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Intra and Inter Spatio-Temporal Patterns of Urbanisation in Indian Megacities

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ABSTRACT

Major metropolitan (tier I) Indian cities have been experiencing rapid urbanisation during the last two decades with globalization and changes in Indian market. These unprecedented market interventions have led to rapid urban expansions with drastic land cover changes affecting the ecology, climate, hydrology and local environment. Unplanned rapid urbanisation in some cities has given way to the dispersed, haphazard growth at city outskirts. These regions lack basic amenities and infrastructure as the planners lack advance information of sprawl regions. This has necessitated understanding and visualization of urbanisation patterns for planning towards sustainable cities. Temporal availability of spatial data at regular intervals through space borne remote sensors coupled with the recent advances in geo-informatics aids in the advance geo-visualization of spatial patterns of urban growth. The urban expansion and the urban growth dynamics elucidated for four major metros of India, using temporal remote sensing data through density gradient approach and pre-validated spatial metrics. The current communication provides vital insights to the intra and inter spatio-temporal patterns of urbanisation across four rapidly urbanising metropolitan cities in India. Analyses of intra spatial patterns reveal that inner gradients (in the vicinity of central business district) have reached the threshold of urbanisation. Landscape metrics highlight the process of aggregation through clumping of patches to form a dominant urban patch with complex to simple shapes and highly domination urban class. Further, Principal component analyses (PCA) highlight that buffer regions are influenced by patches with complex shaped multi class growth, while core city centers have a simple shaped clumped growth.

Keywords: Urbanization, urban growth, spatial metrics, Principal Component Analysis, density gradients

Mathematics Subject Classification : 68T05

Computing Classification System : Information systems~Geographic information systems

1. INTRODUCTION

Urbanization is the physical growth of urban areas or the territorial progress of a region as a result of increase in population due to migration or peri-urban concentration into cities. Urbanization occurs as individual, commercial, and governmental efforts to improve the opportunities for jobs, education, housing, and transportation. Influence of economic, political, geography and social factors among other factors that cause rural to urban transformation with high concentration of population at a particular place (Ramachandra et al., 2012a, 2012b; Bhaskar, 2012; Ramachandra, 2015a). Unpredictable and unprecedented urbanization exerts pressure on natural resources as open and green ecological spaces gets transformed into residential, industrial, and commercial use, threatening the sustainability of natural resources, which requires an immediate attention of the regional planners (Duh et al., 2008, Desai et al., 2009; Ramachandra et al., 2012a), to improve decision-making and ensure sustainability of natural resources. Understanding these dynamic processes requires monitoring of historical land cover changes and this also aid in the forecasting of urban growth with various plausible policy decisions (Shen et al., 2011).

The underlying effect of unplanned urbanisation is the dispersed or haphazard growth, often referred as urban sprawl (Huang et al., 2007), which leads to inefficient resource utilization (Ramachandra et al., 2012a, 2012b; Bharath S, 2012; Ramachandra and Bharath, 2013; Ramachandra et al., 2015b) and local ecology. This spurts major ecosystem changes affecting the provision of ecosystem goods and services (Grimm et al. 2008) due to the creation of fragmented suburbs and urban expansion near the fringes (Schwarz, 2010), resulting in the unsustainable use of natural resources leading to erosion of natural resources stock (Shen et al., 2011). The consequence of unplanned urbanisation is the loss of water-bodies, natural vegetation, agricultural lands (Wear et al. 1998), decline in the availability of surface as well as ground water (Ourso, 2001: Ramachandra et al., 2012a, 2012c), health impacts due to higher pollutants (Horowitz, 2002) apart from enhanced carbon and ecological footprints. This necessitates understanding of urban revolution that has culminated urban processes over years (Ward et al. 2000). Over the past three decades, urban sprawl and its impacts have attracted attention of regional planners and decision makers (Frenkel and Orenstein, 2012), which has also helped in the analysis of urbanisation process while taking advantages in advancements in geo-spatial technologies.

Remote sensing technology through space-borne sensors provides spatial data at regular intervals and this data is available since 1970’s, which has been playing an important role in monitoring the landscape dynamics. Measurements and analysis of urban areas from remotely sensed data aids as an unbiased tool for urban landscape dynamics analyses and allow the user community to overcome data inconsistencies (Yang and Lo, 2002; Serra et al., 2003; Xian and Crane, 2005; Weng, 2007; Huang et al., 2007; Ramachandra et al., 2012b). Spatio-temporal data have been useful to generate information for assessing urbanisation process through explicit understanding of urban extent and structure (Sudhira et al., 2004; Maktav et al. 2005; Potere et al. 2009; Ramachandra et al., 2012a). Spatio-temporal patterns of urbanisation have been captured through landscape metrics such as density, continuity, concentration, clustering, centrality, nuclearity, mixed uses, and proximity (Galster et al., 2001; Frohn and Hao, 2006; Uuemaa et al., 2009), and urban sprawl through density, scatterness, and mixture of land use. Landscape metrics have been useful in measuring and understanding spatio-temporal patterns of the landscape dynamics for various applications (Dietzel et al. 2005, Weng 2007; Charles et al., 2005; Jat et al., 2008a, b; Deng et al.,2009; Ramachandra et al., 2012b, Ramachandra et al., 2016). Spatial metrics and indices such as Shannon entropy is efficient tool in identifying sprawl regions and vital insights of the urban growth (Ramachandra et al., 2012a, c; Lata et al., 2001; Sudhira et al., 2004, Ramachandra et al., 2014a, b)

India is the 2nd most populated country in the world and is undergoing rapid urbanization with drastic land use land cover (LULC) changes in recent years. Urbanization process has gained momentum with the government's push for economic growth subsequent to globalization during early 1990's. 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). Urbanisation of the Indian metropolis fuelling immigration from other cities results in the conversion of natural resources such as forests, open spaces and agricultural lands to urban impervious regions. The irregular and unplanned development of metropolitan cities has an impact on the peri-urban environment with the gaining impetus towards the destruction of open spaces (parks, wetlands, etc.) For infrastructure and developmental activities, which has created imbalance in the ecosystem (Bhaskar, 2012) evident from increased local temperature, decline in groundwater table, enhanced pollutants, unabated dumping of solid waste, contamination of land, water, etc. These cities lack adequate infrastructure facilities such as sanitation, housing, improper drainages, transportation issues etc., (Desai et al., 2009; Ramachandra et al., 2012b). This necessitates advance understanding of urbanisation process by decision makers and planners to plan towards sustainable smart cities.

Urbanisation process is assessed through temporal land use analyses and through computation of spatial metrics in gradients of each zone. The study region includes the current spatial extent of a city with 10 km buffer. Buffer region is considered to account the growth in peri-urban region of a city. Main questions addressed are (i) the role of spatio-temporal data acquired through space-borne sensors to monitor urbanisation, and (ii) the effectiveness of spatial metrics to characterize urban growth.

This aided in the understanding of spatial urban growth for modelling the future likely urban dynamics in the mega metropolitan Indian cities.

2. STUDY AREA

According to Census of India 2001, there were about 35 cities in India, and now increased to 48 cities (census, 2011). Among these, five cities namely Delhi, Mumbai, Kolkata, Bangalore and Chennai are listed in the top 30 mega cities of the world based on population of > 10 million. (City data, 2010) These Indian macro cities have high population densities with Mumbai growing at 2%, Delhi by 3%, Kolkata by 1.3%, and Chennai by 3%. These cities as illustrated in Figure 1 have population of about 8 million to 14 million (World urbanisation prospects, 2011). Figure 2 depicts the cities chosen for the current investigation of urbanisation apart from understanding the spatial patterns of urbanisation.

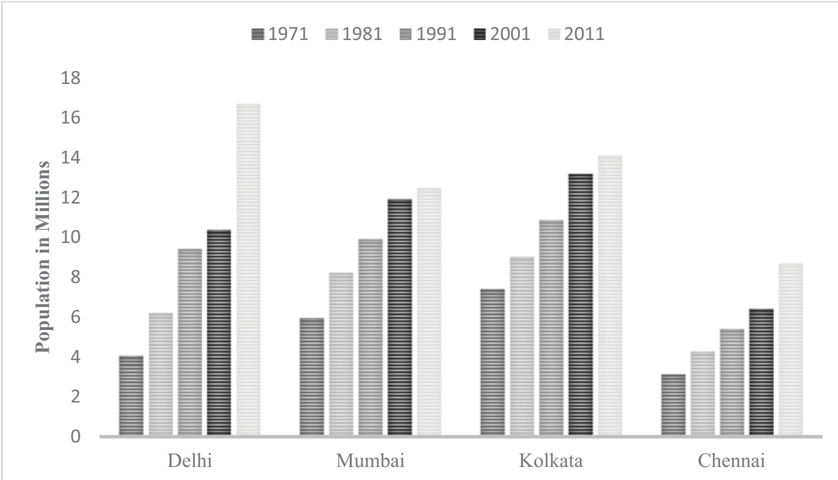


Figure 1. Population growth in 4 megacities of India (In millions)

Figure 2. Metropolitan Indian mega cities - Study regions

3. METHOD

Understanding the urban dynamics and evolution of spatial patterns of urbanization along the gradients (of 1 km incrementing radii) is illustrated in figure 3. The approach involves understanding decadal land use and built-up dynamics, (ii) zone wise (based on directions) gradient analysis (with 1 km gradients), (iii) analyses of spatial patterns of urbanisation through computation of metrics in in each gradient, (iv) Comparing spatial metrics to understand trajectories of urbanization at local levels, (v) analyses of overall patterns of urbanisation through Principal Component Analysis to bring out the intra and inter-regional similarities and variability of urban growth.

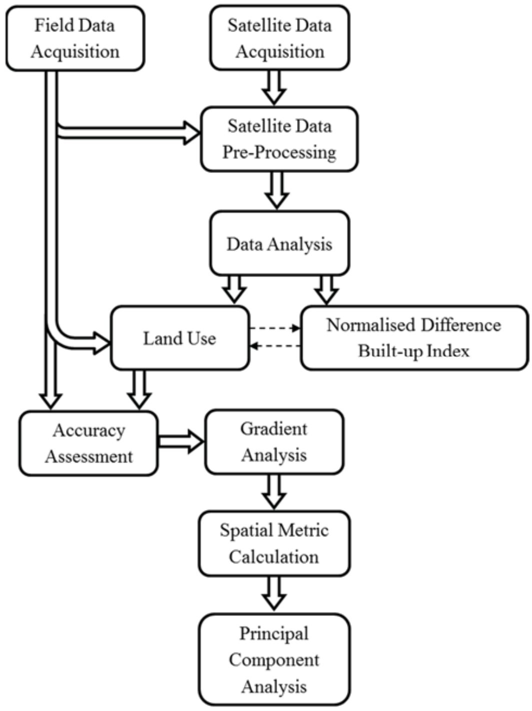


Figure 3. Method adopted for the analysis of spatio-temporal patterns of urbanization

4. DATA

Time series spatial data acquired from the data archive (http://glcf.umiacs.umd.edu/data) of Landsat Series Multispectral sensor (57.5m) and thematic mapper (28.5m) sensors for the period 1973 to 2010. The IRS 1C data (23.5m) of Chennai for the year 2012 was acquired through NRSC (http://nrsc.gov.in), and the field data for the study regions was collected through pre-calibrated Global Positioning System (GPS). In order to rectify geometric errors of the data acquired through space borne sensors the Ground Control Points (GCP's) were collected from field through GPS and also from geo-registered topographic maps of the Survey of India. The data were geometrically corrected and were resampled to 30 m for uniformity in the spatial resolution of Landsat and IRS 1C data. The study region (administrative boundary with 10 km buffer) were cropped from the respective scenes of RS data.

5. DATA ANALYSIS

5.1 Normalised Difference Built-up Index (NDBI)

NDBI is useful to map the urban built-up regions as paved surfaces (such as built-up land, roads, etc.) have relatively higher reflectance in MIR (1.55 to 1.75µm) and NIR (0.76 to 0.90µm) wavelengths in comparison with other surface features of the earth (Li and Liu, 2008, Chen et al., 2013). NDBI is computed using the equation 1 and values range from -1 to +1, and higher NDBI values indicate dense built-up region.

$$\text{NDBI} = \frac{\text{MIR}-\text{NIR}}{\text{MIR}+\text{NIR}} \qquad \ldots\ldots\ldots\ldots.1$$

5.2 Land use

To understand the temporal dynamics of the landscape, land use analyses were done using Gaussian maximum likelihood classifier (GMLC). Classified land uses include built up, water, agriculture and others. Table 1 lists grouping of sub classes for the respective land use category. Analysis involved generation of False Color Composite (FCC) using the data of NIR, Red and Green bands that helps in the identification of heterogeneous patches of landscape (Ramachandra et al., 2013a), training polygons were collected from these select heterogeneous patches covering at least 15% of the study region. Attribute data of these training polygons were collected from field with the help of GPS in addition to Google earth (http://earth.google.com) and Bhuvan (http://bhuvan.nrsc.gov.in). These training data (60%) were used to classify and the remaining were used to validate the classified land use. Classification was carried out using the Gaussian Maximum Likelihood Classifier (Duda et al., 2005, Ramachandra et al., 2013b) based on the probability density function considering the mean and variance. The classification was carried out using the open source GRASS (Geographic Resource Analysis Support System, http://ces.iisc.ernet.in/grass) GIS.

Table 1. Land use categories

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.

Evaluation of the performance of classifier is done through accuracy assessment techniques. Accuracy assessment (Ramachandra et al., 2013b, Bharath and Ramachandra et al., 2013) decides the quality of the information derived from remotely sensed data. The accuracy assessment is the process of measuring the spectral classification inaccuracies by a set of reference pixels. These test samples are then used to create error matrix (also referred as confusion matrix), kappa (κ) statistics and producer's and user's accuracies to assess the classification accuracies. Kappa is an accuracy statistic (Congalton et al 1983, Ramachandra et al., 2102c) that permits us to compare two or more matrices and weighs cells in error matrix according to the magnitude of misclassification.

5.2 Gradient Analysis

Each study region (metropolitan mega cities with 10 km buffer) was divided into four zones (NE, NW, SE, and SW based on directions) and concentric circles of incrementing one km radii (from the center of city) to visualize the spatial patterns of changes at neighborhood level (Ramachandra et al., et al 2011). Direction based gradient analyses aids in identifying/understanding the causal factors, degree and rate of urbanization at local levels in each gradient. Shannon entropy indicator of urban sprawl is used to understand the spatial extent of urbanization (compact growth or fragmented growth). Shannon entropy (H_n) (Lata et al 2013, Sudhira et al 2004) was calculated across directions with respect to the gradients (“n” regions corresponding to concentric circles) for each city. Shannon entropy is given by equation 2.

$$H_n = -\sum_{i=1}^{n} Pi * \log(Pi) \qquad \text{.........2}$$

Where Pi is the proportion of the built-up in the ith concentric circle and n is the number of circles/local regions in the particular direction. Shannon’s Entropy values ranges from zero (maximally concentrated) to log n (dispersed growth).

5.3 Spatial Metrics Analysis

Spatial metrics provides a quantitative description and configuration of the urban land scape (Ramachandra et al., 2012b, Ramachandra et al., 2013c). The metrics were calculated for each gradient using FRAGSTATS (McGarigal and Marks in 1995). The metrics that were calculated includes CLUMPY, IJI, LPI, LSI, NLSI, NP, PD, PLAND and the description of these metrics are given in Table 2.

Table 2. Landscape metrics analysed

	Indicators	Formula
1	Number of Urban Patches (NP)	$NPU = n$ NP equals the number of patches in the landscape.
2	Patch density(PD)	f(sample area) = (Patch Number/Area) * 1000000
3	Normalized Landscape Shape Index (NLSI)	$NLSI = \frac{\sum_{i=1}^{i=N} \frac{p_i}{s_i}}{N}$ Where s_i and p_i are the area and perimeter of patch i, and N is the total number of patches.
4	Landscape Shape Index (LSI)	$LSI = e_i / \min e_i$ 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. min e_i=minimum total length of edge (or perimeter) of class i in terms of number of cell surfaces.
5	Interspersion and Juxtaposition (IJI)	$IJI = \frac{-\sum_{i=1}^{m}\sum_{k=i+1}^{m}\left[\frac{e_{ik}}{E} * \ln\left(\frac{e_{ik}}{E}\right)\right]}{(\ln(0.5 * \lvert m(m-1)\rvert)} * 100$ eik = total length (m) of edge in landscape between patch types (classes) i and k. E = total length (m) of edge in landscape, excluding background m = number of patch types (classes) present in the landscape, including the landscape border, if present.

6	Clumpiness (CLUPMY)	CLUMPY = $\begin{bmatrix} \frac{G_i-P_i}{P_i} \; for\ G_i < P_i\ and\ P_i < 5, else \\ \frac{G_i- P_i}{1-P_i} \end{bmatrix}$ $G_i = \left(\frac{g_{ii}}{\sum_{k=1}^{m} g_{ii}} - min\ e_i\right)$ gii = number of like adjacencies (joins) between pixels of patch type (class) i based on the double-count method. gik = number of adjacencies (joins) between pixels of patch types (classes) i and k based on the double-count method. min-ei = minimum perimeter (in number of cell surfaces) of patch type (class) i for a maximally clumped class. Pi = proportion of the landscape occupied by patch type (class) i
7	Percentage of Land (Pland)	$PLAND = P_I = \frac{\sum_{j=1}^{n} a_{ij}}{A}$ P_i = proportion of the landscape occupied by patch type (class) i. a_{ij} = area (m^2) of patch ij, A =total landscape area (m^2).
8	Largest patch Index (LPI)	LPI = $\frac{{}_{i=1}^{n}\max(a_i)}{A} * 100$ a_i = area (m^2) of patch i A = total landscape area

5.4 Principal Component Analysis (PCA)

Principal component analysis was carried out to explore the overall spatial patterns of intra and inter region variation in urban form considering landscape metrics computed for each gradient corresponding to four zones of cities (Ramachandra et al., 2015b, Narumasa et al 2013, Madugundu 2014). PCA computes the sample mean 'μ' and covariance 'C'of all the parameters 'n'and their measurements 'm' respectively (equations 3 and 4). The covariance matrix is used to compute the Eigen value 'λ' and Eigen vectors 'e' (equation 5). These Eigen vectors represent the principal components of every measurement, the number of Eigen vectors generated would be equal to the number of parameters. The Principal components are then prioritised based on the Eigen vectors.

$$\mu = \frac{1}{n} * \sum_{i=1}^{n} x_n \qquad \text{.... 3}$$

$$C = \frac{1}{n-1} * \sum_{i=1}^{n}\left((x_i - \mu) * (x_i - \mu)^T\right) \qquad \text{......... 4}$$

$$(C - \lambda^* I) * e = 0 \qquad \text{........ 5}$$

The priorotised landscape metrics such as CLUMPY, IJI, LPI, LSI, NLSI, NP, PD, Pland were used as the components and the measurements were made/considered for every city across gradients along the 4 directions for each decade. These landscape indices (measurements) were normalized using Z-Scores (equation 6) prior to Principal Component Analysis.

$$\text{Z-Score} = \frac{x-\mu}{\sigma} \qquad \text{....6}$$

The scatter plot of Principal components that explains maximum variation of data (example PCA1 versus PCA2) helped in eliciting the urbanization patterns across various gradients, directions and cities.

This analysis was helpful to bring out the systematic similarities and differences between the gradients across cities

6. Results and Discussion

Temporal land use analyses reveal of a highly urbanized landscape and the influence of intense urbanisation in core areas on the buffer zones is evident with dispersed growth. Figure 4 illustrates the urban growth in Indian Mega cities during the past 4 decades. Figure 5 describes the land use details in each gradients during 1970 to 2010. All these cities experienced Infilling growth at the center, while post 1900, due to globalization these regions exhibit leap frog developments with dispersed growth at outskirts. The growth of urban pockets in these regions are circular and poly centric and in some locations axial growth depending of influencing agents. Kappa values calculated as part of accuracy assessment gave a median value of 0.85 for all cities considered, with overall accuracy of 89% on an average.

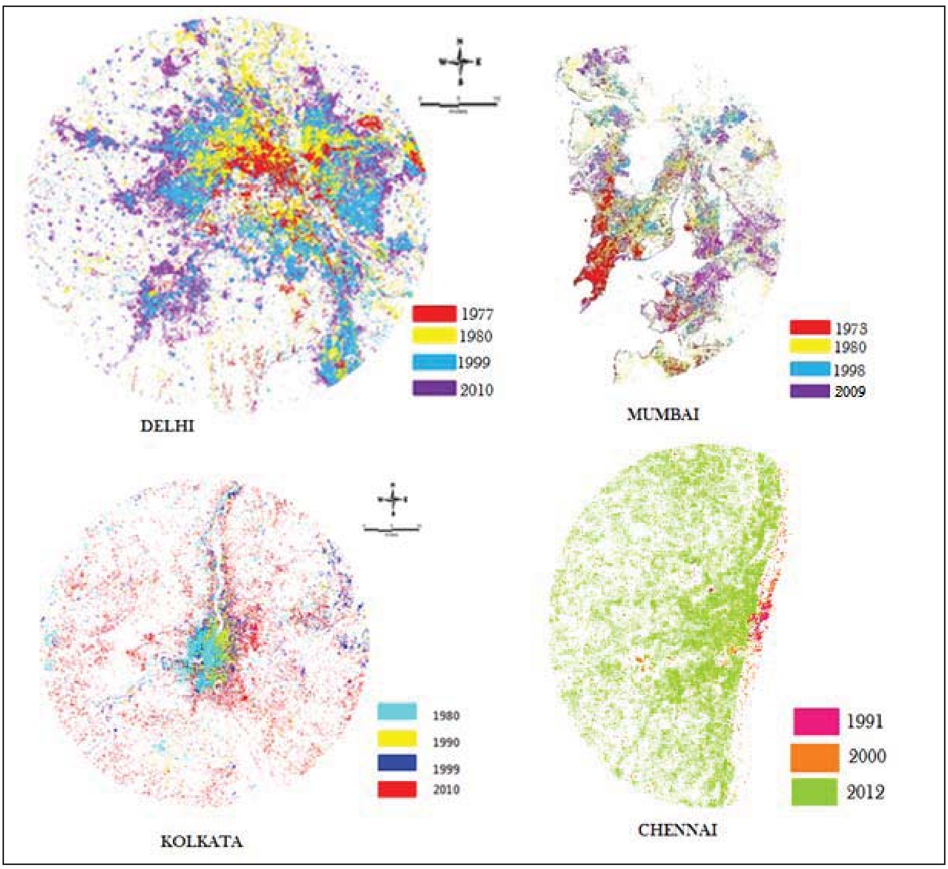


Figure 4. Change detection analysis representing the developments of urban footprint in various Megacities of India.

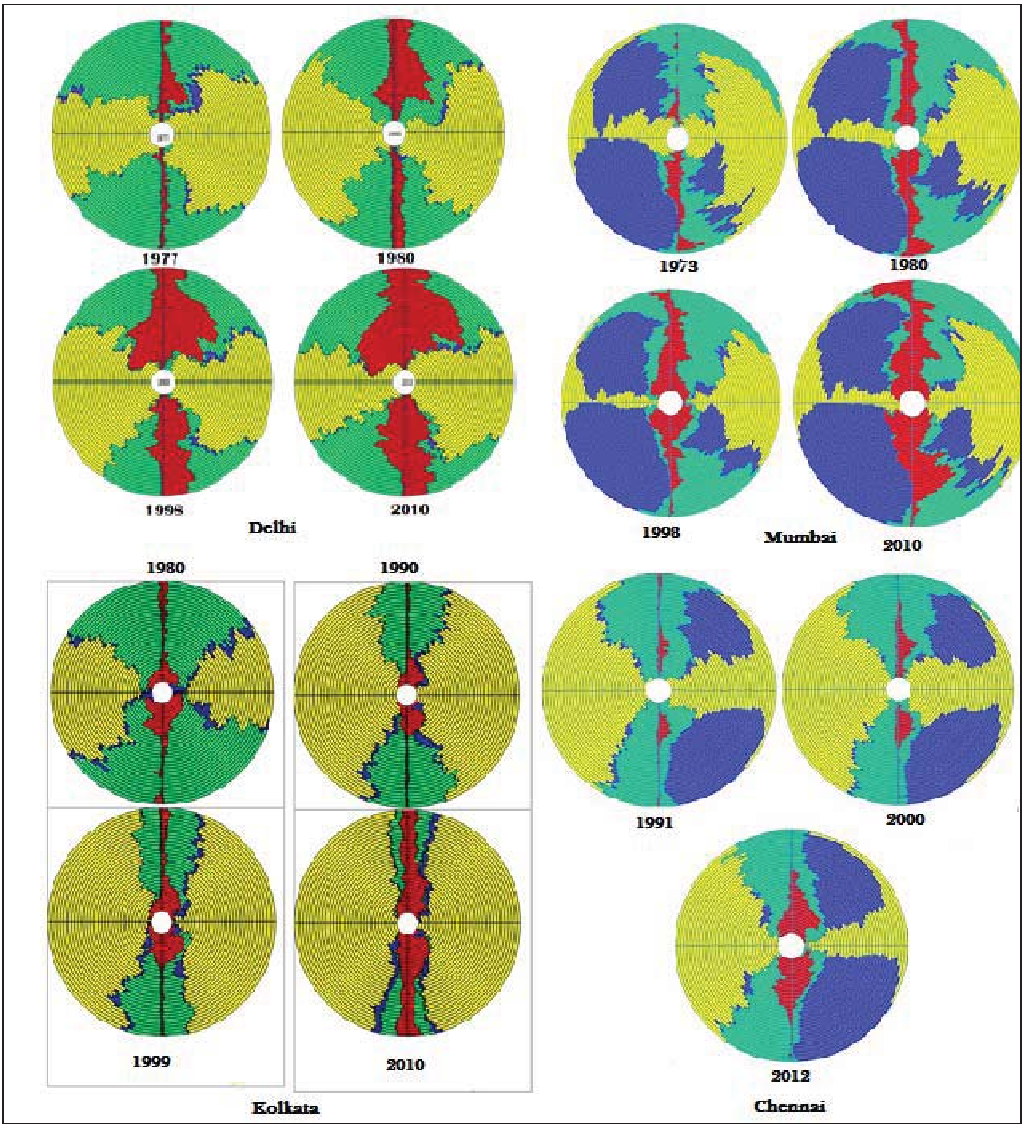


Figure 5. Representation of Gradient wise change land use distribution in 4 decades.

Spatial extent of urban built up computed through Normalised difference building index (NDBI) using temporal RS data are depicted in Figure 6. Comparison of NDBI with land use indicate the Kappa of 0.87 (for Delhi), 0.94 (Mumbai), 0.89 (Kolkata) and 0.88 (Chennai) respectively highlighting relatively accurate land use classification. Further the spatial patterns of urbanisation are assessed through computation of spatial metrics for gradients in four zones.

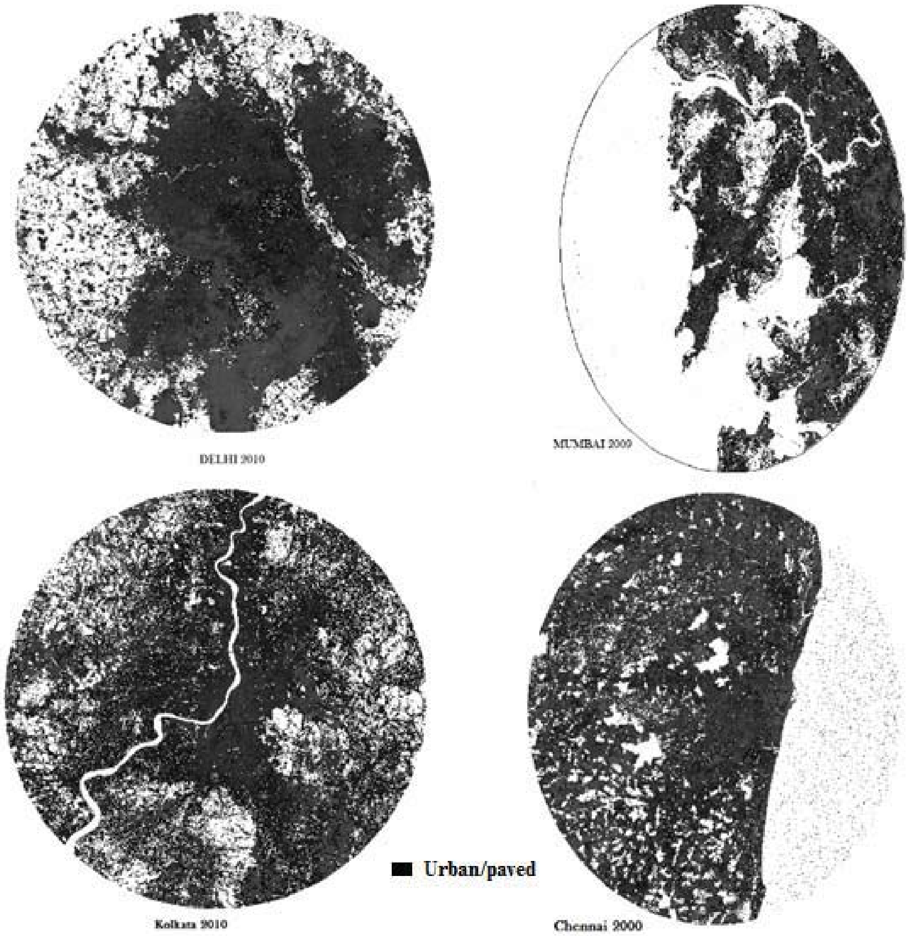


Figure 6. NDBI calculated for all Mega cities

6.1 Understanding the extent of urbanisation

Shannon entropy was computed zone wise as a measure of extent of urbanisation. This helps in identifying the growth as concentrated or urban sprawl (Ramachandra et al., 2012b ; Ramachandra et al., 2013a; Bharath H. A. et al., 2012; Bharath s, et al., 2012). Higher the value of the Shannon entropy and closer to the threshold explains that the city is under the influence of sprawl. Lower the value indicates compact and monocentric urbanisation. Shannon entropy threshold values (log (n)) ranges from 1.49 (Delhi), 1.53 (Kolkata), 1.53 (Chennai) and 1.59 (Mumbai) Shannon entropy calculation for Delhi showed values reaching 0.7 in North east and North west direction, while Mumbai has a highest entropy values in South east and North east with a value reaching 0.45, Kolkata reaching the value of 0.35 in North east and South east in 2010, indicating that these cities experiencing tendency of sprawl and highlight the need for planning towards the provision of basic infrastructure.

6.2 Spatial patterns of urbanisation through spatial metrics and PCA

Landscape metrics were calculated for each gradient of four zones in each city using Fragstat (Figure 7). To examine the overall spatial pattern variations in urban form across cities and over time, principal components analysis (PCA) was done. PCA helped in reducing the dimensionality while explaining variations in spatial data for pre 2000 and post 2000 (2009-12) of cities. This analysis helped in bringing out the similarities and differences between the gradients across cities

Scree plot pre-2000 and post 2000 of all 4 mega cities.is given in Figure 7 as shown below and based on variable representations by first three principal components with eigenvalues of over 1.5 were responsible for a total of 72% of the overall variance in all the metrics.

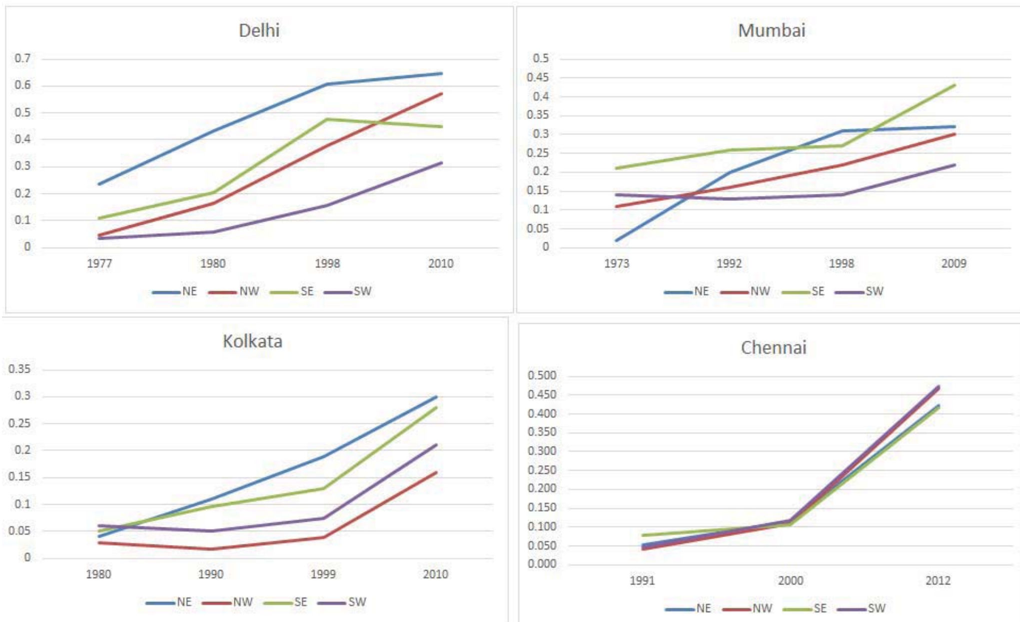
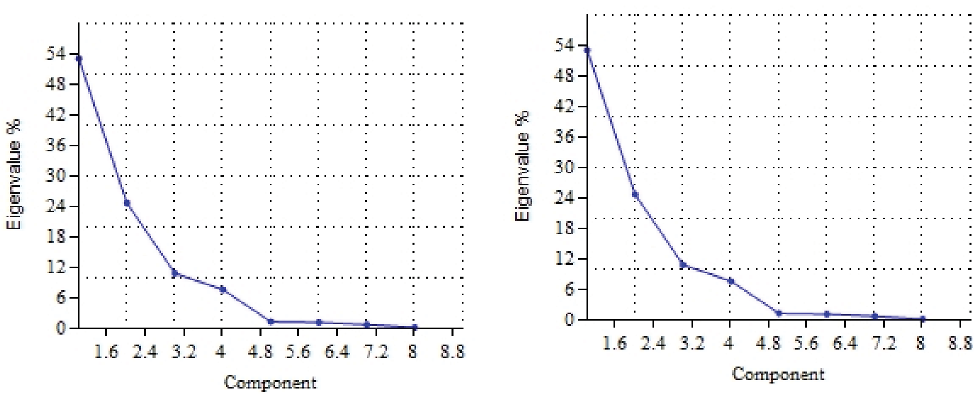


Figure 7. Shannon's Entropy calculated for four Mega cities in India



(a) Pre 2000 (b) Post 2000

Figure 8. Scree plot explaining the variability of respective components

Table 3 indicates that the first principal component is highly correlated with five variables - Clumpy, LSI, LPI, IJI, NP and PD, which are measures of level of fragmentation in the landscape. Further this component suggests irregular shapes in the landscape due to higher patches with patch density. NP and PLAND with correlation of second component indicates large urban patches and higher percentage of urban land forms clusters and gradients. This component is negatively correlated with largest patches and percentage of urban land, which points to the fact that the percentage of urban land is less in these clusters.

Table 3. Correlation of metrics with principal components (pre 2000 data)

	PC 1	PC 2	PC 3
CLUMPY	0.3749	-0.23504	0.16154
IJI	0.14904	0.19067	0.8434
LPI	0.32339	-0.47364	-0.1155
LSI	0.38716	0.39935	0.077559
NLSI	-0.40354	0.25772	-0.2245
NP	0.35867	0.48294	-0.19553
PD	0.38067	0.32158	-0.35593
PLAND	0.38259	-0.3486	-0.16704

Biplot (Figure 9, corresponding to pre 2000) helped in understanding the directional gradient clusters that are formed representing same features in all four metros of India. Gradient clusters formed on extreme right are related with first principal component, of the buffer regions of all four metros which are very few in number. These areas are of very high fragmentation, complex shapes and less clumped (as these metrics are correlated with PCA1).

Further, the clusters located in the midway and closer to the axes correspond to comparatively less fragments (with near simple shapes) and these clusters are dominated by gradients of 1-13 corresponding to a central business district of all 4 metros, representing a compact growth.
Principal component 2 explains mainly the largest patches of urban domination and percentage of urban area in the landscape. Gradients in the top portion of plot are related to this component. Largest patches of urban area in found mainly in buffer zones of Delhi north east and North West. Less large patches of urban area and its dominance is found in the regions of North east of Mumbai, south east of Chennai and North West regions of Mumbai forming separate clusters based on the urban dominance. This analysis showed that these metros are clumped and are concentrated in CBD regions in 1990.

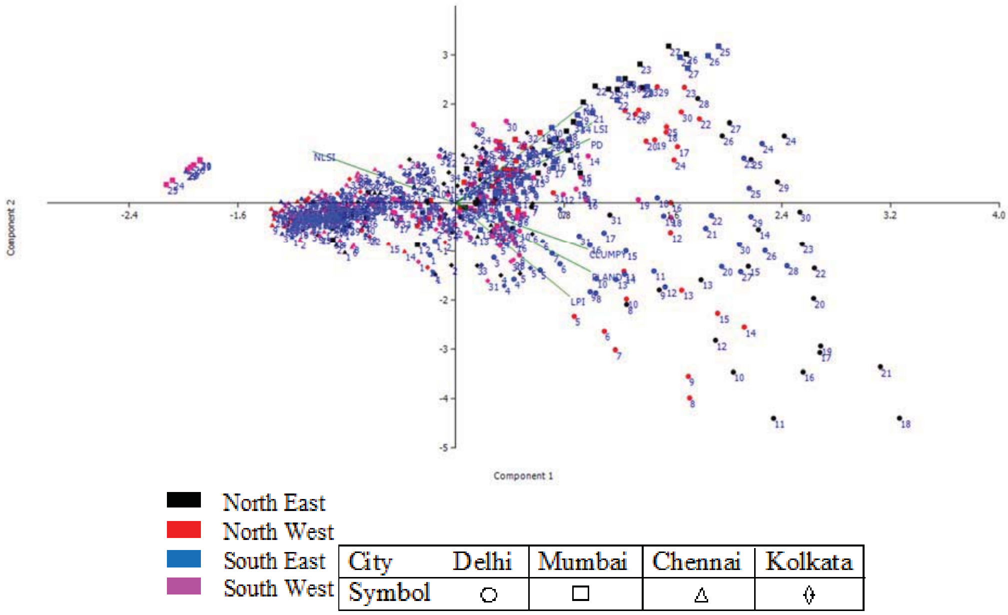


Figure 9. Biplot of principal components based on metrics of pre 2000

Post-2000: urbanisation pattern in four mega cities: As per Scree plot based on variable representations of principal components, first three components deemed useful in explaining the data.

Based on the correlation matrix, as in table 4, the first principal component is strongly correlated with 5 variables of Clumpy, LSI, LPI, NLSI, NP and PD suggesting that there are not much clumped growth, interspersion is less, and lower numbers of largest patches in the landscape. This in turn indicates that high values of patches with high patch density and more irregular shapes in the landscape. The first component strongly correlates with shape and increased patches and form gradient clusters representing irregular shape landscapes with high fragmented patched growth.

Table 4: Correlation of metrics with principal components (post 2000 data)

0	Axis 1	Axis 2	Axis 3
CLUMPY	-0.8557	0.2405	-0.06167
IJI	-0.3626	-0.2174	0.9056
LPI	-0.5575	0.7427	0.049
LSI	0.8447	0.4246	0.07453
NLSI	0.8893	-0.2233	0.06771
NP	0.8539	0.3474	0.09935
PD	0.8758	0.3811	0.1337
PLAND	-0.2747	0.908	0.08079

The second component strongly correlates with LPI and Pland, highlighting clusters and gradients represent large urban patches with higher percentage of urban land and negatively correlated with shapes and interspersion, which indicates more uniform shapes in these clusters and better interspersed. Third component doesn't reveal any reasonable relationship among metrics.

Figure 10 is the plot of principal components which highlight the clustering of gradients with similar attributes in all 4 metros of India. Values on extreme right indicate that the clusters formed at extreme right mainly corresponds to gradients (correlated with PCA 1) of the buffer regions with very high fragmentation, complex shapes and less clumped of all four metros.

Further the clusters with comparatively less fragments with near simple shapes, are located in the midway and closer to the axes. Here the clusters indicate compactness and are dominated by gradients corresponding to circles 10-23, and few gradients of Chennai buffer zones.
Extreme left of Figure 10 shows least related values to the PCA 1 and are dominated by gradients from 1 to 12, corresponding to the regions with high clumped growth, simple shapes and least patches (to form single urban cluster).

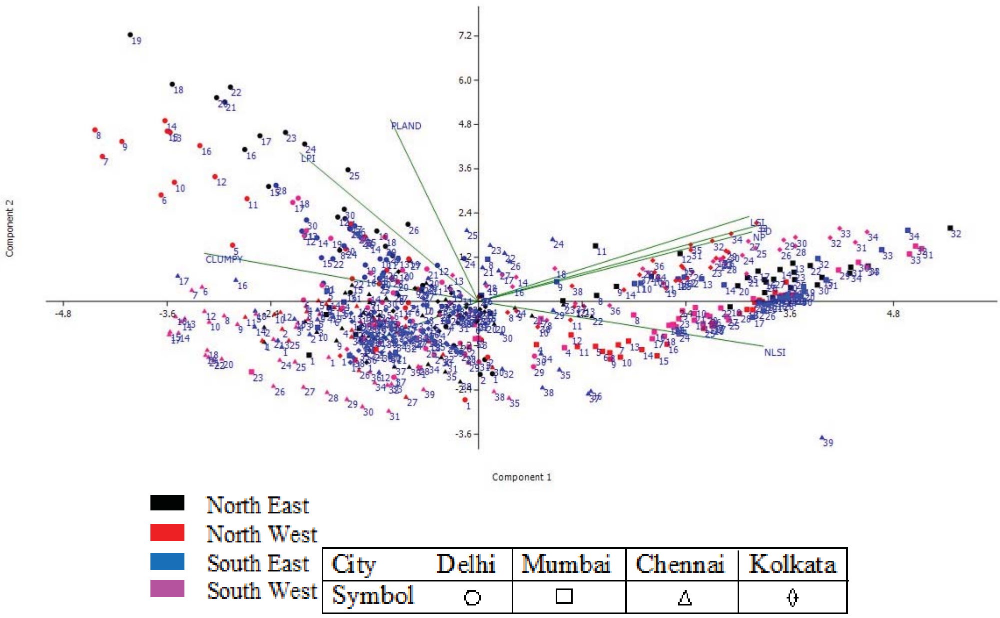


Figure 10. Biplot of principle components based on metrics in 2009

Principal component 2 explains mainly the largest patches highlighting urban domination with higher percentage of urban area in the landscape. Largest urban patches are in buffer zones of Delhi north east and Chennai south east. Compared to this, relatively lesser urban patches and its dominance is found in north east of Mumbai, south east of Chennai and North West regions of Mumbai form separate clusters.

The gradients which are bordering buffer zones and the core area have also bigger urban patches and are comparatively smaller than urban patches in buffer zones. PCA thus aided in delineating highly fragmented urban patches in the buffer zones and highly clumped urban pockets near CBD (core area).

7. CONCLUSION

Temporal land use analyses of spatial data pertaining to four metropolitan Indian cities reveals of a highly urbanized landscape and the influence of intense urbanisation in core areas on the buffer zones is evident with dispersed growth. Principal component analysis enabled the identification of higher urban growths. This denotes spatial patterns of temporal variability, with aggregation or sprawling regions. The findings suggest that the inner core city near the CBD represents the clumped growth, while dispersed growth are in the outer buffer regions. PCA aided in delineating the areas of urban growth with specific urban gradients. This helps in modelling of urban and sub urban regions for planning purposes, which provides valuable insights to urban growth patterns in buffer for evolving appropriate location specific planning strategies.

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