Geographical Indicators for Sustainable Management of Urban Sprawl

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Abstract

By the end of present decade, more than half of the contemporary human society will reside in urban areas. More and more people will migrate to towns and cities for education, jobs, to enjoy city comfort, avail civic facilities, etc. and cities will continue to urbanise rapidly. Currently, the urban growth rate stands at 2.5% annually adding around 55 million people to urban areas around the world. Natural demographic increases have begun to overtake migration as the main cause of urban sprawl and urbanisation. The consequences of rapid urbanisation are transformation of productive agricultural lands, vegetation, water bodies to builtup / settlement and paved surfaces at an alarming rate. Centres like Bangalore who were secondary towns not so long ago, have become metropolitan areas during the past few decades. Bangalore has been experiencing rapid urbanisation and its uncontrolled growth has consequently changed the structure of the landscape impairing its functional capabilities. This has put tremendous pressure on infrastructure, civic amenities and public services in the city and posses several management challenges.

Earth observation satellites provide data over a considerable range of spatial and temporal resolution for understanding the spatial and temporal aspects of landscape change and the impact of urban development on the surrounding environment. These data are classified to derive metrics that are quantitative measures for spatial pattern, which are helpful in understanding the landscape dynamics and linking the agents of change. In this communication, multi-resolution remote sensing data analyses is carried out to study the type and pattern of urban growth in Greater Bangalore by dividing the city into 8 zones for 1973, 1992, 2000, 2006 and 2010. The study reveals that there has been a 584% urban growth with a 66% decline in water bodies and 74% decrease in vegetation cover in the last 37 years. The city was more compact in 1973 and began to disperse in all directions with decreasing lung spaces and increase in the number of urban colonies (patches) as well as urban density. Most large urban patches have developed in west, south-west and southern regions of the city corresponding to the policy decision of setting up small scale industries, Information Technology-Bio-Technology firms and consequent housing projects, where traffic congestion is a serious issue. The abrupt growth of the city in certain directions needs attention of the urban planners so that the resources of the city are well managed and maintained.

Introduction

Rapid urbanisation is quite alarming, especially in developing countries like India. Nature and human systems are getting affected due to growing urbanisation at all geographic scales (Herold et al., 2005). This unprecedented urbanisation process has been fueled by rapid economic growth and even more rapid industrialisation. With most of the value added economic activities and populations located in urban areas, how well cities function as a system will determine the future of Indian cities. One of the factors which will determine the success of growing cities is inevitably the land use and management.

Urban sprawl has increasingly become a major issue facing many metropolitan areas (Ji, 2006). Bangalore is one among the fastest urbanising cities in Asia, undergoing redevelopment for economic purposes and is witnessing tremendous pressure on the infrastructure, civic amenities, public services, etc. A huge migrating population, increasing number of Information Technology and Bio-Technology firms, and large scale real estate developments are demanding more resources within the city, forcing it to expand both horizontally and vertically leading to serious problems like informal settlements, environmental pollutions, destruction of ecological structures, unemployment, etc. This unprecedented growth and urban sprawl are often unnoticed by the planners and policy makers as they are unable to visualise this type of growth patterns. Sprawl patterns are fundamental to many of the spatial-temporal relationships and it is important to understand the factors and trend that influence the growth of the urbanising landscape. Therefore, characterising and understanding the changing patterns of urban growth is critical, given that urbanisation continues to be one of the major global environmental changes in foreseeable future (Rashed, 2008).

The spatio temporal trends of urban sprawl and urbanisation can be characterised by temporal remotely sensed (RS) images acquired through space-borne satellites. Their large area coverage and repeat viewing provide information over a considerable range of spatial and temporal resolutions for mapping land cover (LC) resources (Mas, 2010). They provide additional levels of information about the links between land use and infrastructure change and a variety of social, economic and demographic process (Herold, et al., 2005). RS intertwined with time series modeling and geographical (spatial) metrics (urban indicators) are very effective to understand the growth of urban areas for administration and future planning of the landscape. A landscape is a mosaic of several patches, which is a discrete area of relatively homogeneous environmental conditions whose boundaries are distinguished by differences in environmental character from its surroundings. Spatial metrics are used to improve the understanding and representation of urban dynamics and urban patches and helps to develop alternative conceptions of urban spatial structure and change. In general, a large number of urban patches would suggest a landscape having urban sprawl where it is difficult to introduce a large homogeneous patch of some other land use type such as vegetation. The combined use of RS and spatial metrics leads to new levels of understanding of how urban areas grow and change

(Herold *et al*., 2005) for better planning and sustainable management of natural resources in the region.

Objective: The objective of this paper is to analyse the changes in landscape structure and quantify the spatio-temporal urbanisation pattern in Greater Bangalore using spatial metrics. This involves:

(i.) Analysis of land use dynamics during 1973 to 2010.

(ii.) Understanding the agents of sprawl with the developmental pattern in different localities of the city.

(iii.) Environmental consequences of drastic land use changes in the region.

Data and study area

Greater Bangalore is principal administrative, cultural, commercial, industrial, and knowledge capital of the state of Karnataka with an area of 741 sq. km. and lies between the latitudes 12°39’00’’ to 13°13’00’’N and longitude 77°22’00’’ to 77°52’00’’E. Bangalore city administrative jurisdiction was widened in 2006 by merging the existing area of Bangalore City spatial limits with 8 neighbouring Urban Local Bodies and 111 Villages of Bangalore Urban District to form Greater Bangalore. Now, Bangalore (figure 1) is the fifth largest metropolis in India currently with a population of about 8 million (Ramachandra and Kumar, 2008).

Urbanisation and urban sprawl are more a local phenomenon and location specific. Local urban sprawl tends to increase along ring roads, highways in a certain direction, around service facilities in another direction, which later turn into urban centre hub that extends in all directions. Therefore, understanding the spatio-temporal pattern of urban landscape in different directions becomes necessary and relevant. In this context, the city was divided into 8 zones [North (N), Northeast (NE), East (E), Southeast (SE), South (S), Southwest (SW), West (W), and Northwest (NW)] from the ‘city centre’ or the central business district (figure 1).

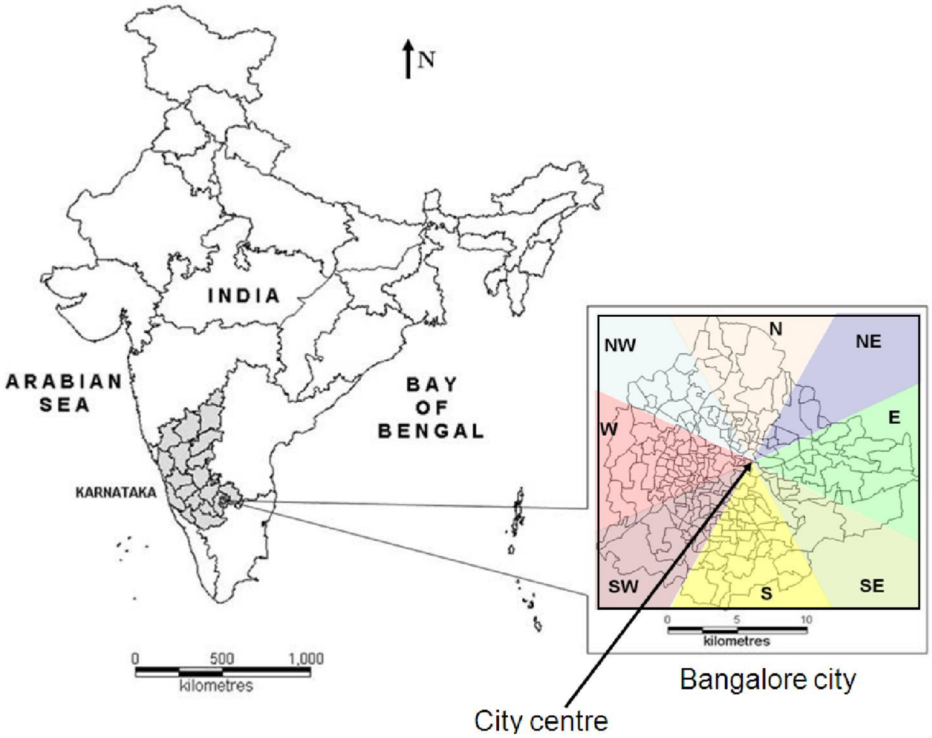


Figure 1: Study Area: Greater Bangalore.

The RS data used to study the temporal changes in landscape pattern were Landsat Multispectral Scanner (MSS) of 1973, Landsat Thematic Mapper (TM) of 1992, Landsat Enhance TM Plus (ETM+) of 2000 and 2010 and IRS LISS-III MSS for 2006. The data were georeferenced, rectified and cropped pertaining to the study area. Landsat ETM+ bands of 2010 were corrected for the SLC-off by using image enhancement techniques, followed by nearest-neighbour interpolation. All these images were resampled to 30m spatial resolution (1130 rows and 1170 columns) for consistency, easy analysis and interpretation. Collateral data such as road network, drainage network, water bodies, etc. were obtained from the Survey of India (SOI) Topographical sheets of scale 1:250, 000 and 1: 50, 000. Handheld GPS (Global Positioning System) were used to collect ground information and Google Earth image (http://www.earth.google.com) were used for validating the classified outputs.

Methodology

Maximum Likelihood classifier (MLC) was used to classify temporal RS data into four land use classes – builtup (urban, concrete roofs, roads, flyovers, pavements), vegetation (parks, gardens), water bodies (lakes, ponds, wetlands) and open area (play grounds, walk ways, etc.) using the signatures generated with the training data obtained from field visits and Google Earth image. MLC is a parametric classifier that can train quickly with a capability to handle huge datasets. In fact, this also aids as 'benchmark' for evaluating the performance of novel classification algorithms. This method constitutes a historically dominant approach to RS-based automated LC derivation (Gao, J., 2004) and has become popular and widespread in RS because of its robustness (Hester et al., 2008). In the absence of historical data, training pixels were collected from the false colour composite of the respective bands (for the year 1973, 1992 and 2000). Since the focus of this study was to analyse the temporal urban growth pattern, so LC categories were grouped into 'urban' and 'non-urban' classes. Further, the classified images were segmented based on 8 cardinal directions. 12 spatial metrics (table 1) were computed using r.li program in GRASS (http://wgbis.ces.iisc.ernet.in/foss) and FRAGSTATS (McGarigal, 1995). The overall procedure is as depicted in figure 2.

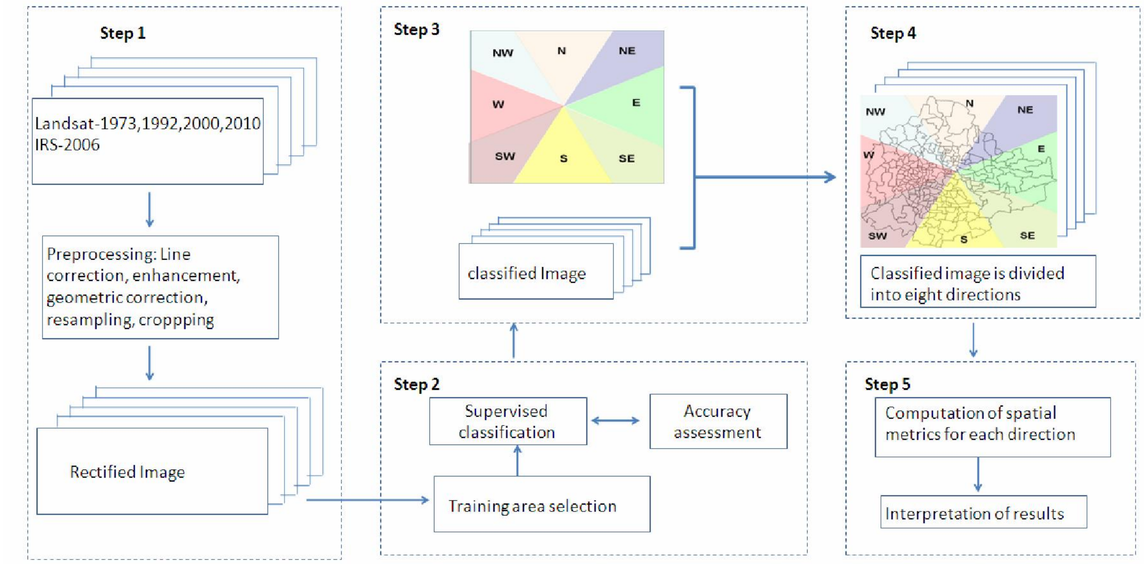


Figure 2: Schematic representation of the methods used in this study

Table 1: Description of metrics used in this study

Sl No.	Indicators	Formula	Description
1.	Largest Patch	Largest patch indicates the largest urban patch in terms of area considered	Largest urban patch in the landscape (in ha).
2.	Largest Patch Index (Percentage of built up)	$LPI = \frac{\max_{i=1}^{n}(a_i)}{A}(100)$ • a_i : area (m^2) of patch i • A: total landscape area Largest Patch Index (Percentage of built up) equals the percentage of built up and landscape comprised by the largest patch respectively.	$0 \le LPI \le 100$. LPI = 0 when largest patch of the patch type becomes increasingly smaller. LPI = 100 when the entire landscape consists of a single patch of, when the largest patch comprise 100% of the landscape.
3.	Number of Urban Patches	$NPU = n$ NP equals the number of patches in the landscape. This is a simple measure of the extent of subdivision or fragmentation of the patch type.	NPU>0,without limit. It is a fragmentation Index

4.	Patch area distribution coefficient of variation (PADCV)	$PAD_{CV} = \frac{SD}{MPS}(100)$ with: **SD**: standard deviation of patch area size $SD = \sqrt{\frac{\sum_{i=1}^{Npatch}(a_i - MPS)^2}{Npatch}}$ Where **MPS**: mean patch area size, **ai**: area of patch i, **Npatch**: number of patch Patch size coefficient of variance (PADCV) is the variability in patch size relative to mean patch size. Mean Shape Index (coefficient of variation) gives the variation in the mean shape of a patch.	PADCV≥0 PADCV is zero when all patches in the landscape are the same size or there is only one patch (no variability in patch size).
5.	Mean Shape index (coefficient of variation)	$MSI = \frac{\sum_{j=i}^{n}\left(\frac{0.25 p_{ij}}{\sqrt{a_{ij}}}\right)}{n_i}$ • P_{ij} is the perimeter of patch i of type j. • a_{ij} is the area of patch i of type j. • n_i is the total number of patches.	MSI ≥ 1, without limit MSI = 1 when all patches of the corresponding patch type are circular or square; MSI increases without limit as the patch shapes becomes more irregular.
6.	Area weighted Perimeter Area Ratio	$PARA = \frac{P_{ij}}{a_{ij}}$ • P_{ij}: perimeter (m) of Patch ij. • a_{ij}: area(m^2) f patch ij. Area weighted Perimeter-Area Ratio is a simple measure of shape complexity but it varies with the size of the patch.	PARA>0, without limit
7.	Mean Patch Fractal Dimension (MPFD) coefficient of variation (COV)	$MPFD = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}\left(\frac{2\ln(0.25 pij)}{\ln aij}\right)}{N}$ $CV = \frac{SD}{MN}(100)$ Where CV (coefficient of variation) equals the standard deviation divided by the mean, multiplied by 100 to convert to a percentage, for the corresponding patch metrics. MPFD-CV indicates the variability in the complexity of	It is represented in percentage.

		urban structure expressed in percentage.	
8.	Compactness Index (CI)	$$CI = \frac{\sum_i p_i / p_i}{N} = \frac{\sum_i 2\lambda\sqrt{s_i/\lambda} / p_i}{N}$$ • s_i and p_i are the area and perimeter of patch i • P_i is the perimeter of a circle with the area s_i • N is the total number of patches. The compactness index (CI) measures not only the individual patch shape but also the fragmentation of the overall urban landscape (Huang et al., 2007). The more irregular the patch shape and patch number, the bigger the CI value.	CI value more increases with regularity of patch shape and when patch number decreases.
9.	ENND coefficient of variation	$$ENN = h_{ij}$$ $$CV = \frac{SD}{MN}(100)$$ Where CV (coefficient of variation) equals the standard deviation divided by the mean, multiplied by 100 to convert to a percentage, for the corresponding patch metrics. ENND-CV represents higher variation in mean Euclidean mean nearest neighbor distance.	It is represented in percentage.
10.	Interspersion and Juxtaposition	$$IJI = \frac{-\sum_{i=1}^{m}\sum_{k=i+1}^{m}\left[\left(\frac{e_{ik}}{E}\right).\ln\left(\frac{e_{ik}}{E}\right)\right]}{\ln\left(0.5\left[m(m-1)\right]\right)}(100)$$ • e_{ik}: 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. Interspersion and Juxtaposition Index (IJI) equals minus the sum of the length of each unique edge type divided by the total landscape edge, multiplied by the logarithm of the same quantity, summed over each unique edge type; divided by the logarithm of the number of patch types times the number of patch types minus 1 divided by 2; multiplied by 100 to convert it to percentage.	$0 \leq$ IJI ≤ 100 Interspersion and Juxtaposition approaches 0 when the distribution of adjacencies among unique patch types becomes increasingly uneven. IJI is equal to 100 when all the patch types are equally adjacent to all other patch types.
11.	Ratio of open space (ROS)	$$ROS = \frac{s'}{s} \times 100\%$$ • Where s is the summarization area of all "holes" inside the extracted urban area, s is summarization area of all patches	It is represented as percentage.

		Ratio of open space measures the open space compared against total urban area. Open space is crucial both as an amenity for residents and sustainability of cities.	
12.	Patch dominance	$$\text{Dominance} = \ln(m) + \sum_{i=1}^{m} pi.\ln(pi)$$ • **m**: number of different patch type • **i**: patch type • **pi**: proportion of the landscape occupied by patch type i Dominance diversity index gives information if there is one dominant class in the image or if all classes have more or less same relative class proportion (Gasper and Menz, 1999).	-

Results and Discussion

The classified images are shown in figure 3 and the statistics are listed in table 2. Overall accuracy for the classified images were 72% (1973), 75% (1992), 77% (2000), 73% (2006) and 71% (2010). Urban density is increasing in all the directions (figure 4) indicating almost a linear growth. There has been a 584% growth in builtup area in the last four decades. Vegetation has decreased by 66% and water bodies have reduced by 74%. The results obtained from each metrics are as depicted in figure 5.

Table 2: Greater Bangalore land use statistics

Class →	Builtup		Vegetation		Water Bodies		Others	
Year ↓	Ha	%	Ha	%	Ha	%	Ha	%
1973	5448	7.97	46639	68.27	2324	3.40	13903	20.35
1992	18650	27.30	31579	46.22	1790	2.60	16303	23.86
2000	24163	35.37	31272	45.77	1542	2.26	11346	16.61
2006	29535	43.23	19696	28.83	1073	1.57	18017	26.37
2010	37266	54.42	16031	23.41	617	0.90	14565	21.27

Urban growth became almost constant in southeast and northwest directions between 1992 and 2000 and then increased linearly. Largest patch developments have taken place in north and east directions (figure 5 (a)) in 2010 and medium urban development have emerged in west, southwest and south (figure 5 (a)). Separate clusters of huge urban patches have come in north (Bangalore International Airport) and east (International Tech Park Limited). Largest Patch Index (percentage of built-up) shows that urban growth is predominant in west, southwest, and south from 2000 to 2010 (figure 5 (b)). Number of patches increased from 1973 to 2000 in all directions (figure 5 (c)) showing urban sprawl. However, the city also continued to become more compact as represented by number of decreasing patches in 2010. Patch size coefficient of variance (PADCV) is the variability in patch size relative to mean patch size. Coefficient of variation of patch area is minimum in 1973 and increases towards 2010 with almost similar values in 2000 and 2006 as shown in figure 5 (d)). MSI-CV - the standard deviation to mean ratio was maximum in 2006 and continued to decrease in 2010 (figure 5 (e)). The highest ratio was in 2000 and it showed increasing trend between 2000 and 2010. Variation in patch shape was maximum in the patch types of new residential areas and industrial areas in south Bangalore. Area weighted Perimeter-Area Ratio (figure 5 (f)) indicates that the landscape shapes were biggest in 1973 and continued to become smaller with time, having smallest patches in 2010. MPFD-CV indicated maximum variability in raggedness of boundary in 2006 and minimum in 1992 with moderate raggedness in 2010 (figure 5 (g)). This metrics helps us to understand inherent variability between and within simple and complex shapes. The compactness index measures not only the individual patch shape but also the fragmentation of the overall urban landscape (Huang et al., 2007). The more irregular the patch shape and patch number, the bigger the CI value (figure 5 (h)). ENND-CV represents higher variation in mean ENND from the neighboring patch in north, northeast, south, and southwest in 1973 and continues to decrease till 2006. In 2010, the variability again increased in all directions except northeast, west and southwest (figure 5 (i)). In 1973, the urban patches were more clustered together segregated from other patch types. From 1992 to 2006, urban areas were in close proximity with non-urban patches with increasing clumpiness towards 2010 (figure 5 (j)). Ratio of open space was more in 1973 and decreased in all directions in 2010 causing limited lung spaces and greenery for the residents (figure 5 (k)). The dominance diversity of largest patch was minimum in 1973 and maximum in 2006 for all directions and decrease towards 2010. The number of dominant urban patches was maximum in 2006 and the patches continued to aggregate in 2010 making it more compact with decreasing dominance diversity (figure 5 (l)).

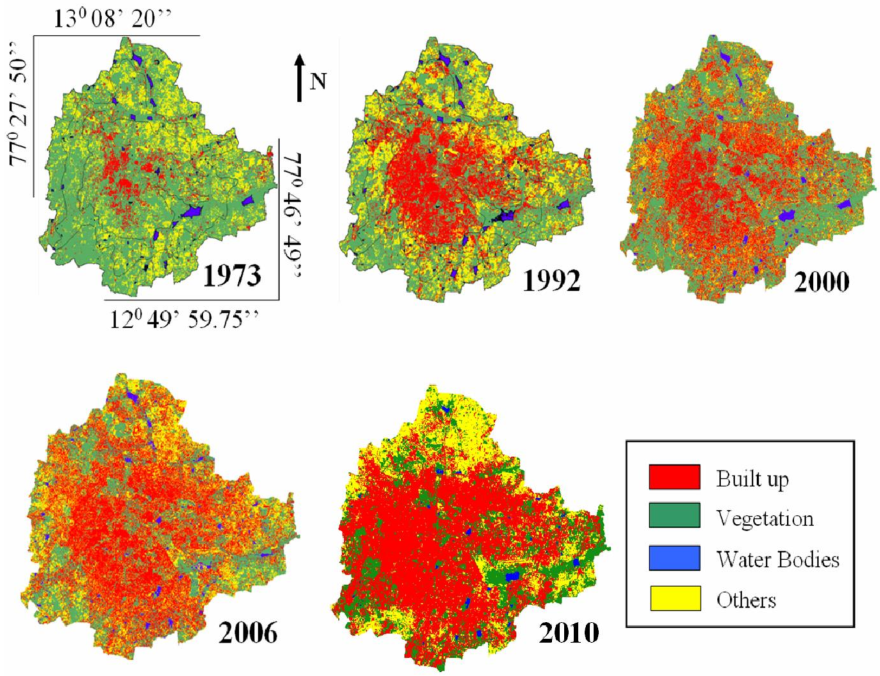


Figure 3: Greater Bangalore from 1973 to 2010

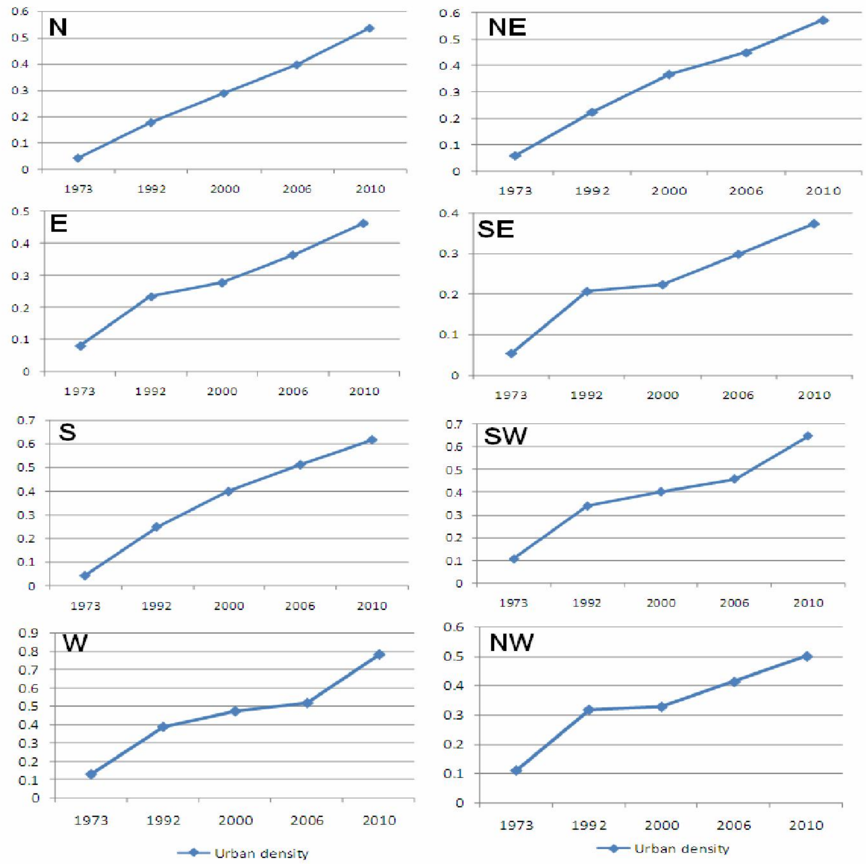
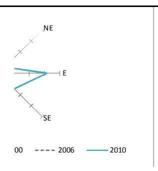
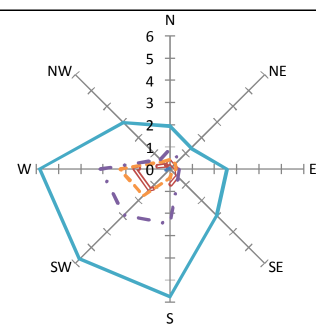


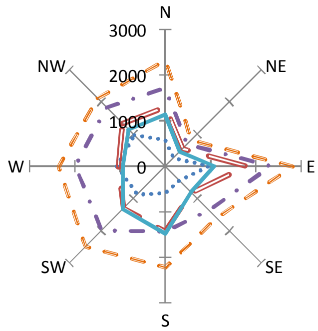
Figure 4: Urban density in eight directions showing rapid growth rate



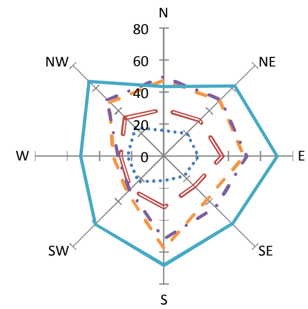
(a) Largest Patch



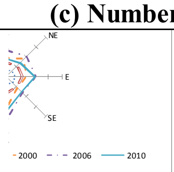
(b) Largest Patch Index (percentage of built-up)



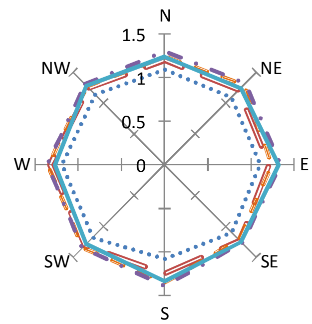
(c) Number of patches



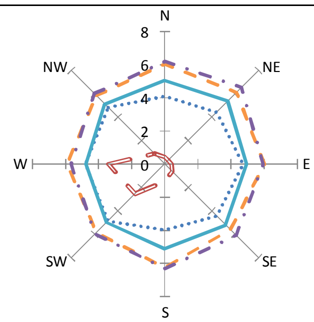
(d) PAD-CV (Patch size coefficient of variance)



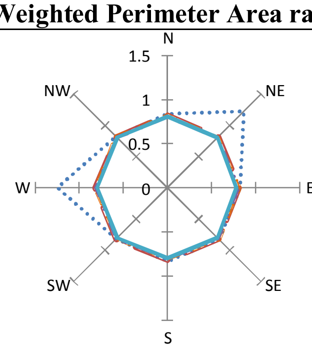
(e) Mean Shape Index (coefficient of variation)



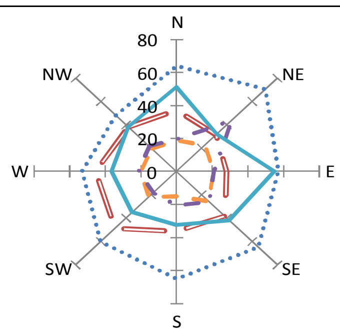
(f) Area Weighted Perimeter Area ratio



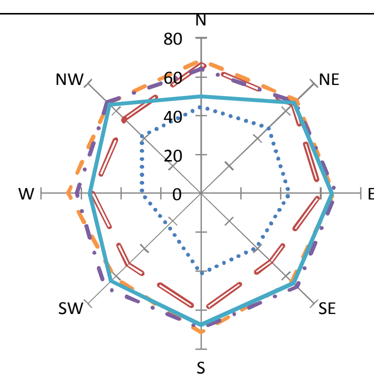
(g) Mean Patch Fractal Dimension coefficient of variation



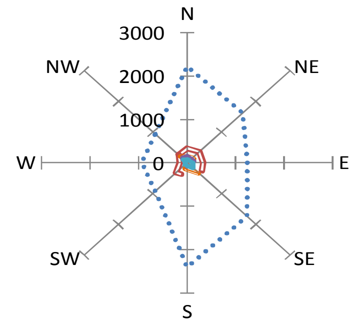
(h) Compactness Index



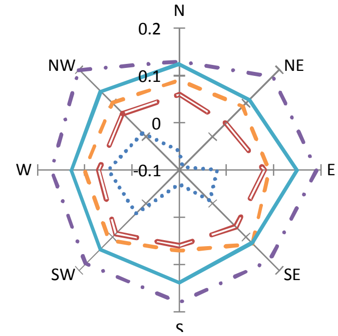
(i) Euclidean mean nearest neighbor distance - coefficient of variation



(j) Interspersion and Juxtaposition



(k) Ratio of open space



(l) Dominance index

Figure 5: Representation of changes in landscape structure described by various metrics.

The study shows not only the types of land use change in various directions, but also help us to understand in a way land was compositionally and spatially organised, that aids to assess the nature of human-environment interaction through the scale, pattern, and process paradigm that is emergent in real world.

Conclusions

The spatial analysis was done to access urban growth pattern of the Bangalore city in various directions through 12 landscape metrics across five time periods. The study showed that Bangalore is rapidly expanding with a significant rise in built-up area. Landscape is aggregating to form a large patch in 2010, while these patches were in small colonies during 1973 to 2006. Earlier, the urban patches were more dispersed; while in 2010, patches are maximally aggregated indicating that the city is becoming more compact in the recent years. Understanding these spatio-temporal aspects of landscapes are very critical for regional planning. The increase in the area of the largest patch also suggests that small patches have clumped together, thereby increasing the compactness of the city and decreasing the ratio of open space. Earlier the patch sizes were small in all the directions but in 2006 these patches started growing in north, west, south, southeast and east directions, also showing these urban patches getting bunched in these directions. Growing unemployment & poverty, malnutrition, social exclusion and environmental degradation are now the main issues to be tackled by urban decision-makers. Many of them will live in poverty and squalor, deprived of their basic needs and rights. Understanding these spatio-temporal aspects of landscape are very critical for regional planning, development of zoning regulations, creating job opportunities, estimation of energy supply, demand and conservation.

Acknowledgement

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