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Exposition of Urban Structure and Dynamics through Gradient Landscape Metrics for Sustainable Management of Greater Bangalore

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Abstract

Understanding urban structure and urban dynamics is fundamental for sustainable management of rapidly urbanising landscapes. Drastic expansion of urban areas affects 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, frequent occurrence of floods, changes in local climate and ecology. In this regard, Earth observation satellites provide synoptic information over a considerable range of spatial and temporal resolution for mapping land cover (LC) to understand the spatial and temporal dynamics of landscapes. Landscape pattern quantification temporally is essential for monitoring and mitigating the environmental consequences of urbanization. Synergistic usage of remote sensing data, landscape metrics with gradient analysis helped in exposition of urban structure and dynamics. Spatio-temporal dynamics of Greater Bangalore's landscape (with 10 km circular buffer) have been investigated for the post Information Technology period (1999-2008) using temporal remote sensing data. The remote sensing data were classified through a supervised technique using a Gaussian maximum likelihood classifier. The classified image of each year was divided into 8 zones diagonally and each zone was further into gradients of 13 concentric circles. Landscape metrics were computed in each gradient to describe the landscape patterns. This aided in the improved understanding and representation of urban structure and dynamics through the spatial regularities and trends of the impact of landscape changes. The study shows that there has been an increase from 11.12 (1999) to 24.47 (2008) of urban area. Metrics reveal concentrated growth at city centre while sprawl at city periphery. This highlights the need for integrated approaches in the regional planning to ensure the sustainability of natural resources.

Keywords

Urban dynamics, Sprawl, Landscape metrics, land use, spatial metrics, gradient analysis.

1.Introduction

Landscape refers to all the visible features of an area of land such as the physical elements of landforms, human elements including land uses, buildings and structures, and water bodies (rivers, lakes and the sea). Land cover is the physical material at the surface of the earth and broadly refers to the region under vegetation and non-vegetation. The human use of land involving the management and modification of natural environment or wilderness into built environment is referred as land use. Urbanization is the most dramatic form of irreversible land transformation (Gao et al., 2004), affecting landscape's traditional integrity. It is a process in which an increasing proportion of an entire population lives in cities and the suburbs of cities. It brings the changes in the employment structure from small industries and agriculture to big industries. Urban areas account for 78% of greenhouse gases contributing significantly to global climate changes (Grimm et al., 2000).

Urbanization involves both social and physical transformation of landscapes, is a powerful, often irreversible and highly visible anthropogenic force (Shu-Li Huanga et al., 2009). Natural ecosystems and also 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, et al., 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 (IT & BT) firms, and real estate projects are demanding more resources within the city, forcing it to expand both horizontally and vertically leading to serious infrastructure problems including 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 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).

Drastic changes in the landscape composition alter the functional ability of cities (Frank, 1999) affecting the regional climate (Orville et al., 2000) and hydrology apart from inducing frequent disasters like floods, etc. (Ramachandra and Kumar, 2008). Urbanizations need to be planned taking into account all components of the landscape with a location specific advance plan. Policy decisions of industrialisation or setting up of commercial complexes would lead to an increase in human population. Economic, social, political etc. factors have a greater influence in the growth of Urbanization. Unplanned urbanization leading to sprawl brings the destruction of habitats, loss of agricultural land with serious impact on the ecology. Urban sprawl is also referred as irresponsible, and often poorly planned development that destroys green space, increases traffic, contributes to air pollution, leads to congestion with crowding and does not contribute significantly to revenue, a major concern. This drives the changes in urban patterns and most often the sprawl regions are devoid of basic amenities such as treated water supply, sanitation, electricity, etc. The urbanization and consequent sprawl are apparent in many regions (Vitousek et al., 1997; Antrop, 2000; Seto and Fragkias, 2005; Jantz et al., 2005; Martinuzzi et al., 2007), which necessitates planned development (Epstein et al., 2002; The Regionalist, 1997; Sierra Club, 1998). This phenomenon has been investigated in the developed countries (Batty et al., 1999; Torrens and Alberti, 2000; Barnes et al., 2001, Hurd et al., 2001; Epstein et al., 2002) and in developing countries (Yeh and Li, 2001; Cheng and Masser, 2003; Jothimani, 1997 and Lata et al., 2001; Sudhira et al.., 2003). Built-up area has been used as the parameter for quantifying urban sprawl (Torrens and Alberti, 2000; Barnes et al., 2001; Epstein et al., 2002; Fang et al., 2004). In this context, the nature and growth of urbanization is to be understood for effective planning considering the temporal aspects of urban dynamics.

Urban planners and land resource managers require information regarding the changes of land use for an effective city planning. The land use master plans of each city are important for guiding their future urban expansion (Hai Minh Pham et al., 2011). To know the land use changes and urban expansions temporal remote sensing data provides very useful information. Spatial data acquired remotely through space-borne sensors at regular intervals provide powerful tools for analysing urban land use changes and have been widely used in detecting and monitoring land cover changes (Pellikka et al., 2004; Seto and Kaufmann, 2003; Weber and Puissant, 2003). Remote sensing data (RS) along with geographic information systems (GIS) enable land planners, managers, and ecologists to display and quantify changes in landscape structure that result from disturbances (Turner and Carpenter, 1998).

Spatial metrics are used to understand the spatial heterogeneity at a specific scale and resolution (Herold et al., 2002). The combined use of remote sensing and spatial metrics will lead to new level of insights to changes in the landscape (Herold et al., 2005). Better city planning at local level requires understanding of the spatio-temporal aspects of landscapes. A spatio temporal landscape metrics analysis across buffer zones is an improvement over using only urban growth rates for comprehensive understanding of the shapes and trajectories of urban expansion (Seto and Fragkias, 2005). Landscape-level metrics have been developed to examine and provide meaningful ways of measuring landscape characteristics (O'Neill et al., 1988; McGarigal and Marks, 1995; Gustafson, 1998; Hargis et al., 1998; Jaeger, 2000). These spatial metrics concentrate landscape information, and reflect the structural composition and spatial configuration of landscape features (Moquan A and Guangjin, 2010). In order to quantify the spatio temporal dynamics with changes in landscape pattern and to describe the regularity of urbanization process, landscape metrics have been used (Wu, et al, 2000; Jenerette, et al, 2001; Grimm, et al, 2000). This communication is based on the analyses of the urban sprawl and changes in landscape using spatio-temporal tools - GIS and RS along with spatial metrics and gradient analysis. The Objective of this study is 1) spatio temporal analysis of land use at local levels 2) computation of landscape metrics to understand the urban dynamics and 3) identify the agents of urbanization and urban sprawl at local levels.

2. Data and Study area

Remote sensing data of Landsat Thematic Mapper (TM) and Landsat Enhanced TM Plus (ETM+) for the period 1999 to 2008 were download from public domain (http://glovis.usgs.gov/, http://glcfapp.glcf. umd.edu:8080/esdi/index.jsp). Data pertains to five years series - 1999, 2000, 2003, 2006 and 2008. Urban dynamics was analysed for Greater Bangalore with circular buffer of 10 km considering the City Business District (CBD) as centre Figure 1. It is the capital city of Karnataka with an area of 741 sq. km., lies between 12°39'00" to 13°13'00"N and 77°22'00" to 77°52'00"E. It is one of the fastest growing cities in India and is branded for heralding and spearheading the growth of Information Technology (IT) based industries in the country. It is the fifth largest metropolis in India The population of Bangalore is about 8 million (Ramachandra and Kumar, 2008; Sudhira et al., 2007).

3. Method

Remote sensing data of Landsat series were downloaded and corrections such as geometric, radiometric and scan-line (for ETM+) were implemented. Methods used in data analysis for landscape dynamics analysis is given in Figure 2. Survey of India (SOI) topo-sheets of 1:50000 and 1:250000 scales were digitised to derive base layers. Data were analysed using GRASS - open source GIS package (http://ces.iisc.ernet.in/grass). Method adopted in analysing urban dynamics using Landscape metrics is given in Figure 2 and various stages in data analyses are:

I. Geometric Correction: Ground control points (GCP's) for geo-rectification and training data for supervised classification of RS data were collected through field investigations using a handheld GPS. Google Earth data (http://earth.google.com) were used during pre and post classification and also for validation.

Bands were geo-corrected with the known GCP's, and projected to geographic latitude-longitude with WGS-84 datum, followed by masking and cropping of the study area. This method is very common and widespread because of its robustness and higher accuracies of classified data (Hester et al., 2008).

II. Supervised classification using Gaussian maximum likelihood Classifier: In supervised classification, the pixel categorisation process is done by specifying the numerical descriptors of the four land use types (urban, vegetation, water and others (eg:-open space)) present in a scene. It involves (i) training, (ii) classification and (iii) output.

III. Accuracy assessment: Accuracy assessments were done with field knowledge, visual interpretation and also referring Google Earth (http://earth.google.com).

IV. Direction and region-wise division of the study area: To understand the landscape dynamics at local level including the understanding of drivers of urban growth the study area is divided direction-wise into 8 zones (North-North-East (NNE), North-East-East (NEE), South-East-East (SEE), South-South-East (SSE), South-South-West (SSW), South-West-West (SWW), North-West-West (NWW), North-North-west (NNW))and each zone is divided into concentric circle of 2 km incrementing radius as shown in Figure 3. Thus classified image was divided into 13 concentric circles in 8 directions, which were cropped. This provided 104 regions almost corresponding to the city Corporation administration wards. The classified data corresponding to cropped regions were used for further analysis.

V. Computation of percentage built-up area: Dynamics of urban built up were assessed using temporal data by computing built up (%) for each region (zone-wise, each circle).

VI. Computation of Shannon entropy: To quantify the degree of spatial concentration or dispersion, direction-wise Shannon's Entropy (Yeh and Li, 2001; Lata et al., 2001; Sudhira et al., 2003) were computed. This is useful and effective for differentiating various levels of urbanisation and sprawl. Shannon's entropy (Hn) can be used to measure the degree of spatial concentration or dispersion of geographical variables among 'n' concentric circles and in 8 directions.

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

Where, Pi is the proportion of the phenomena occurring in the ith concentric circle. As per Shannon's Entropy, if the distribution is maximally concentrated in one circle the lowest value zero will be obtained. Conversely, if it is an even distribution among the concentric circles will be given maximum of log n. This means values closer to zero indicates concentrated growth while values closer to log n indicates the sprawl.

VII. Computation of Spatial metrics for each local landscapes: Landscape metrics listed in Table 1 were then computed for 104 regions for each classified image using GRASS (http://wgbis.ces.iisc.ernet.in /foss) and Fragstats (McGarigal, et al., 2002). However the amount and kind of information that any one metric can offer, or from which information may be inferred may be a limitation and hence a combination of metrics have been used for a more comprehensive understanding of landscape structure and its dynamics (DiBari, 2007). In this study, 25 landscape metrics were computed and then Principal Component Analysis (PCA) was performed using PAST software and only 11 metrics with higher loadings were selected for further study. PCA is a multivariate analysis that reduces a large number of variables down to a smaller number of relatively independent components associated with a set of specific variables (Tabachnick and Fidell, 2001).

S. No.	Indicators	Formula	Description
1	Built up Area		Total built-up land (in ha)
2	Shannon's Diversity Index	$SHDI = -\sum_{i=1}^{m} (P_i \circ \ln P_i)$ Where Pi = Proportion of the landscape occupied by patch type (class) i	SHDI > =0, without limit.
3	Number of Urban Patches	NPU = n NPU equals the no. of urban patches in the landscape.	SHDI > =0, without limit.
4	Mean Nearest Neighbor Distance	$MNN = \frac{\sum_{j=1}^{n'} h_{ij}}{n'_i}$ where h =nearest edge to edge distance n = total no of patches of same type	Mean Nearest Neighbour measures average patch to patch distance. MNN > 0, without limit.
5	Mean Proximity Index)	$MNN = \frac{\sum_{j=1}^{n'} h_{ij}}{n'_i}$	The mean proximity index measures the degree of isolation and fragmentation of the corresponding patch type MPI >=0..
6	Interspersion & Juxtaposition Index	$IJI = \frac{-\sum_{k=1}^{m'}\left[\left(\frac{e_{ik}}{\sum_{k=1}^{m'} e_{ik}}\right)\ln\left(\frac{e_{ik}}{\sum_{k=1}^{m'} e_{ik}}\right)\right]}{\ln(m'-1)}(100)$ eik =total length (m) of edge in landscape between patch types (classes) i and k. m =number of patch types (classes) present in the landscape, including the landscape border, if present.	0 < IJI <=100. IJI approaches 0 when the corresponding patch type is adjacent to only 1 other patch type and the number of patch types increases. IJI = 100 when the corresponding patch type is equally adjacent to all other patch types.
7	Mean Patch Size	$MPS = \frac{\sum_{j=1}^{n} a_{ij}}{n_i}\left(\frac{1}{10,000}\right)$ Where aij = Area (m2) of patch ij n =total no of patches of same type	MPS > 0, without limit

Table 1: Description of Metrics

Sl. No.	Indicators	Formula	Description
8	Aggregation Index	$AI=\left[\sum_{i=1}^{m}\left(\frac{g_{ii}}{\max \rightarrow g_{ii}}\right)P_i\right](100)$ gii =number of like adjacencies (joins) between pixels of patch type (class) i. max-gii = maximum number of like adjacencies (joins) between pixels of patch type class i based on single count method. Pi= proportion of landscape comprised of patch type (class) i.	1≤AI≤100 AI equals 1 when the patches are maximally disaggregated and equals 100 when the patches are maximally aggregated into a single compact patch
9	Landscape Shape Index	$LSI=\frac{0.25\sum_{k=1}^{m} e''_{ik}}{\sqrt{A}}$ e"ik Total length (m) of edge in landscape between patch types (classes) I and k; includes the entire landscape boundary and background edge segments, regardless of whether they represent true edge.	Range: LSI ≥ 1, without limit.
10	Area weighted mean shape index (AWMSI)	$AWMSI=\sum_{j=1}^{n}\left[\left(\frac{0.25p_{ij}}{\sqrt{a_{ij}}}\right)\left(\frac{a_{ij}}{\sum_{j=1}^{n} a_{ij}}\right)\right]$ Where pij = Perimeter (m) of patch ij	AWMSI = 0 when all patches in the landscape are circular or square. AWMSI = 1, without limit AWMSI increases without limit as the patch shape becomes irregular
11	Area weighted Euclidean mean nearest neighbor distance	ENN=hij hij is distance(m) from patch ij to nearest neighboring patch of the same type(class) based on shortest edge to edge distance.	ENN>0, without limit ENN approaches zero as the distance to the nearest neighbor decreases
12	Mean Shape Index	$MSI=\frac{\sum_{j=1}^{n}\left(\frac{0.25p_{ij}}{\sqrt{a_{ij}}}\right)}{n_i}$. Pij is the perimeter of patch i of type j. . aij is the area of patch I of type j. ni is the total number of patches. $CV=\frac{SD}{MN}(100)$ 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.	It is represented in percentage

Table 1: Description of Metrics

4. Results and Discussion

Supervised classification was performed using GMLC and was verified with field knowledge, visual interpretation and Google Earth data (http://googleearth.com). The supervised classified land use of temporal data is given in Figure 4 and class statistics in table 2. The percentage of urban has increased from 11.12 (1999) to 24.47 (2008) in the study region (Greater Bangalore with 10 km buffer). The Vegetation has decreased from 47.93 to 38.84%. Land use dynamics is illustrated in Figure 5, which highlight an increase in urban area with consequent decline of other natural resources - vegetation, water bodies, etc. during 1999 to 2008. An overall accuracy of 88%, 98%, 97%, 96% and 74% were obtained for the data of 1999, 2000, 2003, 2006 and 2008 by using the open source programs (i.gensig, i.class and i.maxlik) of Geographic Resources Analysis Support System (http://wgbis.ces.iisc.ernet.in/ grass). Accuracy assessment is critical to understand the efficacy of classifiers with spatial data (Congalton and Green, 1999; Li et al, 2003; Lunetta and Lyon, 2004). The Overall accuracy of the classification and Kappa coefficient is listed in Table 3. The analyses substantiate that the percentage urban land is increasing in the all directions with respect to time.

Temporal analyses carried out earlier indicate the decline of 34.48% during 1973 to 1992, 56.90% during 1973-2002 and 70.69% of water bodies during 1973-2007 in the erstwhile Bangalore city limits (560 sq.km.). Similar analyses done for Greater Bangalore (i.e Bangalore city with surrounding 8 municipalities - spatial extent of 741 sq.km.) indicate the decline of 32.47% during 1973 to 1992, 53.76% during 1973-2002 and 63.43% during 1973-2008 (Ramachandra and Kumar, 2008). This is correlated with the increase in built up area from the concentrated growth model focusing on Bangalore, adopted by the state machinery, affecting severely open spaces and in particular water bodies.

Shannon's entropy computed direction-wise for 8 zones with 13 concentric circles (n = 13), for Greater Bangalore with 10 km buffer is given in Table 4 for 1999 to 2008 (Figure 6). The entropy values ranges from 0.3701(1999, NE) to 0.8955(2008, SW) which is closer to log (n), i.e. 1.11, indicating the dispersed growth or sprawl. Number of patches (NP) in land-use a measure of the fragmentation under urban category is computed. Larger the NP more is the fragmentation in the landscape. Number of patches increased from the central business district (i.e. city centre) to periphery in all directions from 1999 to 2008. Large number of patches also reveal dispersed growth in the periphery - outer circles. City centre show compact growth in 2008 evident from the decline of number of patches in 2008 compared to earlier years and also compared to outer circles.

Class area (CA) is a measure of landscape composition; specifically, how much of the landscape is comprised of a particular patch type - built up area. Built up area (in hectares) has increased in all directions from 1999 to 2008. The mean proximity index (MPI) measures the degree of isolation and fragmentation of built-up patch and MPI >=0. MPI = 0 if built-up patches have no neighbours of the same type within the specified search radius. MPI increases as patches of the corresponding patch type become less isolated and the patch type becomes less fragmented in distribution. MPI analysis indicates of increase at city centre in all directions from 1999 to 2008. However, there is no a significant increase at outskirts, which indicate that city centre has become more compact in 2008. Interspersion and juxtaposition index measures the extent to which built-up patches are interspersed and varies 0 < IJI <=100. Higher values result from landscapes in which built-up are well interspersed or equally adjacent to each other, whereas

Classes → / Year ↓	URBAN	VEGETATION	WATER	OTHER
1999 (Nov) %	11.12	47.93	1.25	39.69
2000 (Nov) %	13.23	44.56	1.63	40.58
2003 (Nov) %	20.88	38.74	0.45	39.93
2006(Nov) %	22.11	38.58	0.64	38.66
2008 (Nov) %	24.47	38.58	1.04	38.66

Table 2: Land Use Statistics

YEAR	1999	2000	2003	2006	2008
Over All Accuracy	88.00%	98.00%	97.00%	96.00%	74.00%
Kappa Coefficient	0.72	0.97	0.96	0.94	0.61

Table 3: Accuracy assesment of the classification

	NE	SE	SW	NW
1999	0.3701	0.3902	0.5335	0.4818
2000	0.4071	0.4532	0.6141	0.5284
2003	0.5821	0.6811	0.8915	0.7106
2006	0.6129	0.7277	0.8707	0.7057
2008	0.6483	0.8053	0.8955	0.8886

Table 4: Shannon's Entropy

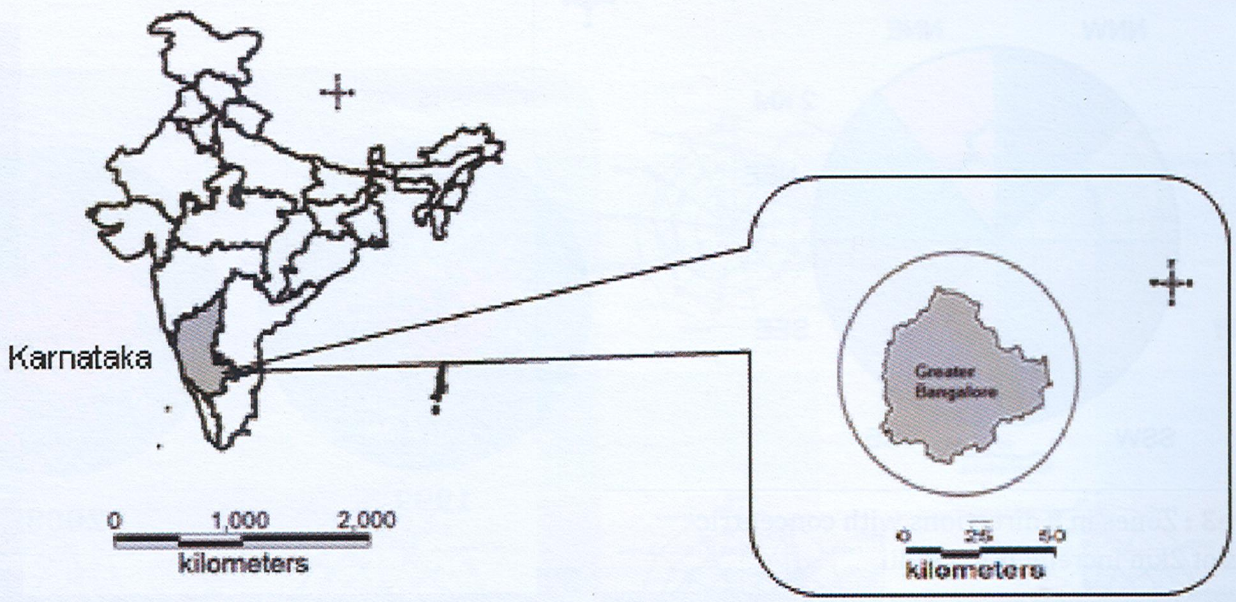


Figure 1 : Study area – Greater Bangalore, Karnataka State, India

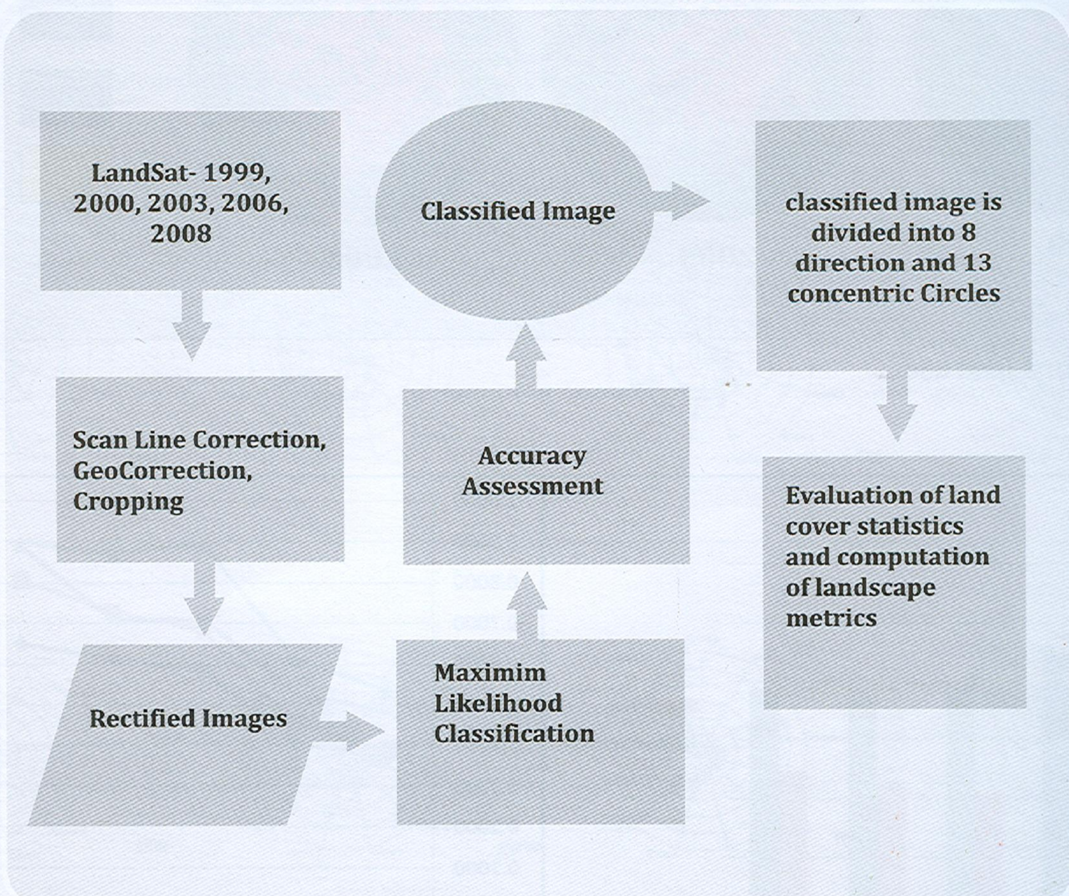


Figure 2 : Method adopted for data analysis

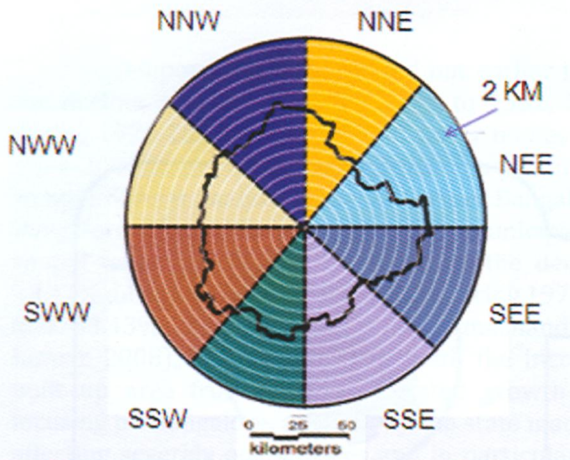
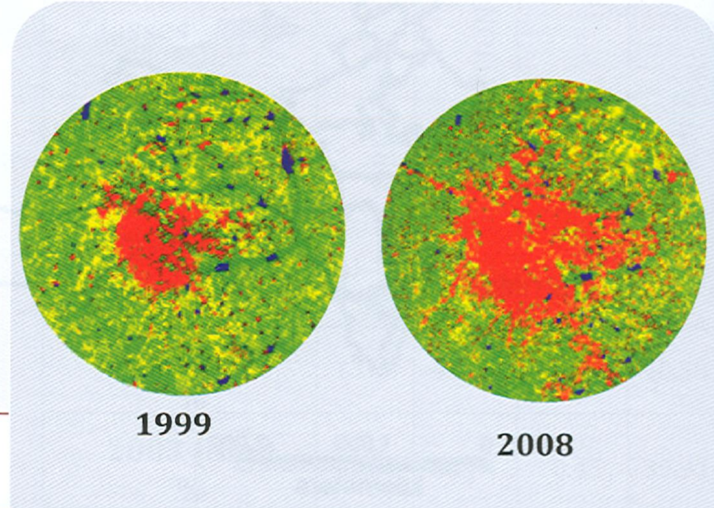


Figure3 : Zones in 8 directions with concentric circles of 2km incrementing radii



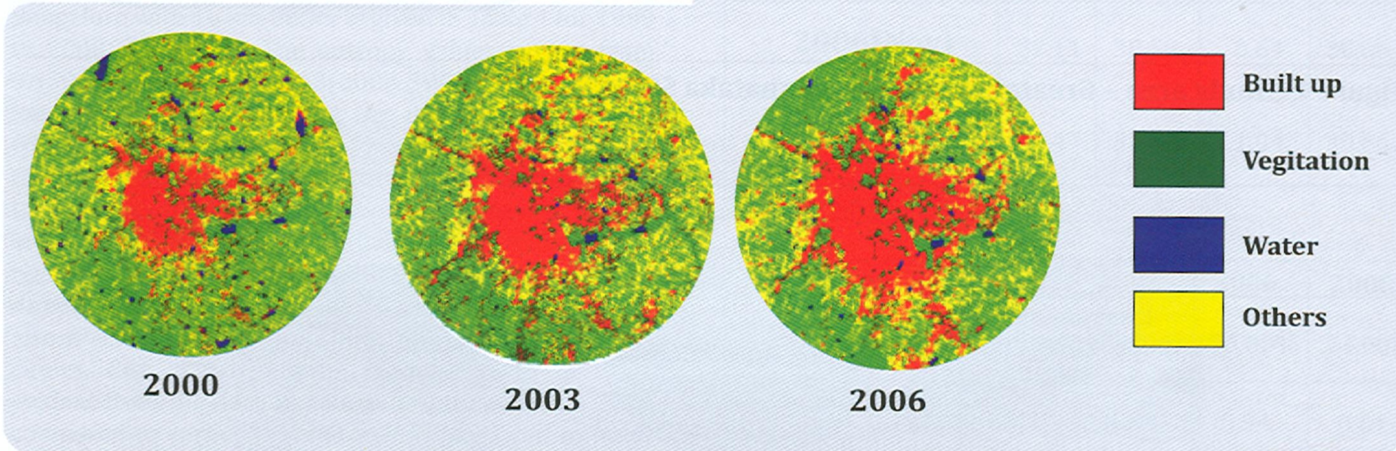


Figure4 : Temporal land use

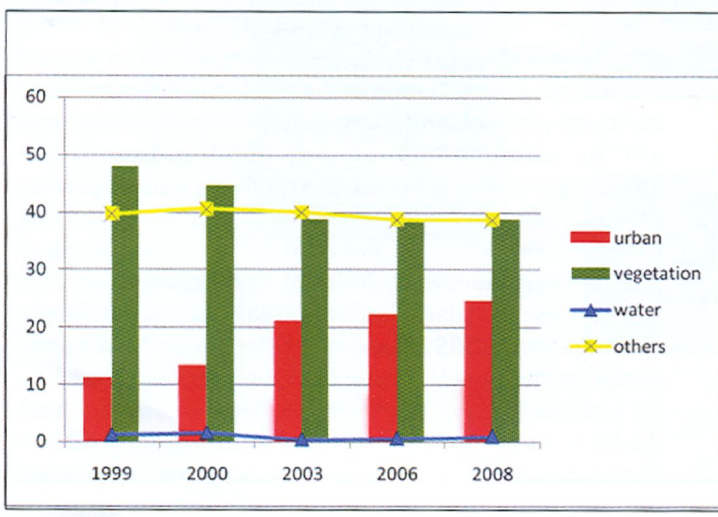


Figure 5 : Land Use dynamics of Bangalore

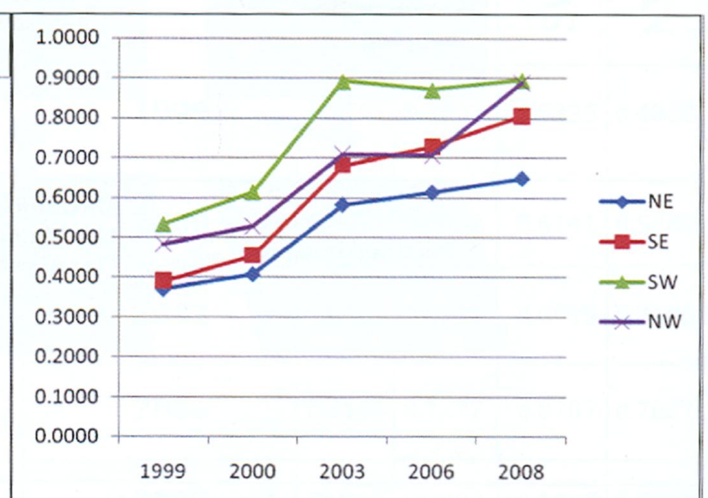


Figure 6 : Direction-wise temporal Shannon Entropy

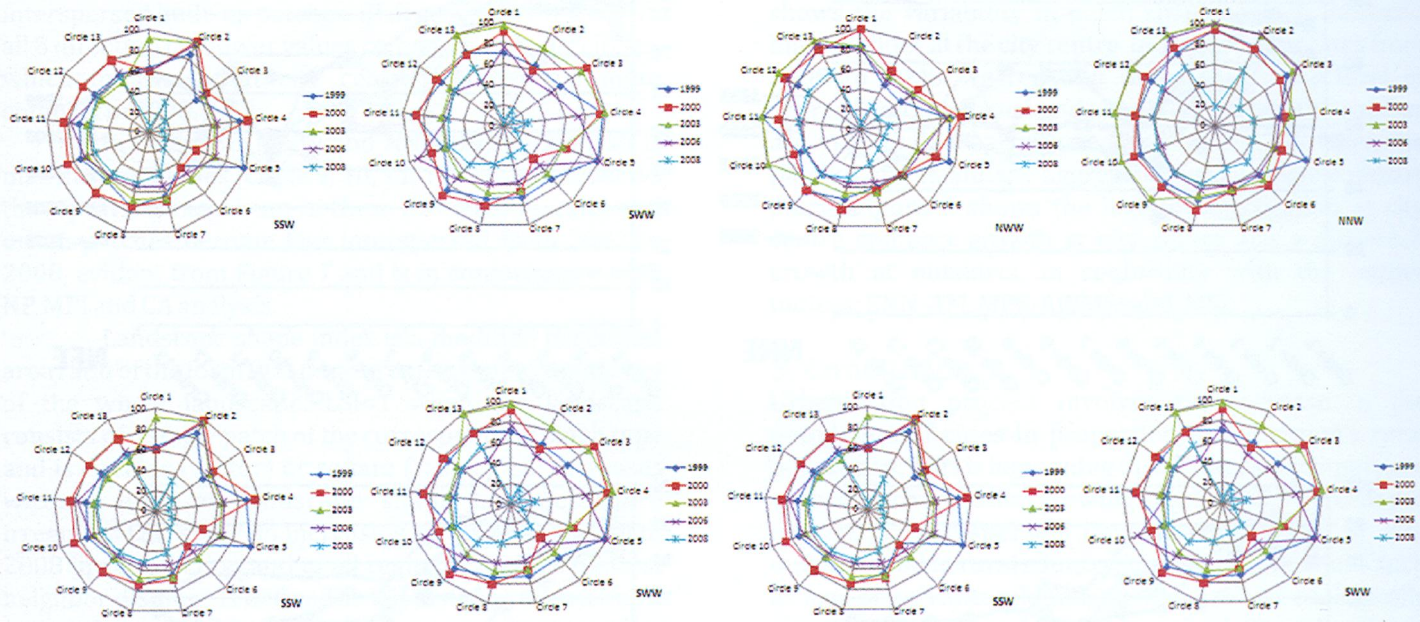


Figure 7 : Interspersion and juxtaposition Index

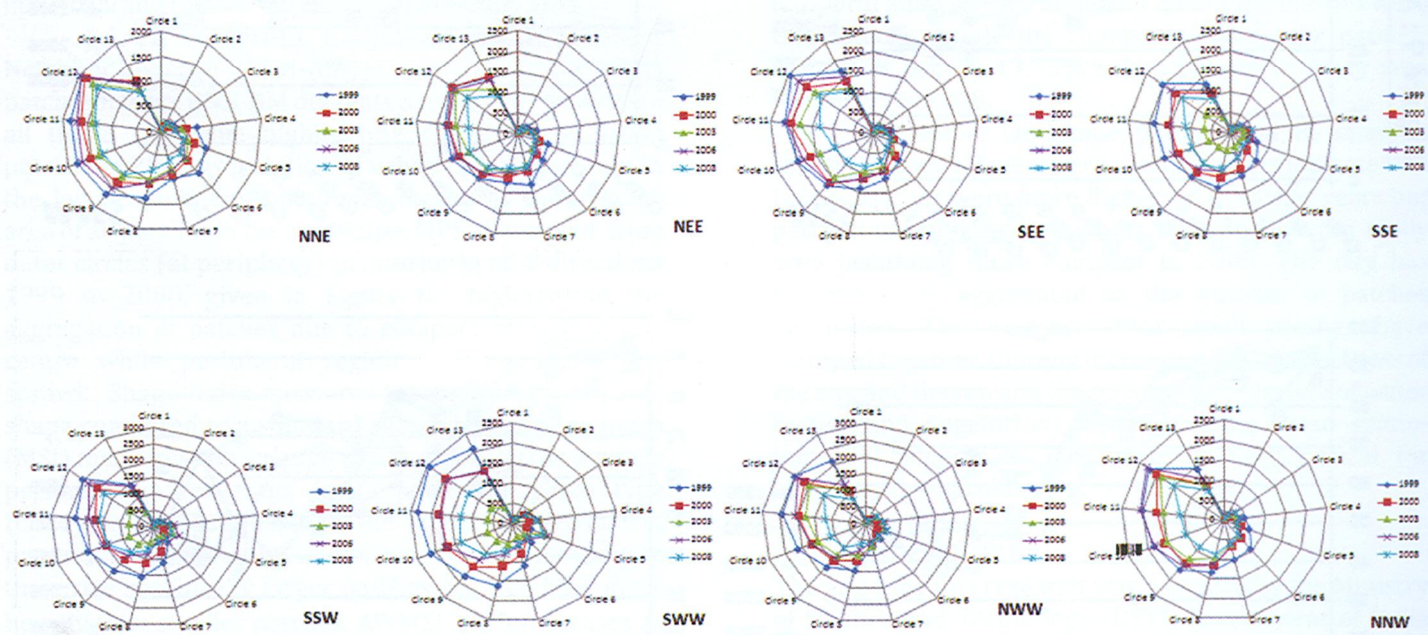


Figure 8 : Mean Patch size

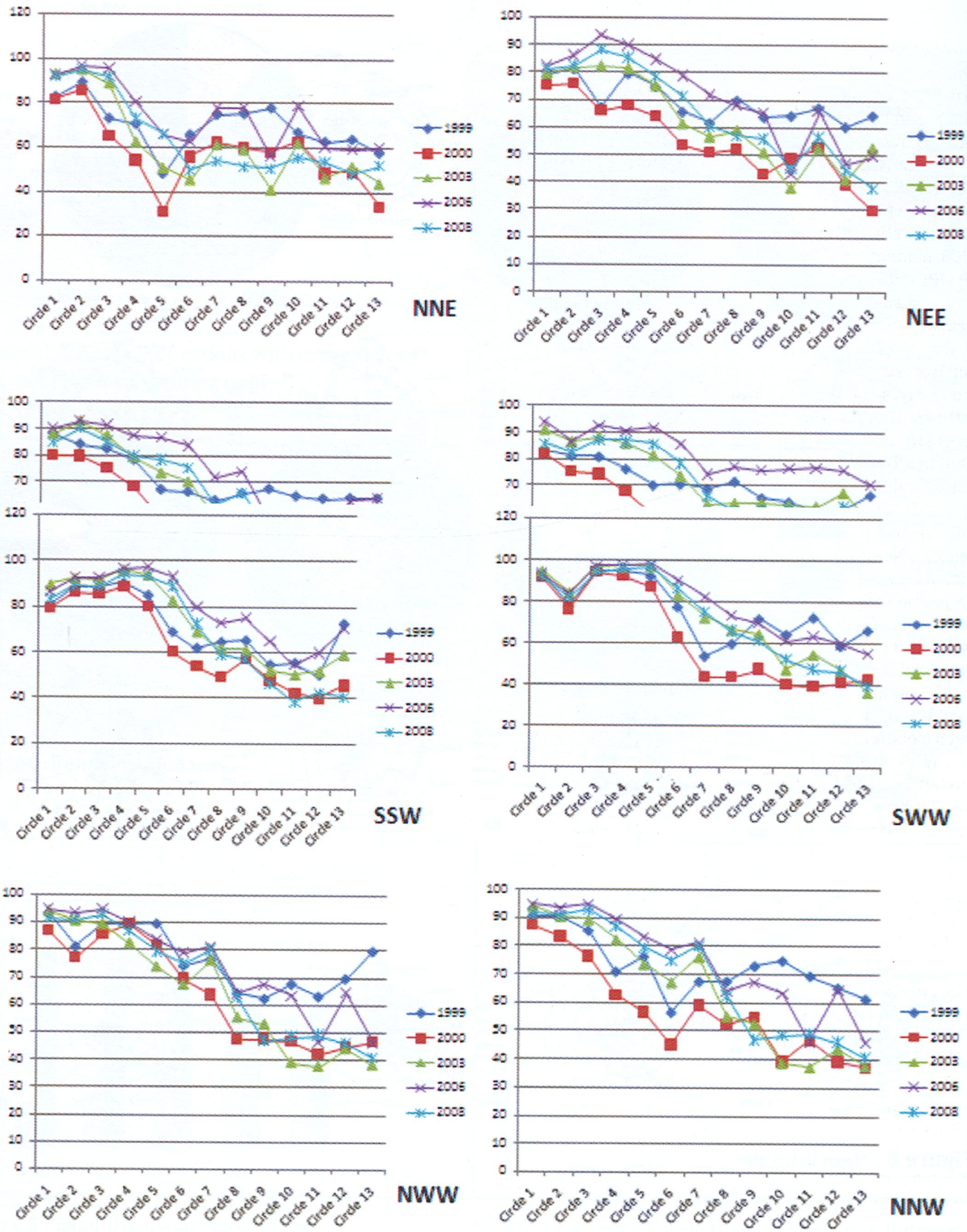


Figure 9 : Aggregation Index

lower values (IJI=0) characterize landscapes with poorly interspersed built-up patches. IJI at city centre in 2008 in all 8 direction has lower values compared to outer circles, which indicates that city centre has become more compact in 2008.

In NEE, SEE, NWW and NNW during 2003 IJI is max in outer circles (circle 9, 10, 11, 12, 13) which shows that sprawl is maximum in these direction in 2003 and urban patches become less interspersed from 2003 to 2008, evident from Figure 7 and is in conformance with NP, MPI and CA analysis.

Landscape shape index is a modified perimeter area ratio of the form that measures the shape complexity of the whole landscape. LSI=1 when the landscape consists of a single patch of the corresponding patch type and is circular (vector) or square (raster). LSI increases without limit as landscape shape becomes more irregular. LSI show an increasing trend during 1999 to 2008 in all direction and in all regions (circles). Nearest neighbor distance is defined as the distance from a built-up patch to the nearest neighboring patch of another built-up patch, based on edge-to-edge distance. Mean Nearest Neighbor measures average patch to patch distance. Less value of Mean nearest neighbor distance in landscape indicates that patches are less insular in the landscape. The nearest neighbor distance in urban patches decreases from 1999 to 2008 because of the industrial and residential growth in the study area.

Area weighted Euclidean mean Nearest Neighbor distance (ENN-AM) is a measure of the urban patch isolation. ENN-AM decreased from 1999 to 2008 in all the 8 direction, highlighting clustering of urban patches in 2008 as isolation of urban patches are less in the landscape. Mean patch size measures the average area of all patches in the landscape. MPS decreased from outer circles (at periphery) to interior in all 8 directions 1999 to 2008, given in Figure 8 highlighting the aggregation of patches due to compact growth at city centre while peripheral region is experiencing the sprawl. Shape index measures the complexity of patch shape compared to a standard shape. Mean shape index (MSI) measures the average patch shape, or the average perimeter-to-area ratio, for a particular patch type (class) or for all patches in the landscape. AWMSI of patches is calculated by weighting patches according to their size specifically larger patches are weighted more heavily than smaller patches. AWMSI ≥ 1 it increases as the patch shape become more irregular. Direction and year-wise AWMSI values show larger patches with irregular patch shape at city centre while at periphery urban patches are simple in structure.

Mean Shape Index coefficient of variation (MSI-CV) shows the variability in patch shapes, which indicates higher values at the city centre in all the 8 directions from 1999 to 2008. Aggregation Index shows the level of aggregation in a region and is equal to 1 when the patches are maximally disaggregated and equals 100 when the patches are maximally aggregated into a single compact patch. Figure 9 shows the level of aggregation at city centre compact growth at city centre and a dispersed growth at outskirts, in conformity with the earlier indices: ENN-AM, MPS, AWMSI and MSI.

5. Conclusion

Urbanisation process involves the increase in the population of cities in proportion to the region's rural population. This is happening in India at a very rapid pace with urban population growing at around 2.3 percent per annum. The dispersed development along in city outskirts and in rural countryside with implications such as loss of agricultural land, open space and ecologically sensitive habitats is referred as sprawl. Sprawl is thus a pattern and pace of land use in which the rate of land consumed for urban purposes exceeds the rate of population growth resulting in an inefficient and consumptive use of land and its associated resources. The study showed that Bangalore is rapidly expanding with a significant rise in built-up area. In this study multi-temporal analysis was done and landscape metrics were calculated to study the changes of landscape pattern. There has been a 13.35% urban growth in study area from 1999 to 2008.

To detect landscape pattern and its changes landscape metrics were very useful. Results indicate that Urban patches were more dispersed in earlier years but patches are aggregating which showed that the study area becoming more compact in 2008. The city has become more aggregated as the number of patches decreased. This suggests that small patches have clumped together, thereby increasing the compactness of the city and decreasing the open spaces (decline of water bodies and vegetation). Understanding these spatio-temporal aspects of landscapes is very critical for effective regional planning.

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