-expansion and outlying growth in a single frame.

2. Justification for selection of the study area

English Bazar Urban Agglomeration is the political and cultural center of Malda District as well as the North Bengal. It is located between latitudes of 24°59' N to 25°04' N and 88°06' E to 88°10' E longitudes of Malda District. It covers an area of approximately 28 km². The topography is mainly characterized by Diara region formed by the fluvial deposition of newer alluvium in the transitional zone between the Barind and Tal tract. English Bazar Urban Agglomeration has got its recognition as an urban agglomeration in the recent 2011 census with more than 3 lakhs population. It alone shares 57.91% of total urban population and comprises of two urban statutory bodies and three census towns.

In between 2001 and 2011 a major change of urbanization happened in Malda District. Number of urban population increases from 240940 in 2001 to 541660 in 2011 (urban decadal growth rate 124.81%). This district observed the highest growth of urbanization in West Bengal. Also in 2011 the number of census town increased to 27 where in 1991 there was none. For this rapid increase of urbanization, different vectors played an important role firstly, the location of Malda district in the middle of West Bengal which has been a leading factor in the development of Malda district as a nodal center and a major urban center of North Bengal (Fig.1). Many other different factors such as, location of NH-34 (National Highway 34) and SH-10 (State Highway 10) across the city and a junction point of N.F.Railway (North-East Frontier Railway) and Eastern Railway have lead the city to grow beyond its municipal limit. But the development of city center and its surrounding area isn't uniform over the fringe areas as far as various viewpoints. As a result, some of the villages have facilities like the core whereas some are lagging behind. From this perspective, the examinations of urban sprawl pattern in these villages are needed for the future planning processes.

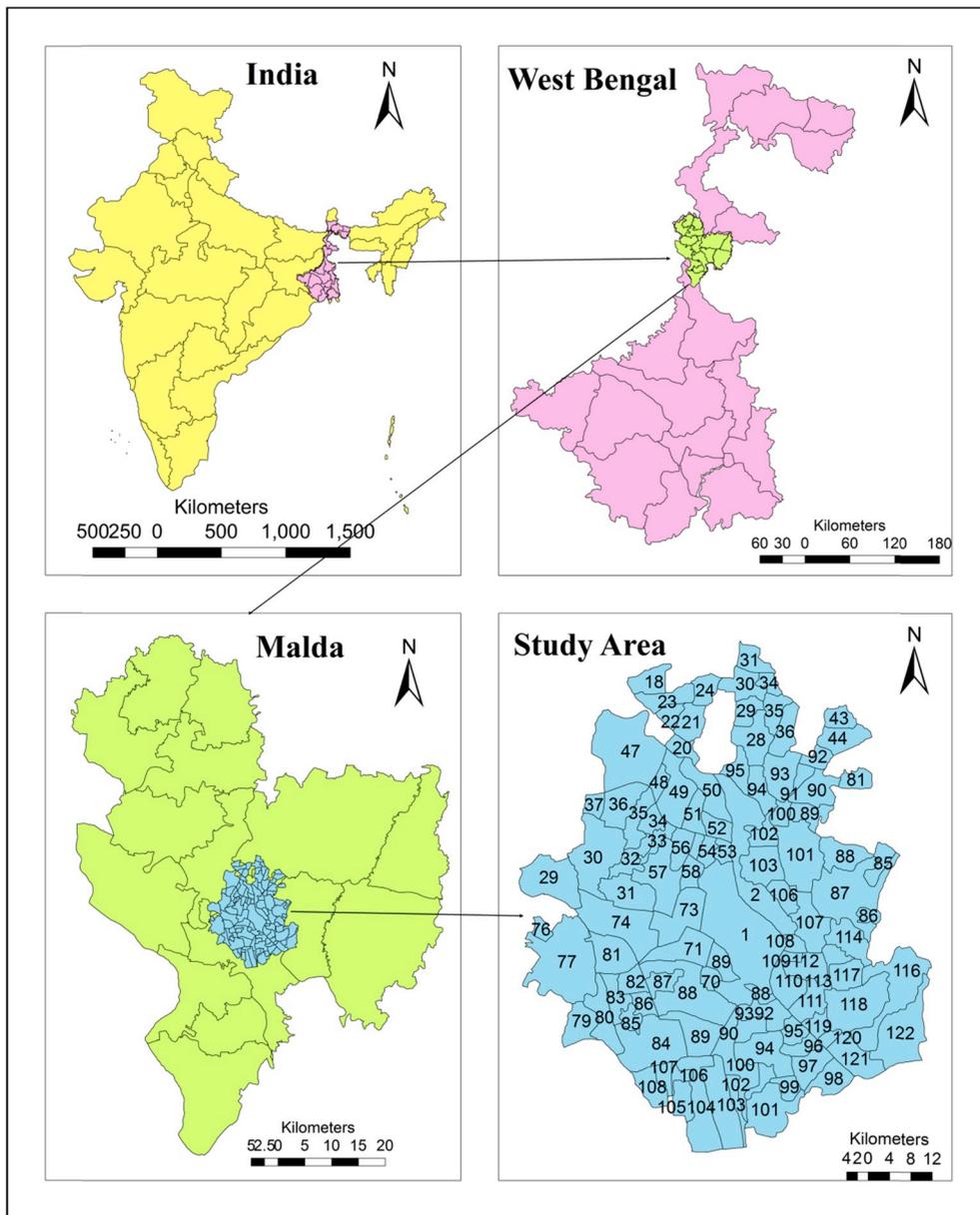


Fig. 1. Location of the study area.

3. Materials and method

Landsat images are used for the purpose of the study as it provides efficient information regarding landscape analysis and such data is regularly updated and easily accessible (Nkeki, 2016, pp. 119–137). The data was taken for four different temporal periods (1991, 2001, 2011 and 2016) (Table 1).

Table 1
Characteristics of multi-temporal satellite data.

Satellite	Sensor	Path/Row	Year	Resolution (m)	Source
Landsat-5	TM	39/43	1991	30	U.S. Geological Survey
			2001		
			2011		
Landsat-8	OLI	39/43	2016	30	U.S. Geological Survey

Note: OLI- Operational Land Imager; TM- Thematic Mapper.

Table 2
Landuse classification.

Landuse Classes	Land uses included in the class
Builtup	Residential areas, industrial areas and all paved surfaces and mixed pixels having built-up area
Water bodies	Rivers, tanks, lakes, reservoirs
Vegetation	Mango garden, water hyacinth
Agricultural	Cropland, plantation and nurseries
Temporary Vacant Land	Fallow land, vacant crop field

(According to authors consideration).

3.1. Landsat image preprocessing and classification

Supervised classification was mainly used for the categorization of the study area in different land use categories (Table 2). The process was done using ErdasImagine 9.2 through collecting of different samples of landuse categories.

For the accuracy assessment of the classified images, Kappa coefficient was used in the post classification analysis. 139 random points were generated for respective time periods for the accuracy assessment, which were then superimposed on the classified images and the characteristics of the underlying pixel or land use types with each point were compared with the characteristics that existed on the ground using Google Earth data and GPS survey. According to Monserud and Leemans (1991), values of 0.4 and less indicates poor agreement, values between 0.4 to 0.75 indicate fair to good agreement, values of 0.75 or more indicate very good to excellent agreement where value 1.0 is perfect agreement between images.

3.2. Zonal analysis

The whole study was divided into five zones; northeast (NE), southwest (SW), northwest (NW) and southeast (SE) and central (CT) parts, to study the uneven distribution of urban growth more precisely. The growth of the urban areas along with the agents of changes is understood in each zone separately through the study of urban sprawl pattern for different periods (Ramachandra et al., 2014).

3.3. Identifying three urban growth types

The pattern of urban growth can be categorized into three parts-infilling, edge-expanding and outlying. Wilson et al. (2003) developed a quantitative method to characterize these three urban growth categories. With the help of GIS, these three types of urban growth have been visualized in this study.

The classified images were converted to vector format to get the three urban growth types. The urban patches which were existed for two consecutive periods are defined as the old urban patches, whereas the patches which were not existed in the last period are defined as the new urban patches (Sun, Wu, Lv, Yao, & Wei, 2011). Fig. 2 illustrates these three types of urban growth.

A metric R was defined for calculating the ration between the length of common edge of newly developed urban patches and existing urban patches (Sun et al., 2011), as:

$$R = \frac{l_c}{l} \tag{1}$$

Where, l_c = the length of the common edge between a newly developed urban patch and an existing urban patch, l = the perimeter of

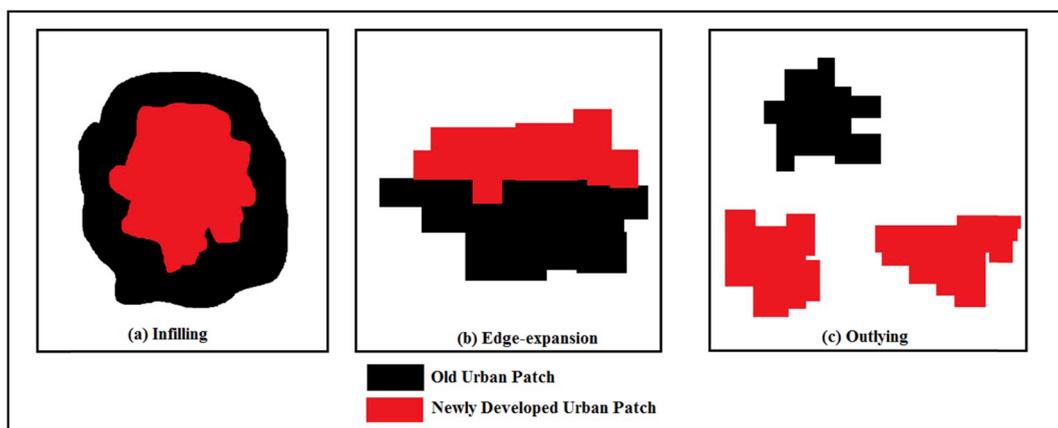


Fig. 2. Three types of urban growth.

the newly developed urban patch.

The value of R ranges from 0 to 1. The range was divided into three classes,

$$\begin{cases} 0.5 < R & \text{Infilling} \\ 0 < R < 0.5 & \text{Edge – Expansion} \\ 0 = R & \text{Outlying} \end{cases}$$

The infilling type of urban growth has $R > 0.5$, and refers to the development of newly developed urban patch surrounded by at least 50% old urban area (Fig. 2a). Edge-expansion urban growth has $0 < R < 0.5$ as it is characterized by the newly developed urban area spreading out from the edge of an existing urban area and surrounded by less than 50% existing urban area (Fig. 2b). Outlying growth is the newly developed urban area without any spatial connection to the existing urban area (Fig. 2c) and hence has $R = 0$.

3.4. Shannon's entropy

Shannon's Entropy index is the most commonly and widely used method of measuring urban sprawl using remote sensing and GIS (Bhatta, 2012; Sudhira et al., 2004). Shannon's entropy (H_n) is an index for measuring the degree of concentration or dispersion of a geographical variable (x_i) among n zones. Shannon's entropy is given by:

$$H_n = - \sum_{i=1}^n P_i \log(P_i) \quad (2)$$

Where P_i is the proportion of the variable in the i th zone (in this case, proportion of built-up area or urban patches in each zone), n is the total number of zones in the region. However, Shannon's entropy value ranges from 0 to $\log(n)$, and indicates compactness of urban patches for values near to 0 and dispersed distribution for values near to $\log_e(n)$. Entropy values (larger) near to $\log_e(n)$ depict dispersion of urban patches or urban lands which is interpreted as the occurrence of urban sprawl.

3.5. Spatial metrics of urban growth and landscape analysis

Spatial metrics are helpful to quantify and measure spatial characteristics of the landscape. These metrics can quantify specific spatial characteristics for different patches, classes of patches or entire landscape mosaics (Ramachandra et al., 2014). Four class level spatial metrics were calculated to represent four dimensions of the urban form, i.e. *complexity*, *centrality*, *compactness* and *porosity*.

(a) Complexity

Complexity measures the irregularity of the patch size (Huang, Lu, & Sellers, 2007; Sun et al., 2011). The Landscape Shape Index (LSI) is a metric which measures the irregularity of the landscape. The value of LSI increases when the urban growth is highly diverse.

(b) Centrality

Centrality is the degree to which the urban development is close to the main urban center. The Euclidean Nearest-Neighbor distance (ENN) measures the distance over all patches of a class to the nearest neighboring patch based on shortest patch edge-to-edge distance, computed from cell center to cell center (Sun et al., 2011).

(c) Compactness

Compactness measures the individual patch shape and the fragmentation of overall urban landscape (Huang et al., 2007). Aggregation Index (AI) shows the degree of patch compactness of an urban area.

(d) Porosity

Porosity measures the ratio of open space compared to the total urban area. This indicator of porosity is also designated the "ratio of open space" (ROS) (Huang et al., 2007).

Table 3 below shows the lists of metrics along with their description that are considered in this study.

4. Results

4.1. Land use/land cover change

4.1.1. Land use change direction

Areas surrounding the English Bazar Urban Agglomeration has witnessed rapid and substantial amount of change in its land use configuration. Such rapid land use changes are initiated mainly by urbanization during the last decade. It has greatly affected agricultural lands in the region. Landsat imageries of different temporal periods were classified using supervised classification by

Table 3
Selected landscape metrics calculated in this study.

Dimensions	Indicator	Formula	Description	Significance
Class level landscape metrics Complexity	Landscape shape index (LSI)	$LSI = \frac{2.5E^*}{\sqrt{A}}$	LSI is 1 when the landscape consists of a single square or maximally compact patch, LSI increases without limit as the patch type becomes more disaggregated.	It measures the complexity of urban growth. High LSI indicates more diverse nature of urban growth.
		$E^* = \text{total length of edge in landscape; includes the entire landscape boundary and some or all background edge segments.}$ $A = \text{total landscape area (m}^2\text{).}$		
Centrality	Euclidean Nearest-Neighbor Distance (ENN)	$\frac{e_i}{\min(e_j)}$ <small>e_i = total length of the edge of class i, $\min(e_j)$ = minimum total length of edge (or perimeter) of class j</small>	ENN increases when the distance over all the patches are high.	It shows the minimum distance between the urban patches.
Compactness	Aggregation index (AI)	$AI = \left[\frac{g_{ii}}{\max(g_{ij})} \right] (100)$ <small>g_{ii} = number of like adjacencies (joins) between pixels of patch i based on the single-count method $\max(g_{ij})$ = maximum number of like adjacencies (joins) between pixels of patch type i based on the single-count method.</small>	AI equals to 0 when the patch types have no like adjacencies. AI equals 100 when the landscape consists of a single patch	It shows the degree of patch compactness of an urban area.
Porosity	ROS	$\frac{s'}{s} * 100\%$ <small>s' = the summarization area of all "holes" inside the extracted urban area, s = summarization area of all the patches</small>	ROS increases when built up area is converted to any other landuses	It measures the total area of the 'holes' in relation to the calculated urban area.

Table 4Landuse statistics and coverage (km²) of the study region by different temporal period.

Source: Computed by Authors

Year	Landuse Categories				
	Agriculture	Water body	Vegetation	Vacant	Built-up
1991	40.07 (18.99)	5.96 (2.82)	20.61 (9.77)	129.65 (61.44)	14.75 (6.99)
2001	135.04 (63.99)	6.29 (2.98)	28.39 (13.45)	24.82 (11.76)	16.51 (7.82)
2011	86.64 (41.06)	9.33 (4.42)	53.05 (25.14)	48.33 (22.90)	13.69 (6.49)
2016	83.58 (39.61)	8.69 (4.12)	42.53 (20.15)	60.44 (28.64)	15.80 (7.49)

Note: values in parenthesis are the corresponding percentage values.

maximum likelihood method in order to acquire land use transition of the mentioned temporal periods. Kappa coefficients of the classified images (1991, 2001, 2011 and 2016) are “0.79, 0.82, 0.81, 0.84” which indicates very good agreement between the classified images and actual land use patterns.

Table 4 tabulates the land use statistics of the classified images of different temporal periods.

Land use analysis in **Table 4** shows that between 1991 and 2001, urban area increased from 6.99% to 7.82% of the overall land of the region and with a decrease of 2.82% in 2011, it turns to 7.49% of the total land in 2016. On the other hand, there is a rapid decline of the vacant land from 129.65 km² in 1991 to 60.44 km² in 2016 and a decline of agricultural land from 135.04 km² to 83.58 km² from 2001 to 2016.

For analyzing the result of the land use transition based on ‘from’ and ‘to’ changes, matrices of land use change detection from 1991 to 2016 were generated and shown in **Table 5**. The transition matrices indicate that between 1991 and 2016, 38.14% of vacant land was converted to agricultural land, while at the same temporal period 1.30% of agricultural land was converted to built-up land. From the other land use categories transformation it is observed that, nearly 17% of vegetation cover has been transformed to agricultural land and 2.33% of it transformed into built-up land.

The rigorous observation over the land use classified maps makes it clear that from 2001 to 2016, vacant land and built up area have changed significantly. Built-up area has increased at the cost of the decrease of vegetation, agricultural land and water body where vacant land has decreased and changed to agricultural land and vegetation cover (**Fig.3**).

Fig. 4 shows the changing direction of built up area. Increased rate of built-up land imply that the urban expansion happened with expenses to the requirement of spaces for urban uses due to the increasing population by the process of urbanization. The areas of cropland conversion are mostly shared by agricultural land, indicating the need to meet the demand of food.

4.1.2. Land use change magnitude

Table 6 and **Fig. 5** describe the magnitude of land use change of each category. During the period of 1991–2016, there is a remarkably decreased of vacant land (79.02 km²), while only 9.81 km² increased. This decrease is significant, as the main reason of this was the transformation of land use from vacant to agricultural land and other land uses. In case of built up land use, it was seen that the difference between decreased and increased area is very low (1.05 km²). The massive increase in agricultural land and vegetation cover is mainly due to more plantation of mango tree and rice paddy in the fields as these two are the main economic activities of rural Malda.

On the other hand, the rate of decrease of the vacant land is nearly 61% which was about eight times higher than the rate of increase (7.57%). This was because of the transforming vacant land to paddy field and mango orchard. The decreasing and increasing rate of built-up area are 12.41% and 19.52% respectively.

Fig. 6 represents the built-up land use thematic maps of the study area by temporal periods. This change pattern revealed that the

Table 5

Landuse change direction.

Landuse Type	Vacant Land	Agricultural Land	Vegetation Cover	Water Body	Built-up Area	Total 1991
Vacant Land	50.63	49.45	25.27	2.54	1.76	129.65
Agricultural Land	6.41	29.08	2.74	1.32	0.52	40.07
Vegetation Cover	2.61	3.43	13.50	0.59	0.48	20.61
Water Body	0.56	1.02	0.38	3.88	0.12	5.96
Built-up Area	0.23	0.60	0.64	0.36	12.92	14.75
Total 2016	60.44	83.58	42.53	8.69	15.80	211.04

(Note: The non-diagonal figures in the table represent the changed area of each LULC class during the period of 1991 to 2016 while the diagonal figures (in bold) represent the unchanged area of LULC of each class during this period. The figures in the row cells depict the area of a specific LULC class (ith) that was converted to other non-ith LULC classes, while the column cells show the area gained by the ith LULC class from the other non-ith classes.).

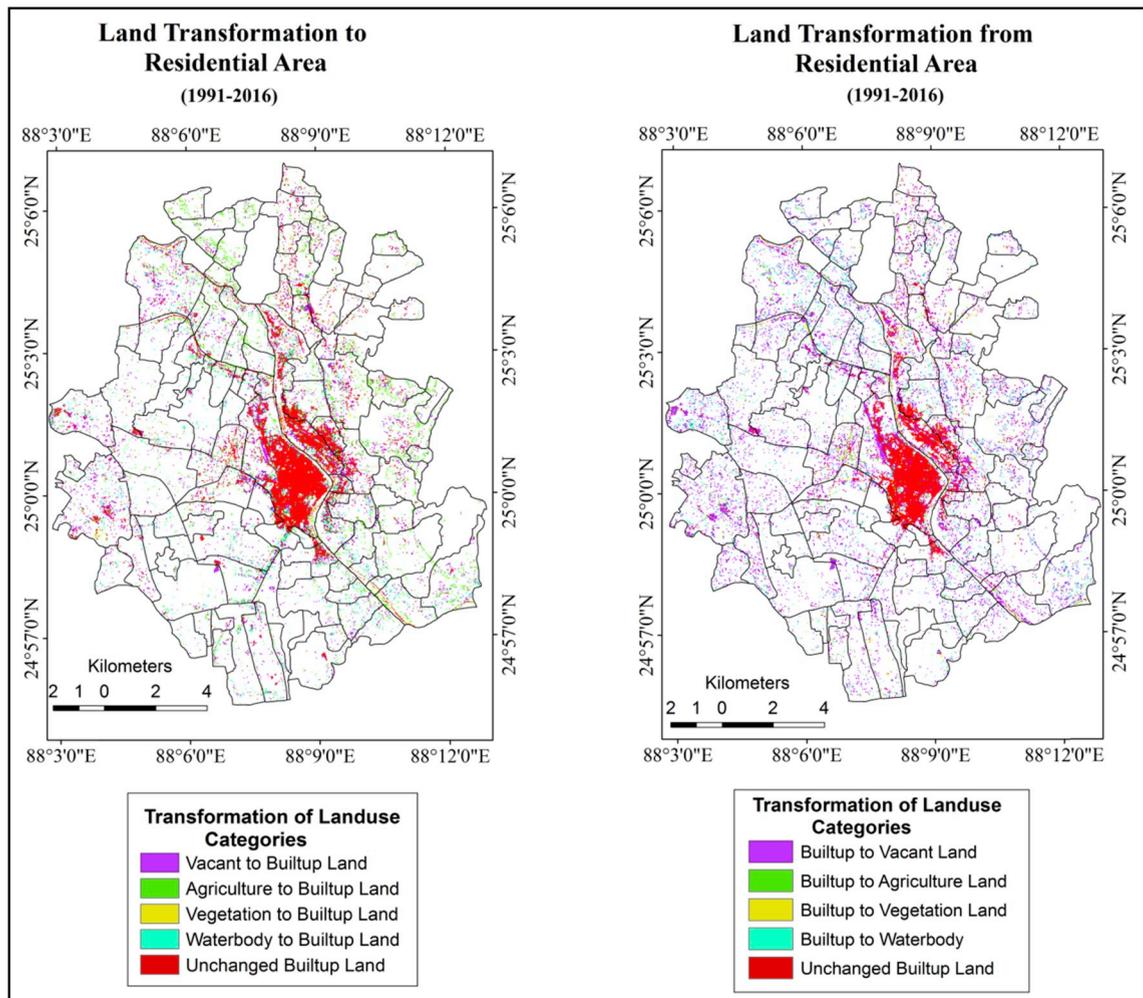


Fig. 3. Land transformation of different category.

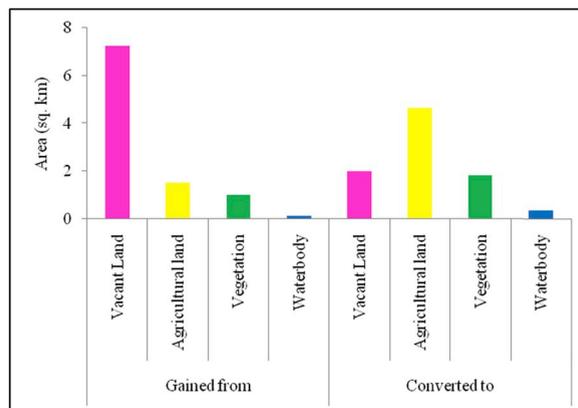


Fig. 4. Direction of built-up area change (1991–2016).

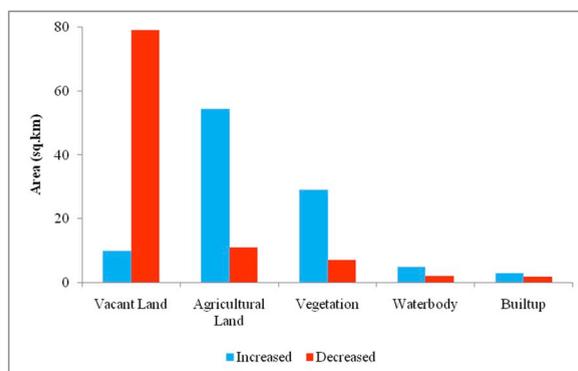
sprawling tendency in the study area was not uniform over the time period. While in 2001 the built-up pixels were more scattered in the northeast part of the study area, during 2016 it is more concentrating along the river or the highways in a linear pattern. Between 2001 and 2016, agricultural land use had been engulfed by urbanization and vegetation which is radiating towards all directions from the center to the periphery.

Table 6

Magnitude of landuse change, 1991–2016

Source: Calculated by Author

Landuse Category	Decreased		Increased		Overall	
	Area (km ²)	Rate (%)	Area (km ²)	Rate (%)	Change (%)	Net-Change (%)
Vacant Land	79.02	60.95	9.81	7.57	68.51	– 53.38
Agricultural Land	10.99	27.43	54.5	136.02	163.44	108.59
Vegetation	7.11	34.50	29.03	140.85	175.35	106.36
Water body	2.08	34.91	4.81	80.73	115.64	45.82
Built-up	1.83	12.41	2.88	19.52	31.93	7.12

**Fig. 5.** Increased and decreased area of each LULC (1991–2016).

4.2. Identifying three urban growth types

The types of three kind of urban growths are illustrated in Fig. 7 for three periods: 1991–2001, 2001–2011 and 2011–2016.

Edge-expansion growth was mainly taken place along the major roads and river. Infilling growth occurred mainly within the free spaces of the main urban core whereas the outlying growth was scattered far from the urban core. As in Fig. 7 distinct urban growth patterns can be shown. It is observed that edge-expanding urban growth type is dominant in all the three different temporal periods. To understand a clear detail of the temporal characteristics of urban growth in the study area, the area of the three urban growth types was calculated for the three temporal periods. Fig. 8 shows the dominance of edge-expanding urban growth in all the three temporal periods as said earlier. As far as the other types of urban growth are concerned, outlying growth was high in the temporal period of 1991–2001, then it decreased in 2001–2011 and again it increased in the last temporal period.

In the first temporal period, more than 6 km² area has observed edge-expanding growth, which reduced to 3.74 km² and then again increased to 5.49 km² are in the next temporal periods respectively. Very little portion of the urban area has accounted for infilling and outlying type of urban growth. The increasing trend of edge-expanding urban growth generally reflects the present kind of formation of sprawl whereas infilling growth refers to the agglomerated urban growth. But the high tendency of edge-expanding urban growth in the study area generally portrays the picture of growth of sprawl.

4.3. Urban sprawl analysis

The pattern of urban growth was also evident from the sprawl characteristics in the study area. The result of the computation of entropy value of the study area is shown in Table 7.

The result shows that the overall structure of the study area for the different temporal periods highlights a strong urban sprawl capability. It revealed that the degree of urban sprawl in the region gradually increases with increase number of years. The upper limit of entropy (\log_e) is 1.61. Highest value of entropy is found in the year of 1991 and 2001 with first decreasing trend in 2011 with a value of 1.30 and further increase in the year 2016 to 1.34. Initial entropy value for 1991 and 2001 was high as the region is mainly characterized by intermitting pattern of dispersed urban area (for example J.L No. 47, 56, 55, 77, 29, 73, 103 etc.). In addition, during 2011 the entropy value decreases because of the clustering pattern (for example J.L No. 95, 94, 73, 88, 71 etc.) and the last period (2016) was characterized by haphazard sprawl pattern with urban edge filling configuration (mainly along roads, for example J.L No. 53, 54, 55, 56, 88, 89, 111, 119, 120, 121 etc.).

Fig. 9 shows the zone-wise distribution of urbanization pattern in the study region is characterized by clustering and dispersion. It shows that the sprawl distribution almost overlapped in the SE, NW and central zones. Values of entropy are found significantly high in the central (CT) region. Variation of urban sprawl is significantly seen in central, SW and NW zones. The values of entropies of central regions are 0.36 for 1991 and 0.34 for 2016, indicating that there is a trend to form a cluster of built-up growth in the central

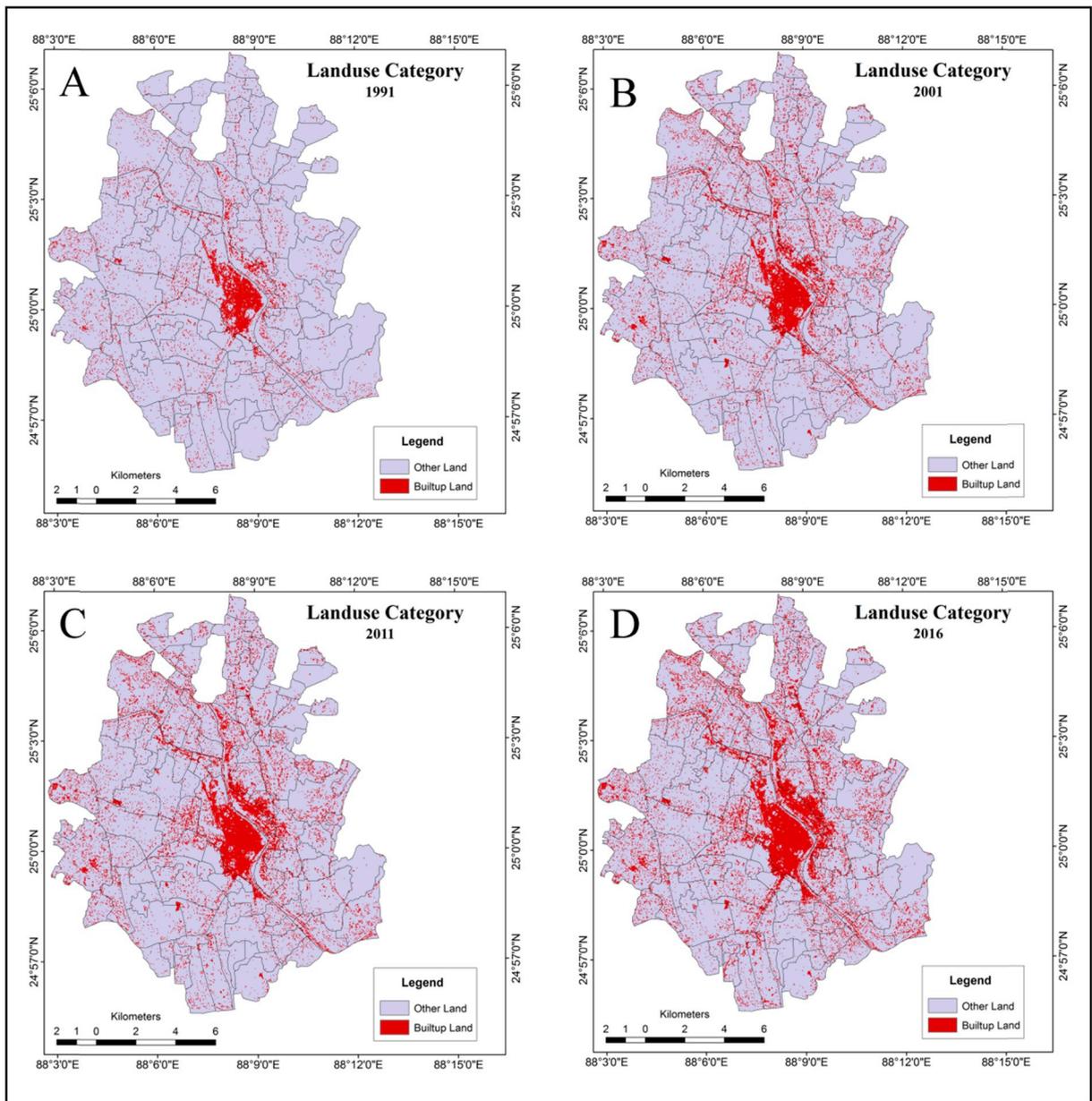


Fig. 6. Classified landuse images of English bazar peri-urban region of different temporal periods.

region. NW and SW zones exhibit a dispersed kind of sprawl trend which is evident from the decrease values of the entropy from 0.21 and 0.24 in 2011 to 0.26 and 0.25 in 2016.

4.4. Landscape dynamics of spatial urban growth

Landscape metrics and urban growth are so much associated with each other. To understand the spatial pattern of urbanization and the dynamic growth, different metrics were computed for each zone. These are quantitative measures of landscape composition that considers the proportion of a landscape in each class depending on patch type, patch richness, patch evenness and patch diversity (Ramachandra et al., 2014). The metrics are discussed below.

(a) Complexity

The value of LSI in NE and central zones decreased through 2011 to 2016. NW and SW zones have observed growth in LSI from 30.58 and 28.94 in 2011 to 34.01 and 31.09 in 2016 respectively.

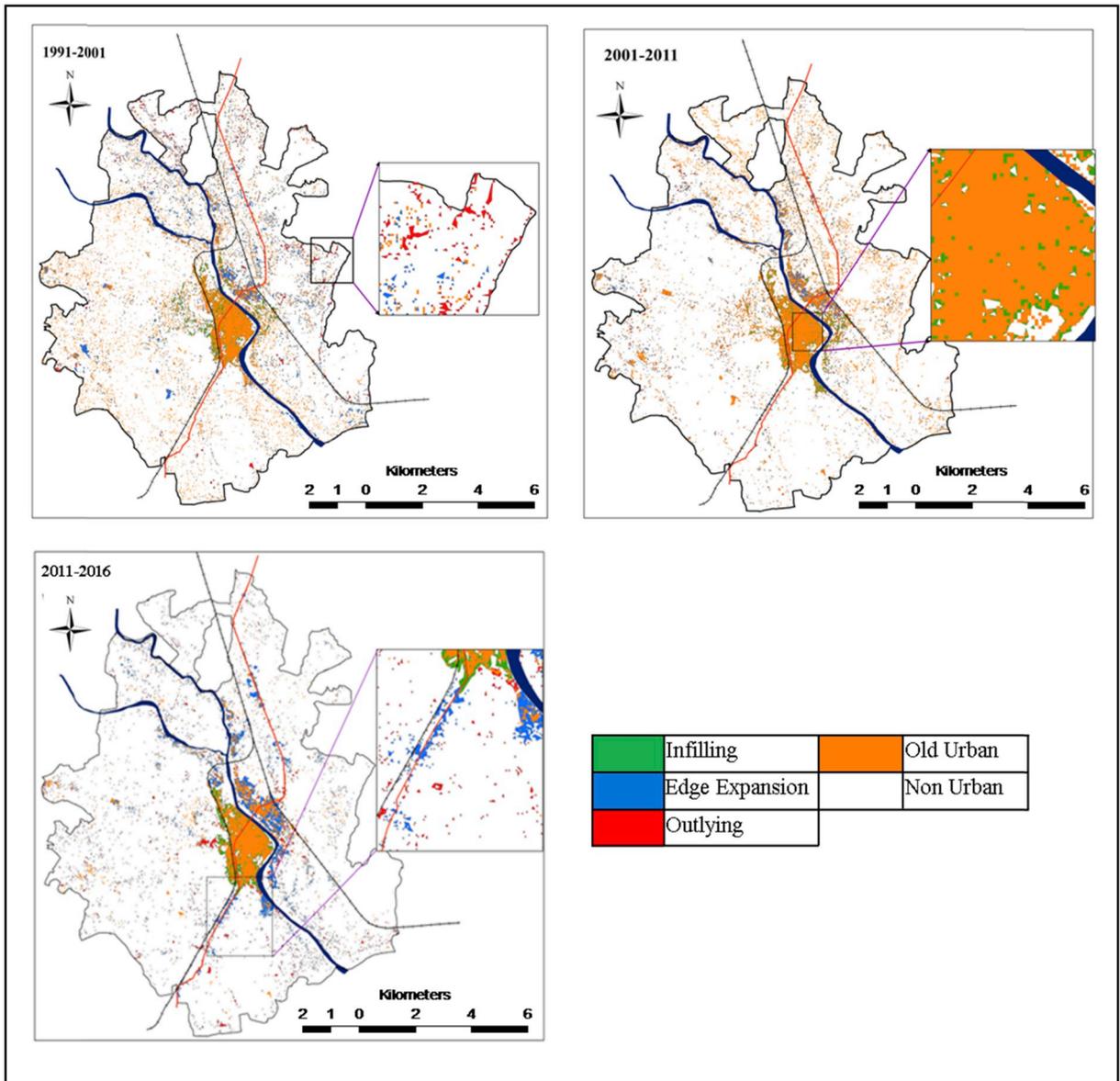


Fig. 7. Spatial distribution of three urban growth types in study area during the periods 1991–2001, 2001–2011, 2011–2016

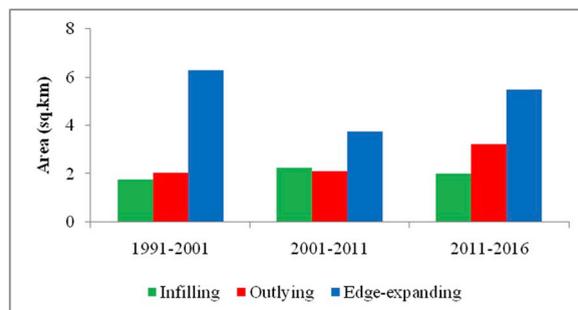


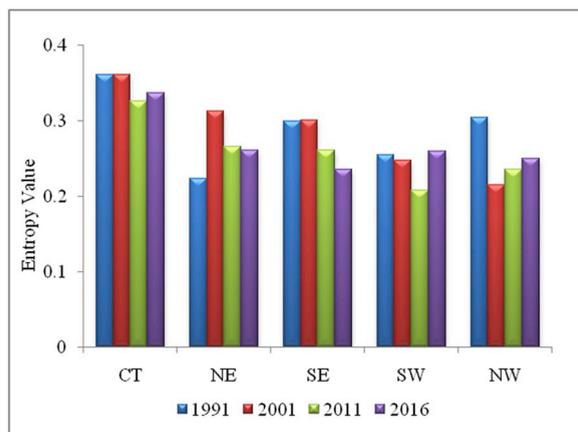
Fig. 8. Area of three urban growth types.

Table 7

Calculated values of Shannon's entropy for different temporal periods.

Source: Computed by Authors

Temporal Periods	1991	2001	2011	2016	Log _e
Shannon's Entropy (H _n)	1.44	1.44	1.30	1.34	1.61

**Fig. 9.** Zone-wise urban sprawl pattern by temporal periods.**(b) Compactness**

It measures the aggregation of urban patches. Fig. 10 (D) indicates that towards 2016, the aggregation happens at the NE and central zones, while the outskirts regions of NW and SW zones were being fragmented. This fragmentation generally occurred for newly developed built-up areas along the national highway and riverside.

(c) Centrality

It shows the centrality of the patches from the core urban center. Largest value of ENN indicates the small urban core. Gradual increase of ENN values at the urban core and NE part of the study area indicates the less dominancy of compact growth over the time periods. Urban expansion along with the both sides of roads and river was increased from 1991 to 2016. This picture is more evident by the peak in four spatial metrics (Fig. 10).

(d) Porosity

Porosity is an important factor for both as an amenity for residents and for the sustainability of cities. Porosity index measures the total area of these “gaps” in relation to the entire urban area. The graphical representation shows that the value of porosity has decreased in a huge rate from 2011 to 2016. This generally caused as a result of the emergence of new built-up land in the open spaces.

The above correlation shows very strong relations among the spatial metrics (Table 8). Complexity index (LSI) correlates very strongly with the overall compactness (AI). This relation indicates that compact landscape result to a more regular shape. Complexity (LSI) and compactness (AI) correlate strongly with open space as measured by ROS (Ratio of Open Space). This suggested that the more fragmented, less compact, and complex the urban landscape, the larger open space compared to the total urban area.

5. Discussions

This section highlights the reflection of the strength and weakness of the theoretical framework and the findings of the study.

This study concerned that ‘urban sprawl’ characterized in the study area not necessarily follows the same pattern of sprawls detected in the large Indian cities. ‘Urban sprawl’ in the study area is displayed by mixed characteristics of dispersed development of low density residential zone and informal peri-urban development. The density of this zone is increasing day by day. Increasing density of population in this region is causing massive transformation of the landuse characteristics.

This study affirmed that, utilization of remote sensing data and different spatial landscape metrics give a precise and detailed comprehension of urban structure at regional level that are important for compelling urban planning in small and medium towns. The transformations of landuse from 1991 to 2016 show that the peri-urban areas of the study area are transforming at a greater rate. This study measures the ‘urban sprawl’ using remote sensing and different landscape metrics. Shannon entropy result shows that the

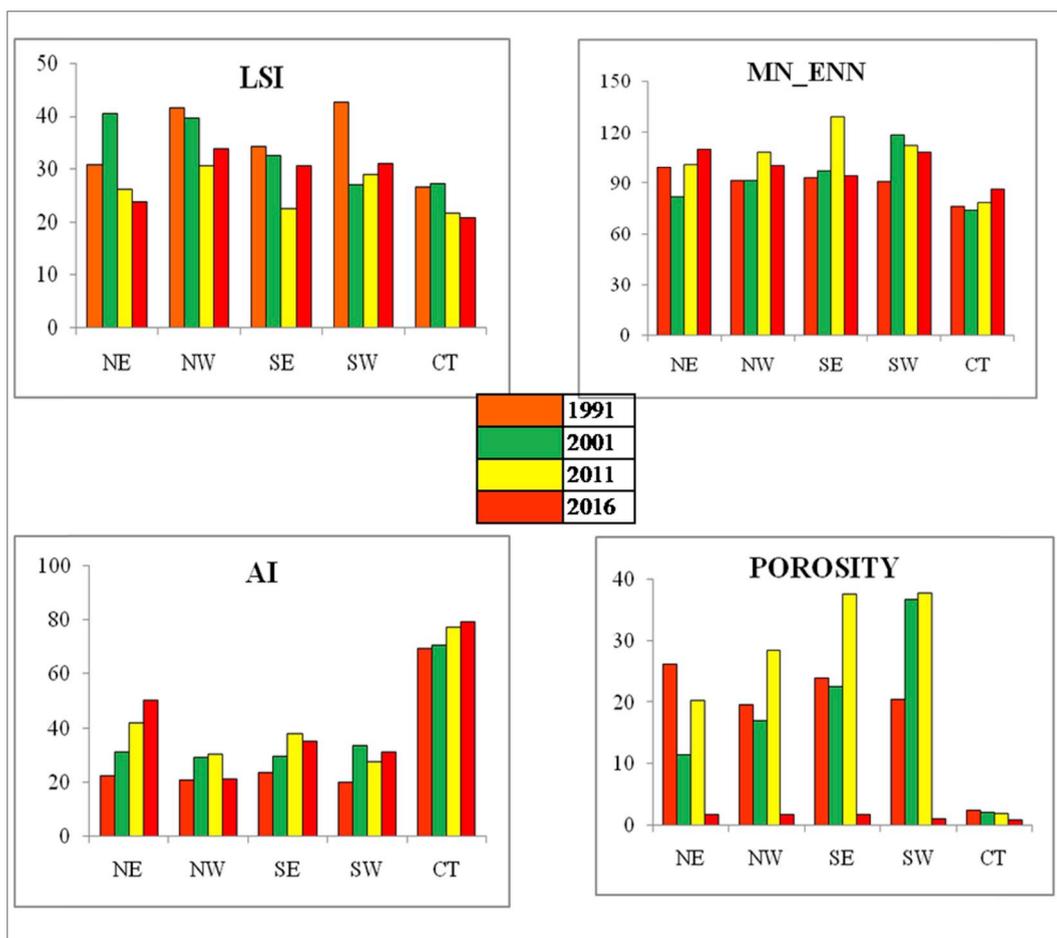


Fig. 10. Spatial metrics of urban growth and landscape characterization (zone-wise).

Table 8
Relation between the different spatial indices.

	LSI	AI	MN_ENN	POROSITY
LSI	1	-.959 ^b	0.318	.928 ^a
AI	-.959 ^b	1	-.549	-.932 ^a
MN_ENN	0.318	-.549	1	0.456
POROSITY	.928 ^a	-.932 ^a	0.456	1

Source: Computed by Authors.

^a Correlation is significant at the 0.05 level (2-tailed).

^b Correlation is significant at the 0.01 level (2-tailed).

tendency of sprawl in the study area has been gradual. High tendency of sprawl is observed in 2001 which decreased in 2011 and again increased in 2016. This affirmed the fact that though ‘urban sprawl’ was decreasing during the first phase, but in the recent phases it is increasing. This argument is also supported by the result of different landscape metrics.

6. Conclusion

In this study, an integrated approach using remote sensing and GIS was encompasses to quantify the different kind of urban growth in the study area and its distribution. For this purpose, multi-spectral remotely sensed data were used. The study revealed that the distribution of urban patches in the study area is capable of identifying three different kind of urban growth; infilling, outlying and edge-expanding. The infilling type of urban growth refers to the development of newly developed urban patch surrounded by old urban area, edge-expansion urban growth is characterized by the newly developed urban area spreading out from the edge of an existing urban area and outlying growth is the newly developed urban area without any spatial connection to the existing urban area.

Study revealed that, edge-expanding growth was dominating over the three different phases of time (1991–2001, 2001–2011, 2011–2016). Along with this the tendency of outlying growth also increased from 2001 to 2016. This edge-expanding growth is mainly taking place along the side of the suburban area of the core city whereas the outlying type of growth is mainly concentrated far from the core city.

The study examined the importance of remote sensing and spatial metrics for monitoring urban growth. This study identified not only how much growth has occurred, but also quantify the types of urban growth and its relation to spatial characteristics of urban landscape. The spatial characteristics of the urban landscape in the study area also revealed a strong relationship among them. This study proposed the need of an encompassing and comprehensive understanding of the pattern of urban growth and changes for a more drastic and dynamically oriented planning and policy structure, since urban expansion and dynamics are difficult to control especially in developing countries like India where existing policies are not adequate and lack multi-dimension (Nkeki, 2016, pp. 119–137). The urban patterns that came up from the study demand for appropriate policy interventions. In this connection, the study suggests some processes for the future development of the area- (i) Increase the role of different private sectors in decision-making processes and the execution of spatial improvement systems in the peri-urban areas. In some parts of the country, private sector including multinational organizations has played a key role in responding to peri-urbanization through local developments. Such organizations helped to fill the gaps caused by the inadequacies of local government. (ii) Special arrangement can be made for ecologically sensitive areas inclined to urban land use conversion. Longer-term spatial and sectoral coordination should be promoted through the making of comprehensive plans. (iii) In this area there is a greater potential for peri-urban coordination and urbanization control at the local level. However there is often no regulated system for inter-local coordination and inter-sectoral integration of planning and improvement at the local level.

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