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Monitoring urbanization and its implications in a mega city from space: Spatiotemporal patterns and its indicators

T.V. Ramachandra [a,b,c,*], A.H. Bharath [a,b], M.V. Sowmyashree [a]

[a] Energy & Wetlands Research Group, Center for Ecological Sciences [CES], Indian Institute of Science, Bangalore, Karnataka 560 012, India
[b] Centre for Sustainable Technologies (ASTRA), Indian Institute of Science, Bangalore, Karnataka 560 012, India
[c] Centre for Infrastructure, Sustainable Transportation and Urban Planning [CiSTUP], Indian Institute of Science, Bangalore, Karnataka 560 012, India

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ABSTRACT

Rapid and invasive urbanization has been associated with depletion of natural resources (vegetation and water resources), which in turn deteriorates the landscape structure and conditions in the local environment. Rapid increase in population due to the migration from rural areas is one of the critical issues of the urban growth. Urbanisation in India is drastically changing the land cover and often resulting in the sprawl. The sprawl regions often lack basic amenities such as treated water supply, sanitation, etc. This necessitates regular monitoring and understanding of the rate of urban development in order to ensure the sustenance of natural resources .Urban sprawl is the extent of urbanization which leads to the development of urban forms with the destruction of ecology and natural landforms. The rate of change of land use and extent of urban sprawl can be efficiently visualized and modelled with the help of geo-informatics. The knowledge of urban area, especially the growth magnitude, shape geometry, and spatial pattern is essential to understand the growth and characteristics of urbanization process. Urban pattern, shape and growth can be quantified using spatial metrics. This communication quantifies the urbanisation and associated growth pattern in Delhi. Spatial data of four decades were analysed to understand land over and land use dynamics. Further the region was divided into 4 zones and into circles of 1 km incrementing radius to understand and quantify the local spatial changes. Results of the landscape metrics indicate that the urban center was highly aggregated and the outskirts and the buffer regions were in the verge of aggregating urban patches. Shannon's Entropy index clearly depicted the outgrowth of sprawl areas in different zones of Delhi.

1. Introduction

Megacities in India are urbanising at an unprecedented and irreversible rate, as the global proportion of urban population has increased from 28.3% in 1950 to 50% in 2010 (World Bank, 2011). Urbanization is one of the demographic issues in the 21st century in India (Ramachandra et al., 2012a,b). Understanding the process of urbanisation would help the city planners to understand and plan and eradicate the problems associated with increased urban area and population, and ultimately build a sustainable city. Urbanisation is one of the few major topics that has been studied focussing on socio-economic, and environmental perspectives in urban areas (Cohen, 2006), to economic perspectives in peri–urban areas (Ravallion et al., 2007), to the loss of vegetation (Ramachandra et al., 2012a,b) and with respect to urban emissions (Banerjee and Srivastava, 2011; Ramachandra and Shwetmala, 2009; Fung et al., 2005). Qualitative attempts have also been made to summarize the development of urbanization studies (Morse, 1965). The urban process refers to the conversion of the rural and natural forms into urban areas due to population immigration into existing urban area. Rural–urban migration is one of the major events that usually accompany economic expansion and hence leads to major agglomerations. Increased density of population has direct impact on the social and economic condition of the cities (Knox, 2009). This phenomenon is particularly significant in developing countries, where the rural–urban areas become one of the very important places of urban growth. These peri-urban areas where the urban sprawl occurs are devoid of basic amenities and are normally left out on most of the civic governing body facilities (Ramachandra et al., 2012b). Urban sprawl considered to be one of the major

* Corresponding author. Energy & Wetlands Research Group, Center for Ecological Sciences [CES], Indian Institute of Science, Bangalore, Karnataka 560 012, India.
E-mail address: cestvr@ces.iisc.ernet.in (T.V. Ramachandra).
URL: http://ces.iisc.ernet.in/energy, http://ces.iisc.ernet.in/foss

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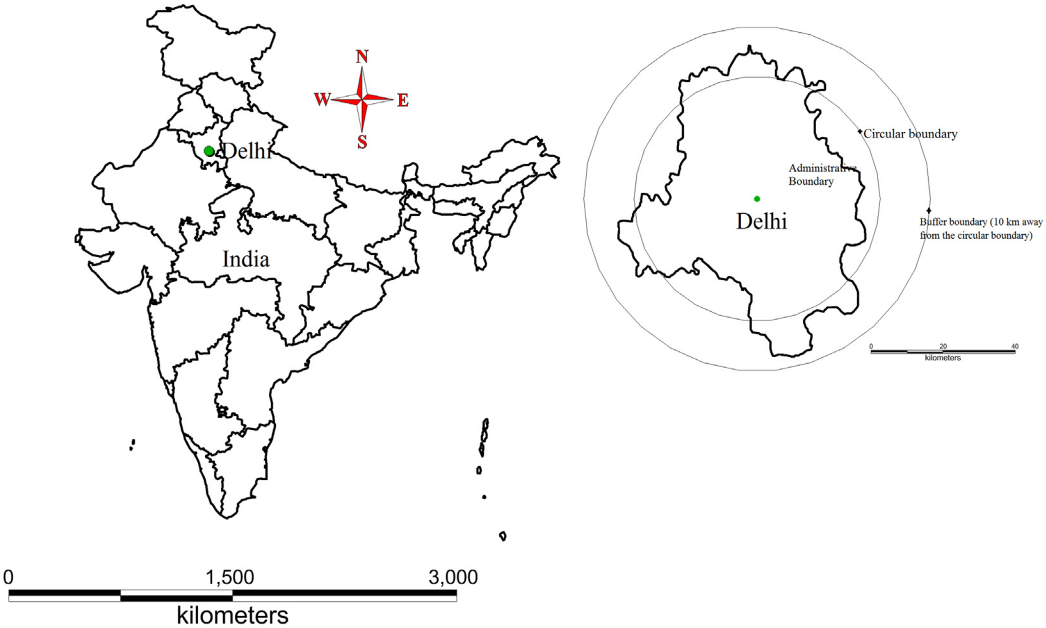


Fig. 1. Map depicts the Delhi administrative boundary.

reasons for rural push and spreading of city towards outskirts. The sprawl takes place at the urban fringes resulted in radial development of the urban areas or development along the highways results in the elongated development of urban forms (Sudhira et al., 2003). The urban sprawl quantifies the urban process and urban pattern. Urban Sprawl further affects the urban core areas by phenomena such as massive congestion, insufficient public transportation and infrastructure, lack of proper sanitation and many other basic amenities. With it come extreme socioeconomic disparities, vulnerability to natural and manmade risks (Fuchs et al., 1994; Mitchell, 1999; Kraas, 2007; Kraas and Nitschke, 2008; Ramachandra et al., 2012a). This necessitates the study of spatial urban growth patterns. Urban pattern refers to the spatial properties and configuration of the area at a particular time (Galster et al., 2001). Urban patterns also deals with physical structure and the spatial characteristics of the urban processes that vary over time (Aguilera et al., 2011). Urbanization process in Delhi has the major impact on the India's urban development. The rapid increase of urbanization resulted in the increased population density. Geoinformatics such as Geographic Information systems (GIS) with the temporal remote sensing data help to quantify changes in landscape structure that result from various disturbances (Turner and Carpenter, 1998). Many landscape-level metrics have been developed to examine and provide meaningful ways of measuring landscape characteristics (e.g., O'Neill et al., 1988; McGarigal and Marks, 1995; Gustafson, 1998; Hargis et al., 1998; Jaeger, 2000; Ramachandra et al., 2012a,b).

Spatial metrics measure the units derived from the spatial data that aid in quantifying the landscape features (Herold et al., 2002; Ramachandra et al., 2012a). The matric based spatial analyses provide quantitative characterizations of the spatial and time composition of landscapes, which would be useful to analyse and understand the changes in landscape structure and patterns (Henebry and Goodin, 2002). The combination of remote sensing and spatial metrics helps to derive spatial information about urban growth, its structure and dynamics that helps in understanding of urban growth processes (Deng et al., 2009; Ramachandra et al., 2012b).

In this backdrop, the objectives of this communication i) understanding the urban dynamics through land cover and land use analysis, ii) understand the local level changes that takes place in the region using directional density gradients, iii) understand and quantify the growth and patterns through spatial metrics. This communication is divided into 4 parts. Part 1 gives details of the study area with its associated attributes. Part 2 discusses the methods adopted in the current research, third part deals with the results and discussion of the results. Final part draws the conclusion based on the analysis of the study area.

1.1. Study area

Delhi is one of the largest metropolis by area and second largest metropolis by population. It is the eighth largest metropolis in the world by population with more than 16.75 million inhabitants in the territory and with nearly 22.2 million residents in the national capital urban region. Delhi is located at 28.61° North latitude and 77.23° east longitude. It borders the Indian states of Uttar Pradesh to the east and Haryana on the north, Rajasthan on the west and south. Delhi is situated on the banks of the River Yamuna. The River Yamuna serves as the bed of agricultural land (Veronique Dupont,

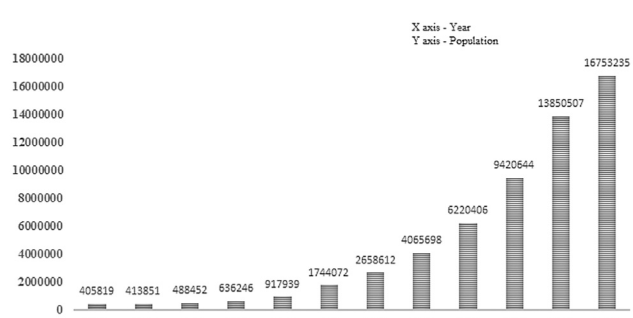


Fig. 2. Growth of population (in number crores) of Delhi from 1901 to 2011.

Table 1
Area, Population and Population density of Delhi (Source: Census India-1971, 1981, 1991, 2001 and 2011).

	Area (sq.kms.)	Year	Population (lakhs)	Population density (persons per sq.km.)
Delhi	2926.03	1971	4,065,698	1207
		1981	6,220,406	1899
		1991	9,420,644	2804
		2001	13,850,507	4371
		2011	16,753,235	5726

2004). Delhi lies about 300 m above the sea level. Fig. 1 depicts the Delhi administrative boundary (with circular boundary) and 10 km buffer considered. The buffer region is expected to reveal the sprawl trend which helps in visualizing the likely urban growth in the region. The National Capital Territory (NCT) of Delhi is spread over an area of 1484 sq km and the Delhi metropolitan area lies within NCT. The NCT has three local municipal corporations: Municipal Corporation of Delhi (MCD), New Delhi Municipal Council (NDMC) and Delhi Cantonment Board (Debnath and Eugene, 2004). The central Delhi is considered as central business district and consists of many industrial and residential areas and Delhi Fort and Jumma masjid are famous monuments found in Central Delhi. The Rastrapathi Bhavan, Parliament House and Supreme Court of India etc. are also located in New Delhi.

Fig. 2 and Table 1 portray the population growth of Delhi during 1901–2011. Table 1 reveals that the population density has increased from 1207 (1970) to 5726 (2011) persons per sq.km. The FDI inflows to Delhi during the period 2000–2006 were found to be Rs.318.61 billion. The total FDI inflows into Delhi is about US$ 20.1 billion according to Economic survey of India. The intensify growth of economy and higher per capita income within the urban district have influenced the real estate's business resulting hike in the costs of land and cost of living.

2. Data used (Table 2)

Table 2
Data used in the analysis.

Data	Year	Purpose
Landsat Series Multispectral sensor (57.5 m)	1973	Landcover and Land use analysis
Landsat Series Thematic mapper (28.5 m) and Enhanced Thematic Mapper sensors	1980, 1998, 2010	Landcover 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

3. Method

Urban dynamics was analysed using temporal remote sensing data of the period 1973–2010. The time series spatial data acquired from Landsat Series Multispectral sensor (57.5 m) and Thematic mapper (28.5 m) sensors for the period 1973–2010 were downloaded from public domain (http://glcf.umiacs.umd.edu/data). Survey of India (SOI) topo-sheets of 1:50,000 and 1:250,000 scales were used to generate base layers of city boundary, etc. The process of the analysis is threefold as described in Fig. 3, which includes

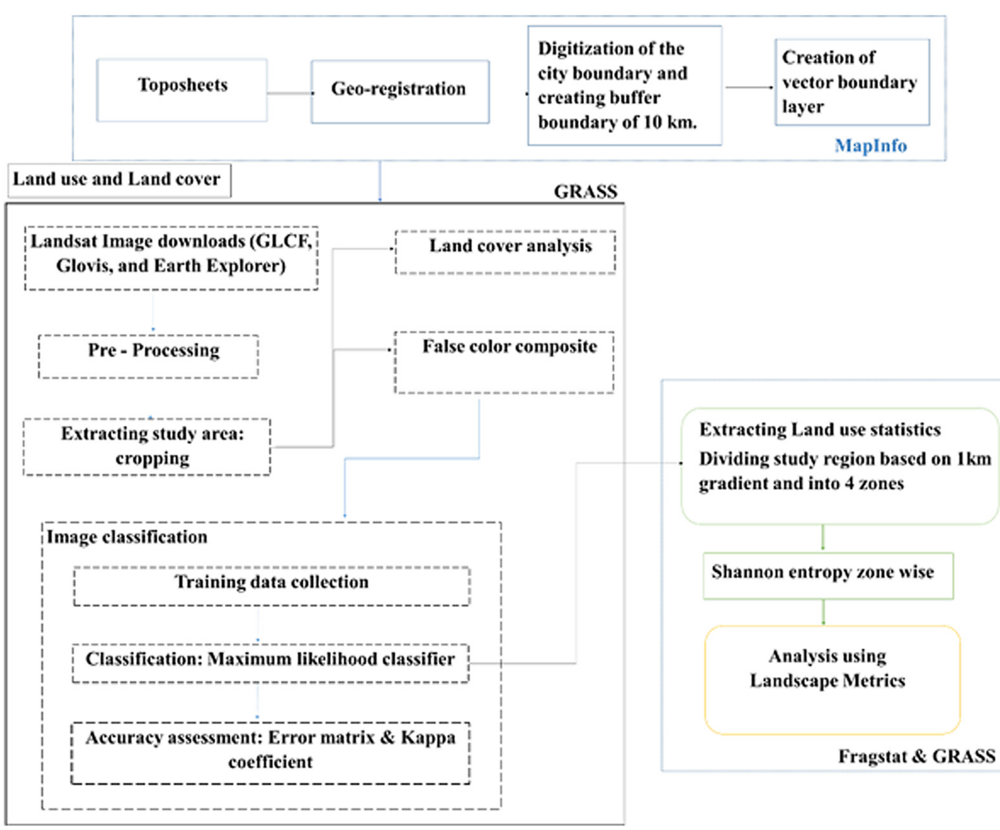


Fig. 3. Procedure adopted for classifying the landscape and computation of metrics.

Table 3
Land use classification categories adopted.

Land use class	Land uses included in the class
Urban	This category includes residential area, industrial area, 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, kaccha roads.

preprocessing, analysis of land cover and land use, finally gradient wise zonal analysis of Delhi.

- Preprocessing: Remote sensing data (Landsat series) for Delhi acquired for different time period 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 pertaining to the study area. Geo-registration of remote sensing data (Landsat data) has been done using ground control points collected from the field using pre calibrated GPS (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 1973 (with spatial resolution of 57.5 m $\times$ 57.5 m (nominal resolution) and 1989–2010 (28.5 m $\times$ 28.5 m (nominal resolution)) were resampled to 30 m in order to maintain uniformity in spatial resolution across different time period. The study area includes the Delhi administrative area with 10 km buffer.
- Land Cover analysis: Land Cover analysis was performed to understand the changes in the vegetation cover during the study period in the study region. Normalised difference vegetation index (NDVI) was found suitable and was used for measuring vegetation cover. NDVI values ranges from values -1 to $+1$. Very low values of NDVI (-0.1 and below) correspond to soil or barren areas of rock, sand, or urban builtup. Zero indicates the water cover. Moderate values represent low density vegetation (0.1–0.3), while high values indicate thick canopy vegetation (0.6–0.8).

Table 4b
Metrics to compute shape complexity of patches (source: McGarigal and Marks, 1994).

Indicator	Formula	Description
Mean Shape Index (Class level) (MSI)	$\mathrm{MSI} = \frac{\sum_{j=1}^{n}\left(\frac{0.25p_{ij}}{\sqrt{a_{ij}}}\right)}{n_i}$ Range: MSI ≥ 1, without limit.	It measures the average patch shape for a particular class. MN (Mean) equals the sum, across all patches of the corresponding patch type, of the corresponding patch metric values, divided by the number of patches of the same type.
Normalised landscape shape Index (NLSI)	$\mathrm{NLSI} = \frac{e_i - \min e_i}{\max e_i - \min e_i}$ Range: 0 to 1	Normalized Landscape shape index is the normalized version of the landscape shape index (LSI) and, as such, provides a simple measure of class aggregation or clumpedness.

- 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 (these correspond to heterogeneous patches in FCC) covering 15% of the study area and uniformly distributed over the entire study area, iii) loading these training polygons co-ordinates into pre-calibrated GPS, vi) collection of the corresponding attribute data (land use types) for these polygons from the field. GPS helped in locating respective training polygons in the field, iv) supplementing this information with Google Earth v) 60% of the training data has been used for classification, while the balance is used 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 are computed using estimate of maximum likelihood estimator. This technique is proved superior classifier as it uses various classification decisions using probability and cost functions (Duda et al., 2000; Ramachandra et al., 2012a,b).

Maximum Likelihood classifier is then used to classify the data using these signatures generated. This method is considered as one

Table 4a
Description of the area metrics.

Indicator	Formula	Description
Class Area (CA)	CA = Area of a class Range: CA > 0, without limit	CA shows how much of the landscape is comprised of one patch type. Equals the sum of the areas (m^2) of all patches of the corresponding patch type, divided by 10,000. a_{ij} area (m^2) of patch *ij*.
Number of patches (Built-up) (NP)	$N = n_i$ Range: NP ≥ 1	NP equals the number of patches of the corresponding patch type. *ni* is the number of patches of a particular type.
Percentage of landscape (Built-up) (PLAND)	$\mathrm{PLAND} = P_i = \frac{\sum_{j=1}^{n} a_{ij}}{A}(100)$ Range: $0 < \%\mathrm{Land} \leq 100$	PLAND equals the percentage the landscape comprised of the corresponding patch type. a_{ij} = area (m^2) of patch *ij*. A = total landscape area (m^2).
Patch Density (PD)	$\mathrm{PD} = \frac{n_i}{A}(10{,}000)(100)$ Range: PD > 0	PD is the number of patch of urban patch divided by total landscape area.
Largest patch Index (Built-up) (LPI)	$\mathrm{LPI} = \frac{\max_{j=1}^{n}(a_{ij})}{A}(100)$ Range: $0 < \mathrm{LPI} \leq 100$	LPI approaches 0 when the largest patch of the built-up patch becomes increasingly small and LPI = 1 when the entire landscape of the patch type of the built-up class.
Mean Patch Size (Class/Landscape) (MPS)	$\mathrm{MPS} = \frac{A}{N_{\mathrm{patch}}}(10{,}000)$ Range: MPS > 0, without limit	MPS equals the sum of the areas (m^2) of all patches of the corresponding patch type, divided by the number of patches of the same type, divided by 10,000.
Patch Area Distribution coefficient of variance (Class level) (PADCV)	$\mathrm{PADcv} = \frac{\mathrm{SD}}{\mathrm{MPS}}(100)$ Range: PADCV ≥ 0, without limit	Calculates coefficient of variation of patch area on a raster map.

Table 4c
Quantification of urban and landscape fragmentation through selected Edge/Border Metrics (source: McGarigal and Marks. 1994).

Indicator	Abbreviation	Formula	Description
Perimeter-Area Fractal dimension (PAFRAC)		$\mathrm{PAFRAC} = \frac{\sqrt[2]{[N\sum_{i=1}^{m}\sum_{j=1}^{n}(\ln P_{ij}\ln a_{ij})]-[(\sum_{i=1}^{m}\sum_{j=1}^{n}\ln p_{ij})(\sum_{i=1}^{m}\sum_{j=1}^{n}\ln a_{ij})]}}{(N\sum_{i=1}^{m}\sum_{j=1}^{m}\ln p_{ij}^{2})-(\sum_{i=1}^{m}\sum_{j=1}^{n}\ln p_{ij})}$ Range: $1 \le \mathrm{PAFRAC} \le 2$	PAFRAC greater than 1 indicating the increase in shape complexity.

Table 4d
Compactness metrics to assess individual patch shape and fragmentation of overall landscape.

Indicator	Formula	Description
Area- weighted Euclidean Nearest Neighbour Distance Distribution (ENN_AM)	$\mathrm{ENN} = hij$	Where hij = distance from patch ij to nearest neighbouring patch of the same type based on patch edge-to-edge distance.
Clumpiness Index (Clumpy)	$G_i = \left[\frac{g_{ii}}{(\sum_{k=1}^{m} g_{ik})-\min e_i}\right]$ $\mathrm{CLUMPY} = \begin{pmatrix} \left[\frac{G_i-P_i}{P_i}\right] & \text{for } G_i < P_i P_i < 5;\text{else} \\ & \frac{G_i-P_i}{1P_i} \end{pmatrix}$ Range: Clumpiness ranges from −1 to 1	Clumpy = −1 when the focal patch type is maximally disaggregated, Clumpy = 0 when the focal patch is distributed randomly and approaches 1, when patch type is maximally aggregated.
Interspersion & Juxtaposition Index (Landscape level) (IJI)	$\mathrm{IJI} = \frac{-\sum_{K=1}^{m}\left(\left[\frac{e\ ik}{\sum_{k=1}^{m} e_{ik}}\right]\ln\left[\frac{e_{ik}}{\sum_{k=1}^{m} e_{ik}}\right]\right)}{\ln 1k\ sca}(100)$ Range: $0 < \mathrm{IJI} \le 100$	eik = total length (m) of edge in landscape between patch types I and k. m = number of patch type present in landscape.

of the superior methods as it uses various classification decisions using probability and cost functions (Duda et al., 2000). Mean and covariance matrix are computed using estimate of maximum likelihood estimator. Land Use was computed using the temporal data through open source program GRASS – Geographic Resource Analysis Support System (http://ces.iisc.ernet.in/foss). Signatures were collected from field visit and help of Google earth. 60% of the total generated signatures were used in classification, 40% signatures were used in validation and accuracy assessment. Classes of the resulting image were reclassed and recoded to form four land-use classes. The excessive noise in the classified images was removed by moving 3 × 3 median filter on it.

- Accuracy assessment methods evaluate the performance of classifiers (Mitrakis et al., 2008). This is done either through comparison of kappa coefficients (Congalton et al., 1983). For the purpose of accuracy assessment, a confusion matrix was calculated. Accuracy assessment, Kappa coefficient, are common measurements used in various publications to demonstrate the effectiveness of the classifications (Congalton, 1991; Lillesand and Kiefer, 2005). Recent remote sensing data (2010) was classified using the collected training samples. Statistical assessment of classifier performance based on the performance of spectral classification considering reference pixels is done which include computation of kappa (κ) statistics and overall (producer's and user's) accuracies. For earlier time data, training polygon along with attribute details were compiled from the historical published topographic maps, vegetation maps, revenue maps, etc.
- Zonal analysis: City boundary along with the buffer region has been divided into 4 zones: North east, Southwest, Northwest, South east for further analysis as the urbanization is not uniform in all directions. As most of the definitions of a city or its growth is defined in directions it was considered more appropriate to divide the regions in 4 zones based on direction. 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.
- Division of these zones to concentric circles (Gradient Analysis): Each zone was divided into concentric circle of incrementing radius of 1 km radius from the center of the city, this analysis helped in visualising the process of change at local level and to understand the agents responsible for changes. This helps in identifying the causal factors and locations experiencing various levels (sprawl, compact growth, etc.) of urbanization in response to the economic, social and political forces. This approach (zones, concentric circles) also helps 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.
- Shannon's entropy: Further to understand the growth of the urban area in specific zone and to understand if the urban area is compact or divergent the Shannon's entropy (Sudhira et al., 2004; Ramachandra et al., 2012a,b) was computed for each zones. Shannon's entropy (Hn) given in Eq. (1), explains clearly the development process and its characteristics.

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

where Pi is the proportion of the built-up in the ith concentric circle. As per Shannon's Entropy, if the distribution is maximally concentrated in one circle the lowest value zero will be obtained.

Table 5
NDVI values generated.

Years	Vegetation	Non-vegetation
	Area (%)	Area (%)
1977	46.47	53.53
1980	41.79	58.21
1998	39.58	60.42
2010	34.87	65.12

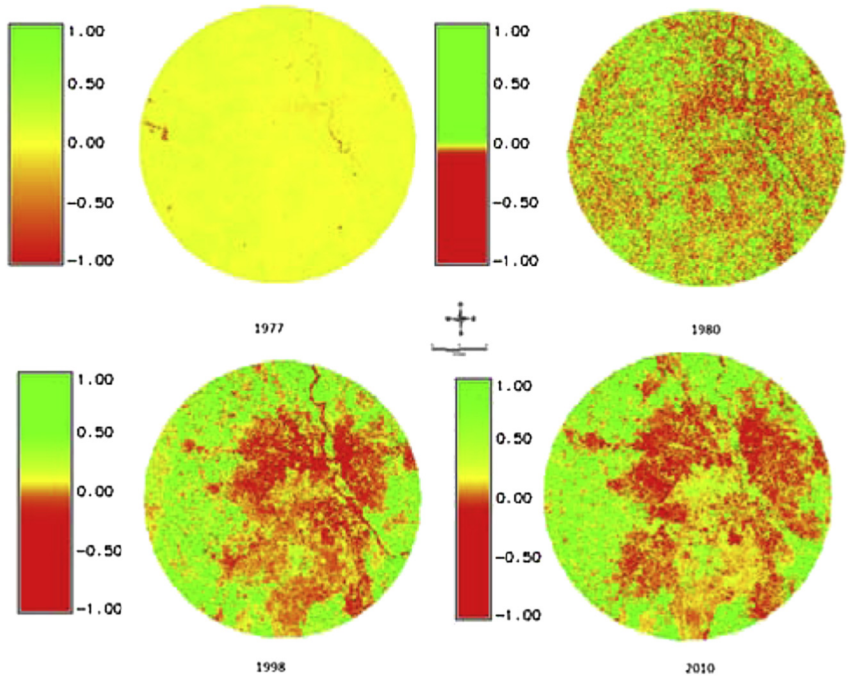


Fig. 4. Extent of vegetation through NDVI.

Conversely, if it is an even distribution among the concentric circles will be given maximum of log n.

Computation of spatial metrics: Spatial metrics are helpful to quantify spatial characteristics of the landscape. Selected spatial metrics were used to analyse and understand the urban dynamics, FRAGSTATS (McGarigal and Marks in 1995) was used to compute metrics at three levels: patch level, class level and landscape level. Tables 4a–d give the list of the metrics along with their description considered for the study.

- *Area metrics*: Area metrics quantifies the composition of the landscape and provides information about the area occupied by various patches in the landscape. Table 4a provides description of area metrics.

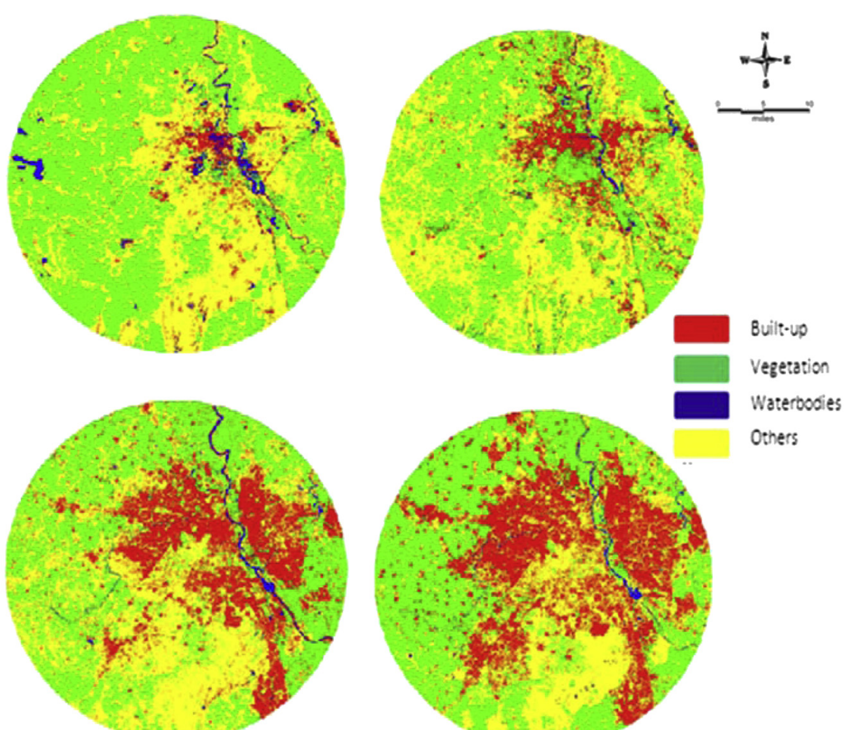


Fig. 5. Temporal land use of Delhi.

Table 6
Land Use statistics of the classified images.

Land use category	Built-up	Vegetation	Water body	Others
Years	Area (%)	Area (%)	Area (%)	Area (%)
1977	3.60	41.30	1.70	54.40
1980	9.71	38.22	0.90	51.17
1998	19.85	34.86	1.47	43.82
2010	25.06	31.39	1.16	42.32

- *Shape Metrics*: Shape metrics listed in Table 4b quantify the landscape configuration by measuring shape complexity of patches at patch, class and landscape level. Shape is a difficult parameter to quantify concisely in a metric (McGarigal and Marks, 1994). All the shape indices are based on perimeter to area ratio and thus they help in interpreting irregularities in urban patches.

Edge/Border Metrics: Edge metrics (Table 4c) quantify length and distribution of the amount of edge between patches (Frohn and Hao, 2006). They represent landscape configuration, even though they are not spatially explicit at all (McGarigal and Marks, 1995). These edge attributes can provide critical information for quantifying and understanding urban and landscape fragmentation.

Compactness Metrics/Contagion and Interspersion Metrics: Compaction is the formation of rounded patches in a circular shape that makes them more compact (Aguilera et al., 2011). These metrics listed in Table 4d quantify landscape configuration. Compactness Metrics is the measure of individual patch shape and fragmentation of overall landscape.

4. Results and discussion

Land cover analysis: Temporal vegetation cover analysis done through the computation of NDVI. This metric helps to understand the changes in the vegetation cover and ranges from values -1 to +1. Very low values of NDVI (-0.1 and below) correspond to soil or barren areas of rock, sand, or urban built-up. Zero indicates the water cover. Moderate values represent low density vegetation (0.1 to 0.3), while high values indicate thick canopy vegetation (0.6 to 0.8).

Table 5 tabulates the NDVI values providing the extent of areas under vegetation versus non-vegetation. Fig. 4 depicts the land cover of the study region during 1977, 1980, 1998 and 2010. Temporal analyses indicate of decline in vegetation by about 75.03%, while the area under non vegetation has shown an increase of 121%.

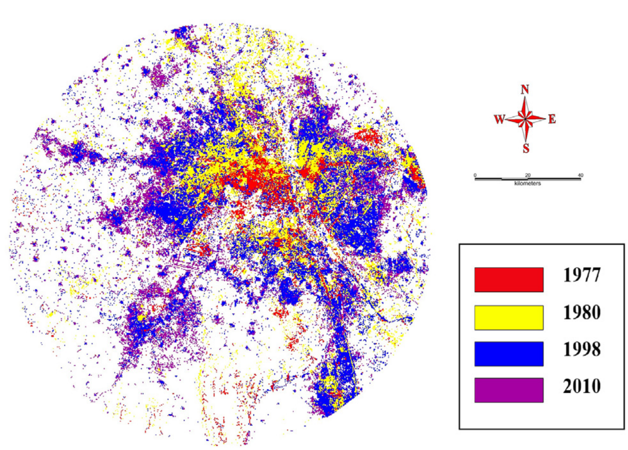


Fig. 6. Delhi urbanization process during 1977–2010.

Further in order to differentiate the impervious layer of urban settlements and other land uses in the non-vegetation category land use analysis was performed.

Landuse Analysis: Land use analyses for the period 1977 to 2010 have been done through the Gaussian maximum likelihood classifier. Fig. 5 depicts the land use during 1977–2010. Table 6 lists land use details which indicate that the area under built-up has increased from 3.6 (1977) to 25.06 (2010)%. Vegetation decreased phenomenally from 41% (in 1973) to 31% (in 2010) with an increase in urban impervious layer. This is significant as this alters the environmental parameters such as ground water recharge, microclimate, etc. Fig. 6 depicts the growth of urban area in the study region in past 4 decades. Accuracy assessment of the classified images was performed by generating the error matrix and kappa statistics. Table 7 depicts the overall accuracy and kappa statistics for the classified images.

Gradient analysis: The study region area was further divided direction-wise into concentric circles and land uses in each subregion were computed. Fig. 7 illustrates the zone and direction-wise temporal land use changes at local levels. The gradient analysis reveals that North East and North West zones show higher urbanisation trend in 2010 with the economic and industrial dominance. Agents such as major air bases such as Indira Gandhi International Airport (IGI) and Indian Air force base (Hindon) have contributed to the urban growth in recent years. Delhi Metro which connected core areas radially outskirts also fuelled the growth. This analysis helped in visualizing the zones of urban expansion. Further to charecterise the growth, Shannon entropy was calculated.

Shannon's entropy (Hn): Shannon's entropy an indicator of growth of urban areas and depicts sprawl rate is computed for all four directions and listed in Table 8. The results indicate that NE and NW regions of the study area are experiencing sprawl. The values of Shannon entropy range from 0 to $\log(n)$. Higher the value or closer to $\log(n)$ indicates the sprawl or dispersed or sparse development. Lower the entropy values the development is either aggregated or compact. The results indicated that the city grew phenomenally in the south east and north west directions during 90's. Fig. 8 depicts that trend urban patches in the northeast and northwest directions are getting fragmented.

4.1. Spatial metrics

Landscape metrics were calculated through Fragstat software using the binary file output from grass.

4.1.1. Class area

Class area metrics calculates the area of the particular class in hectares. This metrics were tabulated for urban class. Fig. 9 below depicts the class area metrics direction wise and gradient wise. Urban area is dominant in 2010 in the NE direction and in the NW direction. Drastic increase in class area occurred in the years 1990's and 2000's (Fig. 9a).

4.1.2. Percentage of Land (PLAND)

PLAND equals the percentage of landscape comprised of the corresponding class patches. Built up percentage was computed to understand the ratio of built up and its increase in the landscape.

Table 7
Overall accuracy and kappa statistics of classified images.

1970s		1980s		1990s		2000s	
OA	$\widehat{\kappa}$	OA	$\widehat{\kappa}$	OA	$\widehat{\kappa}$	OA	$\widehat{\kappa}$
89	0.9432	99	0.9957	97	0.9887	88	0.7163

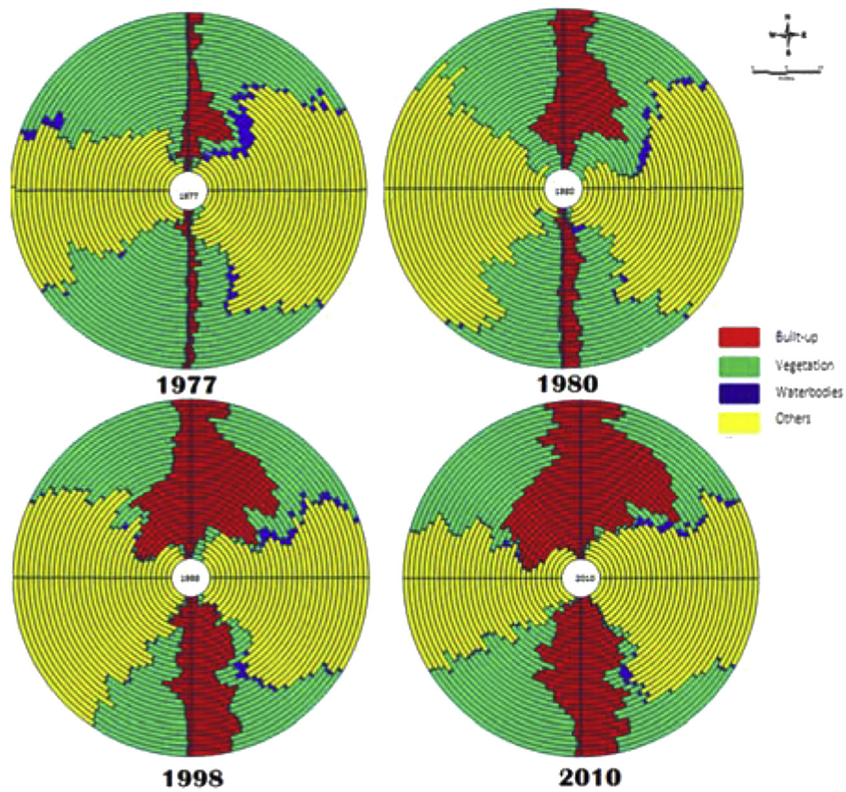


Fig. 7. Circle-wise land use statistics for Delhi.

Table 8
Shows the Shannon's entropy for Delhi region.

	NE	NW	SE	SW	
1977	0.23	0.04	0.10	0.03	Reference value
1980	0.43	0.16	0.20	0.05	1.49
1998	0.60	0.37	0.47	0.15	
2010	0.64	0.57	0.45	0.31	

The analysis shows that percentage of urban landscape is higher in the North-east and South-east direction during 90's and 2000's. For North-west direction maximum patch density found majorly to the core areas in circles ranging from C4 to C15. The overall analysis depicts high rate of urbanization in North- east direction during 90's and in 2010 (Fig. 9b).

4.1.3. Number of patches (NP)

NP equals the number of built up patches in a landscape. It indicates the level of fragmentation in built up landscape. Fig. 9c showed an increasing trend for number of patches from in all directions which also depicts that as we move away from the city center the number of patches increases indicating landscape fragmentation. The higher values for year 1990 in all direction, while in 2010 the patches are combining to from a single compact patch.

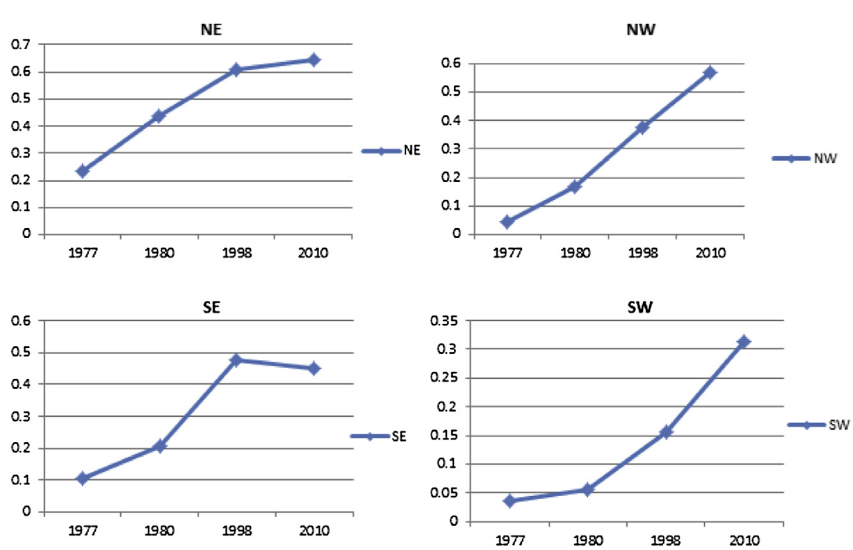
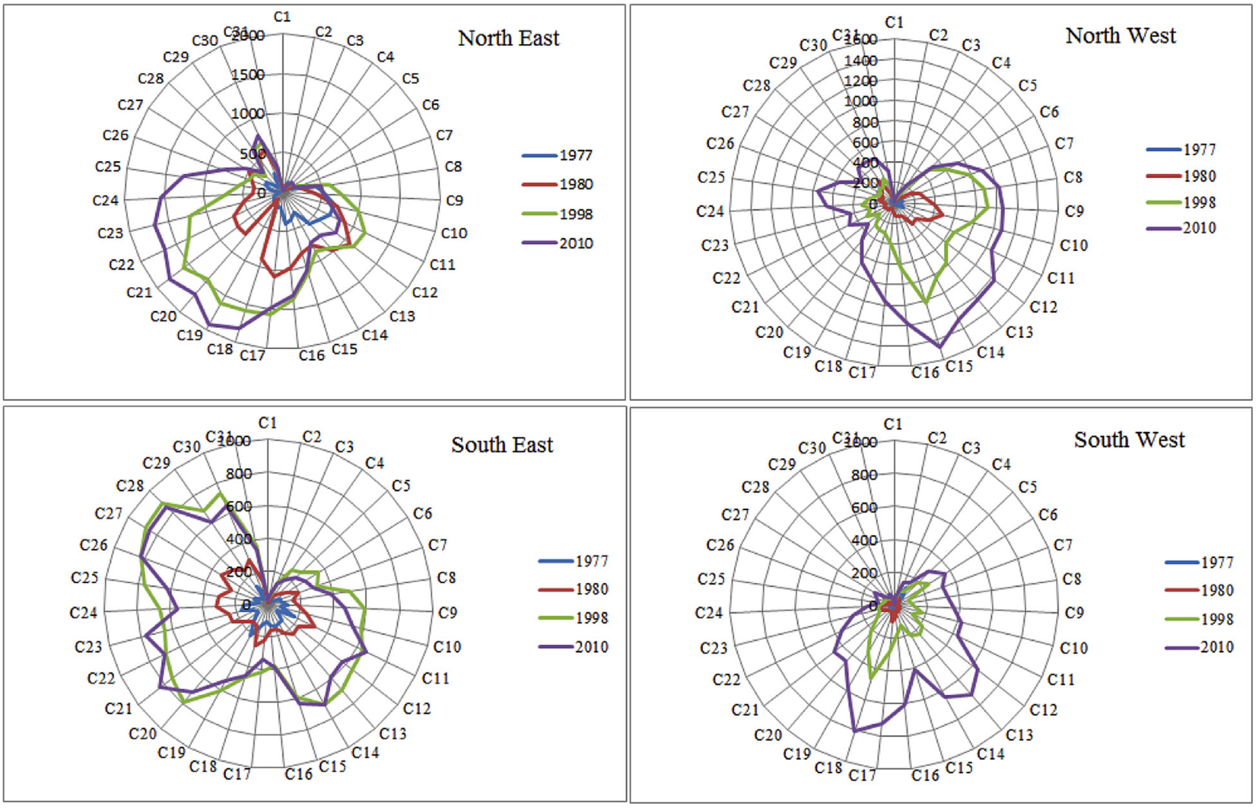
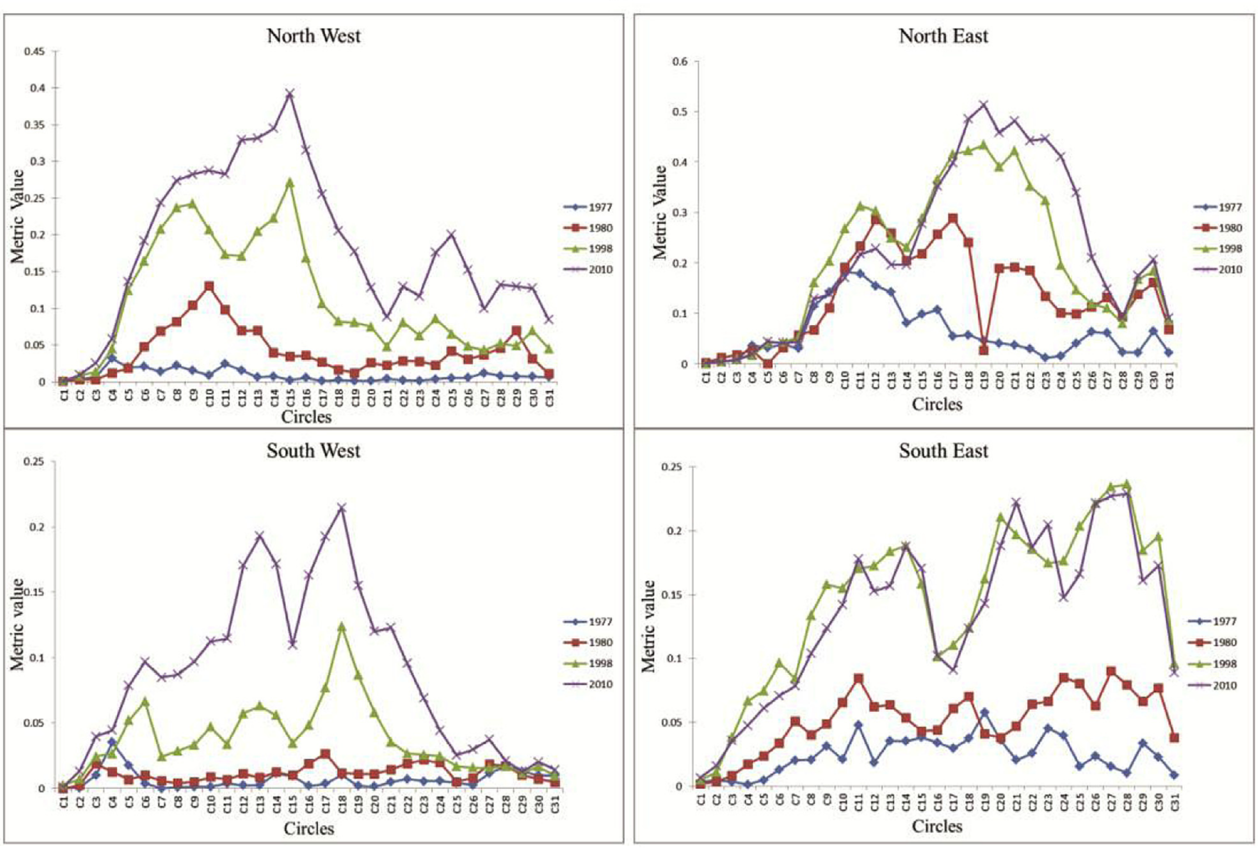


Fig. 8. Shannon's entropy direction-wise for 1977–2010.

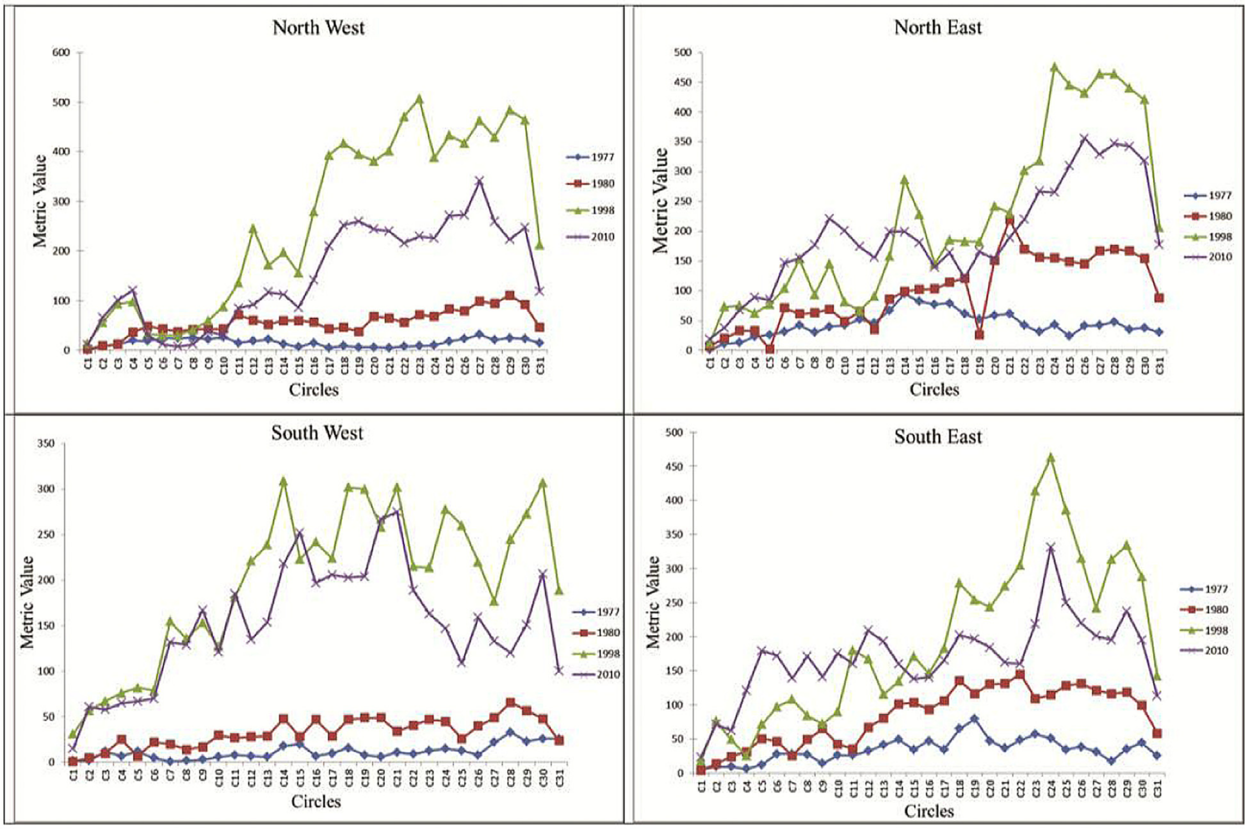


(a)

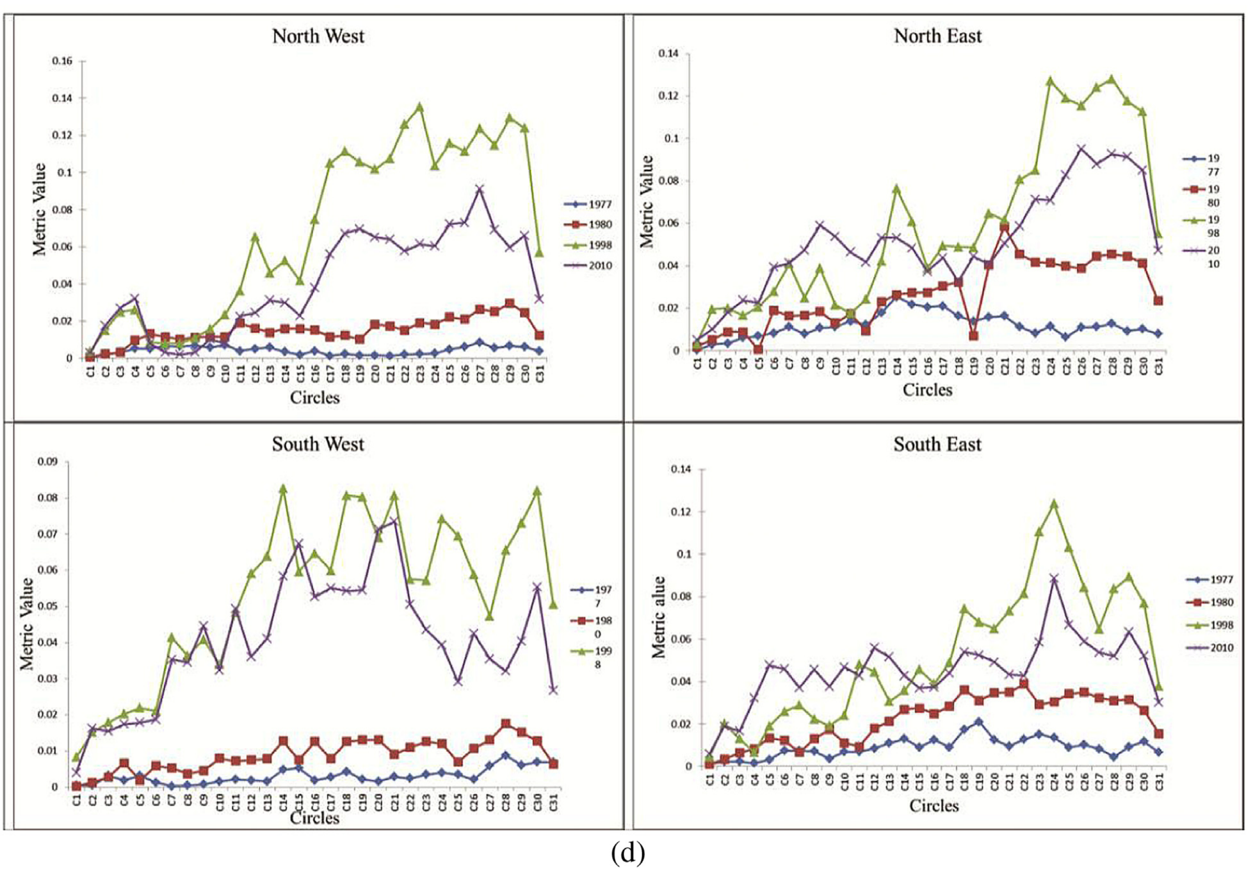


(b)

Fig. 9. a: Urban class area (%). b: Urban PLAND. c: Urban – Number of Patches. d: Urban category patch density. e: Largest Patch Index. f: Mean Patch Size. g: AWMSI – direction and circle wise. h: NLSI of urban landscape. i: Clumpiness. j: IJI.

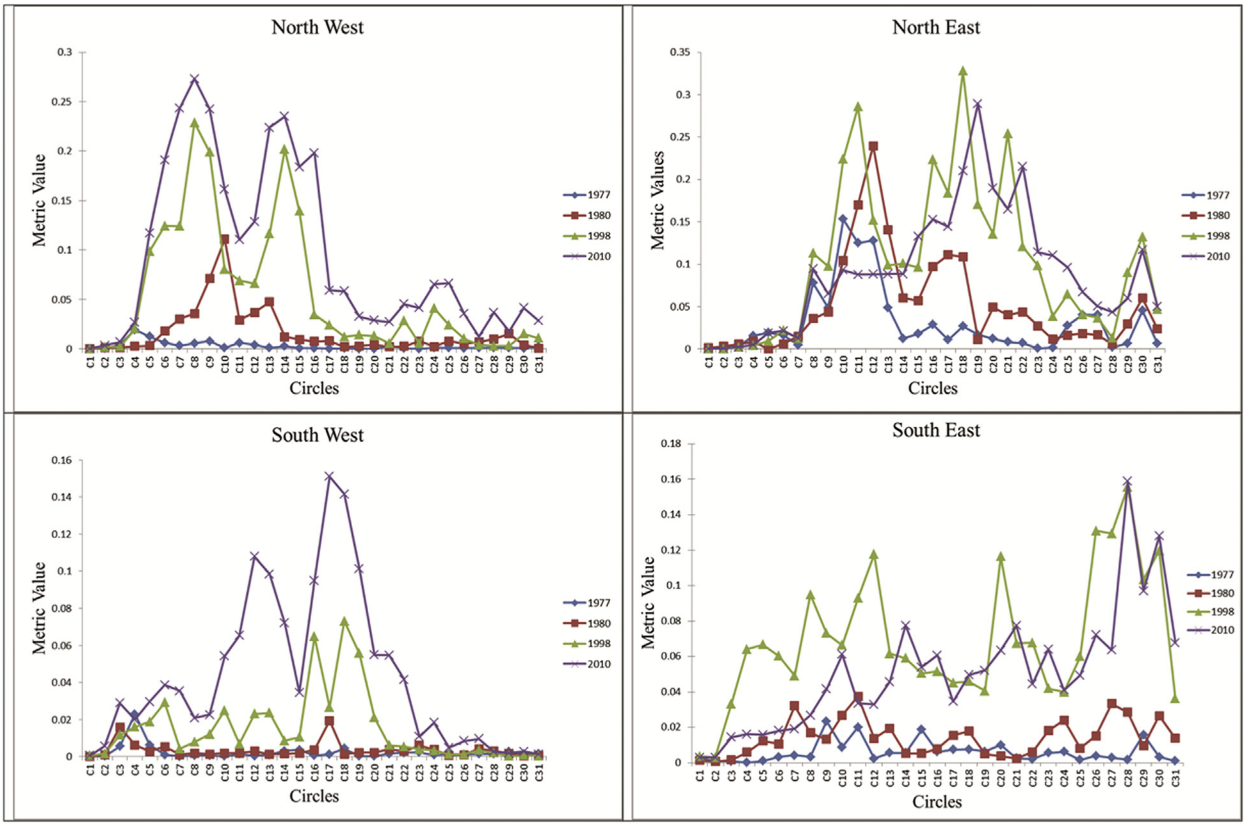


(c)

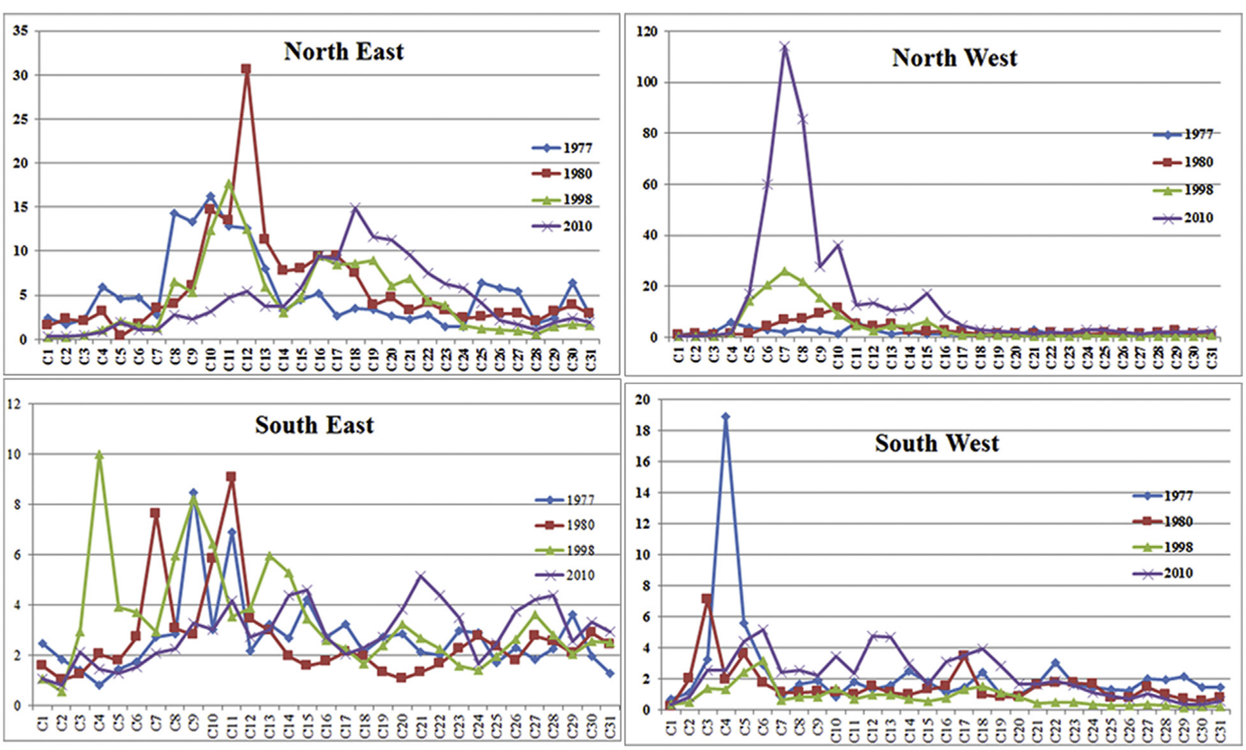


(d)

Fig. 9. (*continued*).

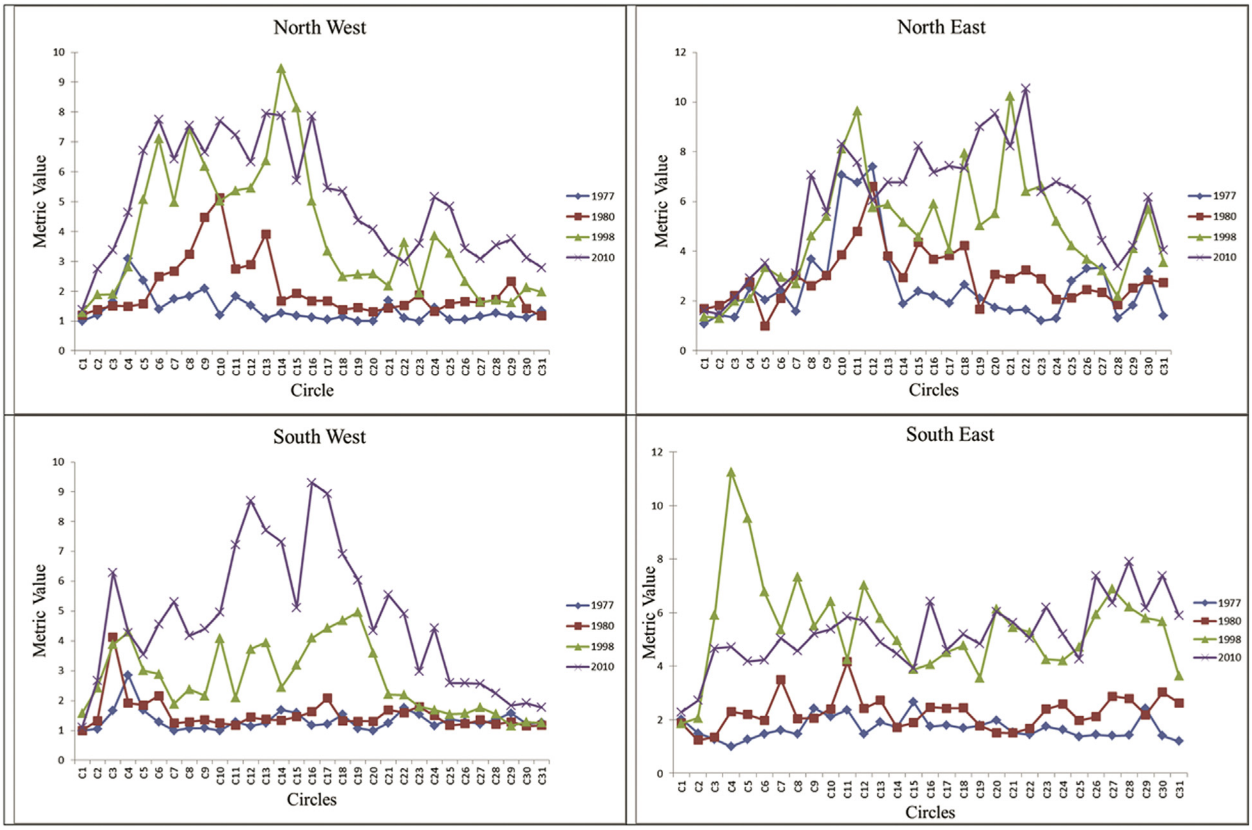


(e)

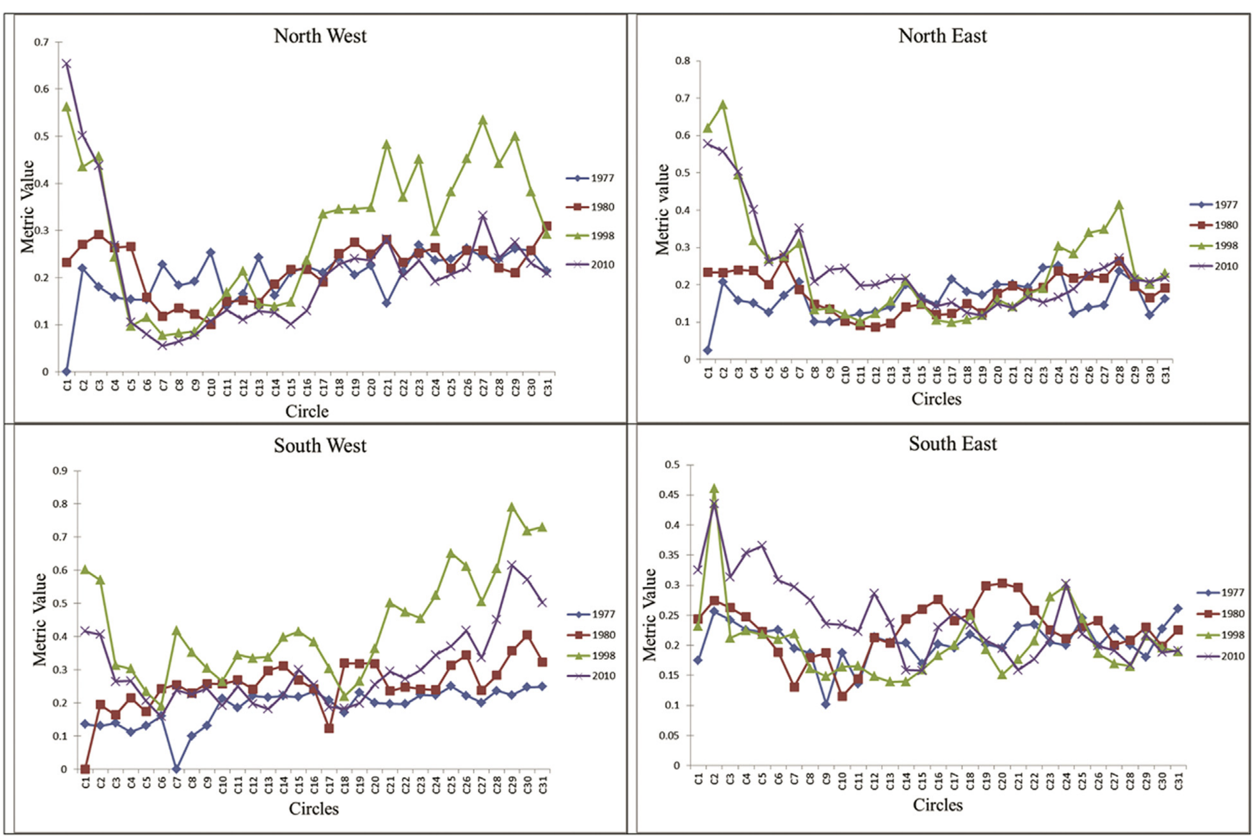


(f)

Fig. 9. (*continued*).

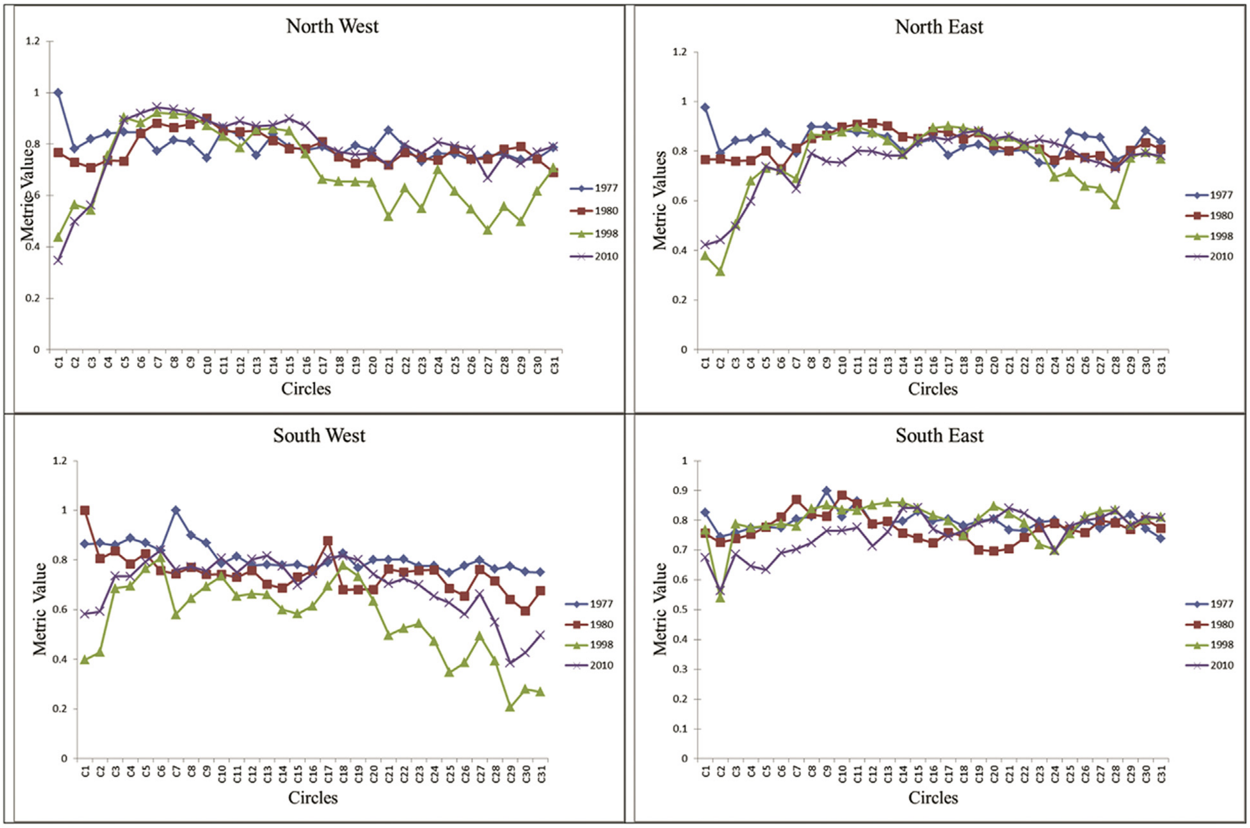


(g)

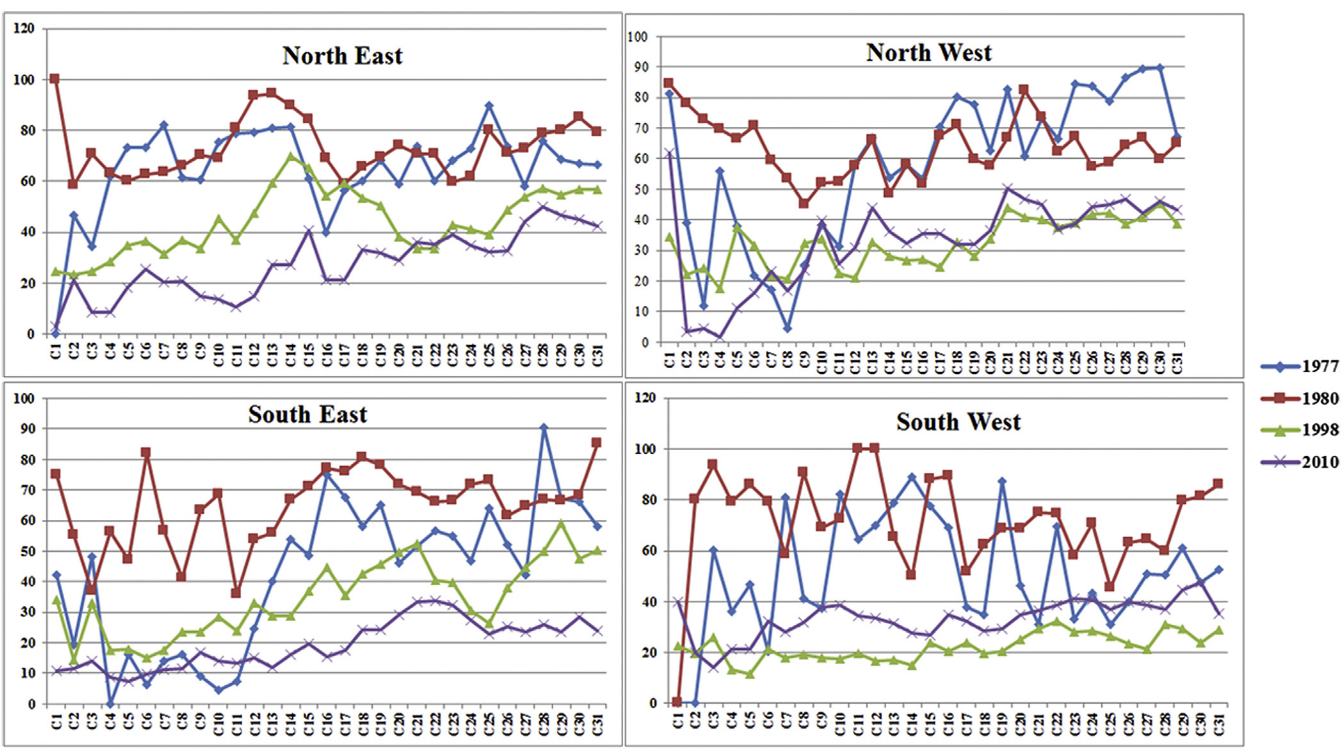


(h)

Fig. 9. (*continued*).



(i)



(j)

Fig. 9. (*continued*).

4.1.4. Patch density

Patch density is an indicator of urban fragmentation. As the number of patches increases, patch density increases which represent higher fragmentation. The patch density also showed the similar trend as the number of patches that is increase in the urban patches in 90's which indicated the more fragmentation of the urban patches and decreased again for 2000's. Fig. 9d represents that the urban patches were more compact in the core areas and gradually increases as we moves away from the core area which indicate the level of fragmentation in the landscape. Higher patch density during 1990 in all direction indicate of fragmentation and hence the sprawl in the region. Patch density values decreased in 2010 indicating that the smaller patches that had come up were aggregating to form a single large patch. Lower patch density in the core area and the fragmented buffer zones has higher Patch density during 2010 emphasise the intense urbanisation at city center and sprawl at the outskirts.

4.1.5. LPI

Largest Patch Index (LPI) represents the largest patch and comparative assessment across the years aids in understanding the urbanisation transitions in the region. Fig. 9e depicts that largest urban patch in circle C11 and C20 in North-east direction (1990's). In North-west direction C8 and C15 showed the maximum values for LPI. In South-east and South-west the largest urban patches were in 2000 This metric helps in identifying the growth poles during different years.

4.1.6. Mean patch size

Mean patch size (MPS) is a measure of subdivision of the class or landscape. MPS of urban class is inversely related to the degree of fragmentation, with lower MPS indicating greater fragmentation and higher value reflects aggregated growth in the city center. Fig. 9f indicates that circles in northeast direction has higher values compared to other direction indicating that the larger patch sizes due to aggregation.

4.1.7. AWMSI

Area weighted mean shape index (AWMSI) was computed in which average shape index of patches was weighted by patch areas so that larger patches are weighed higher than smaller ones. It is used to represent shape irregularities, with smaller values indicating more regular shape and as the value increases complexity and irregularities increases. The area weighted mean shape index (AWMSI) is a robust metric used to describe landscape structure across spatial scales by calculating the complexity of urban patches according to their size (Huang et al., 2009). Fig. 9g highlights of more compact and regular shapes in the core areas because of which the circles near to core area shows minimum value compared to the circles away from the core area which represent complex and fragmented urban patches.

4.1.8. Normalized landscape shape index (NLSI)

NLSI provides a simple measure of class through the measure of shape. Fig. 9h depicts the results of NLSI. The values close to 0 indicate that the landscape is aggregating to form simple shape, values closer to 1 indicate that landscape is fragmented and has convoluted shapes. Analysis indicates of higher values during 1990 as the landscape started fragmenting, whereas during 2010 the values started decreasing this indicated that each fragment is getting clumped to form a single urban landscape Southeast and southwest directions show maximum variations indicating fragmentation and complexity of urban structure.

4.1.9. Clumpiness index (CLUMPY)

CLUMPY is the measure of urban patch aggregation and ranges from 0 (maximally disaggregated) to 1 (maximally aggregated). Temporal analysis of clumpiness index for urban category highlights urban dynamics through the process of aggregation of urban patches. Fig. 9j with the Clumpy values of 1 at core areas (in 1977) indicates of a clumped growth. The process intensified during the post globalization era with higher CLUMPY values at the city centre and fragmented landscape at outskirts (in 2010).

4.1.10. Interspersion and juxtaposition index (IJI)

IJI measures the extents to which patch types are interspersed (not necessarily dispersed). Higher values results when the urban patch types are well interspersed (i.e., equally adjacent to each other), whereas lower values characterize landscapes in which the patch types are poorly interspersed (Mc Garigal and Marks, 1995). IJI ranges from 0 to 100. Values reaching 100 highlight of clumpiness and other patches closer to urban area are becoming rare with time.

5. Conclusions

Temporal land cover analysis indicate of decline in that the vegetation by about 75.03%, while the area under non vegetation has shown an increase of 121%. Land use analyses for the period 1977 to 2010 done through the Gaussian maximum likelihood classifier indicate that the area under built-up has increased from 3.6 (1977) to 25.06 (2010)%. During the past four decades the total urban (built-up) area has increased by more than 638% mainly from the conversion of open areas and other areas including agriculture land. Spatial metrics considering the area, edge, shape, aggregation obtained through the moving window method to quantify the urban builtup land density provide an efficient method for predicting the urban growth pattern. This has aided in visualizing and quantifying the burgeoning urban footprint at Delhi. The analysis also revealed of sprawl and the process of densification has happened around the city centre and has spread out of the core during 1990's and have started to get clumped during 2010. Aggregation and sprawl of built-up land has occurred on cost of fragmentation of various other classes for ex. agriculture land and urban green spaces. Visualisation of urban growth helps the urban planners and decision-makers in formulating appropriate development strategies to mitigate the potential impacts on the urban environment.

Government needs to play a pivotal role in planning sustainable cities with the healthy urban environment and sustenance of natural resources (vegetation, water bodies and open spaces). The results of the current analyses highlight of the significant changes in land cover with the decline in vegetation, water bodies, crop and fallow land. This necessitates an integrated approaches in urban planning to ensure the sustenance of water, moderation of micro climate, etc. Conservative urban planning would take into account the sustenance of natural resources and people's livelihood aspects. The current demand of water as per the recent estimates of Delhi Development authority, is about 1511 billion liters with the shortfall of about 450 billion liters. The annual rain water harvesting potential is about 900 billion liters. Further augmentation of resources is possible through the revival of water bodies that helps in recharging ground water aquifers. Ground water contributes substantially in newly developed localities in Delhi due to insufficient supply of water from Yamuna River. In order to ensure groundwater recharge, the government authorities need to maintain minimum vegetation cover in the region apart from recharge through percolation pits and rain water harvesting. A green belt or native vegetation on either side of banks help in arresting the soil erosion, remediation, minimisation of salinity and improvements in water quality. This entails holistic approaches in urban development to appropriately preserve the areas of various land-use classes considering the ecological and environmental services for maintaining the inter-generational equity.

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