Urban Landscape analysis through Spatial Metrics

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Abstract: Urbanisation reflects metropolitan growth (planned or unplanned) in response to economic, social, political and physical geography of an area. Dynamic urban change processes, especially the tremendous expansion of urban areas affect natural and human systems at multiple scales. Unplanned rapid urbanisation has changed the structure and also influenced the functioning of landscapes as evident from lack of basic infrastructure, amenities, enhanced levels of pollution, changes in local climate and ecology. In this regard, Earth observation satellites provide information over a considerable range of spatial and temporal resolution for mapping land cover (LC) to understand the spatial and temporal aspects of landscapes. 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. Here, we analyse temporal remote sensing data of diverse spatial and spectral resolutions for Greater Bangalore. The city was divided into 8 zones to analyse the landscape metrics using classified data from 1973 to 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. The city was more compact in 1973 and began to disperse in all directions with decrease in the ratio of open space and increase in the number of urban 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.

Keywords: Urbanisation, landscape, spatial metrics, urban planning, remote sensing

1. 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). The rapid and often uncontrolled growth of the urbanising cities brings about numerous changes in the structure and functioning of landscape (Solon, 2009). Urban sprawl, a consequence of socioeconomic development under certain circumstances, 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. The growing migrant population, increasing number of Information Technology and Bio-Technology firms, and real estate projects are demanding more resources within the city, forcing it to expand both horizontally and vertically leading to serious problems like scarcity of food, informal settlements, environmental pollutions, destruction of ecological structures, unemployment etc. The unprecedented growth and urban sprawl are often unnoticed by the planners, as they are unable to visualise this type of growth patterns. Since patterns are fundamental to many of the spatial-temporal relationships that we seek to discover, it is important to understand the factors and trend that influence the interpretation 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 can be characterised by 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). RS has the potential to 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 spatial metrics (urban indicators) are very effective to understand the growth of urban areas for administration and future planning. Derivation of spatial metrics (landscape pattern metrics) from LC maps (Saura and Castro, 2007) aid in studying spatial urban patterns, sprawl, specific spatial model applications and analysis of spatio-temporal urban dynamics at different scales. They are used to quantify the spatial heterogeneity of individual patches, of all patches belonging to a common class, and of the landscape as collection of patches (Herold et al., 2005). They also aid in improved representation of heterogeneous characteristics of urban areas and in understanding the impact of urban development on surrounding environment. A wide variety of indices have been developed to characterise the landscape, some of which describes the proportion of landscape with a particular LC class, the size, number, and perimeter of each LC patch, and the complexity of the shape of the patch (Rashed, 2008). These metrices can be spatially non-explicit, aggregate measures, still reflecting important spatial properties, and, when applied to the multi-scale or multi-temporal data sets, they can be used to analyse and describe change in the degree of spatial heterogeneity (Herold et al., 2005). Since most of the metrics are based on geometric properties of landscape elements, that can provide simple quantitative measurements of a complex pattern, they are frequently adopted in landscape ecological research.

Objective: The objective of this paper is to describe changes in landscape structure and quantify the spatio-temporal urbanisation pattern in Greater Bangalore using spatial metrics. The analysis aims to answer the following questions:

(i.) What is the land use change from 1973 to 2010?
(ii.) How do the landscape metrics for urban areas change over time?
(iii.) Are there significant differences in sprawling pattern in different directions across the city?
(iv.) Which of the metrices highlight significant variations in direction wise developmental pattern in the city?

2. Study area and Data

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 7 million (Ramachandra and Kumar, 2008).

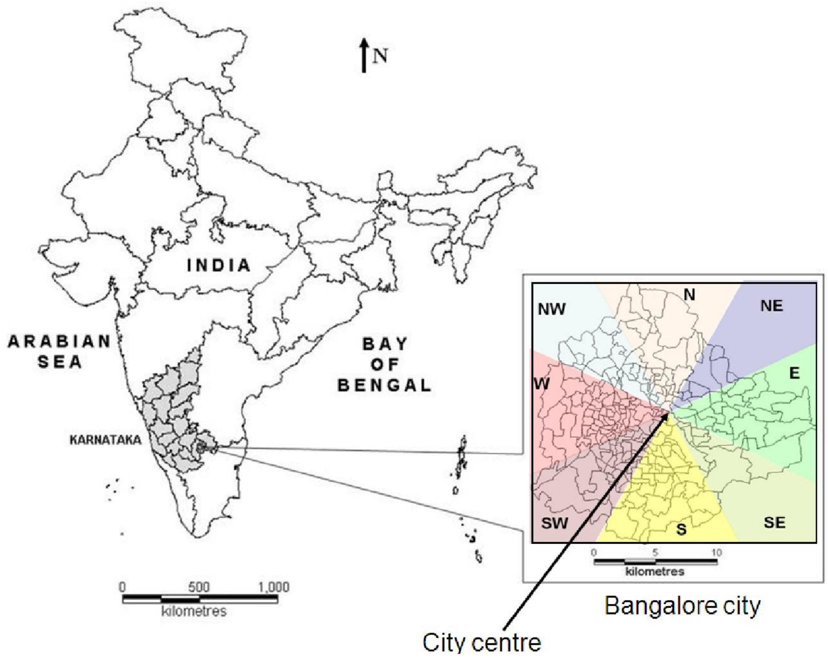


Figure 1: Study Area: Bangalore city, Greater Bangalore.

Since, urbanisation and urban sprawl are more a local phenomenon and site specific than global, local urban sprawl tends to increase along ring roads, highways in a certain direction, around service facilities in another direction, which later become the urban centre hub and extends in all directions. Therefore, a better way to understand the spatio-temporal pattern of a city is to study the urban landscape in different directions from the central business district. Therefore, the city was divided into 8 zones [North (N), Northeast (NE), East (E), Southeast (SE), South (S), Southwest (SW), West (W), and Northwest (NW)] with their origin from the 'city centre' (figure 1).

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 the images were resampled to 30m spatial resolution (1130 rows and 1170 columns) for consistency, easy analysis and interpretation. Layers of 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.

3. Methods

Maximum Likelihood classifier (MLC) was used to classify temporal RS data into 4 LC 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. 10 spatial metrices (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.

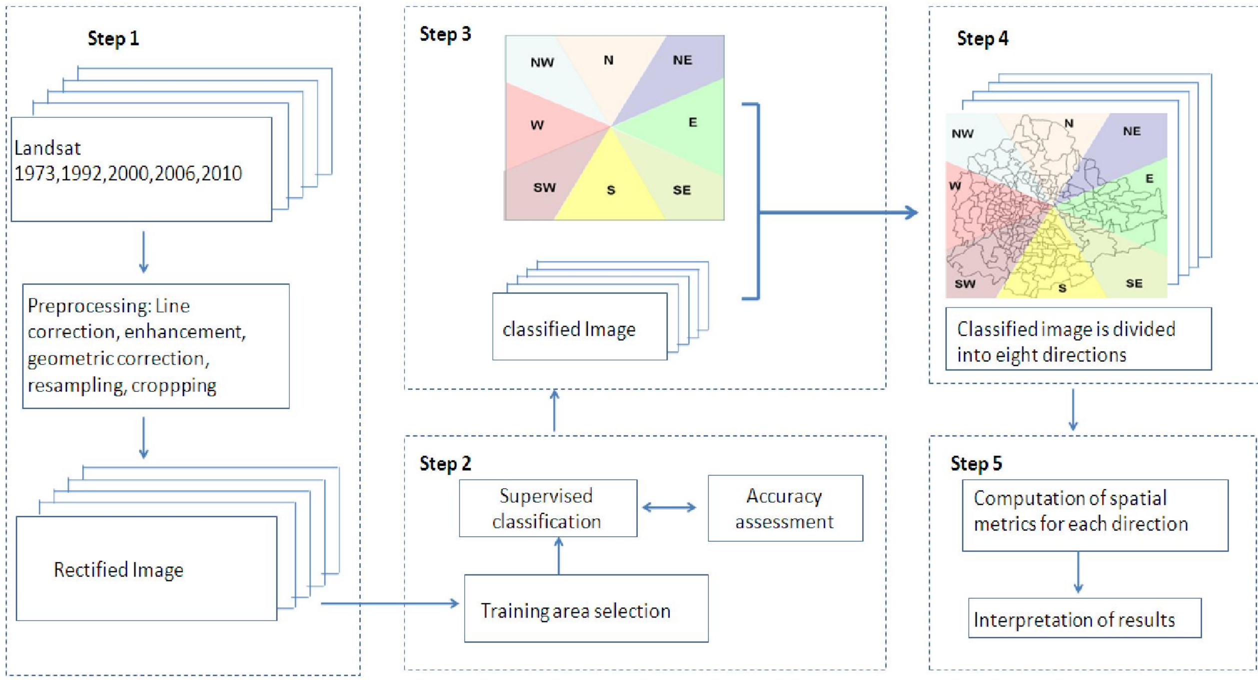


Figure 2: Schematic representation of the methods used in this study.

Table 1: Description of metrics used in this study

Sl No.	Indicators	Formula	Description
1.	Builtup (total land area)	-	Total builtup land (in ha).
2.	Largest patch	-	Largest urban patch in area.
3.	mean patch size	$MPS = \frac{A}{N_{patch}}(10000)$	Calculates mean patch size index on a raster map, using a 4 neighbour algorithm.
4	Number of Urban Patches	$NPU = n$	Fragmentation Index, NP equals the number of patches in the landscape.
5.	Normalized Landscape Shape Index	$NLSI = \frac{\sum_{i=1}^{i=N} \frac{p_i}{s_i}}{N}$	Where s_i and p_i are the area and perimeter of patch i, and N is the total number of patches.
6.	Patch edge density	$ED_K = \frac{\sum_{i=1}^{n} e_{ik}}{AREA}(10000)$	• **k**: patch type • **m**: number of patch type • **n**: number of edge segment of patch type k • $\mathbf{e_{ik}}$:total length of edge in landscape involving patch type k • **Area**: total landscape area
7.	Area weighted mean patch fractal dimension (AWMPFD)	$AWMPFD = \frac{\sum_{i=1}^{i=N} 2\ln 0.25 p_i / \ln s_i}{N} \times \frac{s_i}{\sum_{i=1}^{i=N} s_i}$	Where s_i and p_i are the area and perimeter of patch i, and N is the total number of patches.

8	Compactness Index (CI)	$$CI=\frac{\sum_i p_i/P_i}{N^2}=\frac{\sum_i 2\lambda\sqrt{s_i/\lambda}/p_i}{N^2}$$	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 and N is the total number of patches.
9	Clumpiness	$$CLUMPY=\begin{bmatrix}\frac{G_i-P_i}{P_i} for G_i<P_i \& P_i<5, else\\ \frac{G_i-P_i}{1-P_i}\end{bmatrix}$$ $$G_{i=}\left(\frac{g_{ii}}{\left(\sum_{k=1}^{m} g_{ik}\right)-\min e_i}\right)$$	• 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. • min-e_i =minimum perimeter (in number of cell surfaces) of patch type (class)i for a maximally clumped class. • P_i =proportion of the landscape occupied by patch type (class) i.
10	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.

The spatial metrics employed here are a series of qualitative indices representing physical characteristics of the landscape mosaic. Builtup (total land area) is the total builtup area (in hectares) and largest patch indicates the largest urban patch in terms of area considered in this study. Mean patch size is the average area of all patches in the landscape (in ha) (Buyantuyev, 2009). Number of patches of a particular patch type is a simple measure of the extent of subdivision or fragmentation of the patch type. A simple shape index measures the complexity of patch's boundary by calculating a normalised ratio of its perimeter to its area. Edge density equals the sum of the lengths(m) of all edge segments involving the corresponding patch type, divided by the total landscape area (m^2), multiplied by 10,000 (to convert to hectares). Edge density is zero when there is no class edge in the landscape. AWMPFD metric measures the irregularity of patch shape and describes the raggedness of urban boundary. This fractal dimension approaches "one" for shapes with simple perimeters and approaches "two" when the shapes are more complex. 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. Clumpiness index is calculated from the adjacency matrix, which shows the frequency with which different pairs of patch types (including like adjacencies between the same patch type) appear side by side on the map. 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.

4. 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 4 decades. Vegetation has decreased by 66% and water bodies have reduced by 74%. Urban growth became almost constant in southeast and northwest directions between 1992 and 2000 and then increased linearly. Urban growth is prominent in west, southwest, and south from 2000 to 2010 (figure 5(a)). Largest patch developments have taken place in north and east directions (figure 5 (b)) in 2010 and medium urban development have emerged in west, southwest and south (figure 5 (b)). Separate clusters of huge urban patches have come in north (Bangaluru International Airport) and east (International Tech Park Limited).

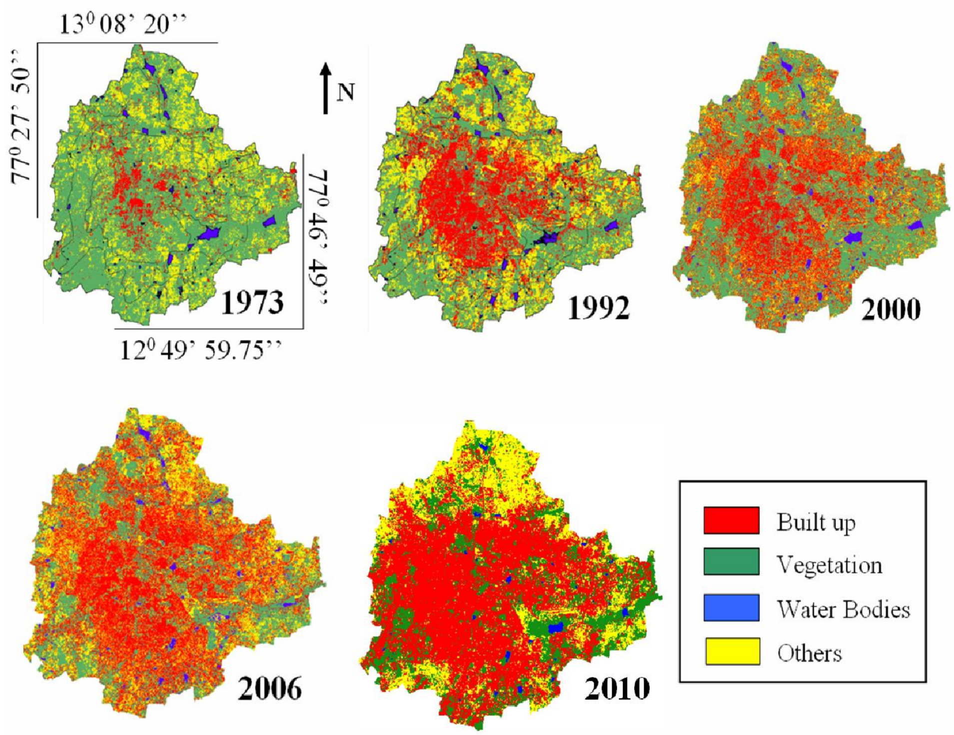


Figure 3: Greater Bangalore from 1973 to 2010.

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

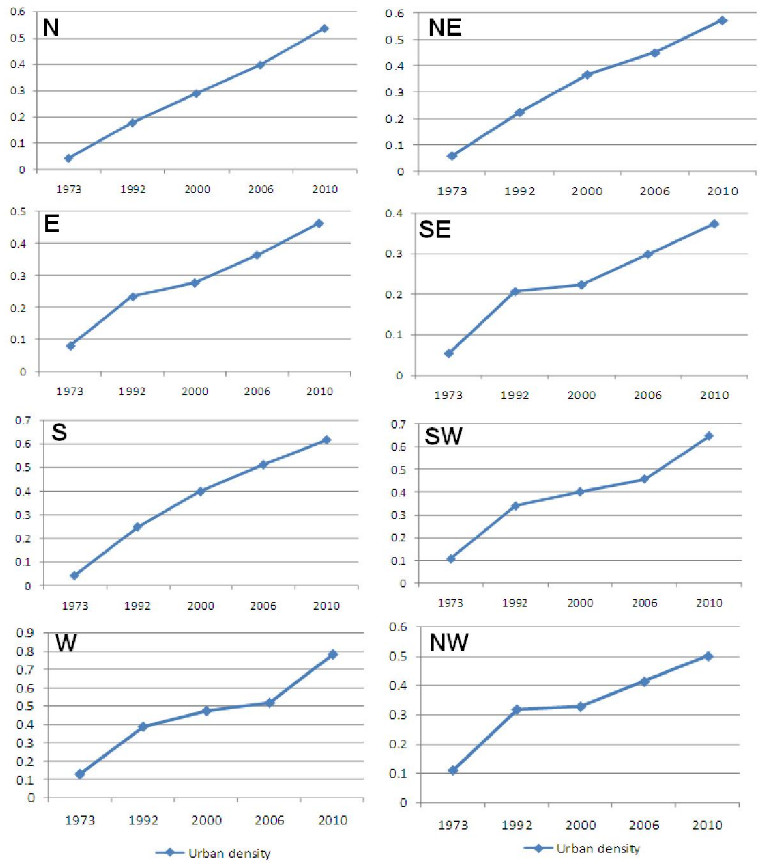
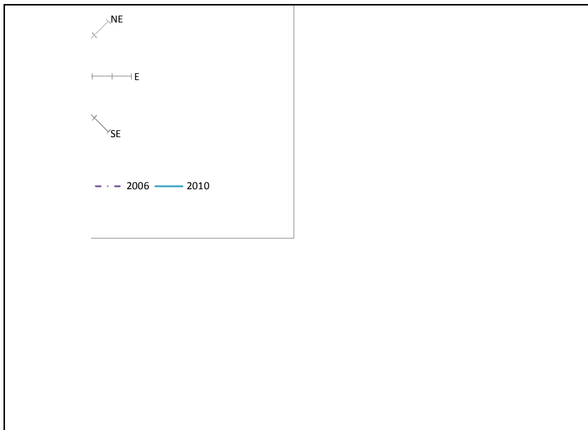
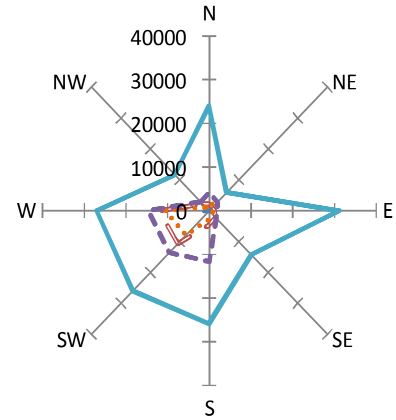


Figure 4: Urban density in eight directions showing rapid growth rate.

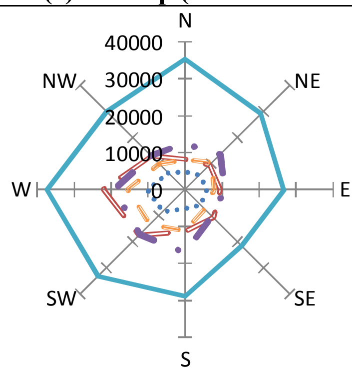
Mean patch size (figure 5 (c)) indicates that the city has been growing in circular fashion. Number of patches increased from 1973 to 2000 in all directions (figure 5 (d)) showing urban sprawl. However, the city also continued to become more compact as represented by number of decreasing patches in 2010. NLSI (figure 5 (e)) indicates that the landscape shapes were biggest in 1973 and continued to become smaller with time, having smallest patches in 2010. Mean shape of the patches were smallest in 1973 and largest in 2006 with decreasing trend in 2010. Edge densities increased from 1973 to 2000 and were predominant in northeast, east, southwest, west and south directions, showing a declining trend towards 2010 and indicating compact nature of the city (figure 5 (f)), with convoluted and irregular fringe. Values of AWMPFD (figure 5(g)) indicated that urban boundaries are non-complex structure. The city was less compact in 1973 in north, east and west directions while it became more compact towards 2010 (figure 5 (h)). In 1973, patches were more regular and less in count in northeast and west while from 1992 to 2010, patches became more regular and increased in number. In the year 2010, the urban patches are maximally aggregated, that is, they are clumped together while in 1973, patches were randomly distributed (figure 5 (i)). Ratio of open space was more in 1973 and decreased in all directions in 2010 causing limited lung spaces and greenery for the residents as indicated in figure 5 (j).



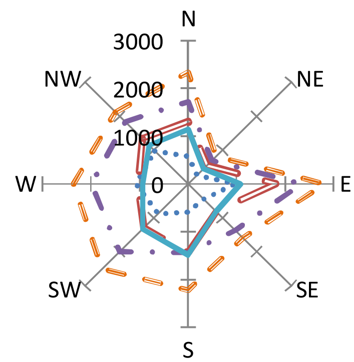
(a) Built up (total land area)



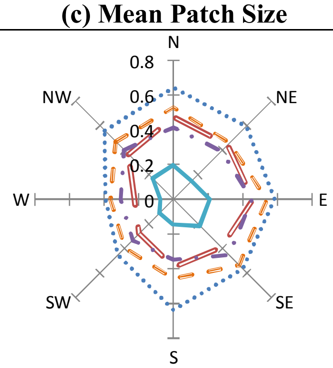
(b) Largest Patch (in area)



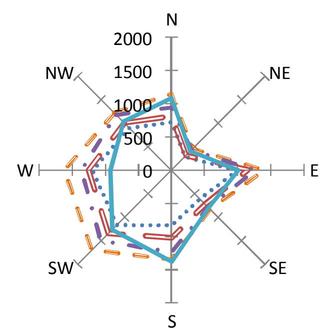
(c) Mean Patch Size



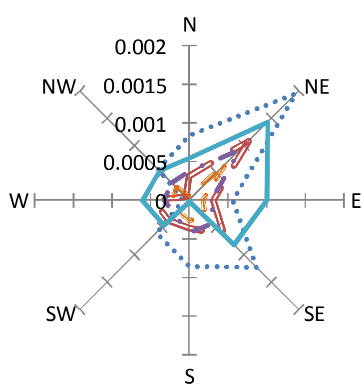
(d) Number of Patches



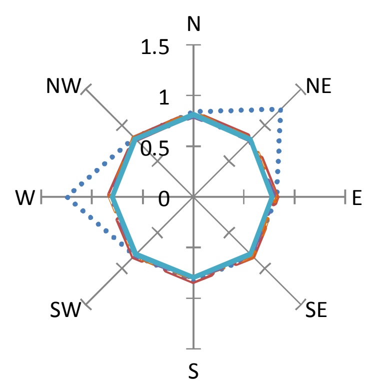
(e) Normalised Landscape Shape Index



(f) Edge density



(g) AWMPFD



(h) Compactness Index

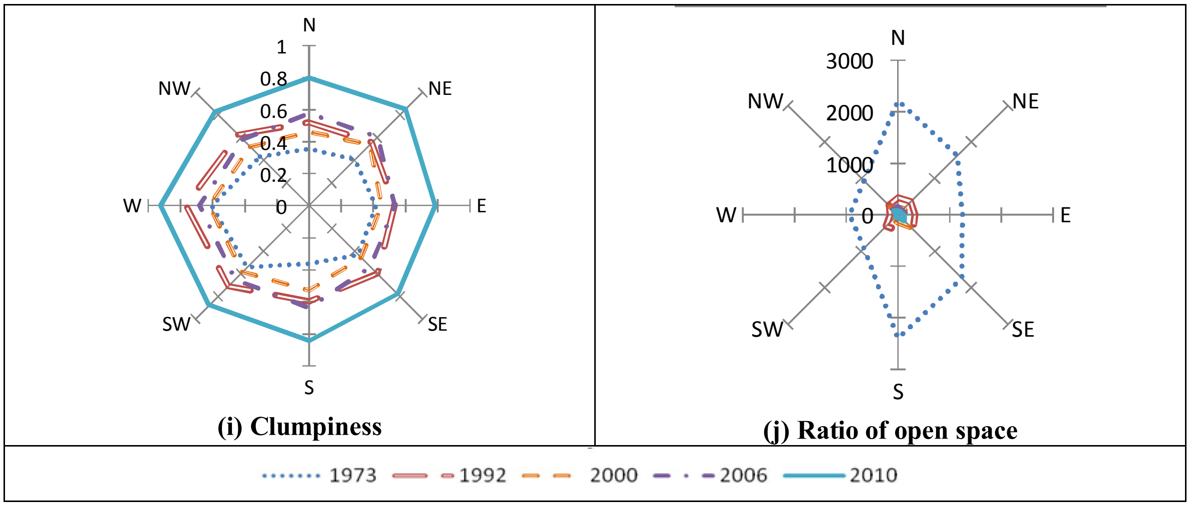


Figure 5: Representation of changes in landscape structure described by metrices in 8 directions.

5. Conclusion

The intent of the analysis was to access urban growth pattern of the Bangalore city in various directions through 10 landscape metrices across five time periods. The study showed that Bangalore is rapidly expanding with a significant rise in builtup area. In 2010 the city has become more aggregated as the number of patches decreased. 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. Understanding these spatio temporal aspects of landscapes are very critical for regional planning.

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