ORIGINAL ARTICLE

Assessment of urban sprawl using landscape metrics and Shannon's entropy model approach in town level of Barrackpore sub-divisional region, India

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Abstract

A city has expanded from the core to peripheral areas through the growth of urbanization process and based on criteria, such as economic development, social, political forces as well as morphological characteristics. Due to increases in the population and anthropogenic activities in a city, the spatial boundary has also extended to provide accommodation along with the fringe areas that lead to fragmentation of urban morphology and influence the local ecology. From the historical past to present conditions and future predictions of urban growth would be able to visualize by space-borne remote sensing techniques to plan the appropriate infrastructure of the city. The present study analyzed the spatio-temporal land-use patterns in the town level in the Barrackpore sub-division area of West Bengal, which has become very compact urban areas in the eastern zone of the country. The spatial assessment of the urban growth pattern of 16 municipalities has been analyzed using remotely sensed data for the year of 1972, 2001 and 2016 with the spatial landscape metrics approach and Shannon's entropy model. The overall scenario of land use changes reveals that the non-urban areas (vegetation, agriculture, wetland and water bodies) have been decreasing, on the other hand, built-up areas are increasing during the decades. Spatial landscape metrics indicate the nature of the fragmentation of the urban landscape, compactness of the towns and provided the intensity about the sprawl characteristics. The results show that the whole urban landscapes of every town are aggregating into a large patch in the recent years (2016) as compared to the past years. The fragmentation of landscape into small patches happened from 1972 to 2001 on a large scale that indicates sprawl; the conversion of small patches to large single urban patches can be seen from 2001 to 2016 pointed out the maximally aggregation of town which would affect the ecological environment. Shannon's entropy model was applied to understand the level of urban growth at every corner of municipalities by the zoning of each town. The value of Shannon's model confirms the dispersed random urbanization in the outskirt of the towns. The spatio-temporal urban sprawl monitoring through these two methods would help the towns' administration, planners to manage and take better planning to build sustainability for livelihood.

Keywords LULC change · Urban sprawl · Landscape metrics · Shannon's entropy index

Introduction

The developing countries in the world have been facing rapid urban population growth and urbanization which is the foremost environmental challenge for governments and planners. This predictable process is expanding within the city, and then crossed beyond the city limits, and goes into the hinterland that should need to adopt effective sustainable planning (Mosamman et al. 2017). Land-use change analyses provide evidence of land and give the clear prospects of spatial patterns, trends and rate of impact on the environment which would help to make ecological planning at the regional level as well as good governance for each spatial unit (Ramachandra et al. 2012). United Nations Reported (UN Report) has reported that 54% of the world population lives in urban areas and it is predicted to cross 6.3 billion in 2050. The developing world cities would be reached with approximately 90% of the urban population soon (UN Report 2015). Especially in African and south-eastern Asian countries will be experienced more urban

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population growth. Moreover, urbanization is a process of conversion of land from rural to urban through migration, socio-economic development, opportunities and the number of facilities increases (Taubenbock et al. 2009; Bhagat and Mohanty 2009). Urban sprawl is defined as a dispersion of spatial expansion of the city or town towards its peripheral and sub-urban areas (Ewing 1997; Galster et al. 2001; Tewolde and Cabral 2011). The causes of urban sprawl, i.e., population growth, economic development, an extension of roads and highway networks, open up huge space from the core city, ribbon development in urban structure, etc.(Ewing 1997; Galster et al. 2001; Sudhira et al. 2003). Three ways of urban sprawl development are (1) ribbon sprawl, (2) leapfrog sprawl and (3) low density (radial) sprawl (Falah et al. 2019). As consequences of globalization, privatization and liberalization, the Indian megacities (like Kolkata, Mumbai, Delhi, Bangalore, etc.) have rapidly expanded in the form of sprawl to accommodate the migrants from rural areas and encroaches adjacent smaller towns and villages (Shaw and Satish 2007). Urban sprawling could impact ecological habitat with increases in impervious areas (Liu and Phinn 2001). Urbanization and land use and land cover change (LULCC) are positively related to the negative impact on the environment (Mosamman et al. 2017). Expanded urbanized areas, environmentally impact on surrounding valuable natural lands by encroaches of agricultural fields, forest lands or wetlands (Pathan and Jothimani 1989; Xu et al. 2000; Kumar et al. 2007), the loss of productive land and biodiversity (McKinney 2002; Atu et al. 2013), degradation of air quality, groundwater quality (Al-Kharabsheh and Ta'any 2003; Poyil and Misra 2015), changes of climatic scenario, urban flooding, increases runoff, etc. (Miller and Hutchins 2017; Patra et al. 2018). Urban sprawl has impacts on socioeconomic dimensions in a way of decline a sense of community and cultural value, reducing the health of people, loss of public spaces, traffic issues (Ewing et al. 1997; Hathout 2002; Bento et al. 2003; Carruthers and Ulfarsson 2003; Nechyba and Walsh 2004; Resnik 2010; Jaeger et al. 2010; Pereira et al. 2014). Monitoring of spatio-temporal land-use changes can help the administration and planners to understand city growth and can make a better plan to build a city in sustainable manners (Ramachandra et al. 2014a, b).

Different new approaches or techniques have been introduced in the last few decades to analyze and monitoring of sustainable urban structure, the form of the city, urban sprawl studies over the spatial context (Mosamman et al. 2017). Based on the indicators some researchers have done sprawl analysis (Burchel et al. 1998; Malpezzi 1999; Galster et al. 2001; Ewing et al. 2002; Hasse and Lathrop 2003). On the other hand, remote sensing (RS)and GIS techniques with statistical analysis have been used to measure sprawl at the regional level by different researchers and scholars (Sarvestani et al. 2011; Hafez 2011; Belal and Moghanm

2011; Rawat and Kumar 2015; Poyil and Misra 2015; Hassan et al. 2016; Subasinghe et al. 2016; Kim 2016; Hassan 2017; Mas et al. 2017; Mosamman et al. 2017; Sahana et al. 2018; Shukla and Jain 2019; Girma et al. 2019).

RS and GIS techniques are a tool and have the flexibility for measuring urban sprawl and LULCC through modeling using satellite imageries from micro to global scale (Pathan and Jothimani 1989; Pathan et al. 1993; Donnay et al. 2001; Zha et al. 2003; Lu and Weng 2005; Deng et al. 2008; Parker et al. 2008). In this technique, multi-resolution data provides a clear picture of the landscape (Lillesand and Keifer 1987). This is useful for mapping of urban expansion and prediction of LULCC over the different periods (Hathout 2002; Mondal et al. 2016; Mosamman et al. 2017; Liping et al. 2018; Falah et al. 2019). Several new models and approaches have also been introduced for sprawling characteristics in the urban landscape, such as Cellular Automata (CA) modeling algorithm (Li et al. 2014a, b; Mondal et al. 2016), logistic regression model (Hu and Lo 2007; Karolien et al. 2012; Sarkar and Chouhan 2020), Markov Chain (Alsharif and Pradhan 2014; Bose and Roy Chowdhury 2020), CA-based SLEUTH (Clarke et al. 1996; Clarke and Hoppen 1997; Chaudhuri and Clarke 2019), geographical weighted regression (Mondal et al. 2015a, b), Artificial neural network (ANN) algorithm (Pijanowski et al. 2005; Mohammady and Delavar 2016), Fuzzy logic approach (Liu and Phinn 2001) and so on. Shannon's entropy model has been introduced in recent days for urban growth analysis(Sudhira et al. 2003, 2004; Batty et al. 2014; Rahaman et al. 2018; Yulianto et al. 2019; Ismael 2020). The urban structure has been studied using landscape metrics and modeling in geospatial sciences. Landscape metrics modeling was used by several scholars over different cities worldwide (Ramachandra et al. 2012; Ramachandra et al. 2014a, b; Ramachandra et al. 2014a, b; Akin and Erdogan 2020). Urban Sprawl measurement is a tabular formation and quantitative approach to visualize a map of space phenomenon between few and far (Das Chatterjee et al. 2016). Through this analysis, it can also be quantified and computes the pattern of urban dynamics and different land features in the city (McGarigal and Marks1 1995). Landscape metrics define patch area, percentage of landscape (PLAND), largest patch index (LPI), fractal dimension index (FRAC), shape index (SHAPE) and ecological sustainability as well (Dewan et al. 2012).

In India, the cities are sprawling, very rapidly. According to the census 2011 report, the urban population is 377.1 million. It was added 9.1 crore during the last 10 years. It was the first time that the absolute number of urban populations has increased than the rural population. The rural–urban population distributions were 68.84% and 31.16%. The level of Urbanism has also been increased by 31.16% in the Census of India 2011and the rural population decreased from 72.19 to 68.84%. The growth of the urban population

has led to the growth of urban land due to mainly migration (Ramachandra and Uttman 2008).

Nationwide, several studies have been done on LULC-Cand urban growth monitoring in several cities of India. Sudhira et al. (2003) used Shannon's entropy index to measure sprawl in Karnataka areas of Mangalore and Udupi coastal cities. Ramachandra et al. (2012) have explained the urban dynamics in Bangalore city using landscape metrics to get depth known about sprawl. The urban gradient and sprawl were measured using Shannon's entropy, which confirms the city growth with dispersed manners. PCA was used for metrics prioritization in this study. Bhatta and Giri (2012) simulated the urban growth over 30 years and predicted future growth up to 2050 of the Kolkata Metropolitan Authority (KMA). Rawat and Kumar (2015) have monitored land use and cover changes in the Hawalbagh block level of Uttarakhand using supervised classification methods. Poyil and Misra (2015) focused on quantitative studies of urban agglomeration in the Malegaon district. The morphological growth of the study area has analyzed using satellite imageries. Mondal et al. (2015a, b) in their article examined the relative changes of each land uses through the calculation of gross gain, gross losses, persistence and net changes in the Kamrup Metropolitan district of Assam. Das Chatterjee et al. (2016) have been carried out the research on Bhubaneswar city using spatial modeling in the measurement and monitoring of land-use changes. The landscape metrics, entropy methods and principal component analysis were used for computing the urban sprawl. Mondal et al. (2016) predicted the future urban sprawl of Kolkata metropolitan areas through using Markov chain simulation. The additional factors (locational force, land use force, market forces, residential force and a group of resistance force) were selected for an explored upcoming urban scenario. Sahana et al. (2018) and Rahaman et al. (2018) analyzed spatial urban sprawl matrix in Kolkata urban agglomeration over the periods of 1990–2015. Shukla and Jain (2019) in their research paper analyzed the process of urbanization of urban, sub-urban, sub-rural and rural levels over the Lucknow city. The pixel-based classification of urbanness or urban densities were categorized into seven classes in the study area. Four types of sprawl are identified and mapped, i.e., infill, extension, leapfrog and ribbon expansion.

Apart from this, the Barrackpore is a sub-divisional area of North 24 Parganas district, West Bengal which contains 16 municipal towns or ULBs (Urban Local Bodies). Industrial locations along the Hooghly river had caused to grow densely population among the municipalities. These urban bodies are under the KMDA (Kolkata Metropolitan Development Authority). A more than a few studies have done on urban growth at KMDA but those were considered the Kolkata city as a core study of urban sprawl in a spatial manner. The aim of the study is to the

monitoring of urban sprawl of these towns (municipalities) can support to take suitable planning and minimizing the environmental problem at the micro-level, such as micro-climate changes, ecosystem fragmentation, water bodies management, proper urban structure, urban green space management, sustainable livelihood. The present study has first analyzed and detected the pattern of land-use changes in temporal order (1972, 2001, 2016) using remote sensing data in every town. The landscape metrics were used to capture the dynamism of urban land surface changes and growth consideration and lastly, to confirm the sprawl, Shannon's entropy model was computed to understand with details the local pattern of growth in the UBLs of the Barrackpore sub-division. The micro-scale study is necessary to develop socioeconomic conditions and need to build appropriate management for the small spatial unit.

Study area

The Barrackpore is one of the old sub-divisional parts of North 24 Parganas, West Bengal. It has historical importance due to colonization and industrial influences in the eastern part of India. Physical settings of the sub-division reveal that it is part of the Bengal Basin. The bank of the Hooghly River lies on the right side of the study area. The administration set up of the sub-division at present is 16 municipalities or ULBs (Urban Local Bodies), 2 CD block, 24 census town 53 Villages, 14 g Panchayat and 13 police stations (Census of India 2011). The huge number of industries in the early days along the bank line like jute mills, cotton mills, petrochemicals, engineering was paving to pay to increase the urban population. More than 90% population resides in urban areas (Census of India 2011); https://www.barrackpore.gov.in/. The climatic condition is a tropical pattern. The seasonal fluctuation in temperature shows the climatic variation. Summer seasons are hot with reach up 45° C and in winter, it reaches below 10 °C. The southwest monsoon brings rainfall during the monsoon season (Das and Angadi 2020) (Fig. 1).

As the research study is focused on 16 municipalities 'micro level to quantify urban sprawl individuals in Barrackpore sub-division. The ULBs are represented by the name code as Kanchrapara (KNP), Halishahar (HSM), Naihati (NHT), Bhatpara (BHP), Garulia (GAR), North Barrackpore (N BKP), Barrackpore (BKP), Titagarh (TGH), Khardah (KDH), Panihati (PHT), Kamarhati (KMH), Baranagar (BN), South Dumdum (S DM), Dumdum (DM), North Dumdum (N DM) and New Barrackpore (NEW BKP). The details of Municipalities are mentioned in Table 1.
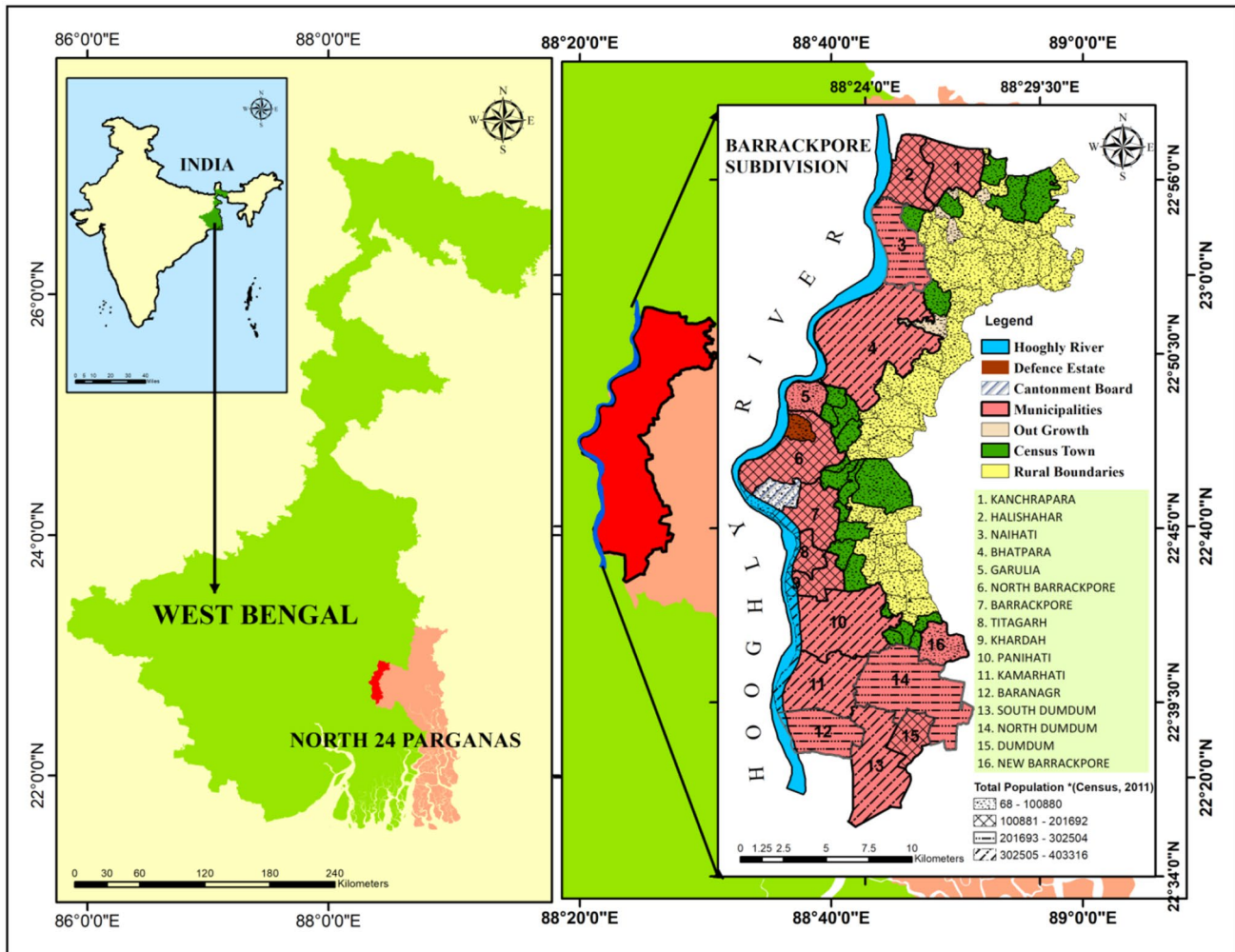
Fig. 1 Location map of the study area

Methods and materials

This piece of research work is the combination of LULCC detection cum landscape analysis and evaluating the urban growth potentiality for every small urban unit in the micro-scale by using the integrated geospatial model techniques. Several types of data are required for the selected domain measures which were obtained from different sources. The methods and materials have been divided into several sections as follows.

Data source

The availability of satellite data of MSS (Multi-Spectral Scanner), TM (Thematic Mapper), and ETM + (Enhanced Thematic Mapper) images for 1972, 2001 and 2016 have been obtained from the USGS earth explorer. The available geo-tiff format images having the projection system of UTM and reference datum is WGS 84. The acquired 60 m (MSS)

and 30 m (TM/ETM) resolution of multispectral data were used for the thematic layer (LULC) production. The town maps of all municipalities have been collected from the different municipalities' offices and geo-referenced the entire map by giving the projection systems (UTM/WGS 84) in ArcGIS software. The Survey of India (SOI) topo-sheet on a scale of 1: 50,000 and Google earth with a spatial resolution of 1 m have been used for accuracy assessment purposes (Table 2).

Pre-processing of data and classification

The acquired images in 1972, 2001 and 2016 with cloud-free for land use classifications were geometrically and radiometrically corrected first. The corrected spectral bands (optical) stacked to obtain multi-bands image for each considered year. The processed images were subset by the boundaries of each town as an area of interest (AOI). The clipped images were used as inputs for performed classification by

Table 1 Details of municipalities or ULBs in Barrackpore Sub-division

SL no	Municipalities/ULBs	Location	Area in hectare (ha)*	Corporation status (year of establishment	Avg. elevation (m)
1	Kanchrapara (KNP)	88° 25′ 50″ E–88° 27′ 30″ E 22° 54′ 00″ N–22° 57′ 00″ N	860.61	1917	14.9
2	Halishahar (HSM)	88° 24′ 10″ E–88° 26′ 40″ E 22° 55′ 00″ N–22° 57′ 00″ N	783.98	1903	17.2
3	Naihati (NHT)	88° 24′ 00″ E–88° 26′ 00″ E 22° 52′ 00″ N–22° 55′ 00″ N	990.51	1869	14.7
4	Bhatpara (BHP)	88° 22′ 10″ E–88° 25′ 40″ E 22° 49′ 00″ N–22° 52′ 00″ N	2953.10	1899	13.5
5	Garulia (GAR)	88° 21′ 00″ E–88° 23′ 40″ E 22° 48′ 30″ N–22° 50′ 00″ N	350.83	1896	12.8
6	North Barrackpore (N BKP)	88° 20′ 00″ E–88° 23′ 30″ E 22° 46′ 00″ N–22° 48′ 30″ N	1290.23	1869	11.60
7	Barrackpore (BKP)	88° 21′ 30″ E–88° 23′ 00″ E 22° 44′ 00″ N–22° 46′ 30″ N	837.23	1916	10.9
8	Titagarh (TGH)	88° 21′ 30″ E–88° 22′ 30″ E 22° 43′ 30″ N–22° 45′ 0″ N	343.09	1895	10.3
9	Khardah (KDH)	88° 21′ 30″ E–88° 23′ 30″ E 22° 43′ 00″ N–22° 44′ 0″ N	501.29	1920	9.4
10	Panihati (PHT)	88° 21′ 40″ E–88° 25′ 00″ E 22° 40′ 00″ N–22° 43′ 0″ N	1869.60	1900	8.8
11	Kamarhati (KMH)	88° 21′ 20″ E–88° 24′ 00″ E 22° 39′ 20″ N–22° 41′ 00″ N	1400.11	1899	7.9
12	Baranagar (BN)	88° 21′ 30″ E–88° 23′ 30″ E 22° 38′ 00″ N–22° 39′ 00″ N	932.06	1869	7.9
13	South Dumdum (S DM)	88° 22′ 30″ E–88° 25′ 30″ E 22° 35′ 50″ N–22° 39′ 50″ N	1537.97	1870	6.5
14	North Dumdum (N DM)	88° 23′ 20″ E–88° 27′ 30″ E 22° 38′ 20″ N–22° 40′ 50″ N	2086.68	1870	7.1
15	Dumdum (DM)	88° 25′ 00″ E–88° 25′ 50″ E 22° 37′ 30″ N–22° 39′ 10″ N	479.05	1929	8
16	New Barrackpore (NEW BKP)	88° 25′ 50″ E–88° 27′ 30″ E 22° 40′ 50″ N–22° 41′ 50″ N	468.66	1965	10.2

*Area in hectare (ha). 100 ha = 1 sq km

Table 2 Applied data and related information

Major data	Year	Topo-sheet no/path: row	Scale/resolution	Source
Topographical map	2011	F45K5 and F45K6	1:50,000	Survey of India (SOI), Kolkata
Google Earth Pro	2016		1 m	Google earth engine
Landsat MSS	1972	148/44	60 m	earthexplorer.usgs.gov
Landsat TM	2001	138/44	30 m	earthexplorer.usgs.gov
Landsat ETM+	2016	138/44	30 m	earthexplorer.usgs.gov
Municipalities boundary map	2016			From different Municipal office
Secondary data on demography	2011			District Census Handbook, Census of India

supervised classification methods. The widely used maximum likelihood classifier (MLC) was applied for the classification (Sudhira et al. 2003; Li and Yeh 2004; Rawat and Kumar 2015). The supervised classification is a decision rule-based technique involved in taking sample area with known feature type in the ground and compared with the spectral signature of the pixel in the image (Lillesand and Keifer 1987). The MLC is a reliable and probability-based technique to apply to multi-temporal classification (Strahler 1980; Rawat and Kumar 2015). This study has used MLC because this algorithm can assemble the spectral signature of the pixel in a particular class and minimize the complexity (Li et al. 2014a, b), on the other hand, the main objective is to study LULC spatial change detections and expansion of urban landscape, not examine the internal feature structure, shape and dimension of built-up areas (Das and Angadi

2020). Several researchers have used the MLC algorithm for the classification (Sudhira et al. 2003; Mondal et al. 2016; Mithun et al. 2016). The signature of each class was tabulated and performed the classification. The LULC classification has been adapted from Anderson et al. 1976 classification system. The most accurate information about the land surface is a challenging task due to heterogeneous features generally occurs the mixed pixel problem in the image (Lu and Weng 2005). Mixed pixels arise in medium spatial resolution data (Jensen and Jungho 2007). In the urban lands includes heterogeneous features, such as buildings, trees, mixed vegetation, water, soil (Lu and Weng 2005; Dewan and Yamaguchi 2009). These problems can be addressed by taking ground GPS points, visual interpretation of local knowledge and using Google earth engine pro for the study area. The six LULC classes have been classified as final

results. The statistics of land use for each town has been quantified for further analysis (1) vegetation, (2) agricultural land/cropland, (3) built-up land, (4) fallow land/open field, (5) water bodies, and (6) wetland.

Accuracy measurement of classified images was tabulated to test and check that the particular pixel has assigned to correct correspondence land features over the surface (Congalton 1991). The level of accuracy depends on the three parameters, i.e., level of classification, resolution of image and scale in the study (Rawat and Kumar 2015). A group of sample points has been taken from field GPS surveys and using the Google earth map system from all over 16 towns as a stratified random sampling to perform for accuracy assessment for the study. The minimum required sample in each category to calculate accuracy is 50 as suggested by (Manandhar et al. 2009). Hence, 100 samples per each class have been assigned in Erdas imagine v14 software to perform an accuracy assessment for each class by identifying the high spatial resolution from Google earth (1 m spatial resolution) and field points. The older year's classification accuracy has been performed by the "historical view" of the google earth engine. A confusion matrix has been tabulated based on reference points and the user's accuracy (error of commission) and producer's accuracy (error of omission) were calculated for each class (Story and Congalton 1986; Congalton and Green 1999). Lastly, the overall accuracy and kappa coefficient for each were calculated and compared between 1972, 2001 and 2016 (Foody 2002, 2004).

Urban sprawl measures: landscape metrics and Shannon's entropy model

The study has been attempted to analyze the process of the built-up growth of towns at Barrackpore Sub-division applying some selected landscape metrics. Although a wide variety of metrics were used to measure the patterns of urban growth by several researchers. The results of metrics depend on the resolution of satellite imagery, the accuracy level of image classification, selection of metrics and so on (Mithun et al. 2016). The different researchers have given a different opinion on the choice of metrics and confirm that many metrics are correlated and could produce redundant information (Ramachandra et al. 2012). In contrast, Shannon's entropy is whispered to be a robust measure of the urban growth process. This method is preferable because it has marginal limitations, but not free from nuisances. Moreover, sometimes the contradictory relation would find in the result of both landscape metrics and Shannon's entropy. Landscape metrics are unable to measure the degree of urban sprawl with black and white categorization (Bhatta and Giri 2012; Mithun et al. 2016). In the present study, Shannon's entropy calculation was separately used to analyze urban growth for

a proposed zoning approach to understand the performance of the selected metrics.

Landscape metrics

Landscape defines as a heterogeneous land area composed of a group of interrelating ecosystems patches that are repeated in a similar form (Forman and Godron 1986). Landscape metrics are an index that can be quantified in nature to describe the pattern and structures of the land (McGarigal and Marks 1995). Landscape metrics are known as spatial metrics through which they can comprehend and describe the causes as well as consequences of urban processes (Bharath et al. 2012). Several types of landscape metrics have been proposed and used to configure individual land class and whole land cover categories (Forman and Godron 1986; Frohn et al. 1996; O'Neill et al. 1999). The applications of landscape metrics include the landscape pattern analysis, biodiversity fragmentation, changes of landscape (Gardner et al. 1993; Dunn et al. 1991), relating landscape structures at different scales (Turner et al. 1989); and complexity of urban land structure (Herold et al. 2002). In the present study, the Fragstats program was used to calculate the landscape metrics (McGarigal and Marks 1994). Therefore, the variety of landscape metrics were derived from the estimation of urban structure for the small towns (ULBs).

- *Area and edge metrics* This group of metrics quantifies the size of the patches and the amount of edge created by this patch in the landscape (McGarigal and Marks 1994, 1995). This section includes CA (class area), PLAND (percentage of land), LPI (largest patch index), MPS (mean patch size) and ED (edge density).
- *Shape metrics* The patch shape and size influence the ecological processes. This group of metric measures the landscape configuration by calculating the shape complexity of patches. The shape metrics represent the regularities and irregularities characteristics of patches (McGarigal and Marks 1994, 1995). This segment includes AWMSI (area-weighted mean shape index).
- *Aggregation metrics* Aggregation metrics quantify the tendency of patches to be spatially aggregated and also refers to as landscape texture. This metric indicates the dispersion, interspersion, sub-division and isolation in the landscape (McGarigal and Marks 1994, 1995). LSI (Landscape Shape Index), CLUMPY, IJI (Interspersion Juxtaposition Index), AI (Aggregation Index) is falling under these metrics.

Table 3 depicts the name of the metrics, formulas and description of the possible range of each landscape is being calculated. The different metric types were selected based on the potential utility to get information for different domains.

Table 3 Description of selected landscape metrics for urban class

Landscape metrics	Formula	Description	Range
Total area (TA)/CA	$CA = \sum_{j=1}^{n} a_{ij}\left(\frac{1}{10,000}\right)$	a_{ij} = area (m^2) of patch ij n_i = number of patches in the landscape of patch type (class) i	CA > 0, without limit
Percentage of land (PLAND)	$PLAND = P_i \frac{\sum_{j=1}^{a} a_{ij}}{A}(100)$	A = total landscape area (m^2)	0 < PLAND ≤ 100
Number of patches (NP)	$NP = n_i$	P_i = proportion of the landscape occupied by patch type (class) i	NP ≥ 1, without limit
Patch density (PD)	$PD = \frac{n_i}{A}(10,000)(100)$	i = ith patch; a = area of patch i;	PD > 0, constrained by cell size
Largest Patch Index (LPI)	$LPI = \frac{\sum_{j=1}^{a}\max(a_{ij})}{2a}(100)$	n = total number of patches	0 < LPI ≤ 100
Mean patch size (MPS)	$MPS = \frac{\sum_{i=1}^{n} a_i}{n_i}\left(\frac{1}{10,000}\right)$	P_{ij} = perimeter (m) of patch ij e_{ik} = total length (m) of an edge in landscape involving patch type (class) i; includes landscape boundary and background segments involving patch type i	MPS > 0, without limit
Edge density (ED)	$ED = \frac{\sum_{k=1}^{m} e_{ik}}{A}(10,000)$		ED ≥ 0, Without limit
Average Weighted Mean Shape Index (AWMSI)	$AWMSI = \sum_{i=1}^{m}\sum_{j=1}^{n}\left[\left(\frac{0.25p_{ij}}{\sqrt{a_{ij}}}\right)\left(\frac{a_{ij}}{A}\right)\right]$		AWMSI ≥ 1, without limit
CLUMPY	$G_i = \left[\frac{g_{ii}}{\sum_{k-1}^{m} g_{ik}}\right]$ $CLUMPY = \begin{cases}\frac{G_{i-P_i}}{1-P_i} & \text{for } G_i \geq P_i \\ \frac{G_{1-P_i}}{1-P_i} & \text{for } G_i < P_i; P_i \geq 5 \\ \frac{P_i - G_i}{-P_i} & \text{for } G_i < P_i; P_i < 5\end{cases}$	g_{ii} = number of like adjacencies (joins) between pixels of patch type (class) i based on the double-count method g_{ik} = number of adjacencies (joins) between pixels of patch types (classes) i and k based on the double-count method	− 1 ≤ CLUMPY ≤ 1
Landscape shape Index (LSI)	$LSI = \frac{.25\sum_{k=1}^{m} e*_{ik}}{\sqrt{A}}$	$e*_{ik}$ = total length (m) of edge in landscape between patch types (classes) i and k, includes the entire landscape boundary and some or all back ground edge segments involving class i	LSI ≥ 1, without limit
Interspersion and Juxtaposition Index (IJI)	$IJI = \frac{-\sum_{k=1}^{m}\left[\left(\frac{e_{ik}}{\sum_{k=1}^{m} e_{ik}}\right)\ln\left(\frac{e_{ik}}{\sum_{k=1}^{m} e_{ik}}\right)\right]}{\ln(m-1)}$		0 < IJI ≤ 100
Aggregation Index (AI)	$AI = \left[\frac{g_{ii}}{\max \to g_{ii}}\right](100)$	Max-g_{ii} = maximum number of like adjacencies (joins) between pixels of patch type (class) i based on the single-count method	0 ≤ AI ≤ 100;

Shannon's entropy model

In recent decades various studies applied Shannon's entropy model to analyze and understand the equilibrium rate of the relative urban phenomenon at state, regional and country levels (Shannon 1948). The entropy is widely used to measure the degree of urban sprawl in a region with the integration of remote sensing and GIS approach and carried out with its spatial database (Das Chatterjee et al. 2016). Shannon's entropy is an index or indicator which can measure the spatial concentration or dispersion in any spatial unit (Ao and Li 1998; Sudhira et al. 2004; Jat et al. 2008; Bhatta and Giri 2012; Mithun et al. 2016; Ramachandra et al. 2014a, b; Sahana et al. 2018). The structure of the model is calculated by using the formula below:

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

where p_i is the proportion of variable (built-up land) in the ith zone $\left(P_i = \frac{x_i}{\sum_{i=1}^{n} x_i}\right)$, x_i is the observed value of the variable in the ith zone and n is the total number of zones. The

entropy value varies from 0 to $\log_{(n)}$. The value closer to zero indicates the compact distribution and the value of near $\log_{(n)}$ indicates the dispersed distribution. Higher values of entropy indicate sprawl (Bhatta and Giri 2012). The halfway mark of $\log_{(n)}$ is measured as a threshold value, therefore if the entropy values are beyond the threshold can be called the sprawling city (Mithun et al. 2016). Relative entropy can be measured to scale up the entropy value into ranges from 0 to 1. The relative entropy (H') for n number of zones can be calculated as (Thomas 1981):

$$H'_n = \frac{H_n}{\log_e(n)}$$

The value 0.5 is considered as a threshold value. The value is higher than the threshold considered sprawl.

In our study, this model was used for evaluating the urban expansion in every ULBs (municipalities). The cities have their well-defined administrative areas. Organizationally these towns have a sub-division of municipal ward level, but these wards are not fixed in number and area, it is changeable with temporal manner. To overcome this problem,

each ULB has been divided into four groups of North East (NE), North West (NW), South East (SE), and South West (SW) zones based on the administrative building point of the respective town. Each zone was further divided into a concentric circle pattern of 200-m radius buffer zones. Because the study aims to emphasize the urban growth in every spatial corner of these small towns. The urbanization process is not uniform and growth is defined in terms of directions (Ramachandra et al. 2014a, b). The questions regarding urban sprawl, i.e., how these small towns are facing rapid urban growth and how much built-up land is expanding through the time. It would be a detailed study on a micro-scale that will be planning oriented for planners to provide sustainable infrastructure.

Results and discussion

The spatio-temporal land use/cover changes in ULBs

LULCC of the municipalities from 1972 to 2016 is shown in the table and figure format (Table 4; Fig. 2). The output displayed that vegetation, agricultural land, wetland, water bodies have been declined in areas' from 1972 to 2016; on the other hand, built-up areas and fallow land are increased during the decades in each town. The results of the overall accuracy of the classification of output images were more than 88% (1972), 93.3% (2001) and 95% (2016). The classified three-time interval images had a kappa index of 0.86, 0.92 and 0.94. The accuracy result indicated strong agreement of classified image and ground truth (Congalton 1991). The present study met the minimum requirement by overall accuracy and k statistics for LULC classification (Anderson et al. 1976). The classification results of 16 towns are described into four divisions; each of them discussed four towns in detail. The first section discussed KNP, HSM, NHT and BHP towns; the second section includes towns of GAR, N BKP, BKP and TGH; the third section contains ULBs of KDH, PHT, KMH and BN and lastly, four section is enclosed S DM N DM, DM and New BKP.

- KNP, HSM, NHT and BHP

These four ULBs lie in the northern part of the subdivision. The KNP is a town where one of the railway workshops in India and jute mills are situated that bring the development and growth of the city. The decadal changes in LULC reveal that the built-up area has increased simultaneously. The vegetation cover has decreased from 53 to 36% (1972–2001) and 19% (2001–2016). Agricultural land and surface water bodies were reduced over time. The built-up land had gained 143 ha in 972–2001; and 126 ha in 2001–2016 intervals (Fig. 2a; Table 4a). Kanchrapara

city contributes only to 3.8% of the residential area in the total sub-division area. The next city is HSM, known as the city of palaces. This town is facing the changing aspects of LULC. The area of Wetland was reduced by 13–1.7% from 1972 to 2016; and vegetation cover was also sharply decreased from 66 to 36% (1972–2001) and from 36 to 19% (2011–2016). Agricultural land had converted into open fallow land in some places of the town. Built-up areas have extended towards the eastern side rapidly. In 1972 built-up area was only 8.92 ha (1.3%), then increased to 108.37 ha (13%) in 2001 and 343.69 ha (43%) in 2016 of the town (Fig. 2b; Table 4b). NHT is one of the old cities. The colonial character has been established since the statute of the city. Changes in different land-use exposed that the city expanded in concreteness by 27–62% from 1972 to 2016. Urban sprawls are happing in this city because it encroached the adjoining Deulpara non-municipal (N.M) area over the period. The total spatial area of the city also has increased by 38%. The proportion of wetlands is gradually decreased in the area (Fig. 2c; Table 4c). BHP is industrial areas and the numbers of slums are more here because the workers from the outside made this area dense populated. It has an outgrowth extension according to the census of India 2011 report. Therefore, the area of the urban land is getting higher during a time interval. The growth rate of built-up land was 65% during 1972–1–2001 and 76% during 2001–2016. As the total area of the town were expanded due to merging with the villages and small census towns (namely ChakMulajor, Gurdaha, Madrail-Fingapara, Narayanpur and Sthitrapar), the statistics show that the other land use classes have added in area coverage during the 1972–2001(Fig. 2d; Table 4d). The urban sprawling is continued to notice in Bhatpara.

- GAR, N BKP, BKP and TGH

These four municipalities are covered in the central part of the study area. Among all ULBs, the GAR municipality is small in size and less developed than others, but still, the built-up growth is continuing here. During the 1972–2001 time period, the built-up land was gain 100 ha (growth of 141%) and 60 ha (60% of growth rate) has added during 2001–2016. Now presently 73% of the land area is covered by built-up land. Local ponds and water bodies are going to be disappearing over time. The loss of surface water bodies was more than 45 ha area for 44 years (Fig. 2e; Table 4e). N BKP is one of the oldest municipal authorities in the study area. Based on the centralized rifle and metal gun factories, the settlements were growing up in this area. Even the older colonial aspects have been found in most places in the ULB. The urban built-up land was 105 ha in 1972; 312 ha in 2001; and 575 ha in 2016. The natural vegetated area and water bodies were dominantly declined from 51 to 26% and 17 to 8% of land throughout the 44 years (Fig. 2f; Table 4f).

Table 4 ULBs wise land-use/land cover changes of classes (area in ha)

| Municipalities/ULBs	Land use classes	YEAR			ULBs	YEAR		
		1972	2001	2016		1972	2001	2016
a. KNP	Vegetation	457.38	314.52	169.11	i. KDH	161.29	81.51	41.54
	Agricultural land/crop land	131.79	118.22	129.08		25.34	45.10	38.08
	Wetland	54.97	24.96	12.33		70.39	9.33	0.00
	Built-up land	96.12	238.94	365.99		75.39	237.85	323.50
	Fallow land/open field	27.26	102.45	125.49		6.59	20.38	9.83
	Water bodies	89.22	59.98	57.68		46.20	39.67	20.52
b. HSM	Vegetation	521.85	428.85	151.35	j. PHT	942.29	462.35	270.52
	Agricultural land/crop land	78.47	77.31	92.80		219.27	212.14	94.28
	Wetland	102.88	39.60	13.38		224.64	36.07	0.00
	Built-up land	8.91	99.99	343.69		105.87	670.33	1141.64
	Fallow land/open field	20.27	52.86	94.36		37.62	123.20	100.97
	Water bodies	47.80	74.85	85.07		221.33	246.13	143.90
c. NHT	Vegetation	302.64	306.33	107.22	k. KMH	516.00	192.48	160.40
	Agricultural land/crop land	52.35	123.38	76.11		45.15	69.56	25.34
	Wetland	80.46	31.04	25.51		138.36	12.50	0.00
	Built-up land	205.13	403.37	615.81		303.57	772.38	892.8
	Fallow land/open field	6.86	62.93	70.67		18.77	43.05	43.22
	Water bodies	98.57	55.77	86.82		225.02	147.02	105.72
d. BHP	Vegetation	500.29	1311.16	667.23	l. BN	284.73	109.90	106.87
	Agricultural land/crop land	90.13	547.59	452.17		47.84	39.53	9.30
	Wetland	160.36	135.11	81.57		87.87	7.36	0.00
	Built-up land	393.34	651.05	1145.53		310.23	616.68	672.3
	Fallow land/open field	19.59	120.39	353.15		23.60	42.48	28.68
	Water bodies	161.60	186.10	249.66		138.55	71.99	66.75
e. GAR	Vegetation	177.06	96.08	41.21	m. S DM	700.66	265.97	201.72
	Agricultural land/crop land	28.92	44.79	16.60		154.22	108.02	13.52
	Wetland	29.73	4.98	0.20		173.30	13.67	0.00
	Built-up Land	67.06	160.51	257.32		279.41	941.07	1161.90
	Fallow land/open field	8.83	28.29	17.81		50.88	110.75	52.24
	Water bodies	37.66	15.71	16.85		163.15	95.24	105.73
f. N BKP	Vegetation	663.42	470.51	340.74	n. N DM	680.40	785.79	420.46
	Agricultural land/crop land	161.31	187.69	99.24		254.28	382.71	71.99
	Wetland	72.21	49.00	5.23		113.18	30.86	0.00
	Built-up land	105.38	311.74	575.34		46.52	493.11	1164.59
	Fallow land/open field	36.96	135.84	137.42		17.65	280.18	348.29
	Water bodies	230.30	114.98	112.55		41.18	110.03	76.80
g. BKP	Vegetation	343.12	162.56	97.01	o. DM	94.60	99.24	89.22
	Agricultural land/crop land	95.16	80.11	45.98		12.84	37.98	2.24
	Wetland	91.90	11.75	0.33		43.71	2.96	0.00
	Built-up land	108.57	366.09	515.60		84.78	274.01	345.91
	Fallow land/open field	23.68	78.26	58.52		2.33	36.58	14.87
	Water bodies	88.04	51.99	33.84		37.12	27.13	25.77
h. TGH	Vegetation	58.21	50.72	40.89	p. New BKP	146.81	264.42	75.86
	Agricultural land/crop land	13.25	18.93	28.91		46.42	26.53	33.79
	Wetland	38.13	5.39	0.09		14.30	16.27	0.00
	Built-up land	143.25	188.09	201.66		4.95	109.62	306.72
	Fallow land/open field	4.57	4.78	6.95		0.31	11.26	17.47
	Water bodies	36.68	25.87	16.35		34.36	36.46	25.60
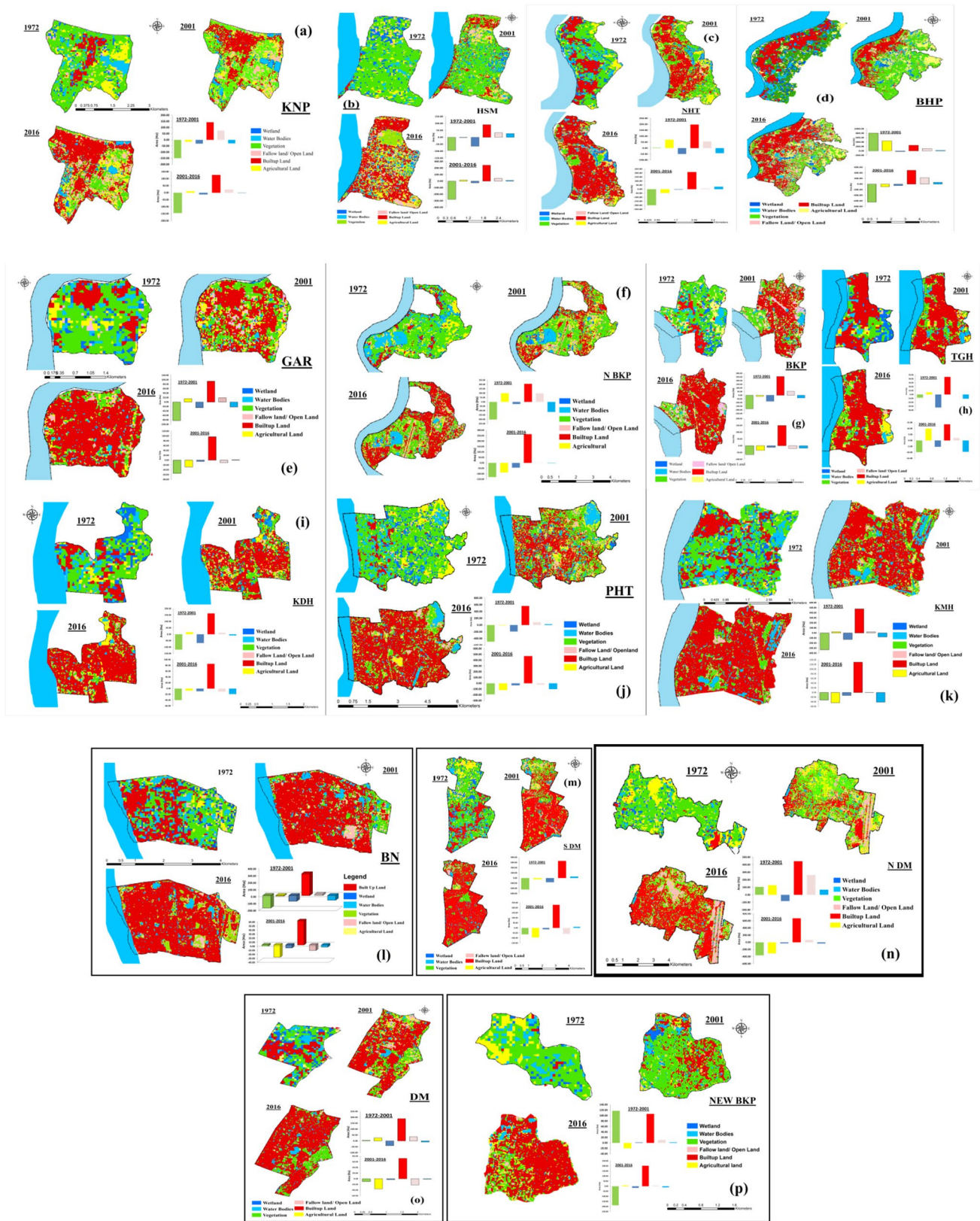
Fig. 2 Land use/cover map of municipalities: **a** KNP, **b** HSM, **c** NHT, **d** BHP **e** GAR, **f** N BKP, **g** BKP, **h** TGH, **i** KDH **j** PHT, **k** KMH, **l** BN, **m** S DM, **n** N DM, **o** DM **p** NEW BKP

BKP is a developed small city that has many socioeconomic facilities with a densely populated area. The sub-divisional administrative activities have been done in this town only. It is a very fast-growing city. Mostly of amenities and facilities had played a role to attract people from adjacent small towns and villages. Every corner of town is full of built-up land. In 2016, 61% area was built up land where it was 12% of the land in 1971. Moreover, the non-built-up land was reduced to more than 50% of the land (Fig. 2g; Table 4g). TGH is mostly an industrial town dominated by many slum areas. It is small in size and compact full of residential areas. It had the highest population density as well as built-up density too. As the compactness of the built-up area has been still since 1972, the growth rate was not much higher. Increasing of built-up land was intruding the other non-built-up land, especially vegetation and surface water surfaces. It was an increase in built-up land from 41 to 54% and then to 58% during 1972–2001 and 2001–2016 (Fig. 2h; Table 4h).

- KDH, PHT, KMH and BN

These ULBs are situated in the southern part of the area The KDH municipality had named the south Barrackpore municipality. In the urban centre, vegetation land, water bodies, wetland and agricultural land have been losing their land by 119 ha, 20 ha, 70 ha and 12 ha respectively; where built-up land and fallow areas were gained 248 ha and 3 ha during 1971–2016. Only 16% of the land was covered by built-up land in 1972, after that, it was increased by 47% in 2001 and lastly by a 64% increase in 2016. The ULB has added Keulia non-municipal village with a 10.9 ha area and expends the total spatial unit from 1972 to 2016 (Fig. 2i; Table 4i). PHT municipality was known as a trade and business center in the early days when the river route was the main source of communication. The name came from 'Pannyahati' (Emporium of the merchandise). These all factors had a role to grow this city densely. The total area of the city is 1867 ha within which 1141 (61%) is covered by built-up land in 2016. The growth rate of built-up land was 533% between 1972 and 2001 that indicates the fastest growth was taking place and 70% between 2001 and 2016. The urban land uses are spreading towards the eastern side of the city which can demolish the ecological balance in terms of loss of wetland, cropland and vegetation (Fig. 2j; Table 4j). In the next KMH urban centre is a total industrial area. This compact urban body shared 12% in 1972, 10% in 2001, and 7.5% of built-up land out of the total built-up land of the sub-division area. The growth rate of the built-up land was less because the settlement has been compact since before decades. The number of slums are huge here. LULCC dynamics reveal that vegetation and wetland were reduced 364 ha and 140 ha of land during 1972–2016 (Fig. 2k; Table 4k). BN municipality is very populated as well as a very denser residential area due to industrial influences and location near to the capital city, Kolkata. The growing residential settlement made this town a more compact urbanized area. The settlement growth process could destroy the natural ecological aspect in terms of reducing the number of water bodies and induced the area of wetland, vegetation and also agricultural land. The statistical evaluation shows that the total area of the ULB is about 890 ha. The Vegetation land was covered by a maximum area of 234 ha (30%) in 1972 and 681 ha (66%) by built-up land in 2016. No such area remains as a wetland. The small water bodies or urban ponds were filled to build the settlement (Fig. 2l; Table 4l).

- S DM N DM, DM, and New BKP

These four ULBs are situated extreme southern part of the study area. The Dumdum zone is a highly developed area. It has three separate municipality boundaries. First, the S DM municipal has maximum urban growth due to its number of socioeconomic facilities for the citizens. The population density is very high over the periods. The built-up land was 18% in 1972; 61% in 2001 and 76% in 2016. It is noticeable how much rapid rate of impervious growth has happened in this town. The location near the capital city had major influences to grow and develop. Transportation and communication are very well connected. Metro rails; railways, the number of roads increased, near to the airport are the causes of fast development. Two villages (Garui and Natkal) have fused with the area of this town (Fig. 2m; Table 4m). Lastly, the N DM municipality has experienced more urban sprawl. The growth rate of urban built-up land over the period explained the settlements patches are increasing. As a result of compactness to neighboring South Dumdum, Dumdum area and near Kolkata city people construct the settlement in these areas. The development and growth would support this place to get broader areas. Near villages (Bandra, Bisarapara, Fattullapur, Finga and part of Sultanpur) were merged up with the town. The total spatial unit has an extent of 920 ha. During 1972–2001, the built-up area has expansions of 446 ha from 2001 to 2016, it gained 671 ha (Fig. 2n; Table 4n). The DM urban centre is a small town, but the growth of the built-up land was very high because it was fused with part of Sultanpur village and extended the spatial unit. The present conditions of the town are compact in the built-up area. More than 72% area was dominated by the impervious areas in 2016. The other non-built-up land had decreased by the area (Fig. 2o; Table 4o). New BKP was a newly built town among the sixteen ULBs, so the number of population, as well as built-up density is less compared to others. But this ULB is facing the fastest built-up land as it is part of the urban agglomeration process of KMDA. In 1972 the area distribution of land use classes was 58%, 18%, 2.05%, 5.7%, 0.12% and 13% of the vegetation, agricultural
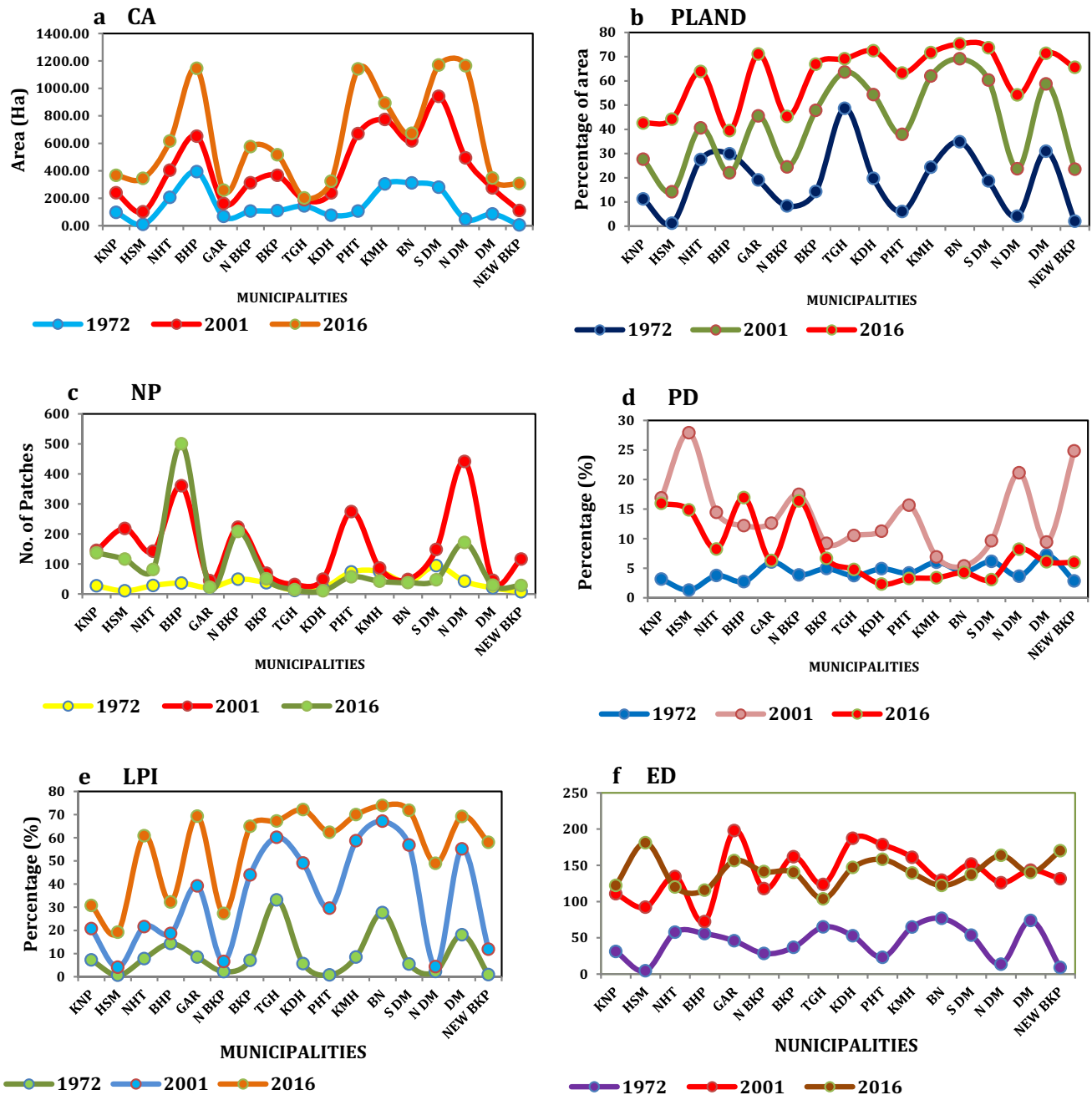
Fig. 3 Class level landscape metrics for municipalities: **a** CA, **b** PLAND, **c** NP, **d** PD, **e** LPI, **f** ED, **g** MPS, **h** AWMSI, **i** LSI **j** CLUMPY, **k** IJI, **l** AI

land, built-up land, wetland, fallow land and water bodies; it has changed the statistics for different land uses in 2001, i.e., 56%, 5%, 23%, 3.4%, 11% and 7% of correspondence land classes; and it was declined to 16%, 7%, 0.04%, 5% for vegetation, agricultural land, wetland and water bodies but increased to 66%, 17% for built-up and fallow land in 2016 (Fig. 2p; Table 4p). The New Barrackpore ULB spatial unit has merged with two adjacent villages (Agapur, Kodalia villages) and expanded it.

Urban expansion (sprawl) analysis

The spatial pattern of urban sprawl by landscape metrics in ULBs

The selected metrics compute the characteristics of entire spatial landscapes in all ULBs. These can quantify the proportion of the landscape in individual class based on fragmentation, shape, edge and contagion. The urban structure
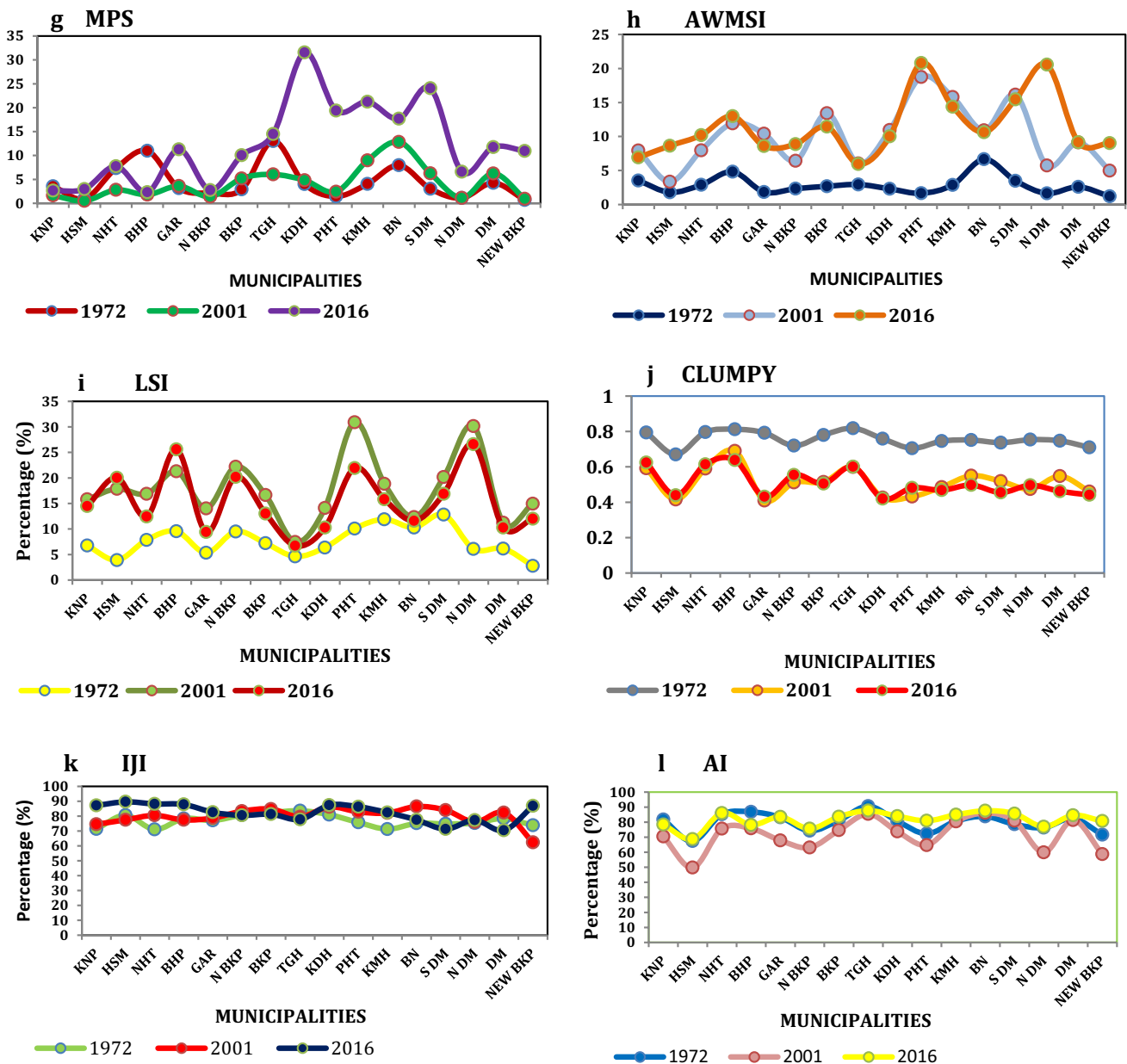
Fig. 3 (continued)

with spatial patterns examined depending on urban patch types, patch density, patch diversity and patch evenness. The complexity, compactness, aggregation, dispersions and sprawling characteristics would measure by these indices in all municipalities that would be suitable to take planning decisions for urban planners and local government in terms of environmental sustainability. The landscape metrics were calculated by using the binary image in Fragstats software. The scores of metrics would justify describing the landscape pattern (Fig. 3).

- Area of urban land (CA)

The class area (CA) is the sum of the areas of all patches in the corresponding land class (McGarigaland Marks 1994). The urban class patches have been calculated by these metrics (Table 5). Figure 3a illustrated that the higher urban area (in hectares) expanded in BN (306.45 ha), BHP (257.52 ha), KMH (468.81 ha), N DM (446.59 ha), PHT (564.47 ha) and S DM (661.66 ha) municipalities during 1972–2001; wherein BHP (494.48 ha), HSM (243.70 ha),

Table 5 Different landscape metrics of urban land use in ULBs

Year	Area of urban land (CA)			Percentage of land (PLAND)			Number of patches (NP)			Patch density (PD)			Largest Patch Index (LPI)			Edge density (ED)		
	1972	2001	2016	1972	2001	2016	1972	2001	2016	1972	2001	2016	1972	2001	2016	1972	2001	2016
KNP	96.12	238.94	365.99	11.23	27.60	42.56	27	145	137	3.14	16.88	15.95	7.24	20.71	30.76	31.07	110.77	122.22
HSM	8.91	99.99	343.69	1.19	14.15	44.15	10	218	116	1.28	27.89	14.84	0.64	4.076	19.17	4.42	92.13	181.00
NHT	205.13	403.37	615.81	27.52	40.55	63.85	28	142	81	3.75	14.44	8.23	7.79	21.62	60.83	57.61	134.31	119.90
BHP	393.34	651.05	1145.53	29.86	22.01	39.44	36	360	500	2.72	12.19	16.93	14.31	18.65	32.22	55.78	72.26	115.55
GAR	67.06	160.51	257.32	19.09	45.47	71.02	21	44	22	6.02	12.59	6.29	8.44	39.19	69.26	45.82	197.80	156.36
N BKP	105.38	311.74	575.34	8.35	24.44	45.28	49	222	208	3.86	17.48	16.38	2.18	6.55	27.29	28.34	117.72	141.18
BKP	108.57	366.09	515.60	14.28	47.81	66.88	37	69	50	4.93	9.19	6.65	7.03	43.94	64.88	36.77	161.83	140.30
TGH	143.25	188.09	201.66	48.64	63.61	69.11	11	31	14	3.73	10.53	4.76	33.16	60.13	67.18	64.93	123.50	103.55
KDH	75.16	237.85	323.50	19.70	54.27	72.39	19	49	10	4.90	11.25	2.29	5.64	49.02	72.10	52.66	187.19	146.94
PHT	105.87	670.33	1141.64	6.00	37.89	63.20	73	274	57	4.18	15.64	3.25	0.72	29.55	62.33	23.01	178.48	158.12
KMH	303.57	772.38	892.8	24.32	61.95	71.62	75	86	42	6.00	6.89	3.36	8.47	58.65	69.94	64.76	161.01	139.27
BN	310.23	616.68	672.3	34.84	69.10	75.27	39	48	38	4.38	5.37	4.25	27.62	67.13	73.90	76.82	129.42	122.03
S DM	279.41	941.07	1169.96	18.63	60.29	73.66	94	148	47	6.13	9.63	3.05	5.46	56.80	71.80	53.48	151.70	137.39
N DM	46.52	493.11	1164.59	4.05	23.69	54.16	42	441	171	3.64	21.13	8.20	2.21	4.36	48.94	13.55	125.92	163.68
DM	84.78	274.01	345.91	30.90	58.73	71.31	20	45	29	7.22	9.40	6.06	18.11	55.17	69.18	73.84	143.26	139.97
NEW BKP	4.95	109.62	306.72	1.99	23.46	65.53	7	116	28	2.82	24.83	5.98	0.87	11.86	58.01	8.96	131.34	170.06

Year	Mean patch size (MPS)			Area weighted Mean Shape Index (AWMSI)			Landscape shape Index (LSI)			CLUMPY			Interspersion and Juxtaposition Index (IJI)			Aggregation Index (AI)		
	1972	2001	2016	1972	2001	2016	1972	2001	2016	1972	2001	2016	1972	2001	2016	1972	2001	2016
KNP	3.57	1.63	2.67	3.52	7.95	6.92	6.76	15.83	14.49	0.79	0.59	0.62	71.33	74.49	87.18	81.68	70.42	78.40
HSM	0.94	0.51	2.97	1.80	3.36	8.64	3.90	17.89	20.05	0.67	0.41	0.44	80.62	77.49	89.61	67.38	49.77	68.68
NHT	7.34	2.81	7.76	2.89	7.97	10.19	7.88	16.88	12.44	0.80	0.59	0.61	71.01	80.51	88.22	85.23	75.61	86.06
BHP	10.97	1.80	2.33	4.83	11.93	13.00	9.56	21.31	25.61	0.81	0.69	0.64	78.39	77.44	87.86	86.84	75.80	78.12
GAR	3.17	3.61	11.28	1.84	10.40	8.59	5.35	14.05	9.42	0.79	0.41	0.43	77.06	78.73	82.60	83.20	67.81	83.51
N BKP	2.16	1.40	2.76	2.33	6.43	8.87	9.52	22.19	20.22	0.72	0.51	0.55	80.69	83.34	80.51	74.29	63.12	75.63
BKP	2.90	5.20	10.05	2.68	13.41	11.44	7.23	16.67	13.04	0.78	0.51	0.50	82.36	84.75	81.31	81.14	74.65	83.60
TGH	13.03	6.04	14.50	2.95	6.04	5.95	4.63	7.46	6.73	0.82	0.60	0.60	83.61	79.56	77.77	90.66	85.41	87.68
KDH	4.02	4.82	31.55	2.30	10.95	10.02	6.37	14.13	10.28	0.76	0.43	0.42	80.97	86.20	87.38	80.64	73.74	83.98
PHT	1.44	2.42	19.41	1.66	18.75	20.80	10.09	30.90	21.95	0.71	0.43	0.48	75.78	82.88	86.32	72.29	64.72	80.91
KMH	4.05	8.98	21.26	2.89	15.81	14.36	11.91	18.87	15.82	0.75	0.49	0.47	71.27	82.10	82.42	80.75	80.43	84.91
BN	7.95	12.85	17.69	6.66	10.91	10.63	10.30	12.34	11.61	0.75	0.55	0.50	75.16	86.44	77.51	83.81	86.09	87.57
S DM	3.04	6.26	24.08	3.49	16.14	15.45	12.81	20.18	16.90	0.74	0.52	0.46	74.79	84.05	71.29	78.56	80.91	85.65

Table 5 (continued)

Year	Mean patch size (MPS)			Area weighted Mean Shape Index (AWMSI)			Landscape shape Index (LSI)			CLUMPY			Interspersion and Juxtaposition Index (IJI)			Aggregation Index (AI)		
	1972	2001	2016	1972	2001	2016	1972	2001	2016	1972	2001	2016	1972	2001	2016	1972	2001	2016
N DM	1.11	1.12	6.60	1.64	5.73	20.57	6.11	30.17	26.63	0.75	0.47	0.50	75.33	75.97	77.33	76.36	59.88	76.90
DM	4.28	6.25	11.76	2.60	9.12	9.15	6.18	11.23	10.27	0.75	0.55	0.46	78.45	82.33	70.45	82.54	81.32	84.57
NEW BKP	0.71	0.95	10.95	1.20	4.98	9.02	2.80	14.96	12.02	0.71	0.46	0.44	73.81	62.29	86.90	71.58	58.71	80.76

NHT (212.43 ha), N DM (671.47 ha) and PHT (471.31 ha) ULBs during 2001–2016.

- Percentage of land (PLAND)

PLAND is the proportion of a particular class in a landscape. The temporal PLAND indicates that the higher growth trend in built-up class over the periods in each municipality. The higher percentage growth of the built-up class has met in BN (34%), BKP (33.53%), DM (27.82%), GAR (26%), KMH (37.62%), KDH (34.57%), PHT (31.88%) and S DM (41.66%) ULBs from 1972 to 2001; where HSM (29.99%), New BKP (42.07%), N DM (30.47%) and PHT (25.30%) ULBs from 2001 to 2016. The built-up percentage increases in the landscape indicate to understand the sprawling characteristics of municipalities (Fig. 3b; Table 5).

- Number of patches (NP)

NP is the total number of built-up patches in a given landscape. It is an indicator to show the level of fragmentation in a specific class in the landscape. The result shows that the number of built-up patches has increased in all ULBs during 1972–2001. In that period, the built-up patches had moved from the city center to the fringe or peripheral areas and exhibits fragmented urban growth in those places. But while in 2016 the reduced number of patches indicates that the merging of patches and form into a single compact patch (Fig. 3c). BHP municipality only has experienced an increase in the number of patches over the periods (Table 5).

- Patch density (PD)

PD is an indicator of urban fragmentation (Ramachandra et al. 2014a, b). Patch density increases as the number of patches increases. A similar trend showed that in 2001 the fragmentation of built-up patches was increased and reduced in 2016. In 2001, the urban patches were gradually increased from the CBD of towns that specifies that the fragmentation of the landscape and it indicates the sprawl in a town. Reducing of patch density indicates that less number of patches because those had combined with the small patches and form a single larger patch unit (Fig. 3d; Table 5). HSM, New BKP and N DM had a higher patch density in 2001. The gradual fragmentation of the urban landscape happened in the BHP municipality over the periods. The completely occupied built-up class with low patch density in the core area, as well as peripheral areas of each ULBs in 2016, indicates the compact urbanization in city centers and the outskirts of sprawl. The Barrackpore sub-divisional all municipalities areas having a sprawling effect.

- Largest patch index (LPI)

LPI equals the area of the largest patch of the corresponding patch type divided by total landscape area, multiplied by 100 (McGarigaland Marks1994). The LPI is widely used as an indicator of landscape fragmentation (Sun et al. 2014; Zhang et al. 2004, 2012). The index has increased year by year. Figure 3e showed that the largest built-up patches were found in BN, DM, BKP, GAR, KMH, KDH, PHT and S DM municipalities in 2001. While in 2016 the maximum value of LPI was in N BKP, New BKP and N DM areas (Table 5; Fig. 3e). This metric helps to identify the growth pole conditions of a town in different years (Ramachandra et al. 2014a, b).

- Edge density (ED)

ED is also an indicator to measure the fragmentation and the spatial heterogeneity of the landscape (Wei and Zongyi 2012). In the study area during 1972–2001, the value of edge density was higher among the all ULBs that compute the level of fragmentation in built-up was more and indicates the sprawl. While in 2016 the compact or clumped urban growth had experiences in BKP, GAR, KMH, KDH, PHT, S DM and TGH municipalities with relatively low edge values and dispersed urban growth was found in BHP, HSM, KNP, New BKP, N BKP and N DM areas with relatively higher values (Fig. 3f; Table 5).

- Mean patch size (MPS)

MPS is the sub-division measures in class or landscape metrics. Mean patch size quantifies the sum of the areas of all patches of the corresponding patch type divided by the number of the same type and convert to hectares (McGarigal and Marks 1994, 1995). There is an inverse relationship between MPS of built-up class and degree of fragmentation. The lower value of the index represents the greater fragmentation while the higher value reveals the aggregated growth of the city. Here, in 2001, the value index was very low among the ULBs that indicate the maximum fragmentation in built-up class and sprawling was happening in the period; but in 2016 the high index value reflects the larger patches due to compactness. Presently the ULBs are becoming compact (Fig. 3g; Table 5).

- Area weighted mean shape index (AWMSI)

The weightage is higher in larger patches and lowers in smaller patches. The metric is useful to analyses the structure of the landscape through the spatial scales by calculating the complexity of urban patches based on their size (Huang et al. 2009). The index represents shape irregularities in the patches. The range smaller to higher value indicates regular to the irregular shape with complexity. In 1972, the AWMSI value was low that represents the compactness of CBD areas in every town; while in 2001 as the value increases indicates the fragmentation of built-up land increases over the ULBs. However, in 2016, it is noticeable that some ULBs had lower values than 2001 time period that indicates the compactness was happening due to the growth and development, while some ULBs had increased the value means fragmented the urban landscape and keep continuing the growth of sprawl in these towns; namely, HSM, New BKP and N DM (Fig. 3h; Table 5).

- Landscape shape index (LSI)

LSI measures the complexity of the patches. The value closer to zero represent compact of urban patches and higher value indicates the desegregation of the patches (Table 5). The LSI quantifies with the lower values in all ULBs in 1972 indicates the compactness of the towns, but the value has increased in 2001 indicates the fragmentation of the landscape and desegregation in all municipalities. However, according to this metric, the trend of sprawl has shown at city outskirts along with the centers of the city due to the decline of value in 2016 excluding Bhatpara and Halishahar municipality (Fig. 3i).

- CLUMPY

CLUPMY estimates the aggregation of urban patches. The range of CLUMPY is '− 1 < 0 > 1'. Disaggregation of the patches are denoted by value '− 1', the random distribution of patch is represented by value '0' and '1' indicates the patch distribution is aggregated. In this study, the ULBs were more aggregated in 1972 with value more than about 0.7; whereas the value was decreased (0.4 − 0.65) in 2001 and 2016 that indicates the desegregation or fragmentation of patches at outskirt (Fig. 3j; Table 5).

- Interspersion and juxtaposition index (IJI)

The IJI method calculates the interspersed of patch types. Higher values indicate the urban patch types are maximally interspersed and juxtaposed to each other's (equally adjacent to each other) and lower values approached the patch types are poorly interspersed. The range varies from the index 0–100. The result (Fig. 3k) also carried out that there has been a growth of built-up parches in 2001and 2016 in peripheral areas (Table 5).

- Aggregation index (AI)

This index measures the aggregation of the town. The higher value of AI is maximally aggregated and the lower values equal to the maximal desegregated. Figure 3l depicts the fact that the urban patches were compact or aggregated in nature in 1972, but the fragmentation was occurring in the landscape with lower values and implies the desegregation of urban patches in the ULBs in 2001. And lastly, in 2016, the small fragmented patches in municipalities peripheral were getting merged up and combined with larger patches that indicate compactness or aggregation of the urban landscape. Therefore, the AI value has increased in 2016. Over the periods, every small town and ULBs have tremendously faced urban growth at centers as well as in peripheral or a fringe region (Table 5).

Shannon's entropy for urban sprawl analysis

The area of built-up area in all municipalities of every buffer zone for each temporal image has been calculated by clipping off the classified vector format. This index is widely used because it can identify both urban sprawl and growth. The results of the Shannon entropy index are presented in table and figure, respectively. The continuously increasing trend with time has been noticed in built-up land at each small ULB (Figs. 4 and 5; Table 6). The elaboration and illustration have been discussed by four groups of ULBs.

- KNP, HSM, NHT and BHP

The results of entropy models in KNP, HSM, NHT and BHP cities reveal that the NW direction was faced with the more urban landscape in KNP town. The log (n) was
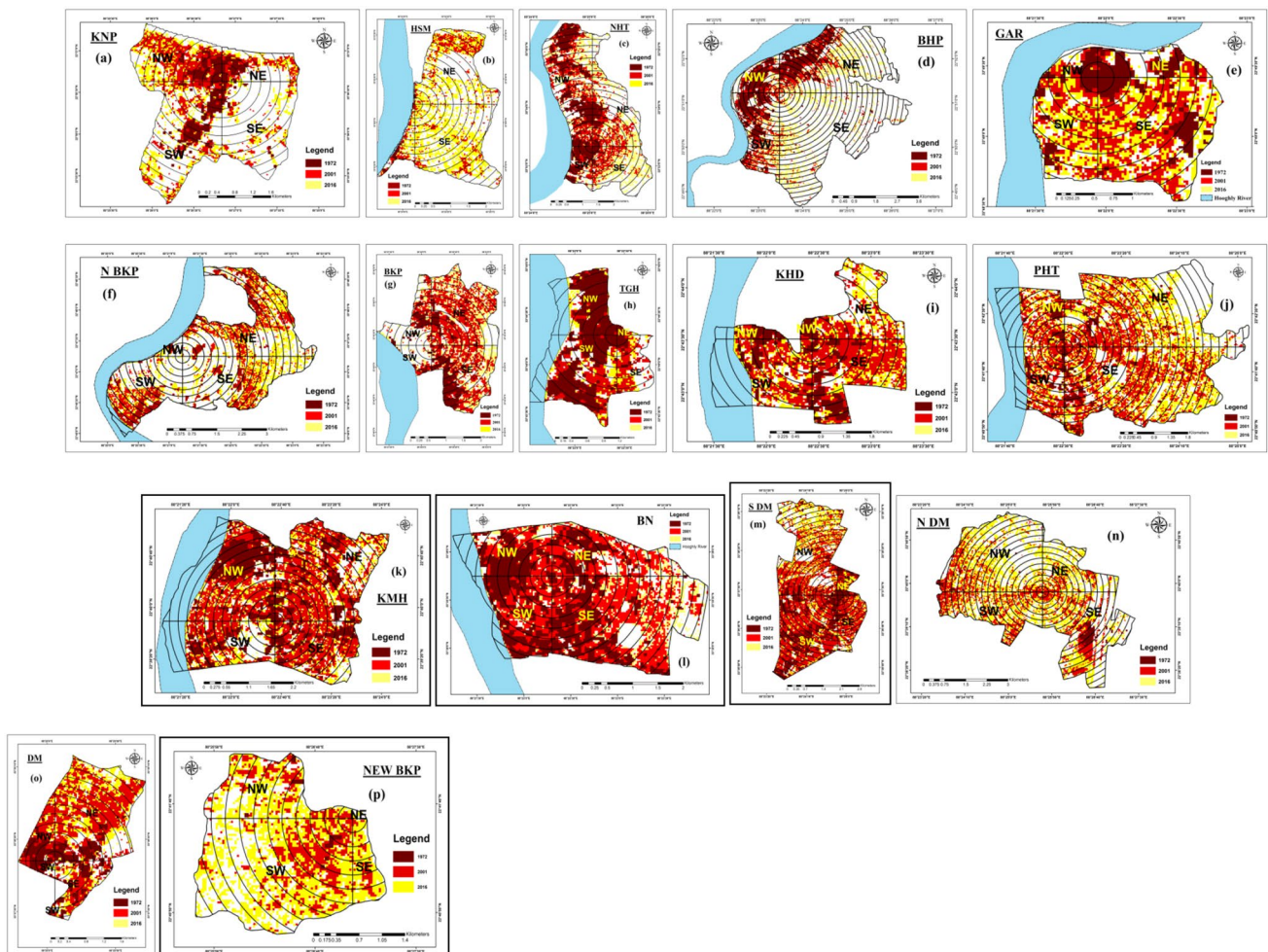

Fig. 4 Zone wise built-up land in 1972, 2001, and 2016 at ULBs: **a** KNP, **b** HSM, **c** NHT, **d** BHP, **e** GAR, **f** N BKP, **g** BKP, **h** TGH, **i** KDH **j** PHT, **k** KMH, **l** BN, **m** S DM, **n** N DM, **o** DM, **p** NEW BKP
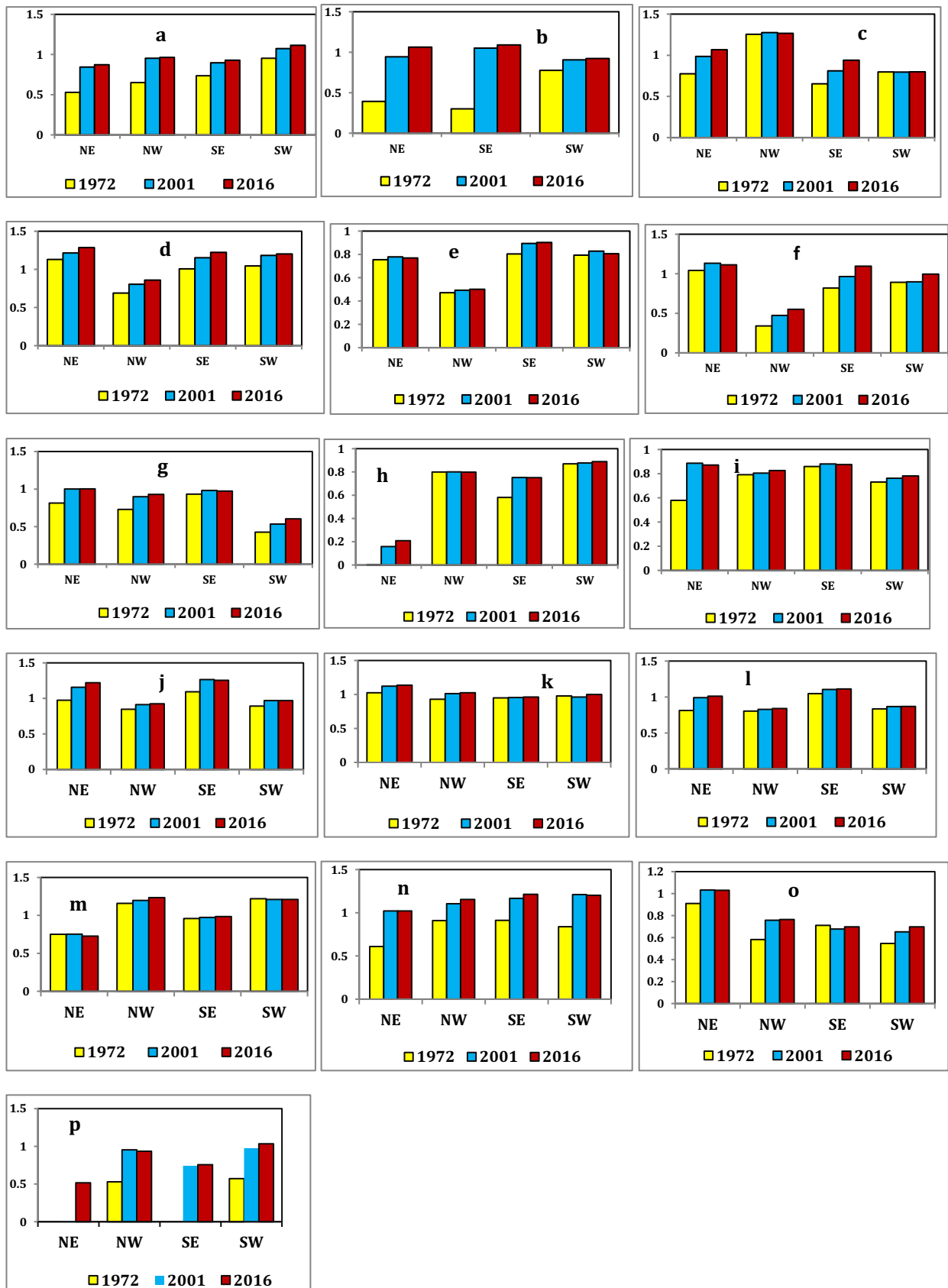
Fig. 5 Zone wise Shannon's Entropy index in 1972, 2001 and 2016 at ULBs: **a** KNP, **b** HSM, **c** NHT, **d** BHP, **e** GAR, **f** N BKP, **g** BKP, **h** TGH, **i** KDH, **j** PHT, **k** KMH, **l** BN, **m** SDM, **n** N DM, **o** DM, **p** NEW BKP

Table 6 Results of the Shannon entropy in ULBs

Year	NE		NW		SE		SW	
	Entropy	Relative entropy	Entropy	Relative entropy	Entropy	Relative entropy	Entropy	Relative entropy
a. KNP								
1972	0.53	0.55	0.65	0.65	0.74	0.68	0.95	0.81
2001	0.84	0.88	0.95	0.95	0.90	0.83	1.07	0.91
2016	0.87	0.91	0.96	0.96	0.93	0.86	1.11	0.95
Log(n)	0.95		1.00		1.08		1.18	
b. HSM								
1972	0.39	0.34	0.00	0.00	0.30	0.25	0.78	0.72
2001	0.94	0.82	0.00	0.00	1.05	0.87	0.91	0.84
2016	1.06	0.93	0.00		1.09	0.91	0.92	0.86
Log(n)	1.15		0.00		1.20		1.08	
c. NHT								
1972	0.78	0.61	1.25	0.96	0.65	0.63	0.80	0.94
2001	0.99	0.77	1.28	0.98	0.81	0.78	0.80	0.94
2016	1.07	0.84	1.27	0.97	0.94	0.90	0.80	0.95
Log(n)	1.28		1.30		1.04		0.85	
d. BHP								
1972	1.13	0.82	0.69	0.69	1.01	0.79	1.05	0.82
2001	1.22	0.88	0.80	0.80	1.15	0.90	1.18	0.93
2016	1.29	0.93	0.86	0.86	1.22	0.96	1.20	0.94
Log(n)	1.38		1.00		1.28		1.28	
e. GAR								
1972	0.75	0.89	0.47	0.78	0.80	0.80	0.79	0.88
2001	0.78	0.92	0.49	0.82	0.89	0.89	0.83	0.92
2016	0.77	0.91	0.50	0.83	0.90	0.90	0.81	0.89
Log(n)	0.85		0.60		1.00		0.90	
f. N BKP								
1972	1.04	0.82	0.34	0.57	0.82	0.64	0.89	0.76
2001	1.13	0.89	0.47	0.79	0.97	0.75	0.90	0.76
2016	1.11	0.87	0.55	0.91	1.10	0.86	1.00	0.85
Log(n)	1.28		0.60		1.28		1.18	
g. BKP								
1972	0.81	0.73	0.73	0.70	0.93	0.86	0.43	0.43
2001	1.00	0.90	0.90	0.86	0.98	0.91	0.53	0.53
2016	1.00	0.90	0.93	0.89	0.97	0.90	0.60	0.60
Log(n)	1.11		1.04		1.08		1.00	
h. TGH								
1972	0.00	0.00	0.80	0.88	0.58	0.75	0.87	0.87
2001	0.16	0.53	0.80	0.89	0.75	0.97	0.88	0.88
2016	0.21	0.69	0.80	0.88	0.75	0.96	0.89	0.89
Log(n)	0.30		0.90		0.77		1	
i. KDH								
1972	0.58	0.61	0.79	0.88	0.86	0.90	0.73	0.73
2001	0.89	0.93	0.80	0.89	0.88	0.92	0.76	0.76
2016	0.87	0.91	0.83	0.91	0.88	0.92	0.78	0.78
Log(n)	0.95		0.90		0.95		1.00	
j. PHT								
1972	0.98	0.72	0.85	0.79	1.09	0.80	0.89	0.86
2001	1.16	0.85	0.91	0.85	1.27	0.93	0.97	0.93

Table 6 (continued)

Year	NE		NW		SE		SW	
	Entropy	Relative entropy	Entropy	Relative entropy	Entropy	Relative entropy	Entropy	Relative entropy
2016	1.22	0.90	0.92	0.86	1.26	0.92	0.97	0.93
Log(*n*)	1.36		1.08		1.36		1.04	
k. KMH								
1972	1.02	0.83	0.93	0.81	0.95	0.91	0.98	0.88
2001	1.12	0.91	1.01	0.88	0.95	0.92	0.96	0.86
2016	1.14	0.92	1.03	0.89	0.96	0.92	1.00	0.90
Log(*n*)	1.23		1.15		1.04		1.11	
l. BN								
1972	0.81	0.73	0.80	0.80	1.05	0.89	0.83	0.87
2001	0.99	0.89	0.83	0.83	1.10	0.94	0.87	0.91
2016	1.01	0.91	0.84	0.84	1.11	0.94	0.87	0.91
Log(n)	1.11		1.00		1.18		0.95	
m. S DM								
1972	0.75	0.97	1.16	0.89	0.96	0.89	1.22	0.94
2001	0.75	0.97	1.20	0.92	0.97	0.90	1.21	0.93
2016	0.73	0.93	1.23	0.95	0.98	0.91	1.21	0.93
Log(*n*)	0.78		1.30		1.08		1.30	
n. N DM								
1972	0.61	0.55	0.91	0.72	0.91	0.70	0.84	0.67
2001	1.02	0.92	1.10	0.88	1.17	0.90	1.21	0.96
2016	1.02	0.92	1.15	0.92	1.21	0.93	1.20	0.96
Log(*n*)	1.11		1.26		1.30		1.26	
o. DM								
1972	0.91	0.82	0.58	0.64	0.71	0.84	0.55	0.70
2001	1.03	0.93	0.76	0.84	0.68	0.80	0.65	0.84
2016	1.03	0.93	0.76	0.85	0.70	0.83	0.70	0.90
Log(*n*)	1.11		0.90		0.85		0.78	
p. New BKP								
1972	0.00	0.00	0.53	0.51	0.00	0.00	0.57	0.50
2001	0.01	0.01	0.95	0.92	0.74	0.88	0.97	0.85
2016	0.52	0.52	0.93	0.90	0.76	0.89	1.03	0.90
Log(*n*)	0		1.04		0.85		1.15	

0.95, 1.0, 1.08 and 1.18 in NE, NW, SE and SW Zone. All entropy values were above the half of the threshold level that indicates sprawl happens over the region. The growth rate of sprawl was from 1972 to 2001 by 59% in NE, 46% in NW, 21% in SE and 12% in SW while during 2001–2016 the growth rate has decreased sharply (Figs. 4a and 5a; Table 6a). The scenario of urban sprawl was rapid in the HSM town. The urban sprawl is noticed in the NE and SE zones. In 1972, the entropy value was below the threshold level in the NE and SE zone due to compact urban land patches; whereas the 140% and 249% growth in entropy in these zones from 2001 to 2016 (Figs. 4b and 5b; Table 6b).

The NHT is becoming a compact town in terms of built-up land. The NE zone and SE zone are kept continues (dispersed) to grow the settlement. However, in the NW and SW zone are aggregated. In 2016, the entropy value reveals that the NW zone had negative growth entropy growth and the SW zone had negative growth in 2001 and very slow growth in 2016 (Fig. 4c and 5c; Table 6c). BHP is one of the Towns which have a settlement patch growth constantly. All zones over the temporal years had an entropy range above the threshold mark. The log (*n*) for four zones were 1.38 (NE), 1.0 (NW), 1.28 (SE) and 1.28 (SW) (Figs. 4d and 5d; Table 6d).

- GAR, N BKP, BKP and TGH

The southern part was affected by urban sprawling in GAR urban centre. Due to the small size of the town maximum extension was happens during 1972–2001. In the NE zone, the entropy values were 0.75, 0.78 and 0.77 for the year of 1972, 2001 and 2016. NW and SW zone was more compact due to the spatial limitation in the western side along with River side. Lastly, in the SE zone had an entropy value with a growth rate of 4.35% in, between 1972 and 2001 and decreased from 2001 to 2016 with, 2.6%. Decreased of entropy values indicate the compact or aggregation of urban land use growth over the spatial unit (Figs. 4e and 5e; Table 6e). The central part of the N BKP municipality is covered by the Air force basement area. Hence, the NE, SE and lower part of the SW zone are residential prone and it's constantly growing. Table 6f shows that during 2001–2016 the NE zone became compact where SE and SW zone are dominantly sprawling areas (Figs. 4f and 5f). The BKP town is situated in the central part of the study area. Here, the town has urban sprawling effects on the eastern side. Due to the dense conditions of the eastern side, now the western side is starting to grow built-up land. The result of entropy revealed that all sectors were above the halfway of log (n) threshold level (Table 6g). The Sharpe decline of the growth rate of entropy explained the aggregation of the urban landscape (Figs. 4g and 5g). The TGH urban centre is full of industries and dense settlement. However, urban sprawling is less over the period because of this the town is in less spatial size. Only on the eastern side has to spread in built-up classes. The entropy value indicates the growth was negative in the NW and SE zone during 2001–2016 (Figs. 4h and 5h; Table 6h).

- KDH, PHT, KMH and BN

The urban sprawl index for these four ULBs showed that the KDH town has grown on the western side. All zone had an entropy value more than the threshold level. During 1972–2001, the growth rate of entropy was 52.06%, 1.67%, 2.41% and 4.29% for NE, NW, SE and SW zone due to dispersions of urban patches. Although it became compact or aggregated due to the decline in the growth rate of entropy during 2001–2016 (Figs. 4i and 5i; Table 6i). The spatial area is larger in the PHT municipality. So the settlement had settled in the peripheral areas of the town over the periods and made this area full of settlement. The result of sprawl measurement evaluated that in the NE zone the value was 0.98, 1.16 and 1.22 {log (n) = 1.36} in 1972, 2001 and 2016; 0.85, 0.91 and 0.92 {log (n) = 1.08} in NW zone; 1.09, 1.27

and 1.26 {log (n) = 1.36} in SE zone; 0.89, 0.97 and 0.97 {log (n) = 1.04} in SW zone of the town (Figs. 4j and 5j; Table 6j). The KMH industrial area has been quite compact since 1972. But still, the town is facing urbanization. The sprawl rate was higher in every zone during 1972–2001 that indicates the dispersion or fragmentation of landscape-level in the town. But the rate of growth of entropy was less during 2001–2016 which specifies the near to aggregation or compact growth (Figs. 4k and 5k; Table 6k). Baranagar town (BN) is a highly populated and dense area. The increasing trend of urban sprawl has observed during 1972–2001 through increases in the entropy value. The decadal growth rate of entropy during 1972–2001 was 22.01%, 2.93%, 5.57% and 3.90% in NE, NW, SE and SW zone. While it has decreased its value to 2.1%, 1.4%, 0.5% and 0.27% in the respective zone between the years of 2001–2016 (Figs. 4l and 5l; Table 6l).

- S DM, N DM, DM and New BKP

These four ULBs are much more compact in the present. The spatial urban sprawl index for these towns revealed that there was a growth of built-up land during the concerning time in SDM town. The entropy value illustrated an increase in entropy from 1972 to 2001 at all zones. It has changed during 2001–2016 and declines the values that quantify the combined small built-up patches into a big urban patch. The character of the city now becomes compact (Figs. 4m and 5m; Table 6m). The N DM town had experienced a higher sprawl impact. A significant increase in entropy is observed in four zones during 1972–2001 to 67.4%, 21.4%, 27.7% and 44.4% rate of growth. It is noticeable that concerning the next entropy values have declined and converted to compact municipal land (Figs. 4n and 5n; Table 6n). The Dumdum municipality is also a very denser built-up area. The zone-wise entropy values exhibited that the entropy value has increased from 0.91 to 1.03 in between 1972 and 2001; and has decreased the next period in the NE zone. The result of dispersion has noticed in the first period. The reasons to decline the entropy due to built-up fill in every corner of the town (Figs. 4o and 5o; Table 6o). The N BKP urban centre has recently built the town and due to overflow population pressure from the adjacent municipality, it has experienced the rapid growth of settlement and built-up land. In 1972, every zone had less built-up land. As time goes up, the built-up land grew up in this town. The entropy value showed that the sprawl happens during 1972–2001 and in 2016 it would become a compact settlement area due to the agglomeration process (Figs. 4p and 5p; Table 6p).

Conclusion

The present research emphasized on town level studied to measure the urban growth dynamics. It considered the municipal administrative boundaries of the Barrackpore sub-division to study the LULCC phenomenon and examine the degree of urbanization at the micro-scale. Moreover, these small towns have data on socioeconomic variables. The urban union contains the diversity of land use characteristics include green vegetation, water surfaces and open space as well. In this study, the dynamics of urban expansion of 16 municipalities have been studied for the period between 1972–2001 and 2001–2016 using landscape metrics and Shannon's entropy index incorporated with remotely sensed data and GIS techniques. The key findings show that the degree and scale of the built-up area have increased expressively over time; where, the vegetation land, Agricultural land and water bodies have significantly declined, which foremost, put a negative impact on the environment in terms of ecology, net productivity and changes of urban micro-climate (Das and Angadi 2020). The presentation of selected metrics was verified for the municipalities and discussed relatively. Different municipalities had different urban growth characters due to their heterogeneity activities. Industrial economy-based towns are dense since the first period. The results of CA indicate that the built-up area is increasing in all ULBs with time. The PLAND analysis demonstrated a similar trend. The outcome of NP and PD analysis illustrated that the urban landscape fragmentation and sprawling during 1972–2001 but declining the number indicates the compactness of the city during 2001–2016. LPI measurement signifies the rate of fragmentation. From 1972 to 2001, most of the municipality had increased the value of LPI excluding BHP, HSM, NEW BKP, N BKP and N Dm, etc.; while LPI was maximum in these ULBs during 2001–2016. ED analysis demonstrated that the sprawling character of the municipalities. MPS and AWMSI indicate the same trend of measurement. Lastly, the four aggregation metrics were applied to analyze municipal aggregation and desegregation in municipalities. All the metrics were performed well. Among the 16 ULBs, particularly, Halishahar, Bhatpara, New Barrackpore, North Dumdum municipality continues to sprawl in the respective landscape. The result of landscape metrics in different ULBs showed that sprawl has happened during the 1972–2001 periods and later these small municipalities had become compact due to more demand for land and population pressures. The small urban class patches at the peripheral zone combined with a single larger patch concerning time. The Shannon's entropy was applied for urban sprawling measurement for ULBs individually with four directions of zones. The result of entropy illustrated that direction and zone wise sprawl of urban land. Mostly eastward direction of towns has a probability to increase in the future while the western side is congested and compact. The index value has provided visualization and quantifying the expanding urban footprint in the study area. Hence, the findings of the study would help to take management and planning for the environmental aspects of the towns. The government needs to do supervision in sustainable planning for the municipalities with good physical shape and sustenance of natural resources. As the current study highlighted that the loss of vegetation, agricultural land and water bodies happened in all small towns so that there would be important to take an integrated approach to protect the natural resources and to ensure the well being of people's livelihood.

Compliance with ethical standards

Conflict of interest It is a declaration that there are no conflicts of interest with respect to the research, authorship and /or publication of this article.

References

Al-sharif AA, Pradhan B (2014) Monitoring and predicting land use change in Tripoli metropolitan City using an integrated Markov Chain and cellular automata models in GIS. Arab J Geosci 7:4291–4301. https://doi.org/10.1007/s12517-013-1119-7

Akin A, Erdogan MA (2020) Analysing temporal and spatial urban sprawl change of Bursa city using landscape metrics and remote sensing. Model Earth Syst Environ. https://doi.org/10.1007/s40808-020-00766-1

Al-Kharabsheh A, Ta'any R (2003) Influence of urbanization on water quality deterioration during drought periods at South Jordan. J Arid Environ 53:619–630. https://doi.org/10.1006/jare.2002.1055

Anderson J, Hardy EE, Roach JT, Witmer RE (1976) A land use and land cover classification system for use with remote sensor data. United States Government Printing Office, Washington

Ao Y, Li X (1998) Sustainable land development model for rapid growth areas using GIS. Int J Geogr Inf Sci 12(2):169–189. https://doi.org/10.1080/136588198241941

Atu JE, Ayama OR, Eja EI (2013) Urban SPrawl effects on biodiversity in peripheral agricultural lands in Calabar, Nigeria. J Environ Earth Sci 3(7):219–231

Batty M, Morphet R, Masucci P (2014) Entropy, complexity, and spatial information. J Geogr Syst 16:363–385. https://doi.org/10.1007/s10109-014-0202-2

Belal A, Moghanm F (2011) Detection urban growth using remote sensing and GIS techniques in Al Gharbiya governorate, Egypt. Egypt J Remote Sens Space Sci 14:73–79. https://doi.org/10.1016/j.ejrs.2011.09.001

Bento AM, Cropper M, Mobarak AM, Vinha K (2003) The impact of urban spatial structure on travel demand in the United States. In: Policy, research working paper series; no. WPS 3007.

Washington, DC: The World Bank, Development Research Group.

Bhagat R, Mohanty S (2009) Emerging pattern of urbanization and the contribution of migration in urban growth in India. Asian Popul Stud 5(1):5–20. https://doi.org/10.1080/17441730902790024

Bharath S, Bharath AH, Sanna D, Ramachandra T (2012) Landscape dynamics through metrics. In: 14th annual international conference and exhibition on geospatial information technology and application.

Bhatta B, Giri B (2012) Urban growth of Kolkata from 1980 to 2014: a remote sensing perspective. In: UGC Sponsored State Level Seminar.

Bose A, Roy Chowdhury I (2020) Monitoring and modeling of spatio-temporal urban expansion and land-use/land-cover using Markov chain model: a case study in Siliguri Metropolitan area, West Bengal, India. Model Earth Syst Environ. https://doi.org/10.1007/s40808-020-00842-6

Burchel RW, Downs A, Seskin S, Moore T (1998) The costs of sprawl-revisited. National Academy Press, Washington

Carruthers JI, Ulfarsson GF (2003) Urban sprawl and the cost of public service. Environ Plan B Plan Des 30(4):503–522. https://doi.org/10.1068/b12847

Census of India (2011) District Census hand book—North 24-Parganas District, West Bengal. Census of India, New Delhi

Chaudhuri G, Clarke KC (2019) Modeling an Indian megalopolis- a case study on adapting SLEUTH urban growth model. Comput Environ Urban Syst 77:1–15

Clarke KC, Hoppen S (1997) A self-modifying cellular automaton model of historical urbanization in the san Francisco Bay area. Environ Plan B Plan Des 24:247–261

Clarke KC, Hoppen S, Gaydos LJ (1996). Methods and techniques for rigorous calibration of a cellular automation model of urban growth. In: Third International conference/workshop on integrating GIS and environmental modeling. Santa Fe, New Mexico

Congalton R (1991) A review of assessing the accuracy of classification of remotely sensed data. Remote Sens Environ 37(1):35–46. https://doi.org/10.1016/0034-4257(91)90048-B

Congalton R, Green K (1999) Assessing the accuracy of remote sensed data: principles and practices. CRC Press, Boca Raton

Das Chatterjee N, Chatterjee S, Khan A (2016) Spatial modeling of urban sprawl around Greater Bhubaneswar city, India. Model Earth Syst Environ 2(14):2–21. https://doi.org/10.1007/s40808-015-0065-7

Das S, Angadi DP (2020) Land use-land cover (LULC) transformation and its relation with land surface temperature changes: a case study of Barrackpore Subdivision, West Bengal, India. Remote Sens Appl Soc Environ 19:1–28. https://doi.org/10.1016/j.rsase.2020.100322

Deng J, Wang K, Deng Y, Qi G (2008) PCA-based land use change detection and analysis using multi-temporal and multi-sensor satellite data. Int J Remote Sens 29(16):4823–4838. https://doi.org/10.1080/01431160801950162

Dewan AM, Yamaguchi Y (2009) Land use and land cover change in Greater Dhaka, Bangladesh: using remote sensing to promote sustainable urbanization. Appl Geogr 29:390–401. https://doi.org/10.1016/j.apgeog.2008.2.005

Dewan A, Yamaguchi Y, Rahman M (2012) Dynamics of land use/cover changes and the analysis of landscape fragmentation in Dhaka Metropolitan, Bangladesh. GeoJournal 77(3):315–330. https://doi.org/10.1007/s10708-010-9399-x

Donnay JP, Barnsley MJ, Longly P (2001) Remote sensing and urban analysis. Taylor and Francis, London, pp 228–239

Dunn C, Sharpe D, Guntensbergen G, Stearns F, Yang Z (1991) Methods for analyzing temporal changes in landscape pattern. In: Turner M, Gardner R (eds) Quantitative methods in landscape ecology. Springer, Berlin, pp 173–198

Ewing R (1997) Is Los Angeles-style sprawl desirable. J Am Plan Assoc 63(1):107–126. https://doi.org/10.1080/01944369708975728

Ewing R, Pendall R, Chen D (2002) Measuring sprawl and its impact. Smart Growth America, Washington. https://smartgrowthamerica.org/app/legacy/documents/MeasuringSprawlTechnical.pdf. Accessed 18 Feb 2020

Falah N, Karimi A, Harandi AT (2019) Urban growth modeling using cellular automata model and AHP (case study: Qazvin city). Model Earth Syst Environ 6:235–248. https://doi.org/10.1007/s40808-019-00674-z

Foody G (2002) Status of land cover classification accuracy assessment. Remote Sens Environ 80:185–201

Foody G (2004) Thematic map comparison: evaluating the statistical significance of difference in classification accuracy. Photogramm Eng Remote Sens 70:627–633

Forman R, Godron M (1986) Landscape ecology. John Wiley & Sons, New York, p 619

Frohn R, McGWIRE K, Dale V, Estes J (1996) Using satellite remote sensing analysis to evaluate a socio-economic and ecological model of deforestation. Int J Remote Sens 17(16):3233–3255. https://doi.org/10.1080/01431169608949141

Galster G, Ratcliffe M, Hanson R, Wolman H, Coleman S, Freihage J (2001) Wrestling sprawl to the ground: defining and measuring an elusive concept. Hous Policy Debate 12(4):681–717. https://doi.org/10.1080/10511482.2001.9521426

Gardner R, O'Neill R, Turner M (1993) Ecological implications of landscape fragmentation. In: Pickett S, McDonnell M (eds) Humans as components of ecosystems. Springer, New York, pp 208–226

Girma Y, Terefe H, Pauleit S, Kindu M (2019) Urban green spaces supply in rapidly urbanizing countries: the case of Sebeta Toen, Ethiopia. Remote Sens Appl Soc Environ 13:138–149. https://doi.org/10.1016/j.rsase.2018.10.019

Hafez AA (2011) Evaluation of change detection techniques for monitoring land-cover changes: a case study in New Burg El-Arab area. Alex Eng J 50(2):187–195. https://doi.org/10.1016/j.aej.2011.06.001

Hassan MM (2017) Monitoring land use/land cover change, urban growth dynamics and landscape pattern analysis in five fastest urbanized cities in Bangladesh. Remote Sens Appl Soc Environ 7:1–35. https://doi.org/10.1016/j.rsase.2017.07.001

Hassan Z, Shabbir R, Ahmad SS, Malik AH, Aziz N, Butt A (2016) Dynamics of land use and land cover change using geospatial techniques: a case study of Islamabad Pakistan. SpringerPlus 5(812):1–11. https://doi.org/10.1186/s40064-016-2414-z

Hasse JE, Lathrop RG (2003) Land resource impact indicators of urban sprawl. Appl Geogr 23:159–175. https://doi.org/10.1016/j.apgeog.2003.08.002

HathoutS, (2002) The Use of GIS for monitoring and predicting urban growth in east and west St Paul Winnipeg, Manitoba, Canada. J Environ Manag 66:229–238

Herold M, Scepan J, Clarke K (2002) The use of remote sensing and landscape metrics to describe structures and changes in urban land uses. Environ Plan A 34:1443–1458. https://doi.org/10.1068/a3496

Huang SL, Wang SH, Budd WW (2009) Sprawl in Taipei's peri-urban zone: responses to spatial planning and implications for adapting global environmental change. Landsc Urban Plan 90(1):20–32. https://doi.org/10.1016/j.landurbplan.2008.10.010

Hu Z, Lo CP (2007) Modeling urban growth in Atlanta using logistic regression. Comput Environ Urban Syst 31:667–688

Ismael HM (2020) Urban form study: the sprawling city—review of methods of studying urban sprawl. GeoJournal. https://doi.org/10.1007/s10708-020-10157-9

Jaeger JA, Bertiller R, Schwick C, Kienast F (2010) Suitability criteria for measures of urban sprawl. Ecol Ind 10:397–406. https://doi.org/10.1016/j.ecolind.2009.007

Jat MK, Garg P, Khare D (2008) Monitoring and modeling of urban sprawl using remote sensing and GIS techniques. Int J Appl Earth Obs Geoinf 10:26–43. https://doi.org/10.1016/j.jag.2007.04.002

Jensen J, Jungho I (2007) Remote sensing change detection in urban environments. In: Jensen RR, Gartrell JD, McLean D (eds) Geospatial technologies in urban environments. Springer, Berlin, pp 7–31. https://doi.org/10.1007/978-3-540-69417-5_2

Karolien V, Anton VR, Maarten L, Eria S, Paul M (2012) Urban Growth of Kampala, Uganda: pattern analysis and scenario development. Landsc Urban Plan 106:199–206

Kim C (2016) Land use classification and land use change analysis using satellite images in Lombok Island, Indonesia. For Sci Technol 12(4):183–191. https://doi.org/10.1080/21580103.2016.1147498

Kumar J, Pathan S, Bhandari R (2007) Spatio-temporal analysis for monitoring urban growth: a case study of Indore city. J Indian Soc Remote Sens 35:11–20. https://doi.org/10.1007/BF02991829

Lillesand T, Keifer R (1987) Remote sensing and image interpretation. John Willey and Sons, New York

Liping C, Yujun S, Saeed S (2018) Monitoring and predicting land use and land cover changes using remote sensing and GIS techniques—a case study of a hilly area, Jiangle, China. PLoS ONE 13(7):1–23. https://doi.org/10.1371/journal.pone.0200493

Liu Y, Phinn SR (2001) Developing a cellular automaton model of urban growth incorporating fuzzy set approaches. Comput Environ Urban Syst 27:637–658

Li X, Yeh A (2004) Analyzing spatial restructuring of land use patterns in a fast-growing region using remote sensing and GIS. Landsc Urban Plan 69(4):335–354. https://doi.org/10.1016/j.landurbplan.2003.10.033

Li M, Zang S, Zhang B, Li S, Wu C (2014) A review of remote sensing image classification techniques: the role of spatio-contextual information. Eur J Remote Sens 47(1):389–411. https://doi.org/10.5721/EuJRS20144723

Li X, Liu X, Yu L (2014) A systematic sensitivity analysis of constrained cellular automata model for urban growth simulation based on different transition rules. Int J Geogr Inf Sci 28(7):1317–1335. https://doi.org/10.1080/13658816.2014.883079

Lu D, Weng Q (2005) Urban classification using full spectral information of Landsat ETM+ imagery in Marion Country, Indiana. Photogramm Eng Remote Sens 71(11):1275–1284

Malpezzi S (1999) Estimates of the measurement and determinants of urban sprawl in US metropolitan areas. University of Wisconsin Centre for Urban Land Economics Research, Madison

Manandhar R, Odeh IO, Ancev T (2009) Improving the accuracy of land use and land cover classification of landsat data using pst-classification enhancement. Remote Sens 1:330–344

Mas JF, Rodriguez R, Gonzalez-Lopez R, Lopez-Sanchez J, Pina-Garduno A, Herrera-Flores E (2017) Land use/land cover change detection combining automatic processing and visual interpretation. Eur J Remote Sens 50(1):626–635. https://doi.org/10.1080/22797254.1387505

McGarigal K, Marks B (1994) Fragstats-spatial pattern analysis program for quantifying landscape structure. Oregon State University, Corvallis

McGarigal K, Marks B (1995) FRAGSTATS: spatial pattern analysis program for quantifying landscape structure. USDA Forest Service General Technical Report PNW-351.

McKinney ML (2002) Urbanization, biodiversity and conservation the impacts of urbanization on native species are poorly studied, but educating a highly urbanized human population about these impacts can greatly improve species conservation in all ecosystems. Biosciences 52(10):883–890. https://doi.org/10.1641/0006-3568(2002)052[0883:UBAC]2.0.CO;2

Miller JD, Hutchins M (2017) The impacts of urbanization and climate change on urban flooding and urban water quality: a review of the evidence concerning the United Kingdom. J Hydrol Reg Stud 12:345–362. https://doi.org/10.1016/j.ejrh.2017.06.006

Mithun S, Chattopadhyay S, Bhatta B (2016) Analyzing urban dynamics of metropolitan kolkata, india by using landscape metrics. Pap Appl Geogr 2(3):1–14. https://doi.org/10.1080/23754931.2016.1148069

Mohammady S, Delavar MR (2016) Urban sprawl assessment and modeling using Landsat images and GIS. Model Earth Syst Environ 2(155):1–14. https://doi.org/10.1007/s40808-016-0209-4

Mondal B, Das DN, Dolui G (2015) Modeling spatial variation of explanatory factors of urban expansion of Kolkata: a geographically weighted regression approach. Model Earth Syst Environ 1:1–13. https://doi.org/10.1007/s40808-015-0026-1

Mondal M, Sharma N, Kappas M, Garg P (2015) Critical assessment of land use land cover dynamics using multi-temporal satellite images. Environments 2:61–90. https://doi.org/10.3390/environments2010061

Mondal B, Nath D, Bhatta B (2016) Integrating cellular automata and Markov techniques to generate urban development potential surface: a study on Kolkata agglomeration. Geocarto Int 32(4):401–419. https://doi.org/10.1080/10106049.2016.1155656

Mosamman HM, Nia TJ, Khani H, Teymouri A, Kazemi M (2017) Monitoring land use change and measuring urban sprawl based on its spatial forms. The case of Qom city. Egypt J Remote Sens Space Sci 20:103–116. https://doi.org/10.1016/j.ejrs.2016.08.002

Nechyba TJ, Walsh RP (2004) Urban sprawl. J Econ Perspect 18(4):177–200

O'Neill R, Ritters K, Wickham J, Bruce Jones K (1999) Landscape pattern metrics and regional assessment. Ecosyst Health 5(4):225–233

Parker D, Manson S, Janssen M, Hoffmann M, Deadman P (2008) Multi-agent systems for the simulation of land use and land cover change: a review. Ann Assoc Am Geogr 93(2):314–337. https://doi.org/10.1111/1467-8306.9302004

Pathan S, Jothimani P (1989) Mapping and identification of land cover feature around Madras metropolitan area from IRS-1A. Landsat TM and SPOT MLA/PLA data NNRMS bulletin, Bangalore

Pathan S, Sampat K, Rao M (1993) Urban of growth trend analysis using GIS technique—a case study of Bombay Metropolitan region. Int J Remote Sens 14(17):3169–3179. https://doi.org/10.1080/01431169308904431

Patra S, Sahoo S, Mishra P, Mahapatra SC (2018) Impacts of urbanization on land use/cover changes and its probable implications on local climate and groundwater level. J Urban Manag 7(2):70–84. https://doi.org/10.1016/j.jum.2018.04.006

Pereira P, Monkevicius A, Siarova H (2014) Public perception of environmental, social and economic impacts of urban sprawl in Vilnius. Soc Stud 6(2):259–290

Pijanowski BC, Pithadia S, Shellito BA, Alexandridis K (2005) Calibrating a neural network-based urban change model for two metropolitan areas of the Upper Midwest of the United States. Int J Geogr Inf Sci 19(2):197–215. https://doi.org/10.1080/13658810410001713416

Poyil RP, Misra AK (2015) Urban agglomeration impact analysis using remote sensing and GIS techniques in Malegaon City, India. Int J Sustain Built Environ. https://doi.org/10.1016/j.ijsbe.2015.02.006

Rahaman M, Dutta S, Sahana M, Das DN (2018) Analyzing urban sprawl and spatial expansion of Kolkata urban agglomeration using geospatial approach. In: Rani M, Chandra Pandey P, Sajjad H, Chaudhury B, Kumar P (eds) Applications and challenges of

geospatial technology. Springer, Switzerland, pp 205–221. https://doi.org/10.1007/978-3-319-99882-4_12

Ramachandra T, Uttman K (2008) Wetlands of Greater Bangalore, India: automatic delineation through pattern classifiers. Electron Green J 5:545. https://doi.org/10.5070/G312610729

Ramachandra T, Aithal BH, Sanna D (2012) Insight to urban dynamics through landscape spatial pattern analysis. Int J Appl Earth Obs Geoinf 18:329–343. https://doi.org/10.1016/j.jag.2012.03.005

Ramachandra T, Aithal BH, Sowmyashree M (2014) Urban structure in Kolkata: metrics and modeling through geo-informatics. Appl Geomat 6:1–16. https://doi.org/10.1007/s12518-014-0135-y

Ramachandra T, Bharath A, Sowmyashree M (2014) Monitoring urbanization and its implications in a megacity from space: spatiotemporal pattern and its indicators. J Environ Manag 148:67–81. https://doi.org/10.1016/j.jenvman.2014.02.2015

Rawat J, Kumar M (2015) Monitoring land use/cover change using remote sensing and GIS techniques: a case study of Hawalbagh block, district Almora, Uttarakhand, India. Egypt J Remote Sens Space Sci 18:77–84. https://doi.org/10.1016/j.ejrs.2015.02.002

Resnik DB (2010) Urban sprawl, smart growth, and deliberative democracy. Am J Public Health 100(10):1852–1856. https://doi.org/10.2105/AJPH.2009.182501

Sahana M, Hong H, Sajjad H (2018) Analyzing urban spatial patterns and trend of urban growth using urban sprawl matrix: a study on Kolkata urban agglomeration, India. Sci Total Environ. https://doi.org/10.1016/j.scitotenv.2018.02.170

Sarkar A, Chouhan P (2020) Modeling spatial determinants of urban expansion od Siliguri a metropolitan city of India using logistic regression. Model Earth Syst Environ 5:545. https://doi.org/10.1007/s40808-020-00815-9

Sarvestani MS, Ibrahim A, Kanaroglou P (2011) Three decades of urban growth in the city of Shiraz, Iran: a remote sensing and geographic information systems application. Cities 28(4):320–329. https://doi.org/10.1016/j.cities.2011.03.002

Shannon CE (1948) A mathematical theory of communication. Bell Syst Tech J 27(3):379–423. https://doi.org/10.1002/j.1538-7305.1948.tb01338.x

Shaw A, Satish M (2007) Metropolitan restructuring in post-liberalized India: separating the global and the local. Cities 24(2):148–163. https://doi.org/10.1016/j.cities.2006.02.001

Shukla A, Jain K (2019) Critical analysis of rural-urban transition and transformation in Lucknow city, India. Remote Sens Appl Soc Environ 13:445–456. https://doi.org/10.1016/j.rsase.2019.01.001

Story M, Congalton R (1986) Accuracy assessment: a user's perspective. Photogramm Eng Remote Sens 52(3):397–399

Strahler AH (1980) The use of prior probabilities in maximum likelihood classification of remotely sensed data. Remote Sens Environ 10:135–163

Subasinghe S, Estoque RC, Murayama Y (2016) Spatiotemporal analysis of urban growth using GIS and remote sensing: a case study of the Colombo Metropolitan Area, Sri Lanka. Int J Geo-Inf 5(197):1–19. https://doi.org/10.3390/ijgi5110197

Sudhira H, Ramachandran T, Kaup J (2003) Urban sprawl pattern recognition and modeling using GIS. Proc Map India, New Delhi

Sudhira H, Ramachandra T, Jagadish K (2004) Urban sprawl: metrics and modeling using GIS. Int J Appl Earth Obs Geoinform 5:29–39. https://doi.org/10.1016/j.jag.2003.08.002

Sun Y, Zhao S, Qu W (2014) Quantifying spatiotemporal patterns of urban expansion in three capital cities in Northeast China over the past three decades using satellite data sets. Environ Earth Sci 73(11):7221–7235. https://doi.org/10.1007/s12665-014-3901-6

Taubenbock H, Wegmann M, Roth A, Mehl H, Dech S (2009) Urbanization in India—spatiotemporal analysis using remote sensing data. Comput Environ Urban Syst 33(3):179–188. https://doi.org/10.1016/j.compenvurbsys.2008.09.003

Tewolde MG, Cabral P (2011) Urban sprawl analysis and modeling in Asmara, Eritrea. Remote Sens 3:2148–2165. https://doi.org/10.3390/rs3102148

United Nations (2015) World urbanization prospect: the 2015 revision. Department of Economics and Social Affairs, Population Division, New York

Thomas RW (1981) Information statistics in geography. In: Concepts and Techniques in Modern Geography, no 31. Geo Abstracts, Norwich

Turner MG, O'Neil R, Gardner R, Milne B (1989) Effects of changing spatial scale on the analysis of landscape pattern. Landsc Ecol 3(3/4):153–162

Wei Y, Zongyi Z (2012) Assessing the fragmentation of construction land in urban areas: an index method and case study in Shunde. China Land Use Policy 29(2):417–428. https://doi.org/10.1016/j.landusepol.20.08.006

Xu H, Wang X, Xiao G (2000) A remote sensing and GIS integrated study on urbanization with its impact on arable land: Fuqing City, Fujian Province, China. Land Degrad Dev 11(4):301–314. https://doi.org/10.1002/1099-145X(200007/08)

Yulianto F, Fitriana H, Sukowati K (2019) Integration of remote sensing, GIS, and Shannon's entropy approach to conduct trend analysis of the dynamics change in urban/built-up areas in the Upper Citarum River Basin, West Java, Indonesia. Model Earth Syst Environ 6:383–395. https://doi.org/10.1007/s40808-019-00686-9

Zhang L, Wu J, Yu Z, Shu J (2004) A GIS-based gradient analysis of urban landscape pattern of Shanghai Metropolitan Area, China. Landsc Urban Plan 69(1):1–16. https://doi.org/10.1016/j.landurbplan.2003.08.006

Zhang S, Abigail YM, Christopher BG, Shrestha M (2012) Methodological advances in the spatial analysis of land fragmentation. Prof Geogr 65(3):512–526. https://doi.org/10.1080/00330124.2012.700501

Zha Y, Gao J, Ni S (2003) Use of normalized difference built-up index in automatically mapping urban areas from TM imagery. Int J Remote Sens. https://doi.org/10.1080/01431160304987