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ANALYSIS OF SPATIAL PATTERNS OF URBANISATION USING GEOINFORMATICS AND SPATIAL METRICS

T.V. RAMACHANDRA
Energy and Wetland Research Group, Centre for Ecological Science
Indian Institute of Science, Bangalore, Karnataka, 560 012, India
cestvr@ces.iisc.ernet.in

H. A. BHARATH
Centre for Sustainable Technology
Indian Institute of Science, Bangalore, Karnataka, 560 012, India
bharath@ces.iisc.ernet.in

M. V. SOWMYASHREE
Energy and Wetland Research Group, Centre for Ecological Science
Indian Institute of Science, Bangalore, Karnataka, 560 012, India

Abstract
Urbanisation process heralds land use changes and consumption of energy which contribute significantly to global warming. This necessitates developing sustainable cities, which entails evolving effective urban planning strategies with the regular monitoring of landscape dynamics. In this context, the current communication reports of urban growth in Hyderabad - the IT capital of India based on the analysis of spatial and temporal heterogeneity of the urban land use changes that helped in the identification of urbanized and sprawling areas. The land use analysis through remote sensing data of the period 1975 to 2009 shows a significant urban growth with an increase in impervious surface from 0.17% to 13.55%. Gradient based spatial metrics analysis reveals the tendency of sprawl at outskirts and the clumped or aggregated growth in core areas. This spatially explicit information helps in the advanced visualization of urban growth for an appropriate and strategic future planning of the city.

Keywords: Urbanisation, Urban sprawl, spatial patterns, Hyderabad, spatial metrics, Land use, Gradients.

1. INTRODUCTION

Urbanisation is the social process referring to the physical growth of urban areas with the increase in population either due to migration or amalgamation of peri-urban areas into cities. The urban population in India has increased from 10.8% in 1901 to 17.3% in 1951, 28.5% in 2001 and 31.5% in 2011. More than 50% of the world population residing in urban areas (United Nations, 2009) consume more than

65% of the world's energy and emit 75% of global greenhouse gas (GHG) emissions. Large scale land cover changes have led to the loss of habitats, ecosystem's productivity and also the ability to sequester carbon. Urban areas have a very high ecological footprint (Herold et al., 2003; Liu & Lathrop, 2002) as urban expansions are associated with problems such as destruction of vegetation, changes in local and global climate and the environmental factors in and around the region (Grimm et al., 2000, Ramachandra et al., 2012a). Unplanned urbanisation have led to a much skewed growth in the region, evident from the dispersed growth in peri-urban areas with the higher consumption of land and without basic amenities and infrastructure.

Unplanned urbanization has brought huge environmental impacts and developed various problems in modern growing cities in India. The urban pattern growth analysis aids in understanding the underlying effects of urbanisation such as sprawl, loss of rural land (Huang et al., 2009) and sensitive habitats. The absence of prior visualization of sprawl regions leads to ineffective administration as these areas are not documented in the administrative policy documents and hence deprived of basic amenities. Sprawl refers to disordered and unplanned growth of urban areas often used to describe the awareness of an unsuitable development (Sudhira et al., 2003; Sudhira et al., 2004; Ramachandra et al., 2012a, 2012b). Agents responsible for sprawl are intense urbanisation in core areas, population increase, and population migration. Environmental problems associated with urban sprawl necessitates better techniques to understand the spatial patterns of temporal urbanisation for sustainable management of natural resources in rapidly urbanizing regions (Lambin et al, 2000). Remote sensing data acquired through space borne sensors at high temporal and spatial resolution available for four decades aids in assessing the spatial patterns of urbanisation (Hall et al, 1995; Lewis et al., 1997; Narumalani et al., 1998; Netzband et al., 2005; Ji, 2000; Steele and Redmond, 2001; Herold et al., 2002; Herold et al., 2003; Bhatta et al., 2009, Ramachandra et al., 2012a, 2012b).

Remote sensing techniques provide economical and reliable spatial data (with diverse spectral and temporal resolutions) required to derive useful information for city managers and planners (Jensen & Cowen, 1999; Yuan et al, 2005; Jat et al, 2008; Wu et al, 2006; Bhatta et al., 2009; Taubenböck et al., 2009a, Taubenböck et al., 2009b, Ramachandra et al., 2012a, 2012b) through the quantification of land use changes, especially quantifying the urban form and to monitor the dynamic changes at regular intervals, (Turner, 2003; Milesi et al, 2003; Sudhira et al., 2004; Anindita et al., 2010; Ramachandra et al., 2012a). Availability of the temporal remote sensing data of the earth's surface helps in mapping and monitoring of landscape. The gradient approach is adopted to identify the local pockets of urbanisation and the spatial patterns of urbanisation are assessed through spatial metrics. Spatial metrics aid in quantifying the urban structure and patterns of urban growth.

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The historical spatial data available since 1970's aids to visualize the urban growth, quantify and understand its pattern (Netzband et al., 2005; Ramachandra et al., 2012a). Landscape geometric pattern analysis through spatial metrics based on land use classifications is gaining importance in recent years (Fu and Chen 2000; Wu, 2004; Li and Wu 2007; Bharath et al., 2012; Bharath s et al., 2012; Herzog and Lausch 2001; Seto and Fragkias 2005; Huang et al. 2006; Cushman, 2008; Malaviya et al., 2010; Ramachandra et al., 2012a, 2012b; Bharath s et al., 2012).

Landscape metrics have been applied extensively to describe the structures of urban land-use classes (Herold et al., 2002 and 2003) and for explaining the interrelationship of intra and inter land uses and the drivers of urbanisation (Guo, 2001, Matthews, 2006; Deng et al., 2009; Ji. Ma et al., 2006; Lacitignola et al, 2007; Nakagoshi, 2006; Schneider & Woodcock, 2008; Huang et al., 2007; Schwarz, 2010; Ramachandra et al., 2012a). The current study demonstrates the potential of multi-temporal Landsat data to provide an accurate, economical means supplemented with landscape metrics and Shannon's Entropy incorporating the zonal and gradient approach to understand the urban growth trends of Tier I city, Hyderabad, capital of Andhra Pradesh state, India, considering temporal remote sensing data of the period 1975 to 2009. The study region includes the city's administrative boundary with 10 km buffer to account for sprawl in peri-urban areas.

2. STUDY AREA

Hyderabad, located at bank of River Musi at 17.368° N and 78.476° E in the Deccan Plateau, is the sixth most populous metropolitan area in India and also ranked sixth largest urban agglomeration in the country. The city remains warm throughout the year with an average temperature of 26 °C to 40 °C during summer and 13°C to 17 °C during winter. Krishna and Godavari rivers serve the water requirements of the region. The current population of Hyderabad is 7 million (2011, http://www.censusofindia.gov.in) compared to 3.6 million in 2001 (census, 2001). The city of Hyderabad is governed by Greater Hyderabad Muncipal Corporation which covers an area of 652 sq. km. Hyderabad has a GDP of 74 billion and is one of the top ten contributors of India's GDP.

3. MATERIALS AND METHODS

Landsat satellite image scenes corresponding to the study area (Hyderabad) of different time periods were downloaded from Global Land Cover Facility (GLCF) (http://www.glcf.umd.edu/index.shtml), United States Geological Survey (USGS) Earth Explorer (http://edcsns17.cr.usgs.gov/NewEarthExplorer/). Table 1 provides the details of the data that were used in the study. Survey of India (SOI) topographic maps of 1:50000 and 1:250000 scales were used to generate base layers of city boundary, etc. City map were digitized from the city administration map. Ground control points to register and geo-correct remote sensing data were collected using hand held pre-calibrated GPS (Global Positioning System), Survey of India topographic maps and Google Earth (http://earth.google.com, http://bhuvan.nrsc.gov.in).

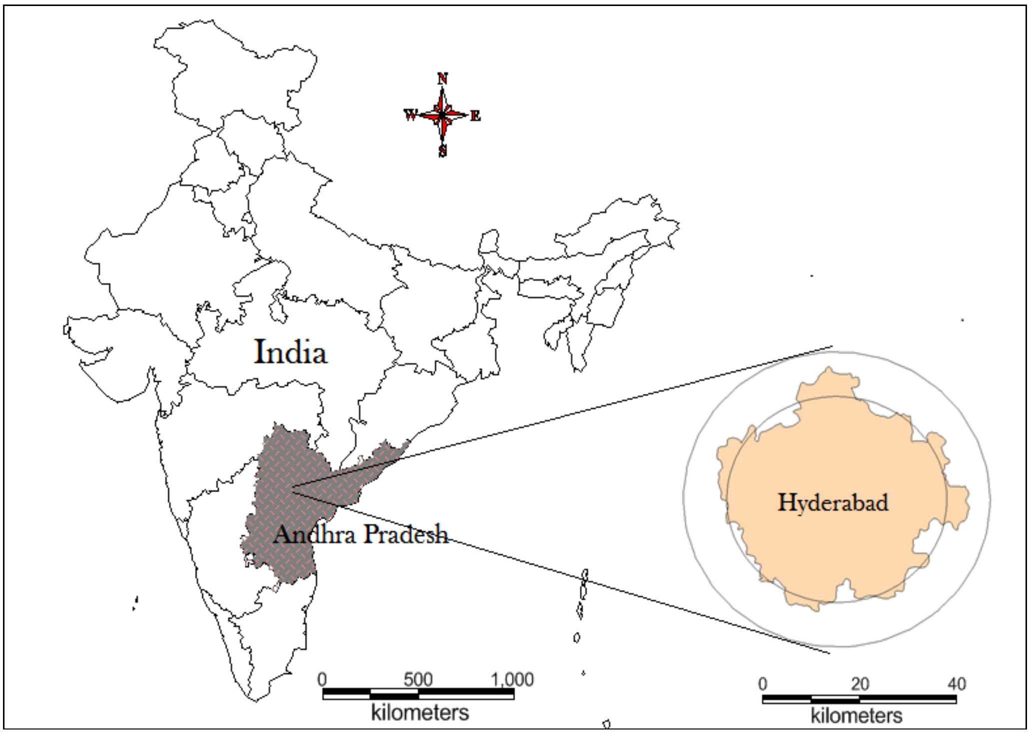

FIGURE 1 - STUDY AREA-HYDERABAD CITY AND ENVIRONS.

TABLE 1 - DATA USED IN THE ANALYSIS

Data	Year	Purpose
Landsat Series Multispectral sensor(57.5m)	1975	Land cover and Land use analysis
Landsat Series Thematic mapper (28.5m)	1989, 1999, 2009	Land cover and Land use analysis
Survey of India (SOI) toposheets of 1:50000 and 1:250000 scales		To Generate boundary and Base layer maps.
Field visit data –captured using GPS		For geo-correcting and generating validation dataset

Data analysis methods are outlined in Figure 2, which include preprocessing, assessment of vegetation cover, land use analysis and finally gradient wise computation of spatial metrics for each zone to assess the spatial patterns of urbanisation. *Preprocessing:* The remote sensing data obtained were geo-referenced, geo-corrected, rectified and cropped pertaining to the study area. The Landsat satellite images were resampled to 30m in order to maintain uniformity in spatial resolution. The area of the data included the Hyderabad administrative area and 10 km buffer from the administrative boundary.

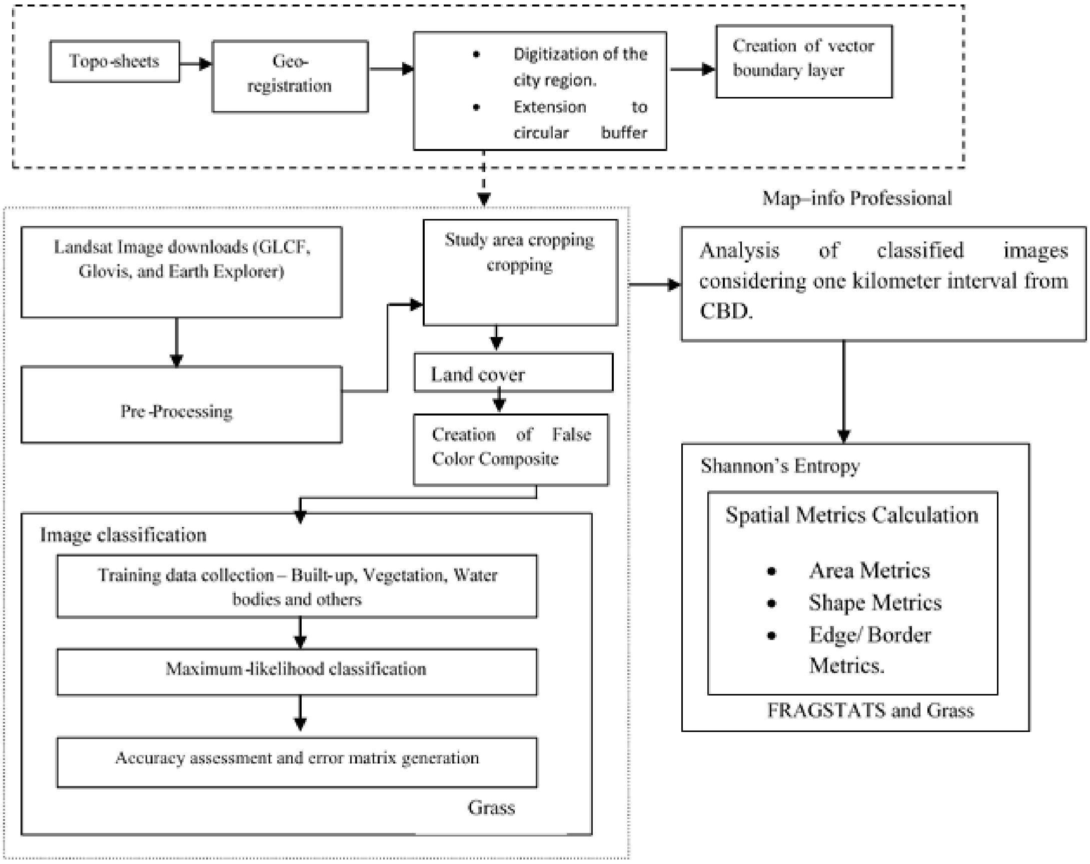

FIGURE 2 - THE PROCEDURE ADOPTED FOR CLASSIFYING THE LANDSCAPE AND COMPUTATION OF METRICS.

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 -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 to 0.3), while high values indicate thick canopy vegetation (0.6 to 0.8). *Land use analysis:* Land use categories were classified using supervised classifier based on Gaussian Maximum likelihood (GML) algorithm. Remote sensing data were classified using signatures from training sites that include all land use types (detailed in Table 2). False color composite of remote sensing data (bands – green, red and NIR), was generated to visualise the heterogeneous patches in the landscape. The signatures were digitized as polygons from heterogeneous patches (covering at least 15% of the study region) and the attribute information corresponding to these polygons were obtained from the field using pre-calibrated Global Positioning System (GPS) and latest Google Earth (http://www.googleearth.com). Among the training data, 60% is used for classification using GML and the balance is used for validation of classified information/accuracy assessment.

TABLE 2 - 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.

Gaussian Maximum Likelihood Classifier (GMLC) uses various classification decisions using probability and cost functions (Duda et al., 2000). Mean and covariance matrix are computed using the 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). Classes of the resulting image were reclassed and recoded to form four land-use classes.

Accuracy assessment methods evaluate the performance of classifiers (Ramachandra et al., 2012a). This is done through comparison of kappa coefficients (Congalton et al., 1983) and computation of overall accuracy assessment through a confusion matrix. Accuracy assessment and Kappa coefficient are common measurements used to demonstrate the effectiveness of the classification (Congalton, 1991; Lillesand & Kiefer, 2005; Congalton, 2009).

Zonal Analysis: The study region consisting of the city boundary and 10 km buffer is divided considering the Central pixel (Central Business district) into 4 zones based on directions as Northeast (NE), Southwest (SW), Northwest (NW), and Southeast (SE). This has been done as most of the definitions of a city or its growth are defined based on directions. . The growth of the urban areas was assessed in each zone through the computation of temporal urban density.

Gradient Analysis - division of zones into concentric circles: Each zone was further divided into concentric circles of incrementing radii of 1 km from the center of the city for understanding the process of changes at local levels and also to visualize the agents responsible for changes. This helps the city administrators and planners to identify the causal factors of urbanization in response to the economic, social and political decisions and it also helps in visualizing the forms of urban sprawl.

Shannon's Entropy: Further, to understand the growth of the urban area in specific zones and to understand if the urban area is compact or divergent, the Shannon's entropy (Sudhira et al., 2004; Ramachandra et al., 2012a) given in equation 1 was computed for each zone. Shannon's entropy (Hn), explains the development process and its characteristics such as explaining if the growth over a period of time was concentrated or dispersed.

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

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TABLE 3 - LANDSCAPE METRICS TO USED IN THE ANALYSIS TO UNDERSTAND THE STATUS OF OVERALL LANDSCAPE

Spatial metrics	Formula	Description
Number of patches (Built-up) (NP)	$N = n_i$ Range: NP≥ 1	NP equals the number of patches of the corresponding patch type. n_i is the number of patches of a particular type.
Normalised landscape shape Index (NLSI)	$NLSI = \frac{e_i - \min e_i}{\max e_i - \min e_i}$ 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.
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.	Provides a simple measure of class aggregation or clumpedness.
Total Edge (TE)	$TE = \sum_{k=1}^{m} e_{ik},$ where: e_{ik} = total length (m) of edge in landscape involving patch type (class) i; includes landscape boundary and background segments involving patch type i.	This metric explains the patchiness in the landscape using number of edged present in the landscape
Interspersion & Juxtaposition Index (Landscape level) (IJI)	$IJI = \frac{-\sum_{K=1}^{m}\left(\left[\frac{e\ ik}{\sum_{k=1}^{m} e_{ik}}\right]\ln\left[\frac{e_{ik}}{\sum_{k=1}^{m} e_{ik}}\right]\right)}{\ln 1k\ sca}(100)$ Range: 0 < IJI ≤ 100 eik = total length (m) of edge in landscape between patch types I and k. m= number of patch type present in landscape.	This is also measure of aggregation and fragmentation
Clumpiness Index (Clumpy)	$G_i = \left[\frac{g_{ii}}{\left(\sum_{k=1}^{m} g_{ik}\right) - \min e_i}\right]$ $CLUMPY = \left(\begin{matrix}\left[\frac{G_i - P_i}{P_i}\right] \text{for } G_i < P_i\ P_i < 5; \textit{else} \\ \frac{G_i - P_i}{1\ P_i}\end{matrix}\right)$ 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.
Aggregation Index	$AI = \left[\frac{g_{ii}}{\max g_{ii}}\right](100)$ g_{ii} = number of like adjacencies (joins) between pixels of patch type (class) i based on the single-count method. max-g_{ii} = maximum number of like adjacencies (joins) between pixels of patch type (class) i (see below) based on the single-count method.	This index explains the focal class disaggregation or aggregation as a measure of class
Cohesion	$Cohesion = \left[1 - \sum_{j=1}^{n} P_{ij} \Big/ \sum_{j=1}^{n}(P_{ij})\sqrt[2]{a_{ij}}\right]\left[1 - 1/\sqrt[2]{A}\right]^{-1} * 100$ p_{ij} = perimeter of patch ij in terms of number of cell surfaces. a_{ij} = area of patch ij in terms of number of cells. A = total number of cells in the landscape	measures the physical connectedness of the corresponding patch
Percentage of Like Adjacencies (PLADJ)	$PLADJ = \left(\frac{g_{ij}}{\sum_{1}^{m} g_{ik}}\right)(100)$ g_{ii} = number of like adjacencies (joins) between pixels of patch type (class) i based on the *double-count* method. g_{ik} = number of adjacencies (joins) between pixels of patch types (classes) i and k based on the *double-count* method.	PLADJ equals the number of like adjacencies involving the focal class, divided by the total number of cell adjacencies involving the focal class; multiplied by 100 (to convert to a percentage).

Where, Pi is the proportion of the built-up in the ith concentric circle. If the distribution is maximally concentrated, the lowest value (zero) of Hn will be obtained. Conversely, if the population is dispersed or if there is even distribution among the concentric circles, Hn will be equivalent to log n (where n = number of gradients). *Computation of spatial metrics:* Spatial metrics have been used to quantify the spatial characteristics of a landscape. Select spatial metrics were used to anlayse and understand the urban dynamics (Ramachandra et al., 2012a). FRAGSTATS (McGarigal and Marks in 1995) software was used to compute metrics at three levels: patch, class and landscape. Table 3 lists the metrics with their description considered for the current study.

4. RESULTS AND DISCUSSIONS

Remote sensing data corresponding to the study region downloaded from Landsat public repositories were preprocessed as described in the methods section. The preprocessed data were then used to derive the land cover of the region for different time periods using Normalised Difference Vegetation Index (NDVI). Figure 3 illustrates the land cover computed for the period 1975 to 2009 through NDVI for Hyderabad region.

The negative value indicates the absence of vegetation and presence of land cover such as built-up, water, sand, etc. The increasing value from 0 indicates the presence of vegetation.

The results of the land cover analysis (Table 4) showed that the vegetation cover has declined during the past four decades with the increase in non-vegetative area (buildings, open space, water etc.). Land use analysis is done to understand the status of various land use classes in the region.

TABLE 4 - LAND COVER CHANGES DURING 1975 TO 2009 IN HYDERABAD REGION.

	Vegetation (%)	Non- vegetation (%)
1975	96.23	3.77
1989	95.64	4.36
1999	93.28	6.72
2009	82.67	17.4

The preprocessed images of Hyderabad were then classified to extract land use classes using GMLC for all time periods. Figure 4 depicts the temporal land uses in the region and Table 5 lists the land use statistics. Urban growth is evident with the increase in built-up area from 0.17 (1975) to about 13 % (2009). Accuracy assessment of the classified images was done through the computation of overall accuracy and kappa statistics (Table 6).

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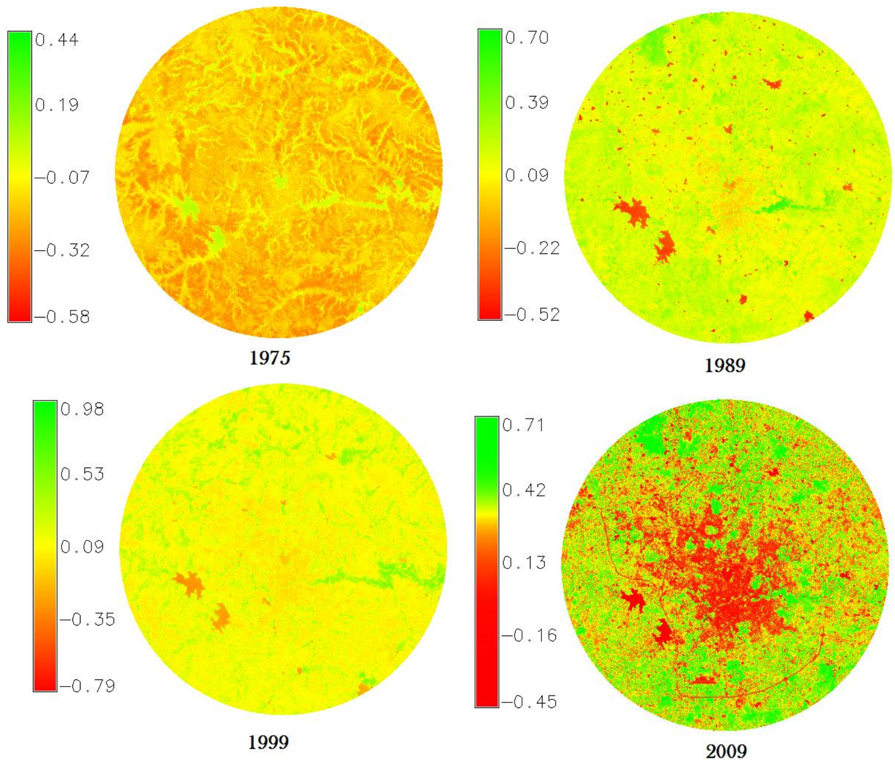

FIGURE 3 - NDVI DERIVED FOR HYDERABAD REGION.

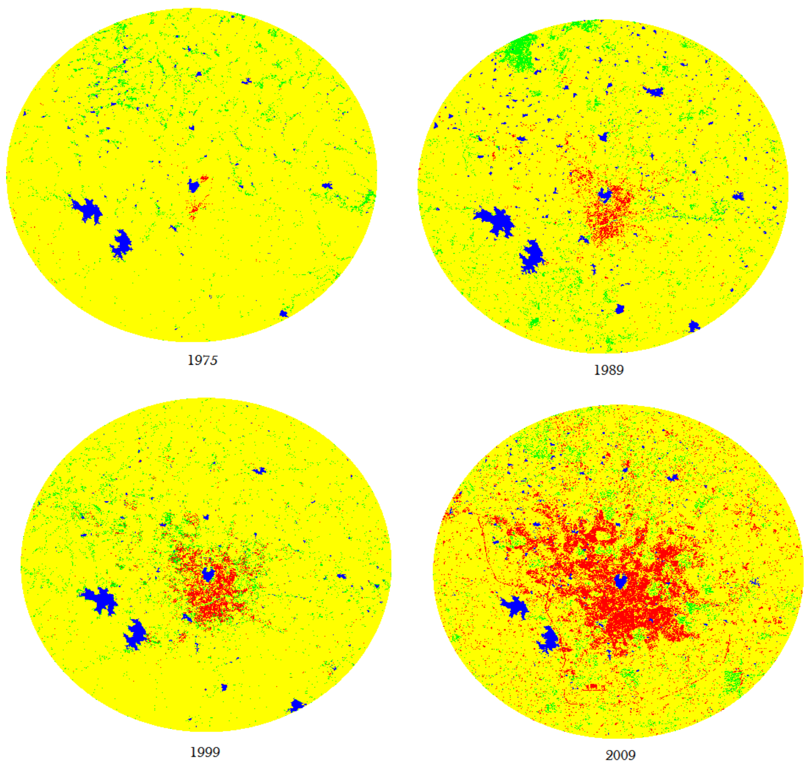

FIGURE 4 - CLASSIFIED IMAGES OF HYDERABAD.

TABLE 5 - LAND USE STATISTICS OF THE CLASSIFIED IMAGES.

Years	Built-up	Vegetation	Water body	Others
	Area (%)	Area (%)	Area (%)	Area (%)
1975	0.17	2.98	1.41	95.44
1989	1.75	4.06	2.71	91.49
1999	2.55	3.88	1.63	91.94
2009	13.55	3.87	1.66	80.92

TABLE 6 - OVERALL ACCURACY AND KAPPA STATISTICS OF CLASSIFIED IMAGES

1975		1989		1999		2009	
OA	kappa	OA	kappa	OA	kappa	OA	kappa
78	0.6532	94	0.7309	87	0.8558	90	0.9079

Figure 5 shows the urban growth during 1975 to 2010. Major increase is noticed during post 2000 with the government policy of supporting IT sector in the state.

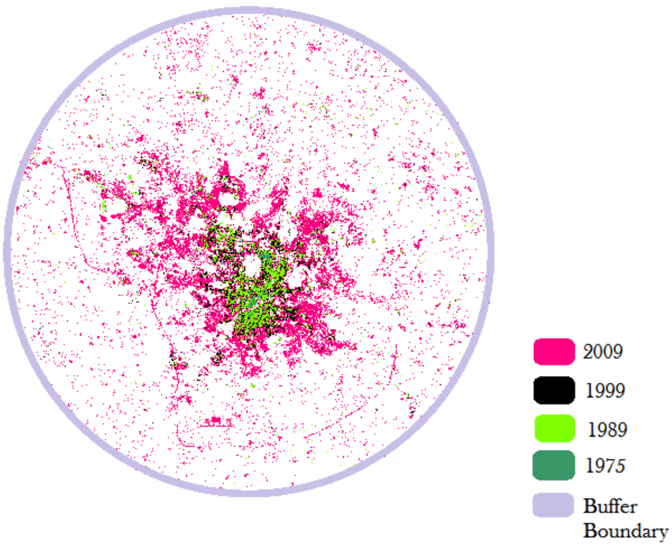

FIGURE 5 - URBANIZATION PROCESS FROM 1975- 2010

Urban analysis: Shannon's entropy is computed using the derived gradients to assess the level of urbanization. Table 7 and Figure 6 lists the direction-wise Shannon's entropy values. The values close to 0 indicates of a compact growth, which can be seen in 1975, but the values have increased temporally to 0.3, indicating the tendency of sprawl/dispersed or fragmented outgrowth.

TABLE 7 - SHANNON'S ENTROPY CALCULATED FOR HYDERABAD.

	NE	NW	SE	SW	LOG N
1975	0.012	0.03	0.05	0.04	1.585
1989	0.0292	0.04621	0.08188	0.05572	
1999	0.03437	0.05282	0.10674	0.09663	
2009	0.24913	0.32605	0.35492	0.32119	

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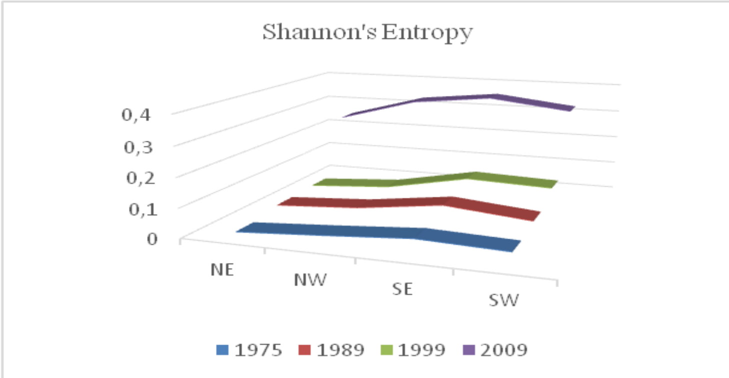

FIGURE 6 - TEMPORAL SHANNON'S ENTROPY FOR THE STUDY REGION

Spatial Analysis through Landscape Metrics

Figure 7 illustrates the spatial patterns of urbanisation (Note: X-axis represents gradients considered and Y-axis represents the respective spatial metrics).

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. Figure 7a represents the direction and gradient wise number of urban patches during different decades. A significant increase in number of patches from 1975 to 2009 in all directions, in all gradients indicates that the landscape is getting more fragmented after the year 2000. The gradients close to the city center show a decreasing number of patches, explaining the process of clumping or aggregation of urban patches. NW and NE directions show a significant increase and there is a significant increase of urban patches in all gradients. The increased number of patches in the buffer region indicates of sprawl due to intense urbanisation at the core area of the city.

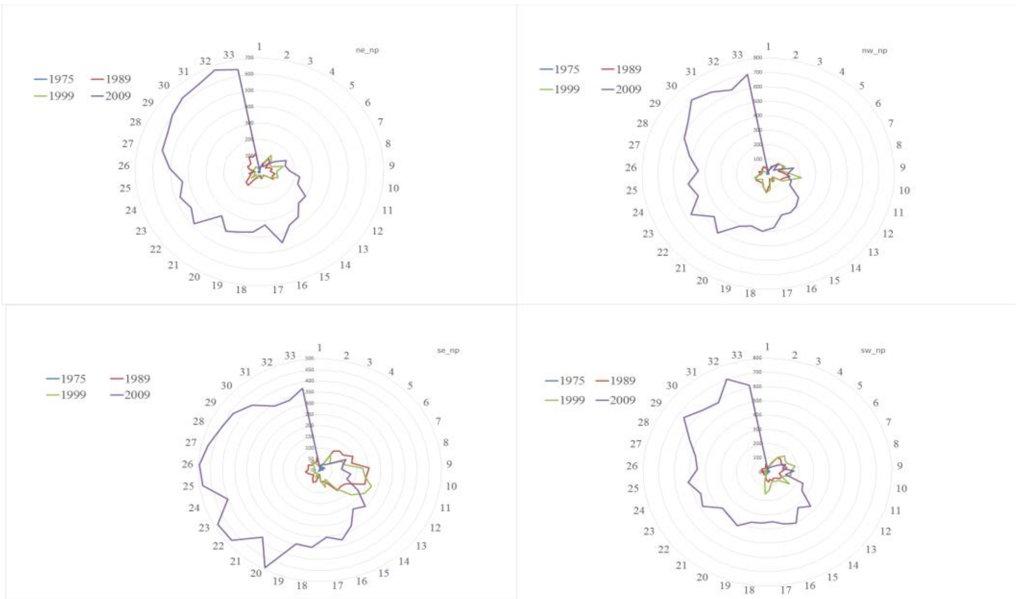

FIGURE 7a - NP METRIC

Landscape Shape Index (LSI) and Normalized Landscape Shape Index (NLSI): Landscape Shape Index provides a simple measure of class aggregation or disaggregation. Aggregation is measured via class edge. Normalized Landscape Shape Index is similar to Landscape Shape Index, but this represents the normalized value. Figure 7b and Figure 7c indicate lower values after the year 2000 at the city centre indicating simpler shapes and compact urban patches. However, fringes show increased values indicating complex shape with the fragmented growth as highlighted by NP in 2009 and development of complex patches.

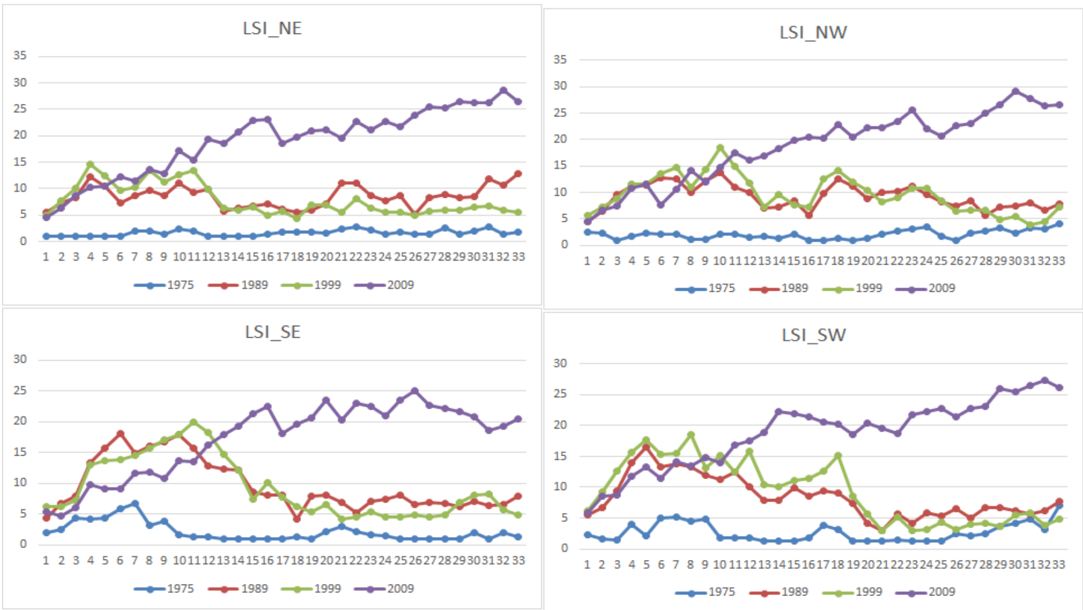

FIGURE 7b - LANDSCAPE SHAPE INDEX

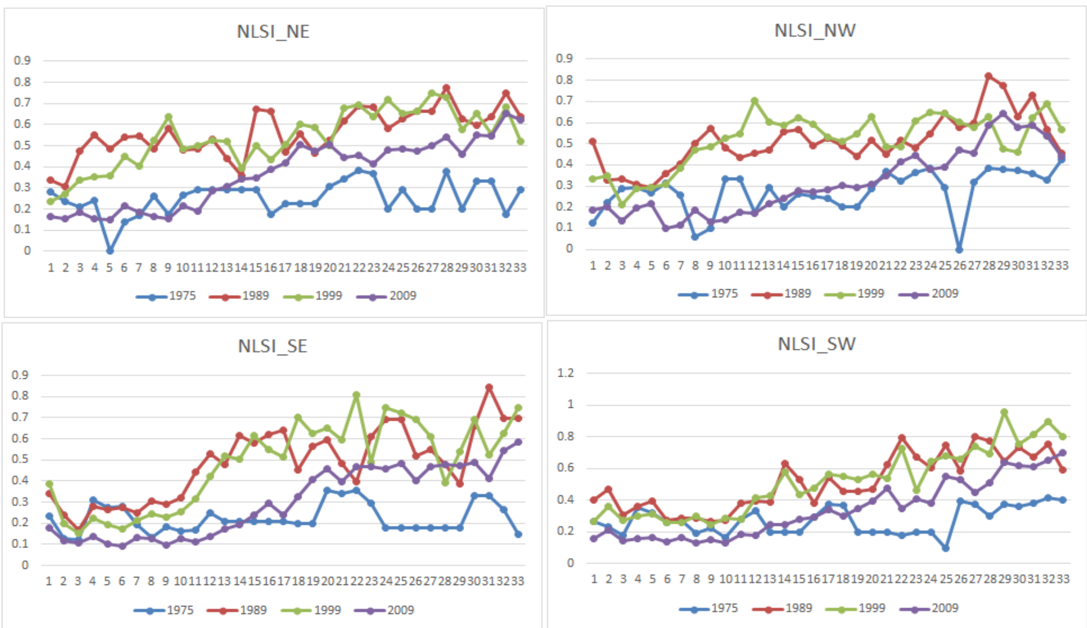

FIGURE 7c - NORMALIZED LANDSCAPE SHAPE INDEX

Clumpiness (CLUMPY) and Aggregation Index (AI): Clumpiness Index is the measure of patch aggregation. It measures the clumpiness of the overall urban patches. Clumpiness ranges from -1 to 1 where Clumpy = -1 when the urban patch type is maximally disaggregated, Clumpy = 0 when the patch is distributed randomly and approaches 1 when urban patch type is maximally aggregated. Aggregation Index gives the similar indication as Clumpiness i.e., it measures the aggregation of the urban patches, Aggregation Index ranges from 0 to 100.

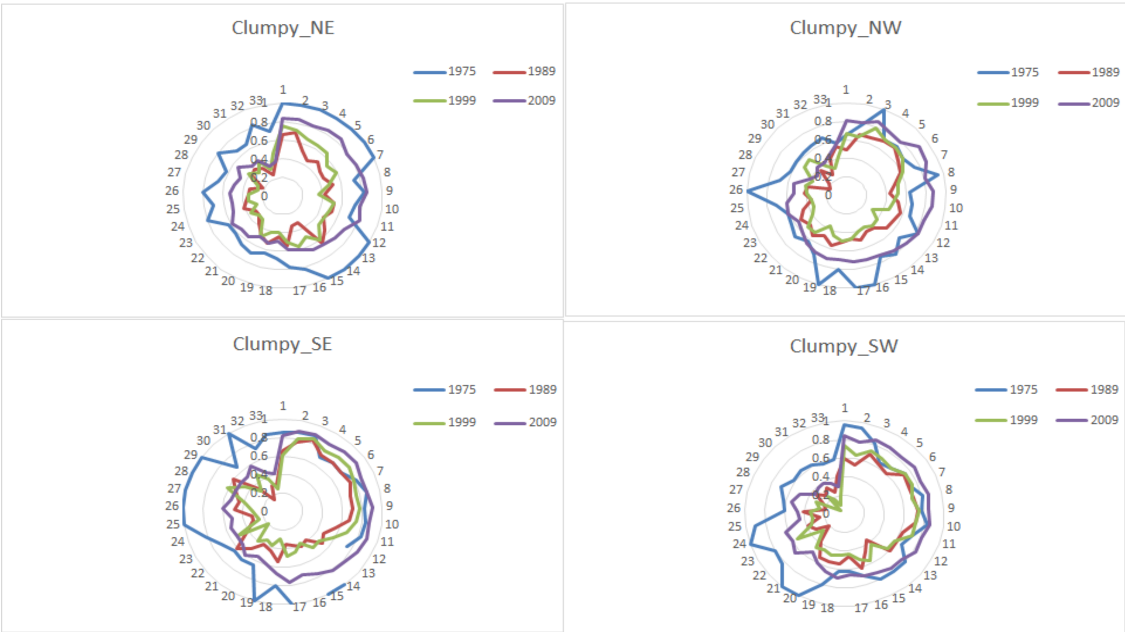

FIGURE 7d - CLUMPINESS INDEX

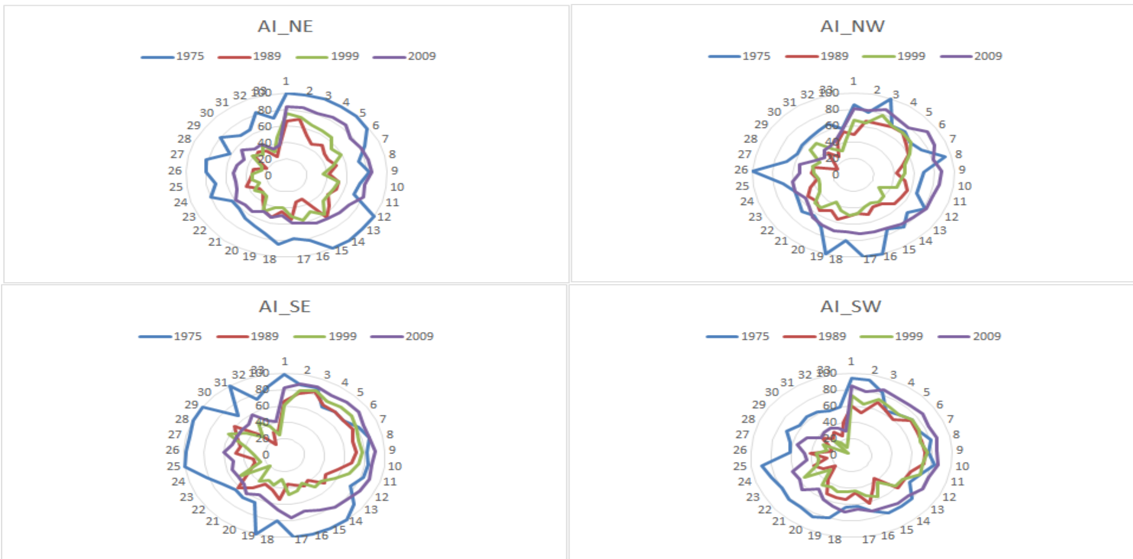

FIGURE 7e. AGGREGATION INDEX

The results of Clumpiness Index (Figure 7d) represent the status of urban landscape. In 1995 the region had simple clumped growth at the center and minimal growth at the outskirts, with the values close to 0 at the center and few random patches at the outskirts or buffer regions. The situation has changed in 2009 with a highly fragmented growth or non-clumped growth in outskirts and completely clumped growth at the center. The Aggregation Index (Figure 7e) showed a similar trend as the Clumpiness Index. This highlights that the center part of the city is in the process of forming a homogeneous patch whereas the outskirts are growing as fragmented urban patches.

Patch Cohesion Index measures the physical connectedness of the corresponding patch type. Figure 7f describes the results of the analysis of physical connectedness of the urban patch with the higher cohesion value (in 2009) indicating that the urban count is higher in the study region. Lower values in 1975 illustrate that the urban patches were rare in the landscape and were well connected which also points to the fact about clumped growth in the centre, whereas higher values in 2009 is indicative of the dominance of urban patches in the buffer regions.

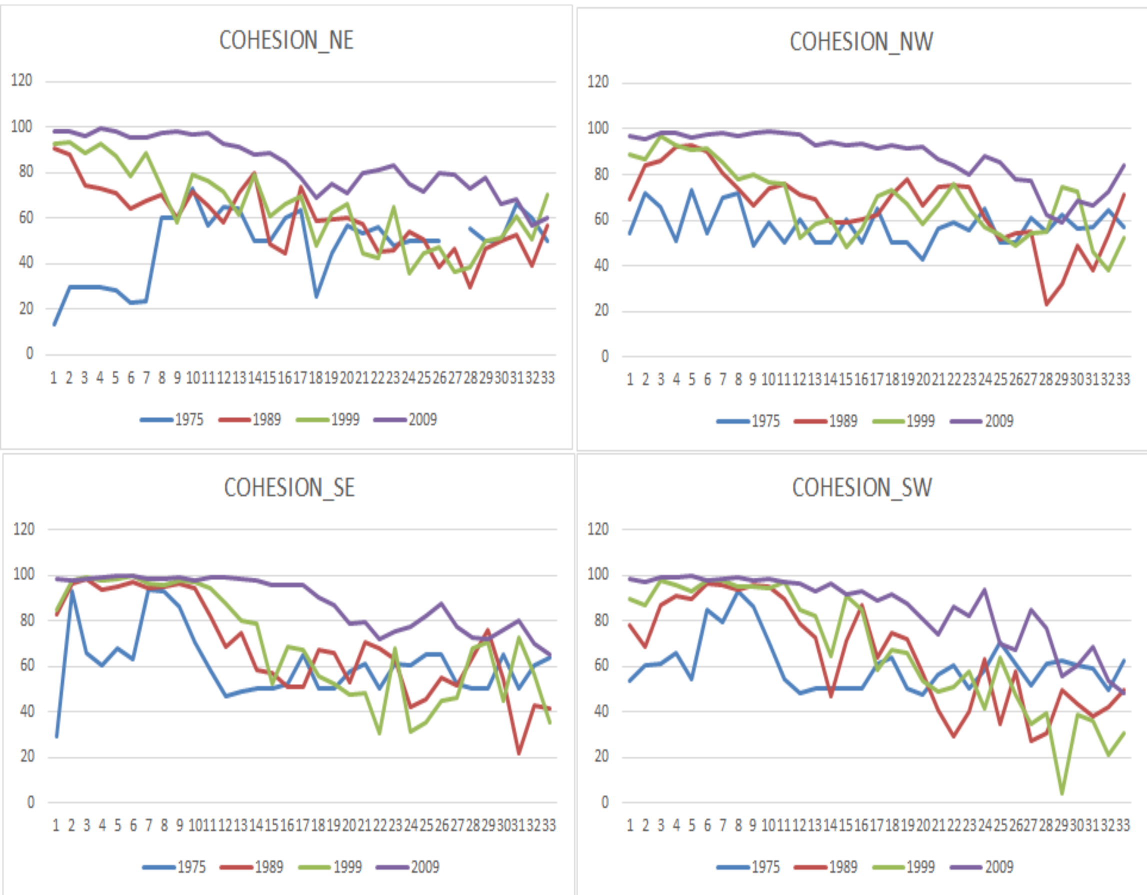

FIGURE 7f. PATCH COHESION INDEX

Percentage of Like Adjacencies (PLADJ) indicates the percentage of cell adjacencies involving the corresponding patch type. Figure 7g indicates that the urban patches in the landscape is most adjacent to each other in 2009 compared to 1975 and 1999, indicating urban land uses forming a single patch in 2009.

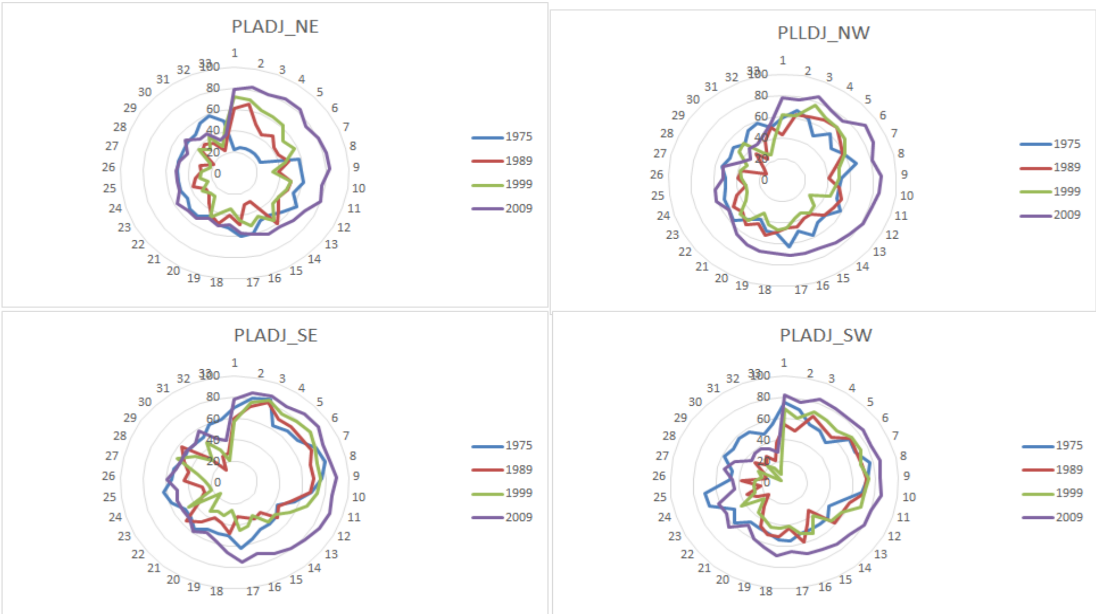

FIGURE 7g - PERCENTAGE OF LIKE ADJACENCIES (PLADJ)

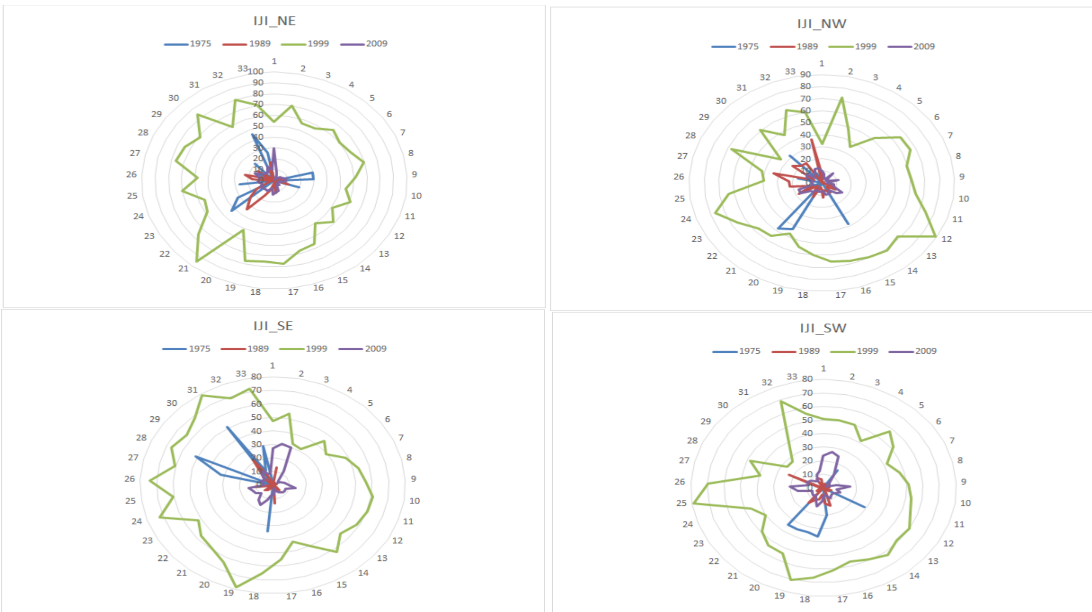

FIGURE 7h - INTERSPERSION AND JUXTAPOSITION INDEX

Interspersion and Juxtaposition Index (IJI) measures the extents to which patch types are interspersed. Higher values result 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 i.e., disproportionate distribution of patch type adjacencies (Mc Garigal and marks, 1994). IJI values range from 0 to 100. IJI values are in the verge of reaching 100 indicating that the patches next to urban areas are becoming rare with time and the urban dominance can be seen in 2009 (Figure 8h). Compared to this, in 1975 and 1989 the dominance of urban patches were less in all gradients, though a few central gradients showed slightly higher values (Fig. 7h).

Total Edge (TE) is the absolute measure of total length (perimeter) of each class of a particular patch in landscape in meters. TE considers true edges and the value is greater than or equal to zero. Larger edge values indicate larger continuous patches. Figure 7i indicates that during 1989 and 1999 the edges were smaller and hence there were discontinuous patches as the landscape was fragmented. In 2009, larger edges indicated that the urban edges are ubiquitous and continuous.

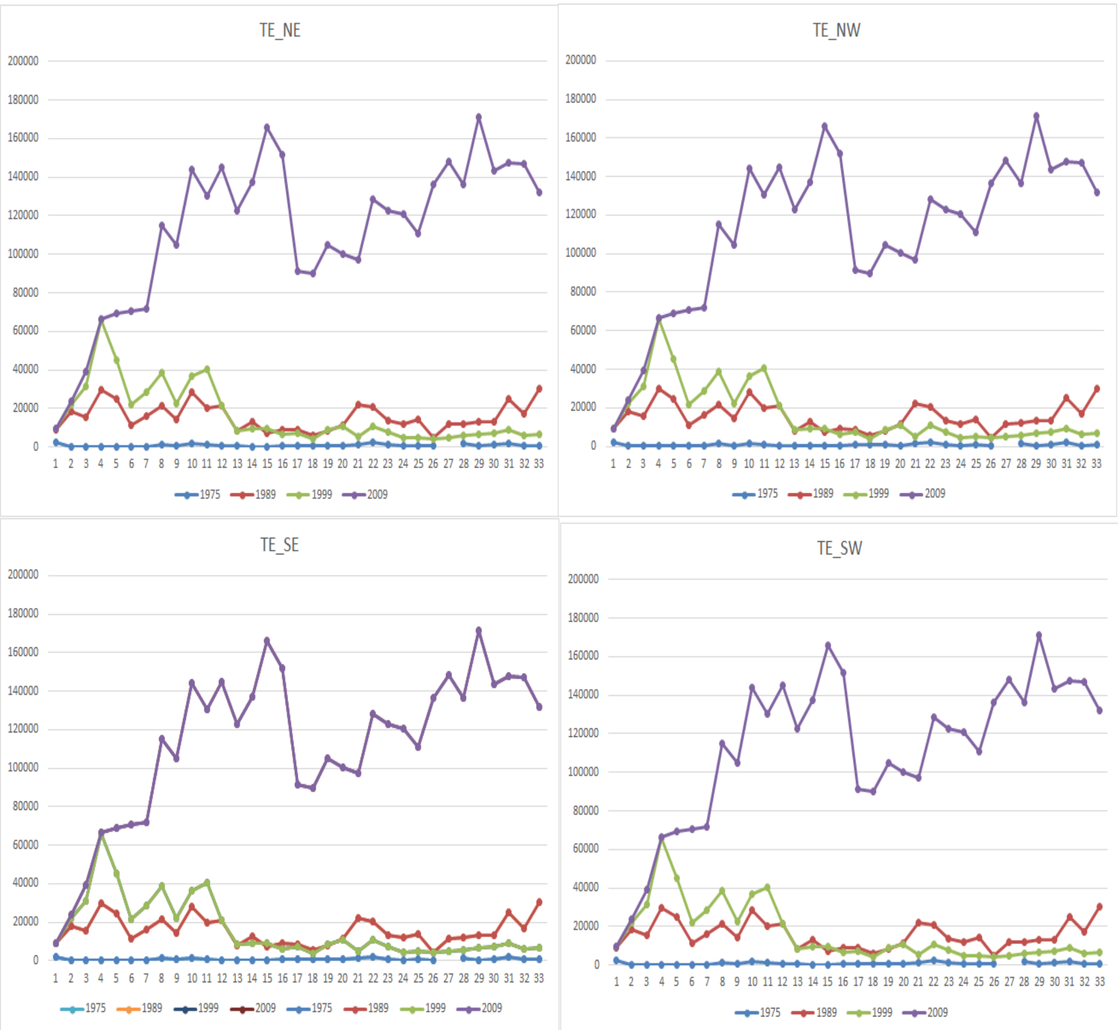

FIGURE 7i - TE METRIC

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5. CONCLUSIONS

Urbanisation process involves land use changes affecting the local ecology. This necessitates effective urban planning strategies with the regular monitoring of landscape dynamics. The current study demonstrates the potential of multi-temporal Landsat data to provide an accurate, economical means supplemented with landscape metrics and Shannon's Entropy incorporating the zonal and gradient approach to understand the urban growth trends. Land cover analysis showed that the vegetation cover has declined during the past four decades, with the increase in the area under non-vegetation (Buildings, open space, water etc.). Urban growth is evident with the increase in built-up area from 0.17% (1975) to about 13 % (2009). The gradients close to the city center show a decreasing number of patches, explaining the process of clumping or aggregation of urban patches. NW and NE directions show a significant increase and there is a significant increase of urban patches in all gradients. The increased number of patches in the buffer region indicates sprawl due to intense urbanisation at the core area of the city. All other metrics (area, shape, edge and compactness) indicate a similar trend.

This has largely resulted in unprecedented changes in its landscape structure, feature and composition, as seen and explained by metrics temporally. The current study demonstrates the potential of multi-temporal remote sensing data to provide an accurate and economical means supplemented with landscape metrics and Shannon's Entropy incorporating the zonal and gradient approach to understand the urban growth trends.

The analysis has provided the evidences of spatial patterns at local levels, which would help the city development authority and city planners to understand the current growth while visualizing the future growth.

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