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Urban structure in Kolkata: metrics and modelling through geo-informatics

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Abstract Urbanization connotes to the growth of a metropolis on being subjected to criteria such as economic, social and political forces as well as the geomorphology of the metropolis. As population and its activities increase in a city, the boundary of the city expands to accommodate growth along the urban fringes, leading to fragmented urban morphology, thereby impacting local ecology. Towns and cities had bloomed post-independence in India, causing changes in the land use along the myriad landscapes and ecosystems of the country. These urban ecosystems were a consequence of unplanned development of industrial centres and uncontrolled growth of residential colonies, which altogether became hubs for economic, social, cultural, and political activities. A visualization of the past trends and patterns of growth enable the planning machineries to plan for appropriate basic infrastructure facilities (water, electricity, sanitation, etc.). This communication analyses the spatial patterns of Kolkata municipality—the 13th most populous and 8th largest urban agglomeration in the world. It has been one of the most prominent urban areas in eastern India which was once considered the capital of India during the erstwhile British colonial rule. The spatial patterns of urbanization of Kolkata with 10 km buffer have been analysed using temporal remote sensing data with zonal gradients and spatial metrics. The study area was divided into four zones and each zone was further divided into concentric circles of 1 km incrementing radii to understand the patterns and extent of urbanization at local levels. Its land use analysis has revealed a decline of vegetation from 33.6 % (1980) to 7.36 % (2010). During 2010, Kolkata's built-up had constituted 8.6 %, water bodies comprised of 3.15 %, whereas other categories made up about 80.87 %. Increased Shannon's entropy during the last decade highlights the tendency of sprawl that necessitated policy interventions to provide basic amenities. Spatial patterns through metrics indicated a compact and simple structured growth at the centre of the city and a distributed complex shape in the buffer region. Further, these metrics indicated that the city is on the verge of becoming a single large urban patch that would affect its ecological integrity. Temporal analyses of spatial patterns of urbanization help the city administration and city planners to visualize and understand the growth of the city so that they can provide better resource planning to create a sustainable city.

Keywords Urbanization · Urban sprawl · Urban pattern · Remote sensing · Spatial metrics · Kolkata

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Introduction

Urbanization refers to an irreversible physical process involving large-scale land cover changes of an area with an increase in the number of people living in it as well as an increase of its built-up density (Maiti and Agrawal 2005; Ramachandra et al. 2012) that would thereby affect the area's ecology and environment. The urbanization process has gained momentum during the last two decades due to globalization and its accelerated economic activities. Employment opportunities at

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Table 1 Population growth in Kolkata during 1971–2011

City	Area (sq. km)	Year	Population	Population density (persons per sq. km)
Kolkata	3,638.49	1971	7,420,000	2,039
		1981	9,030,000	2,482
		1991	10,890,000	2,993
		2001	13,217,000	3,632
		2011	14,112,536	3,879

urban centres have been a catalyst in causing large-scale migrations from rural to urban pockets. As a consequence to intense urbanization at core regions, dispersed growth or sprawl occurred at peri-urban areas and city outskirts. As this growth was not visualized during the planning process, most sprawl regions are now devoid of basic infrastructure facilities and amenities such as treated water supply, sanitation, electricity, etc. (Sudhira et al. 2004; Ramachandra et al. 2012). Usually, sprawl occurs along urban fringes, at the edges of urban areas or alongside highways. Sprawl generally alters regions by imbibing in them a highly fragmented urban morphology; agricultural lands, open spaces and ecologically sensitive habitats are all disturbed in the process. Some of the causes of sprawl include population growth, economic factors, civil activities such as construction of buildings and roads and development of infrastructure using taxes. Thus, urbanization dramatically changes the rate of growth of urban areas with the core centre of the city bearing simple and compact urban features whereas the urban fringes or suburban regions tend to become more complex and diverse thereby reflecting a highly fragmented urban morphology. The trend analysis of urban growth helps us to understand the spatial patterns of the built-up area and sprawl.

Many towns in India are growing fast due to various infrastructural developments. The urban population in India is presently growing at the rate of 2.3 % per annum. The global urban population has increased from 13 % (220 million in 1900) to 49 % (3.2 billion, in 2005), and it is projected to escalate to 60 % (4.9 billion) by 2030 (Ramachandra and Kumar 2008). The increase in urban population in India in response to the growth in urban areas is mainly due to migration. There are 48 urban agglomerations/cities in India having a population of more than one million (in 2011). However, in 2001, the number of these agglomerations was only 30. It has been projected that more than half of the world's population will become urban dwellers as the urban population is expected to reach 81 % by 2030 (United Nations Population Fund 2007).

The main problem of unplanned urbanization is sprawl by which there are conversions of urban–rural fringes into urban areas although without basic facilities and amenities. Urban sprawl is currently occurring at an unprecedented rate that is having a marked effect on the natural functioning of the immediate environment (Turner 1994). Sprawl is generally associated with the loss of all environment-friendly land uses and is proportional to the increase of urban density in small spatial locations in and around urban areas due to lack of integrated and holistic approaches in regional planning (Sudhira et al. 2007; Ramachandra et al. 2012). The landscape undergoing unplanned growth due to various anthropogenic activities requires to be monitored to understand the rates of

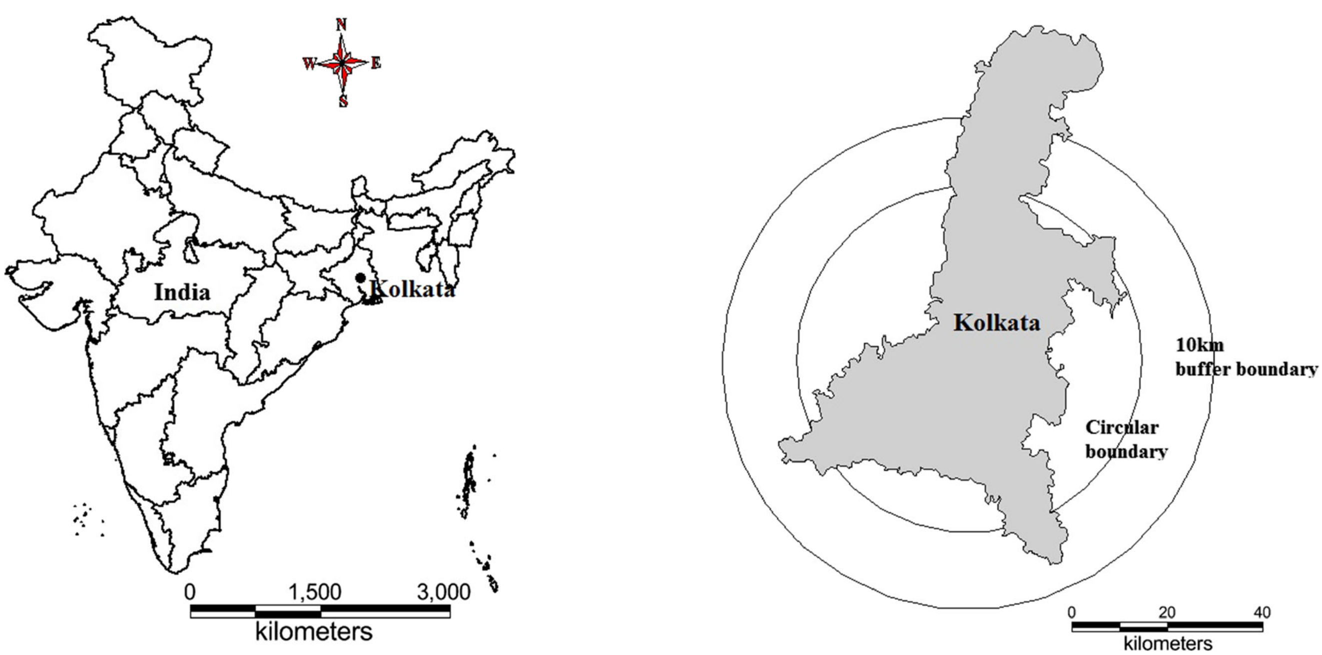


Fig. 1 Study area—Kolkata administrative boundary with 10 km buffer

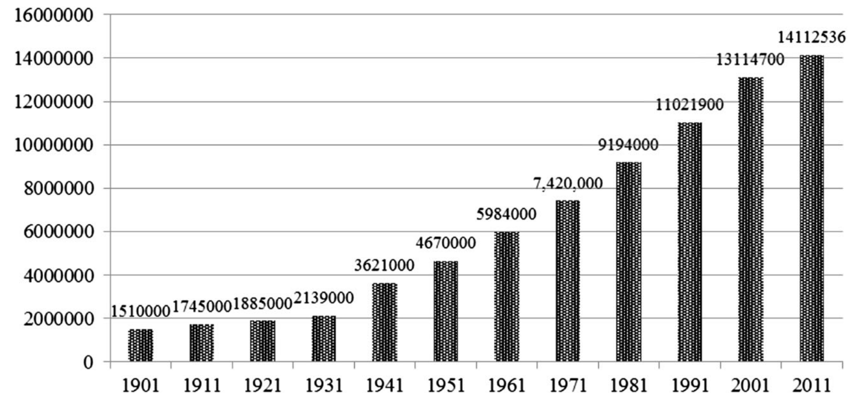


Fig. 2 Population growth since 1901 (Source: Census of India)

changes in urban land use (Peiser 2001; Stow and Chen 2002). Monitoring urban structure brings out the various spatial characteristics of the land surface apart from elucidating the impacts on the surrounding environment (Yeh and Li 1999; Lillesand and Keifer 2002; Sudhira et al. 2004; Ramachandra et al. 2012). In rapidly urbanizing regions, there are mass migrations of people from rural areas to urban areas and also from smaller towns to urban metropolises. The process of urbanization in India gained momentum with the industrial revolution of 1970s, followed by globalization of 1990s, both of which caused the disappearance of other land uses (Rahman 2007) affecting local ecology and environment.

This rapid urbanization has demanded immediate interventions through inventorying, mapping and monitoring of various advanced mapping techniques such as remote sensing and satellite technologies (in order to understand the dynamics of land uses). The usage of these technologies helps the city administrators and planners understand the problems which accompany such urban processes (Maktav and Erbek 2005; Bhatta 2009; Ramachandra et al. 2012). The temporal spatial data acquired through space-borne sensors help in the understanding of urban growth pattern, urbanization rate and the underlying problems of urbanization such as urban sprawl. These, ultimately, aid in better administration by assisting in garnering basic amenities (Ramachandra et al. 2012). Urban sprawl has been characterized considering indicators such as growth, social conditions, aesthetics, decentralization factor, accessibility conditions, density, open space availabilities, dynamics, costs and social benefits (Bhatta 2009, 2010). Further, Galster et al. (2001) have identified additional parameters for quantifying sprawl which are density, continuity, concentration, clustering, centrality, nuclearity, proximity and mixed uses. In this study, firstly, the pattern of the land use changes has been studied temporally using remote sensed satellite data. Landscape metrics were computed to quantify the patterns of urban dynamics (McGarigal and Marks 1995). These spatial metrics capture the dynamics of the land surface under consideration (Gustafson 1998; Turner et al. 2001). These metrics are been used as indicators of the pattern of land surface changes (Herold et al. 2002; Herold et al. 2003; Zhang et al. 2004; Angel et al. 2007: Jiang et al. 2007; Taubenbock et al. 2008a; Taubenbock et al. 2008b; Bhatta 2010; Ramachandra et al. 2012). Further, in order to understand the local patterns of growth, density gradients were obtained which provided the localized information on the land use pattern (Torrens and Alberti 2000; Ramachandra et al. 2012). These studies confirmed that temporal remote sensing data with gradients and spatial metrics techniques provide the accurate and detailed understanding of urban structure at local levels that are necessary for effective urban planning.

The main objective of the current study is to understand the underlying land use dynamics using temporal remote sensing data along with spatial patterns of urban growth through density gradients and spatial metrics.

Table 2 Data used in the analysis

DATA	Year	Purpose
Landsat Series Multispectral sensor (57.5 m)	1979	For land cover and land use analysis
Landsat Series Thematic mapper (28.5 m) and Enhanced Thematic Mapper sensors	1990, 1999, 2010	For land cover and land use analysis
Survey of India (SOI) toposheets of 1:50,000 and 1:250,000 scales		To generate boundary and base layer maps
Field visit data—captured using GPS		For geo-correcting and generating validation dataset

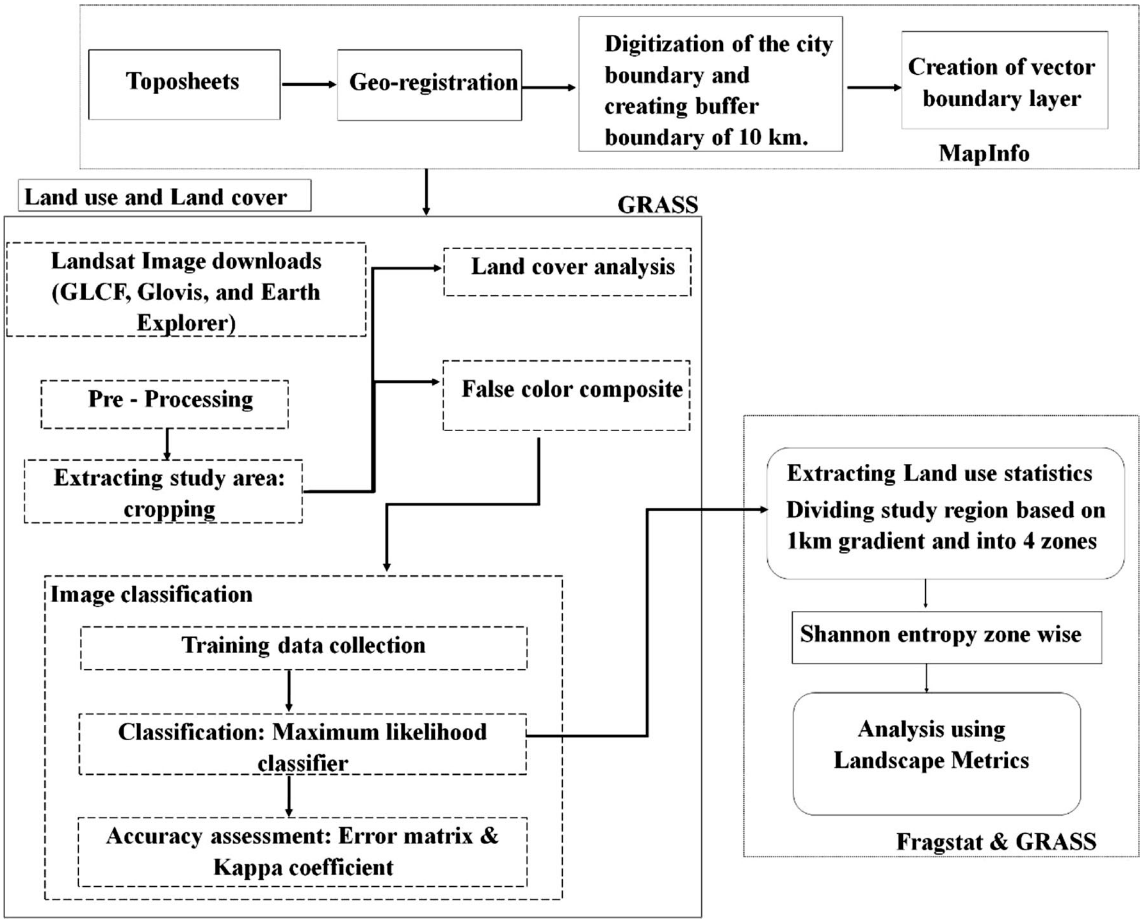


Fig. 3 Procedure adopted for classifying landscape and computation of metrics

Materials and methods

Study area Indian city Kolkata, the capital of West Bengal, has been considered for the analysis. Kolkata is located in the eastern part of India and is situated on the eastern bank of Hooghly River, adjacent to Assam, Sikkim and borders of Bangladesh (Bunting et al. 2002). Kolkata is the third most populous city in India, 13th most populous and 8th largest urban agglomeration city in the world, having a population of approximately 14.11 million (Census 2011). Its population density has increased from 2,039 persons per sq. km (in 1971) to 3,879 persons per sq. km (in 2011) (Table 1). Kolkata lies at 22°34′N and 88°24′E. It is at an altitude of 6 m above mean sea level and a distance of 96 km from the Bay of Bengal. Its temperature ranges from 12 to 27 °C in winters and 24 to 38 °C in summers. The average rainfall is about 160 cm which keeps the city cool after a hot summer (Bunting et al. 2002). Kolkata has mainly alluvial soil and the main crops/plantations cultivated are rice, jute, mango, coconut, jackfruit, guava and black berries. Kolkata is an important centre for art, literature, architecture and cultural heritage. Thriving since the pre-colonial age, Kolkata has preserved many of its beautiful monuments, sculptures and historical buildings, a prominent one of which is the renowned Indian Museum that was established in 1814, which today is considered as the oldest museum in Asia. Kolkata is considered a historical landmark that had laid the foundations for quite a few British monuments such as the Marble palace and the Victoria Memorial. Kolkata was once the capital of India during the British rule, but in 1911, it lost that status to Delhi due to its improper geographic location in India. Due to rapid urbanization in the current years, Kolkata is now facing problems such as traffic congestion and pollution. Kolkata is one of the major commercial and financial hubs of

Table 3 Land use classes

Land use class	Land uses included in the class
Urban	Residential areas, industrial areas and all paved surfaces and mixed pixels having built-up area
Water bodies	Tanks, lakes, reservoirs
Vegetation	Forest, cropland, nurseries
Others	Rocks, quarry pits, open ground at building sites, unmetalled roads

Table 4 Landscape metrics calculated in the analysis

Indicator	Formula	Description
Class level landscape metrics		
Number of patches (Built-up) (NP)	$N=n_i$ n_i = number of patches in the landscape of patch type i Range, NP≥1	NP is the number of patches of a corresponding patch type
Percentage of landscape (built-up) (PLAND)	$\mathrm{PLAND} = P_i = \frac{\sum_{j=1}^{n} a_{ij}}{A}(100)$ a_{ij} = area (m^2) of patch ij A = total landscape area (m^2) Range, 0<PLAND≤100	PLAND is the percentage of landscape comprised of a corresponding patch type
Patch Density (PD)	$\mathrm{PD} = \frac{n_i}{A}(10,000)(100)$ N = total number of patches in the landscape A = total landscape area (m^2) Range, PD>0	PD is the number of urban patches divided by total landscape area
Normalized landscape shape index (NLSI)	$\mathrm{NLSI} = \frac{e_i - \mathrm{min} e_i}{\mathrm{max}\ e_i - \mathrm{min} e_i}$ e_i = total length of edge (or perimeter) of class i in terms of number of cell surfaces; includes all landscape boundary and background edge segments involving class i Range, 0 to 1	Normalized Landscape Shape Index is the normalized version of the landscape shape index (LSI) and provides a simple measure of class aggregation or Clumpiness
Area weighted mean shape index (AWMSI)	$\mathrm{AWMSI} = \sum_{i=1}^{m} \sum_{j=1}^{n} \left[\left(\frac{0.25 p_{ij}}{\sqrt{a_{ij}}} \right) \left(\frac{a_{ij}}{A} \right) \right]$ a_i and p_i are the area and perimeter of patch i, and N is the total number of patches Range, AWMSI ≥1, without limit	It weighs patches according to their size; larger patches carry more weight than smaller ones It is also used to represent shape irregularities with small values indicating a regular shape and as the values increase, complexity and irregularities increase
Edge density (ED)	$\mathrm{ED} = \frac{\sum_{k=1}^{m} e_{ik}}{A}(10,000)$ e_{ik} = total length (m) of edge in landscape involving patch type (class) i; includes landscape boundary and background segments involving patch type i A = total landscape area (m^2). Range, ED≥0	ED standardizes edge on a per unit area basis that facilitates comparison between landscapes of different sizes
Clumpiness index (Clumpy)	$\mathrm{CLUMPY} = \left(\begin{array}{c} \left[\frac{G_i - P_i}{P_i} \right] \text{for } G_i < P_i P_i < 5; \text{else} \\ \frac{G_i - P_i}{1\ P_i} \end{array} \right)$ $G_i = \left[\frac{g_{ii}}{\left(\sum_{k=1}^{m} g_{ik} \right) - \mathrm{min} e_i} \right]$ g_{ii} = number of like adjacencies (joins) between pixels of patch i based on the double-count method g_{ik} = number of adjacencies (joins) between pixels of patch types i and k based on the double-count method Min-e_i = minimum perimeter (in number of cell surfaces) of patch type i for a maximally clumped class P_i = proportion of the landscape occupied by patch type i. Range, [−1,1]	Values of the clumpy index close to −1 is a measure of maximally disaggregated land use, whereas values of clumpy index close to 0 is indicative of distributed random patch and when clumpy index approaches 1, urban patch type is maximally aggregated
Aggregation index (AI)	$\mathrm{AI} = \left[\frac{g_{ii}}{\mathrm{max} g_{ii}} \right](100)$ g_{ii} = number of like adjacencies (joins) between pixels of patch type i based on the single-count method max-g_{ii} = maximum number of like adjacencies (joins) between pixels of patch type i based on the single-count method.	AI equals 0 when the patch types have no like adjacencies. AI equals 100 when the landscape consists of a single patch
Interspersion and juxtaposition index (landscape level) (IJI)	$\mathrm{IJI} = \frac{-\sum_{K=1}^{m} \left(\left[\frac{e_{ik}}{\sum_{k=1}^{m} e_{ik}} \right] \ln \left[\frac{e_{ik}}{\sum_{k=1}^{m} e_{ik}} \right] \right)}{\ln(m-1)}(100)$ e_{ik} = total length (m) of edge in landscape between patch types i and k. m = number of patch type present in landscape Range, 0<IJI≤100	IJI approaches 0 when the corresponding patch type is adjacent to only 1 other patch type and the number of patch types increases. IJI = 100 when the corresponding patch type is equally adjacent to all other patch types

northeastern India. In 2009, Kolkata's GDP was about \$150 billion which made it the third highest among all Indian cities. Its industries largely produce engineering products, electronic components, electrical equipment, textiles,

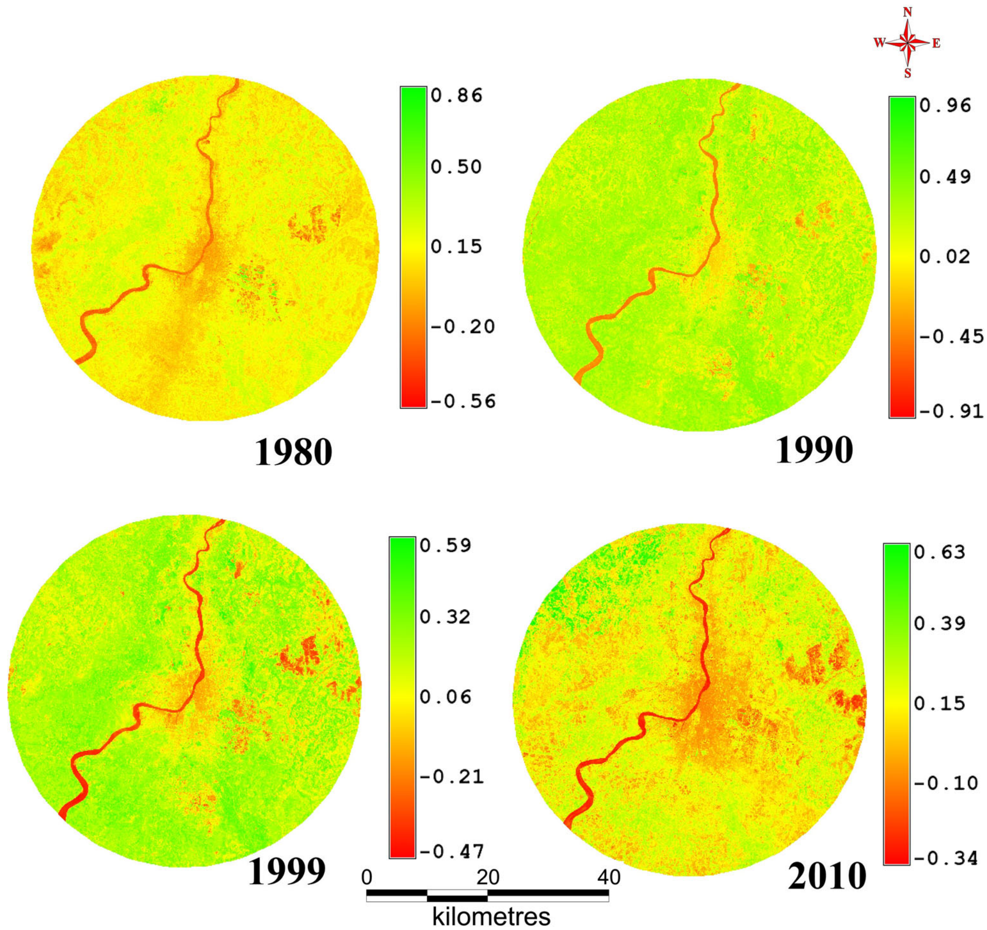


Fig. 4 Vegetation cover (NDVI) in the study region

jewellery, chemicals, tobacco, food products and jute products, all of which add significantly to the economic development of the city. Information Technology industries also play a prominent role in adding to its economic growth by attracting many software and telecoms firms from across the country as well as from the rest of the world. The GDP of Kolkata is about $150 billion which make it economically strong compared to other cities except Mumbai and Delhi.

Urban development planning and infrastructure The Kolkata Metropolitan District is a planning unit of Kolkata that covers 3 municipal corporation units, 34 municipalities and the Greater Kolkata on the whole (Bonnerjee 2012). The urban planning development of Kolkata is undertaken by the Kolkata Municipal Corporation (KMC) which constitutes the administrative core of the city while the planning for the wider agglomeration surrounding Kolkata Municipal Corporation is undertaken by Kolkata Metropolitan Authority (Gregory 2005). KMC is responsible for the infrastructural development and the administration of the city. Kolkata Metropolitan Development Authority (KMDA) is the development authority for the Kolkata Metropolitan Area (KMA). The KMDA also undertakes city planning, creates townships and develops infrastructure in the city. The planning begins with the gathering of information about a particular location in a systematic manner. Due to rapid urbanization in the city, planning becomes a challenging task with constraints such as high rates of pollution, dispersed growth at outskirts (peri-urban regions), traffic congestion and reduced green spaces, open spaces and small lakes. In order to understand the urban dynamics, Kolkata City has been analysed by considering administrative boundaries with 10 km buffer (Fig. 1).

Kolkata is a highly populated city in India that has a population of 14.11 million as per provisional census of 2011. Figure 2 describes the temporal increase in population during the last 100 years.

Data Urban dynamics was analysed using temporal remote sensing data for the period between 1973 and 2010. The time series spatial data acquired from Landsat Series Multispectral sensor (57.5 m) and thematic mapper (28.5 m) sensors for the period between 1979 and 2010 were downloaded from a public domain (http://glcf.umiacs.umd.edu/data) as indicated in Table 2. Base layers and training data (for classifying remote sensing data) were derived from the Survey of India (SOI) topographic maps of scales 1:250,000 and 1:50,000. Features such as extent of water bodies, certain roads, etc. were derived

Table 5 Results quantified for the study region

	Vegetation (%)	Non-vegetation (%)
1980	35.68	64.24
1990	29.37	70.5
1999	25.16	73.26
2010	13.14	86.86

from 1:50,000 map, while 1:250,000 was used mainly for training data. Further, these layers were resampled to 30 m.

Data analyses Figure 3 outlines the process of data analyses, which includes preprocessing, analysis of vegetation cover and land use, and lastly, the gradient wise zonal analysis of Kolkata using landscape metrics.

- Preprocessing: Remote sensing data (Landsat series) for Kolkata of different time periods were downloaded from Global Land Cover Facility (http://www.glcf.umd.edu/index.shtml and http://www.landcover.org/), United States Geological Survey (USGS) Earth Explorer (http://edcsns17.cr.usgs.gov/NewEarthExplorer/) and Glovis (http://www.glovis.usgs.gov). The remote sensing data obtained were geo-referenced, geo-corrected, rectified and cropped with respect to the study area. Geo-registration of remote sensing data (Landsat data) was done using ground control points collected from the field using pre-calibrated GPS receiver (Global Positioning System) and also from known points (such as road intersections, etc.) collected from geo-referenced topographic maps published by the Survey of India. The Landsat satellite data of 1980 (with spatial resolution of 57.5 m × 57.5 m (nominal resolution)) and that of 1990–2010 (with spatial resolution of 28.5 m × 28.5 m (nominal resolution)) were resampled to 30 m each in order to maintain uniformity in spatial resolution across different time periods. The study area included the Kolkata administrative area with 10 km buffer.
- Vegetation cover analysis: Vegetation cover analysis was performed to understand the changes in the land cover (area under vegetation and non-vegetation) during 1980–2010. Normalized difference vegetation index (NDVI) was found suitable and was used for measuring vegetation cover (Ramachandra et al. 2012; http://wgbis.ces.iisc.ernet.in/energy/paper/comparitive/methodlogy.htm). NDVI values ranges between −1 and +1. Very low values of NDVI (−0.1 and below) correspond to non-vegetation (soil, sand, urban built-up, etc.), whereas 0 indicates water cover. Moderate values represent low density vegetation (0.1 to 0.3), whereas high values indicate thick canopied vegetation (0.6 to 0.8).
- Land use analysis: The method involves (i) generation of False Colour Composite (FCC) of remote sensing data (bands—green, red and NIR). This helped in locating heterogeneous patches in the landscape, (ii) selection of training polygons (corresponding to heterogeneous patches in FCC) covering 15 % of the study area that were uniformly distributed over the entire study area, (iii) loading these training polygons coordinates into pre-calibrated GPS receiver. Pre-calibration involved range corrections by finding the shift (if any) of locations (with GPS receiver) and known ground control points (derived from survey benchmarks, topographic maps). Range correction

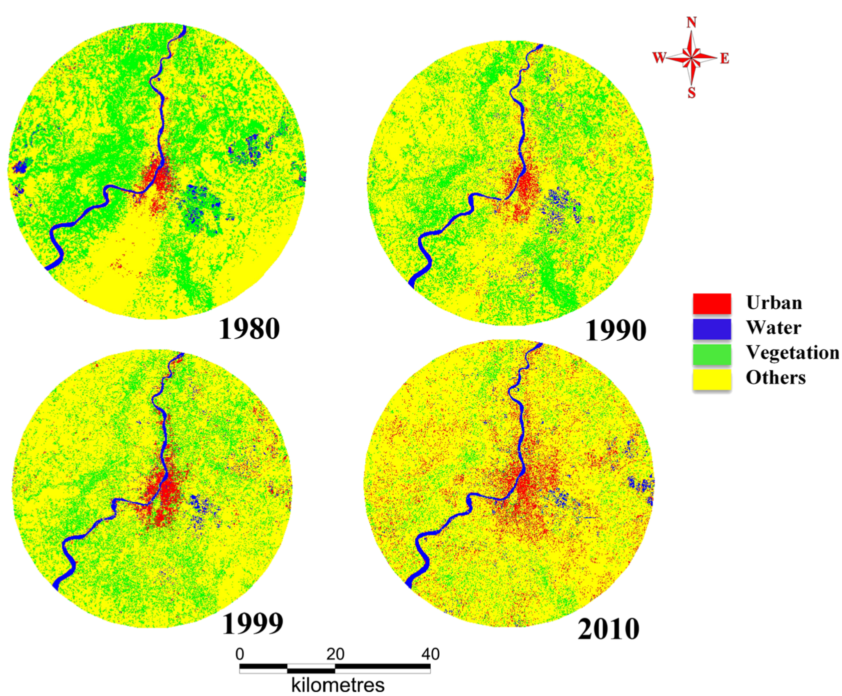


Fig. 5 Temporal land uses in Kolkata

Table 6 Land use changes during 1980 to 2010

Land use category	Built-up		Vegetation		Water body		Others	
Year	Area (sq. km)	Area (%)	Area (sq. km)	Area (%)	Area (sq. km)	Area (%)	Area (sq. km)	Area (%)
1980	72.66	2.0	1,222.9	33.6	102.8	2.83	2,240.2	61.5
1990	79.27	2.2	852.7	23.4	103.5	2.84	2,608.5	71.5
1999	132.4	3.6	740.8	20.3	97.2	2.67	2,666.2	73.32
2010	314.3	8.6	268.1	7.36	114.6	3.15	2,947.3	80.87

constitute an important component as most of the GPS receivers have an error of 2–10 m, (iv) collection of the corresponding attribute data (land use types) for these polygons from the field. GPS receiver helped in locating respective training polygons on the field, (v) supplementing this information with Google Earth, and (vi) using 60 % of the training data for classification, while using the rest for validation or accuracy assessment.

Land use analysis was carried out using supervised pattern classifier—Gaussian maximum likelihood algorithm. Remote sensing data was classified using signatures from training sites that include all the land use types detailed in Table 3. Mean and covariance matrix were computed using estimates of maximum likelihood estimator. Maximum Likelihood classifier is used to classify the data using these signatures generated. This technique is proven to be a superior classifier as it uses various classification decisions using probability and cost functions (Duda et al. 2000; Ramachandra et al. 2012). Mean and covariance matrix are computed using estimates of maximum likelihood estimator. Land uses during different time periods were estimated using the temporal data through open source program Geographic Resource Analysis Support System (GRASS, http://ces.iisc.ernet.in/grass). Signatures were collected from field visits and with the help of Google Earth. Sixty percent of the total generated signatures were used in classification, and 40 % signatures were used in validation and accuracy assessment. Classes of the resulting image were reclassified and recoded to form four land use classes. The noise in the classified image of 1980 was removed by smoothing filter (3×3 median filters).

- Accuracy assessment: These methods evaluate the performance of classifiers (Mitrakis et al. 2008). This is done through comparison of kappa coefficients (Congalton et al. 1983), which are common measurements used to demonstrate the effectiveness of the classifications (Congalton 1991; Lillesand and Kiefer 2002). Recent remote sensing data (2010) were classified using the collected training samples. Statistical assessment of classifier performance, based on the performance of spectral classification considering reference pixels, was done which included computation of kappa (κ) statistics and overall (producer's and user's) accuracies. For earlier time data, training polygon along with attribute details was compiled from earlier published topographic maps, vegetation maps and revenue maps.
- Zonal analysis: City boundary along with the buffer region was divided into four zones: northeast (NE), southwest (SW), northwest (NW) and southeast (SE) for further analysis as urbanization is not uniform in all directions. As most of the definitions of a city or its growth are defined in terms of directions, it was considered more appropriate to divide the regions into four zones based on directions. Zones were divided considering the Central pixel (Central Business district). The growth of the urban areas along with the agents of changes is understood in each zone separately through the computation of urban density for different periods.

Table 7 Overall accuracy and kappa statistics of classified data

	1980		1990		1999		2010	
Kolkata	OA	$\hat{k}$	OA	$\hat{k}$	OA	$\hat{k}$	OA	$\hat{k}$
	99	0.0144	88	0.9495	93	0.9687	93	0.9922

Division of zones into concentric circles (Gradient Analysis): Each zone was divided into a concentric circle of incrementing radius 1 km from the centre of the city. The gradient analysis helped in visualizing the changes at local levels with the type and role of agents. This helped in identifying the causal factors and locations experiencing various levels (sprawl and compact growth) of urbanization in response to the economic, social and political forces. This approach (zones, concentric circles) also helped in visualizing the forms of urban sprawl (low density, ribbon, leaf-frog development). The built-up density in each circle is monitored overtime using time series analysis. This helps the city administration in understanding the urbanization dynamics to provide appropriate infrastructure and basic amenities.

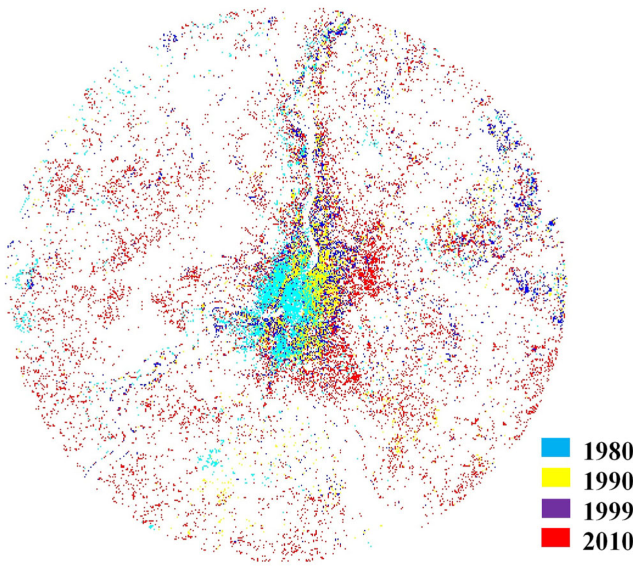


Fig. 6 Kolkata's urbanization process during 1980–2010

- Shannon's entropy: Further, to understand the growth of an urban area in a specific zone, and to understand if the urban area is compact or divergent, the Shannon's entropy (Sudhira et al. 2004; Ramachandra et al. 2012) was computed. Shannon's entropy (Hn), given in Eq. 1, clearly explains the growth process and its characteristics.

$$\mathrm{Hn} = -\sum_{i=1}^{n} \mathrm{Pi}\log(\mathrm{Pi}) \quad (1)$$

Where Pi is the proportion of built-up in the *i*th concentric circle. As per Shannon's entropy, if the distribution is maximally concentrated in one circle, the lowest value zero will be obtained.

- Computation of spatial metrics: Spatial metrics are helpful to quantify spatial characteristics of the landscape. These metrics quantify specific spatial characteristics of patches, classes of patches or entire landscape mosaics. Selected spatial metrics were used to analyse and understand the urban dynamics; FRAGS TATS (McGarigal and Marks 1995) was used to compute metrics at three levels: patch level, class level and landscape level. There are many quantitative measures of landscape composition that include the proportion of the landscape in each patch type, patch richness, patch evenness and patch diversity. Table 4 below gives the list of metrics along with their description that were considered for the study.

Results

Vegetation cover analysis Figure 4 depicts NDVI computed temporally (1980–2010) and Table 5 indicates the temporal NDVI values, highlighting the decline of area under vegetation from 36 % (in 1980) to 13 % (in 2010). Land use analyses were done to understand the class (urban, vegetation, water bodies, others) distribution temporally.

Land use analysis Preprocessed data of all temporal periods were classified using Gaussian maximum likelihood classifier as discussed in methods section and given in Fig. 5. Accuracy assessment of the classified images was performed using the

Fig. 7 Circle-wise land use (*x*-axis—gradients at 1 km, *y*-axis—metric value)

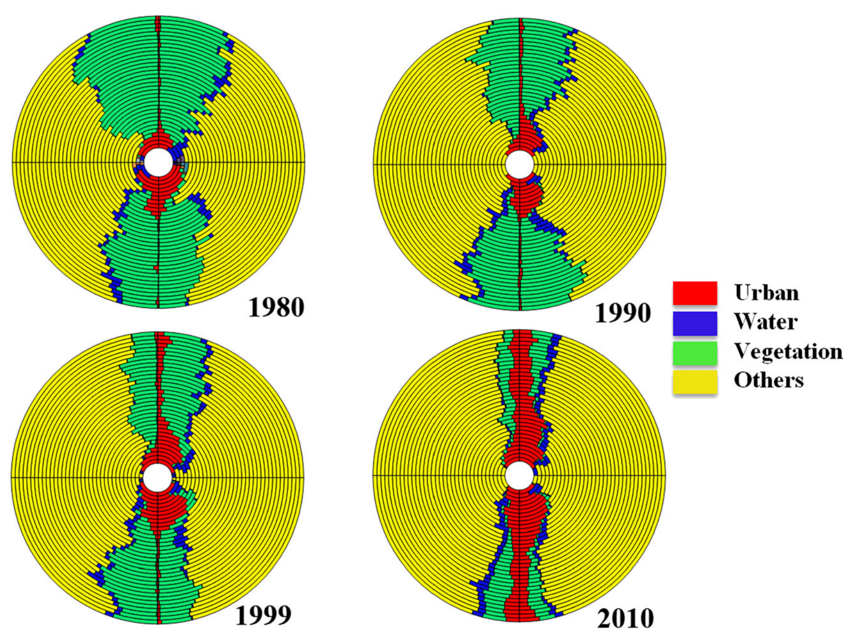


Table 8 Shannon's entropy

	NE	NW	SE	SW	Reference value
1980	0.04	0.03	0.05	0.06	1.53
1990	0.11	0.02	0.09	0.05	
1999	0.19	0.03	0.13	0.07	
2010	0.3	0.16	0.28	0.21	

error matrix and kappa statistics (using the module r.kappa in GRASS). Table 6 tabulates land use statistics of classified images and Table 7 tabulates the results of accuracy assessment. Land use analysis reveals an increase in urban area from 2 % (in 1980) to 8.6 % (in 2010) with a decline of vegetation from 33.6 % (in 1980) to 7.36 % (in 2010) and a significant increase in 'others' category (which includes degraded forest land, open area and cultivation land).

Figure 6 illustrates the pattern of urbanization and sprawl in the study region (Kolkata with buffer), and land uses at local levels is (gradient wise) depicted in Fig. 7, which highlights an increase in built-up areas in NE and SE directions with declining vegetation cover.

Shannon's entropy (Hn) Shannon's entropy, an indicator of sprawl (Table 8, Fig. 8), highlights that the land use is fragmented in all directions due to emergence of new urban pockets with time. Concentrated growth is observed at the city's centre. Figure 8 highlights an increase of entropy values during the last three decades, indicating the tendency of sprawl that demands appropriate policy interventions for the provision of basic amenities.

Landscape metrics analysis These metrics quantify spatial characteristics of patches, classes of patches or entire landscape mosaics. These are quantitative measures of landscape composition that considers the proportion of a landscape in each class depending on patch type, patch richness, patch evenness and patch diversity. Gradient-based metrics' analyses illustrate the urban structure with spatial patterns based on fragmentation, shape, edge and contagion metrics.

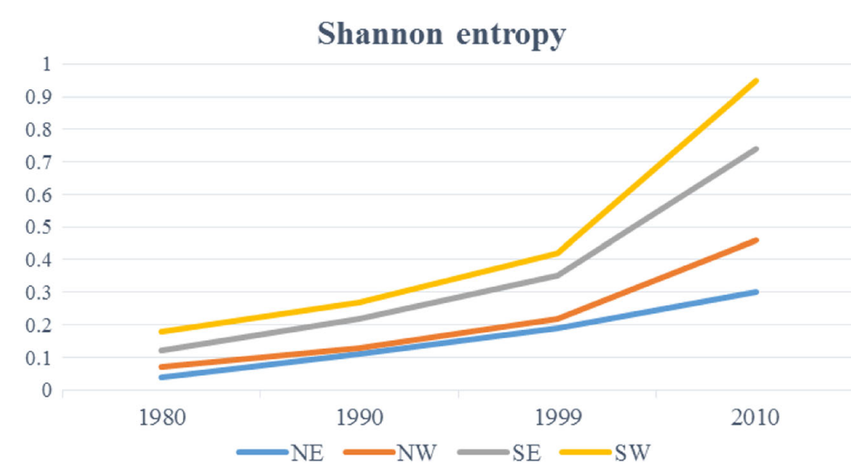
(i) Percentage of landscape (PLAND): PLAND represents the proportion of a respective class in a landscape. Temporal PLAND (Fig. 9a) indicated a higher proportion of built-up class in all directions in 2010. The most alarming aspect is the high growth trend (indicating sprawl) in the outer regions (from circle or buffer region 12). NE and SE recorded maximum percentage of land use under urban classes in 2010.

(ii) Number of patches (NP): NP calculates the number of built-up patches in terms of hectares in a given landscape. It is considered an indicator of the level of fragmentation in a particular class in the landscape. The results (Fig. 9b) of the analyses show an increasing number of urban patches towards the city fringes and peri-urban areas, exhibiting fragmented urban growth in those regions. The city's centre has almost reduced to a single urban patch without any other dominating land uses in 2010. Fragmented growth in peri-urban areas has increased in 2010. This metric is in conformity with Shannon's entropy values illustrating sprawl.

(iii) Patch density (PD): PD analyses the urban patches, which, as given in Fig. 9c, show an increasing urban patch density near the fringes and peri-urban areas, whereas it has lower values in the city centre. This is comparable to NP that indicates peri-urban areas getting fragmented with sprawl by 2010.

(iv) Area weighted mean shape index (AWMSI): This metric was computed in which average shape index of patches was weighted by patch areas. It is a robust metric used to describe landscape structure across

Fig. 8 Shannon's entropy—1980 to 2010



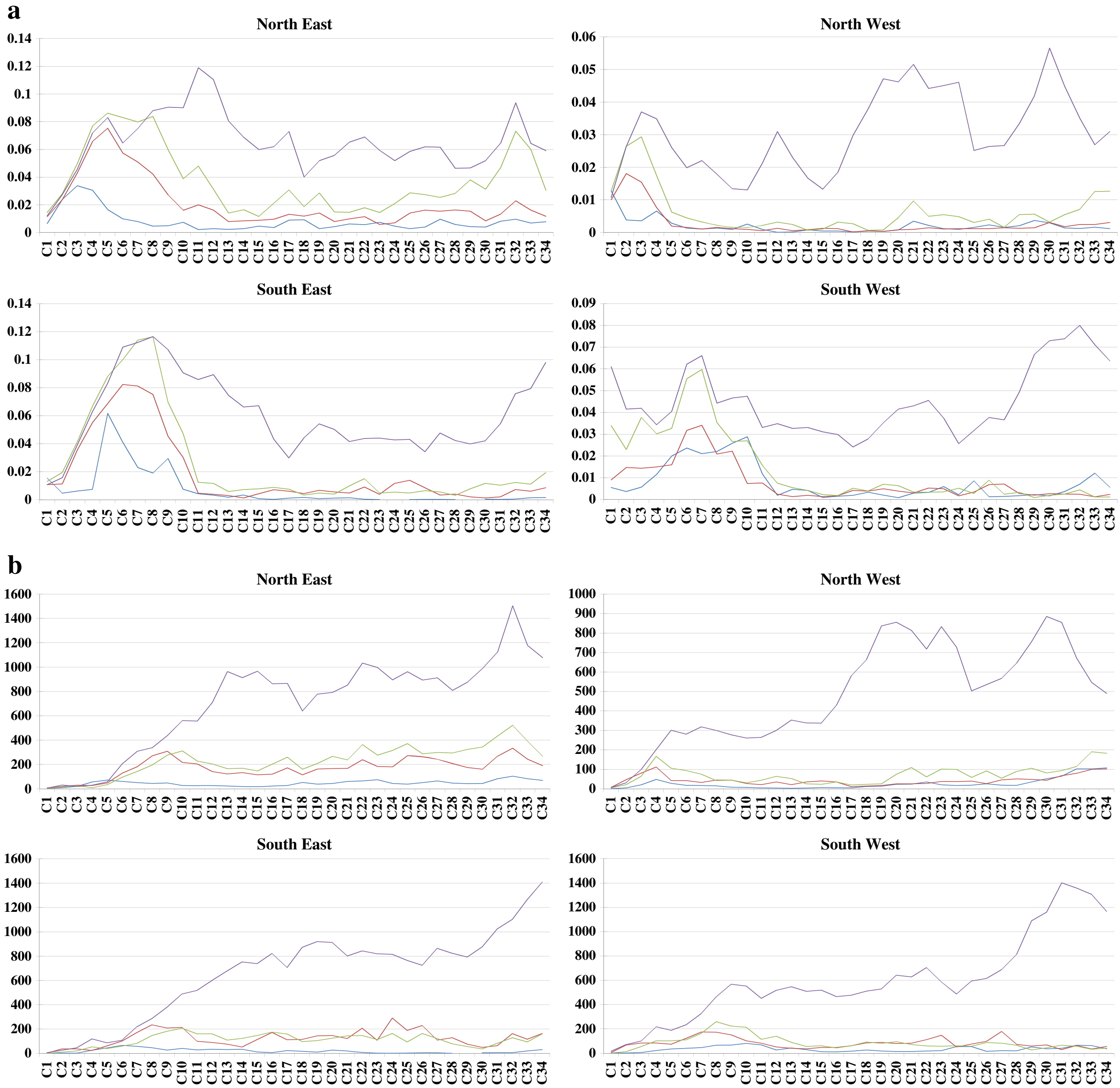


Fig. 9 **a** Percentage of urban landscape. **b** Number of urban patches in the landscape. **c** Patch density of urban class in the landscape. **d** AWMSI index. **e** Normalized landscape shape index. **f** Edge density. **g** Clumpiness index. **h** IJI—interspersion and juxtaposition index. **i** Aggregation index

spatial scales by calculating the complexity of urban patches according to their size. Circles near to the city centre show high values indicating complexity and irregular shapes (in all directions) by 2010 (Fig. 9d) as aggregated urban patches are weighed higher than smaller ones. Lower values in 1980 for core as well as buffer regions (peri-urban areas) indicate a mix of heterogeneous classes.

(v) Normalized landscape shape index (NLSI): This index explains the phenomena of aggregation or disaggregation through shapes, which means if the values are close to zero the land use is of a simple and compact shape, or otherwise, depending on complexity of the land use, the value increases with the maximum being 1. Figure 9e illustrates that the central patch is a simple shaped patch indicating

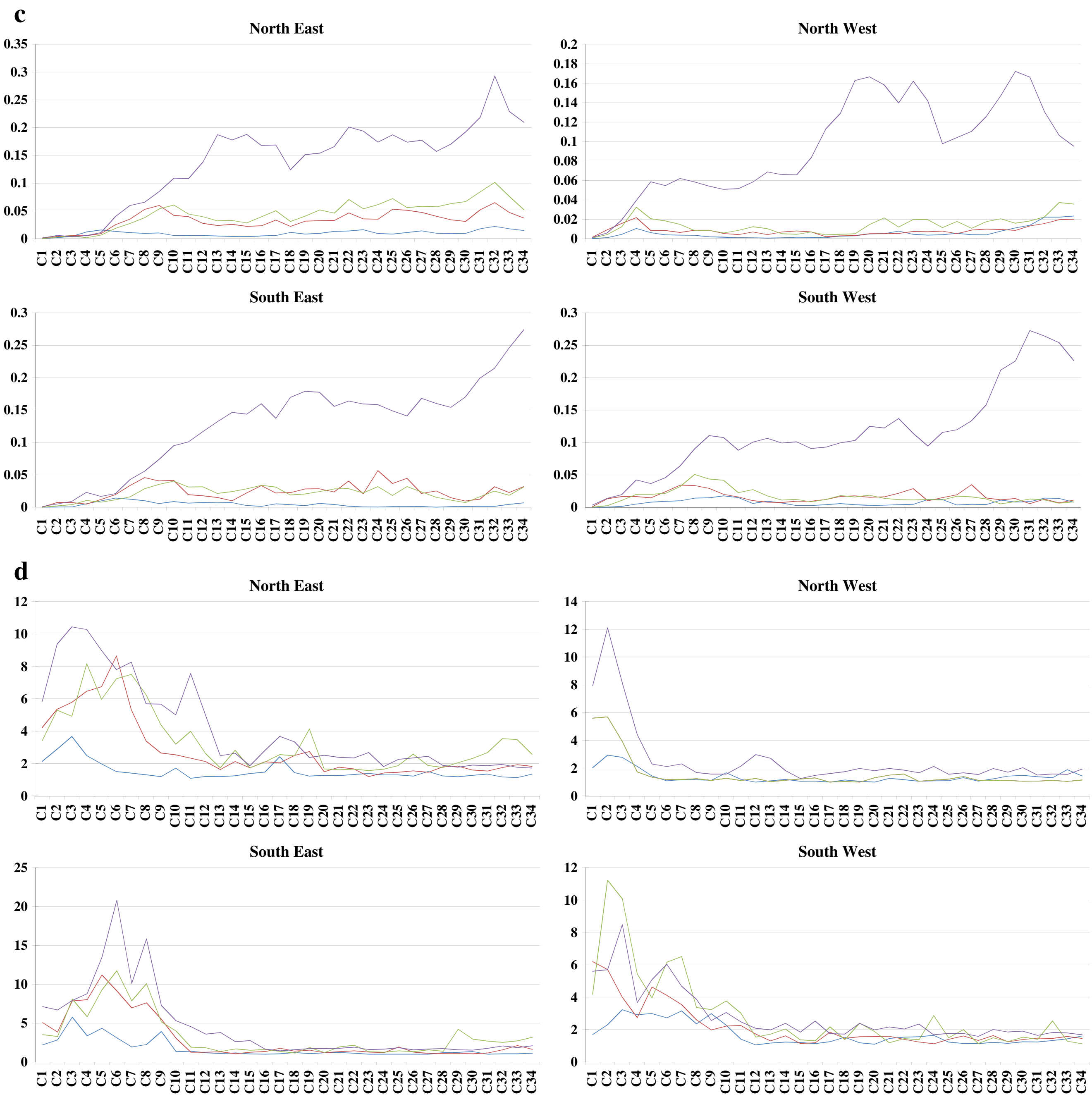


Fig. 9 (continued)

aggregated growth, whereas the buffer regions and outskirts show values greater than 0.4 that indicate the presence of complex shaped land uses and disaggregated growth.

(vi) Edge density (ED): This refers to the ratio of total number of edges of all patches to total area, and it is the measure of fragmentation of the landscape. High ED values (Fig. 9f) of 0.4 along the periphery indicates fragmentation, whereas the core area near the centre with relatively low values indicates clumped growth in accordance with other landscape metrics.

(vii) Clumpiness index (CLUMPY): This is the measure of patch aggregation. Figure 9g shows a decreasing trend (mostly in 1990) with values closer to zero as urban patches are randomly distributed. Similarly, in 2010, the city centre has values close to 1 which indicate aggregated growth while values closer to zero in the buffer regions indicate fragmented growth.

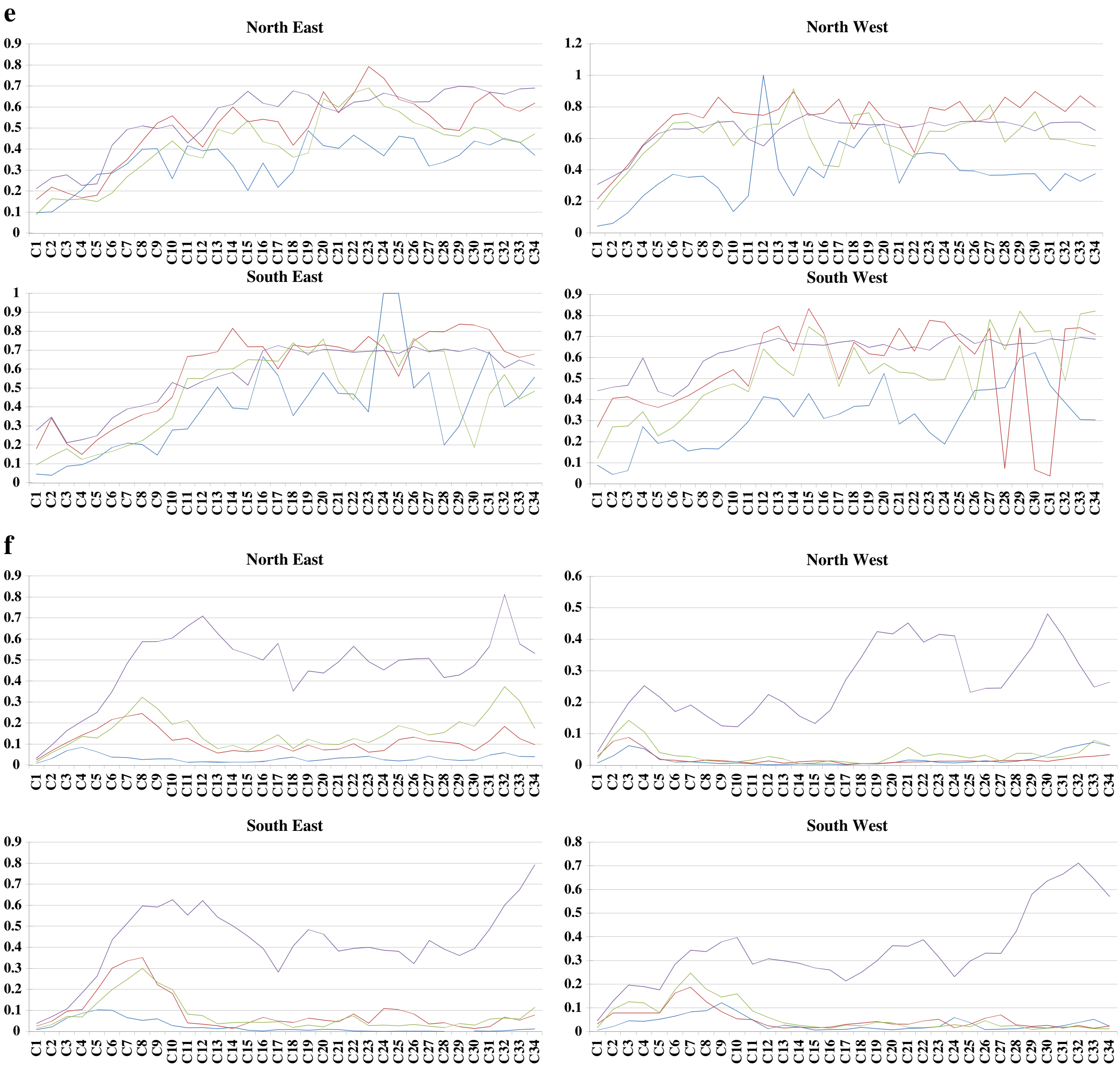


Fig. 9 (continued)

(viii) Interspersion and juxtaposition index (IJI): The IJI measures the extents to which patch types are interspersed. Higher valued results (greater than 20) assert that the urban patch types are well interspersed (i.e. equally adjacent to each other), whereas lower values characterize landscapes whose patch types are poorly interspersed (i.e. disproportionate distribution of patch type adjacencies) (McGarigal and marks 1995). The results (Fig. 9h) also bring out the fact that there has been tremendous growth of urban patches in the outskirts and buffer regions in 2010, thereby indicating sprawl, while the central region showed clumped growth in 2010.

(ix) Aggregation index (AI): Aggregation index gives a similar meaning to clumpiness index, wherein it measures the aggregation of urban patches. Figure 9i indicates that towards 2010 the aggregation happened at the centre, while outskirts and the buffer regions were being fragmented as their number of patches increased as highlighted by other spatial metrics.

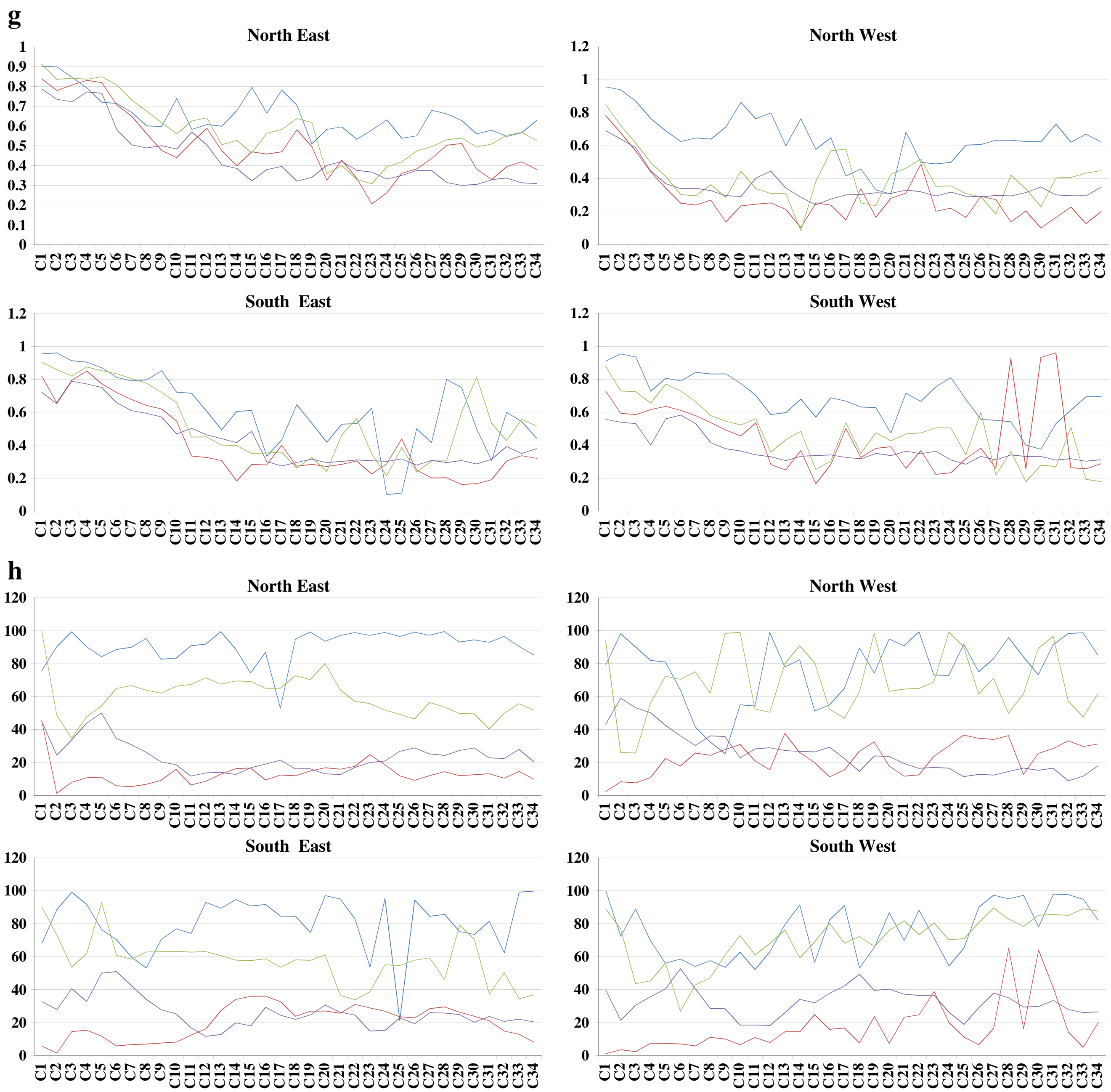


Fig. 9 (continued)

Conclusion

Kolkata is the 13th most populated and 8th largest urban agglomeration in the world, having a population of approximately 14.11 million. Population density has increased from 2,039 persons per sq. km (in 1971) to 3,879 (in 2011) persons per sq. km. Urban structure refers to the heterogeneous alignment of terrestrial objects and characteristics of land uses (such as built-up, vegetation, water bodies and open spaces) in a region. Rapid urbanization involving large-scale land transitions necessitates the understanding of urban dynamics (spatial extent, up-to-date data, etc.). The current endevour demonstrates the quantification of urbanization with its spatio-temporal aspect, pattern and structure through temporal remote sensing data along with density gradients and spatial metrics. Urbanization analysis using temporal remote sensing data for Kolkata reveals that area under vegetation has declined from 36 % (1980) to 13 % in 2010. Land use analysis

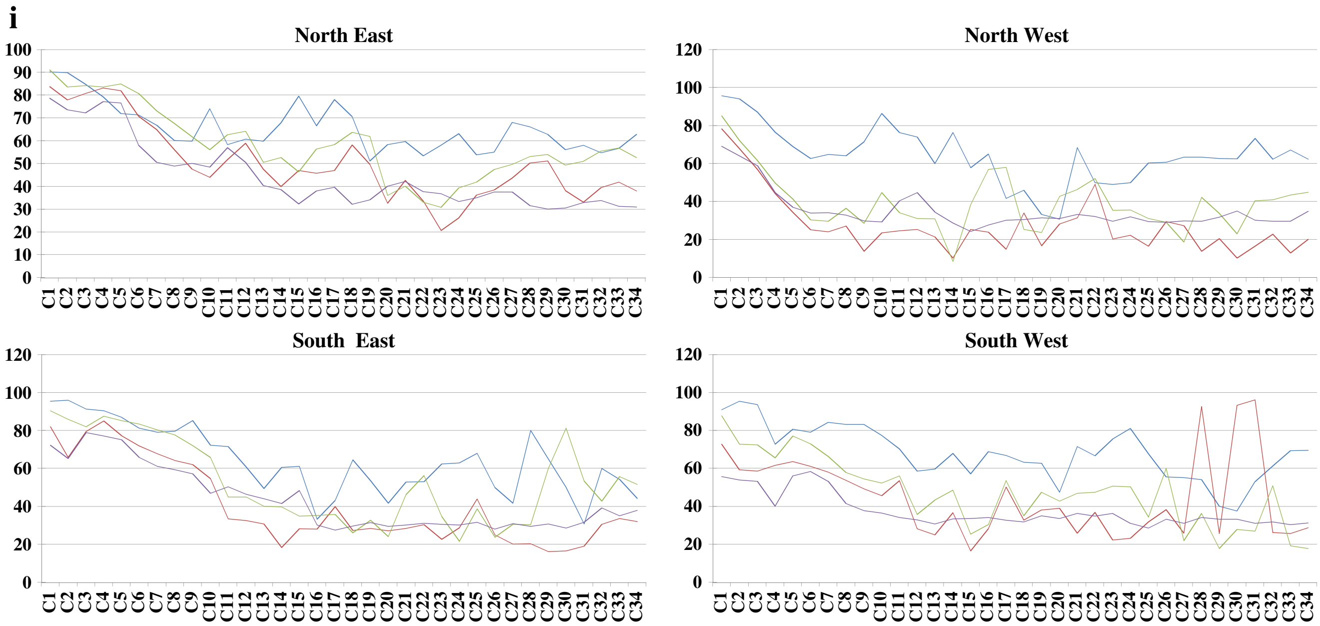


Fig. 9 (continued)

reveals a decline of vegetation from 33.6 % (1980) to 7.36 % (2010). During 2010, built-up constitute 8.6 %, water bodies 3.15 % and other categories about 80.87 %. Increasing Shannon's entropy values highlight the tendency of sprawl that demands for appropriate policy interventions to provide basic amenities in the regions. Temporal remote sensing data with Shannon's entropy have provided substantial multi-purpose information at both regional and local levels for describing, understanding and monitoring the spatial configuration of urban growth to support decision making in complex urban systems.

Spatial metrics computed in density gradients helped in elucidating spatio-temporal patterns of urbanization at local levels and support sustainable urban planning and management decisions. Metrics PLAND show an increase in urban pixels. Contagion metrics (such as number of patches, patch density, edge density, IJI, AWMSI) highlight urban sprawl at outskirts and in the buffer regions, while aggregation indices (Clumpiness, aggregation, NLSI) highlight the process of aggregation at the city centre. The urban pattern analysis through spatial metrics provided insights about the spatial patterns temporally and quantitatively. The metrics highlighted the anthropogenic pressures on the landscape. This indicates that the landscape at the outskirts is highly fragmented and city administration needs to plan in a phased manner to provide basic amenities. Proper land use planning with temporal monitoring would aid in sustainable planning. Coexistence of economic activities, ecological integrity, infrastructural deficits, poverty alleviation and population growth are posing serious challenges to urban planning. These require integrated interdisciplinary studies to understand the multi-dimensional and complex interactions of urban systems to analyse effects of different measures.

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References

Angel S, Parent J, Civco D (2007) Urban sprawl metrics: an analysis of global urban expansion using GIS. Proceedings of ASPRS 2007 Annual Conference, Tampa, Florida May 7–11.URL: http://clear.uconn.edu/publications/research/tech_papers/Angel_et_al_ASPRS2007.pdf

Bhatta B (2009) Analysis of urban growth pattern using remote sensing and GIS: a case study of Kolkata, India. Int J Remote Sens 30(18): 4733–4746

Bhatta B (2010) Analysis of urban growth and sprawl from remote sensing data. Springer, Berlin

Bonnerjee S (2012) Multi-functional role of the urban waterways: a case study of Kolkata. In Proceedings of Internal River Symposium, at Melbourne, Australia, 8–12 Oct. 2012

Bunting SW, Kundu N, Mukherjee M (2002) Situation analysis of production systems and natural resource use in PU Kolkata. Institute of Aquaculture, Sterling

Census of India, 2011, (http://censusindia.gov.in/)

Congalton RG (1991) A review of assessing the accuracy of classifications of remotely sensed data. Remote Sens Environ 37:35–46

Congalton RG, Oderwald RG, Mead RA (1983) Assessing Landsat classification accuracy using discrete multivariate analysis statistical techniques. Photogramm Eng Remote Sens 49:1671–1678

Duda RO, Hart PE, Stork DG (2000) Pattern classification. 2nd edn. Wiley, New York, ISBN 9814-12-602-0

Galster G, Hanson R, Ratclfee MR (2001) Wrestling sprawl to the ground: defining and measuring an elusive concept. Hous Policy Debate 12(4):681–717

Gregory P (2005) A synthesis of peri- urban research of Kumasi, Hubli Dharwad and Kolkata peri-urban interfaces, Development Planning Unit (DPU), University college London. Available at www.nrsp.org/database/documents/2812.pdf

Gustafson EJ (1998) Quantifying landscape spatial pattern: what is the state of the art? Ecosystems 1:143–156

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

Herold M, Goldstein N, Clarke K (2003) The spatiotemporal form of urban growth: measurement, analysis and modeling. Remote Sens Environ 86:286–302

Jiang F, Liu S, Yuan H, Zhang Q (2007) Measuring urban sprawl in Beijing with geo-spatial indices. J Geogr Sci 17:469–478

Lillesand TM, Kiefer RW (2002) Remote sensing and image interpretation, 4th edition, Wiley, New York, ISBN 9971-51-427-3. 215–216

Maiti S, Agrawal PK (2005) Environmental degradation in the context of growing urbanization: a focus on the metropolitan cities of India. J Hum Ecol 17(4):277–287

Maktav D, Erbek FS (2005) Analyse of urban growth using multi-temporal satellite data in Istanbul, Turkey. Int J Remote Sens 26(4):797–810

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

Mitrakis NE, Topalogou CA et al (2008) A novel self-organising neuro-fuzzy multilayered classifier for land cover classification of a VHR image. Int J Remote Sens 29:4061–4087

Peiser R (2001) Decomposing urban sprawl. Town Plan Rev 72(3):275–298

Rahman A (2007) Application of remote sensing and GIS techniques for urban environmental management and sustainable development of Delhi, India, applied remote sensing for urban planning, governance and sustainability. Springer, New York, pp 165–197

Ramachandra TV, Kumar U (2008) Wetlands of greater Bangalore, India: automatic delineation through pattern classifiers. Electronic Green J 26:1076–7975

Ramachandra TV, Bharath AH, Durgappa DS (2012) Insights to urban dynamics through landscape spatial pattern analysis. Int J Appl Earth Obs Geoinformation 18:329–343

Stow DA, Chen DM (2002) Sensitivity of multi-temporal NOAA AVHRR data of an urbanizing region to land use/cover changes and mis-registration. Remote Sens Environ 80:297–307

Sudhira HS, Ramachandra TV, Jagadish KS (2004) Urban sprawl: metrics, dynamics and modelling using G1S. Int J Appl Earth Obs Geoinformation 5:29–39

Sudhira HS, Ramachandra TV, Bala Subramanya MH (2007) City profile: Bangalore. Cities l24 (4):379–390

Taubenbock H, Esch T, Thiel M et al (2008a) Urban structure analysis of mega city Mexico City using multi-sensoral remote sensing data. In Proceedings of SPIE-Europe (international society for optical engineering) conference, Cardiff, Wales

Taubenbock H, Wegmann M, Berger C, Breunig M, Roth A, Mehl H, (2008b) Spatiotemporal analysis of Indian megacities. In Proceedings of the international archives of the photogrammetry, remote sensing and spatial information sciences, XXXVII: 75–82, Part B2

Torrens PM, Alberti M (2000) Measuring sprawl. Working paper no. 27, Centre for Advanced Spatial Analysis. University College, London

Turner BL (1994) Local faces, global flows: the role of land use and land cover in global environmental change. Land Degrad Dev 5:71–78

Turner MG, Gardner RH, O'Neill RV (2001) Landscape ecology in theory and practice: pattern and process. Springer, New York

United Nations Population Fund (2007) The state of world population 2007: unleashing the potential of urban growth, United Nations publications, and chapter 1

Yeh AGO, Li X (1999) Economic development and agricultural land loss in the Pearl River delta, China. Habitat Int 23:373–390

Zhang L, Wu J, Zhen Y, Shu J (2004) A GIS-based gradient analysis of urban landscape pattern of Shanghai metropolitan area, China. Landsc Urban Plan 69:1–16