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Spatio-Temporal Pattern of Landscape Dynamics in Shimoga, Tier II City, Karnataka State, India

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***Abstract*— Urbanisation and associated growth patterns (urban sprawl) are characteristic of spatial temporal land use changes taking place at regional levels. Unplanned urbanization and consequent impacts on natural resources including basic amenities has necessitated the investigation and understanding of mechanisms and dynamics of land use and land-use change on a range of spatial scales and evaluate the environmental consequences of these changes at the landscape scale. Rapid urbanization subsequent to globalization in Karnataka state show dominant changes in land use during the last two decades. Urban regions are getting urbanized at much faster rates while peri-urban areas are experiencing sprawl.**

These processes have negative impacts on natural resources, economic health, and community characteristics. Quantitative estimations of urbanisations patterns are required to help local and regional land use planners to better identify, understand and provide appropriate infrastructure and basic amenities. Multi-temporal remote sensing data would help in understanding land cover and land use changes. A combination of land cover, land use dynamics with gradient analysis and spatial metrics, would help in characterizing spatiotemporal patterns of landscape dynamics. This communication is based on the analysis of urbanization process and landscape fragmentation of a tier II city in Karnataka. Supplementary data including historical maps, qualitative data have also been used to understand the urbanization process and fragmentation patterns. Spatial metrics aided in characterizing long-term trends and patterns of urban growth. Quantitative and qualitative analyses of spatial results helped in visualizing the pattern of growth, in order to highlight future land use trends. The results of the analysis shows of dispersed growth initially causing increased fragmentation. Gradually the growth filled in vacant non-urban area, resulting in more compact or aggregated urban pattern. Improved understanding of urban growth, helps in effective and suitable regional planning.

***Keywords* - Urbanisation, urban sprawl, spatial metrics, Tier II cities, Landscape dynamics.**

I. INTRODUCTION

Human induced land use and land cover (LULC) changes have been the major drivers for the changes in local and global environments. Land cover dynamics involving conversion of natural resources (vegetation, water bodies, green spaces) into urban space have affected various natural and ecological process . Urbanisation is a dynamic complex phenomenon involving large scale changes in the land uses at local levels. Analyses of changes in land uses in urban environments provide a historical perspective of land use and give an opportunity to assess the spatial patterns, correlation, trends, rate and impacts of the change, which would help in better regional planning and good governance of the region (Ramachandra, et al., 2012). Urban growth is a spatial and demographic process, involving concentration of human population to the land area which has high economy (Bhatta, et al., 2010a; Luck & Wu, 2002; Ramachandra et al., 2012).

Urban growth pattern, have a direct influence on urban development process, which extends its influence on the neighborhood (Bhatta, 2009; Nelson, 2010), leading to Urban sprawl, which is often referred as peri-urban growth. Urban sprawl refers to a small clusters of medium to low-density urban growth in the outskirts without proper basic amenities (Bhatta et al., 2010b; Ramachandra et al., 2012; Petrov et al., 2009; Sudhira et al., 2004). This form of peri urban low density growth apart from lacking basic amenities also have a number of social, economic and environmental disadvantages (Bhatta et al., 2010b; Ramachandra et al., 2012).
A quantitative and qualitative analysis of the landscape structure is essential to analyse of the patterns of landuse change. Thematic land-use and land-cover maps generated allow us to quantify characteristics such landscape

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heterogeneity (Baldwin etal., 2004) and landscape fragmentation (Benedek et al., 2011; Gao & Li, 2011; Sudhira et al., 2004). Spatio-temporal data (Remote Sensing (RS) data) with Geographic Information System (GIS) are helpful in data acquisition and analysis of LULC changes and for qualitative and quantitative results to understand the changes (Ramachandra et al., 2012; Sudhira et al., 2003). Temporal RS data has been used to analyze and understand the changes and impacts of human activities on the natural ecosystem (Yang et al., 2003; Herold et al., 2005; Cowen and Jensen, 1998; Xu et al., 2005; Berberoglu and Akin, 2009). Urban growth is captured based on spatial configuration and its dynamics (Muller et al., 2010; Seto & Fragkias, 2005; Xian & Crane, 2005; Sudhira et al., 2003). Spatial metrics have been used for describing landscape structure (McGarigal, 2002; McGarigal et al., 2002; Sudhira et al., 2004; Ramachandra et al., 2012) and for a wide range of applications, including the assessments of land-use change (Iverson, 1988 ; Turner & Ruscher, 1988; Ramchandra et al., 2012), required for landscape planning and management (Botequilha Leitão & Ahern, 2002), detection of changes in vegetation patterns (Fernandez, Aguiar & Ferreira, 2011; Kelly et al., 2011), changes in landscape structure (Pocas et al., 2011; Ramachandra et al., 2012, Bharath et al., 2012), for assessing the impacts of urbanization on the landscape (Gao & Li, 2011; Li et al., 2010; Ramachandra et al., 2012; Sudhira, 2004, Bharath et al., 2012). Common spatial metrics have been computed for describing the structural characteristics and growth patterns of the built-up area. Herold et al., (2003), for instance, used spatial metrics to characterize urban growth patterns in four administrative regions of Santa Barbara. Calculation of the metrics for each region was based on a visually interpreted land-use map representing the landscape as patches of a built and non-built class. Ramachandra et al.(2012) and Bharath et al., (2012) have examined land-use changes encompassing the urban area and peri urban area using spatial metrics at the class level. This work adopted gradient and direction analysis to locate and understand the local dynamics of changes in urban pattern. Further using Concentric buffer zones (Seto & Fragkias, 2005, Settur et al., 2012) , transects or rectangular sample plots (Weng, 2007, Luck & Wu, 2002) were also used for the sprawl analysis. Spatial metrics have been proved as a valuable tool in comparing urban form and land-use dynamics (Huang et al., 2007; Schwarz, 2010). The review illustrates thatsignificant research contributions ranging from gradient analyses to geospatial tool applications have been made to understandthe urban growth pattern, quantification of complex patterns or processes of urban growth (Dietzel et al., 2005; Herold et al., 2003; Peng et al., 2010; Ramachandra et al., 2012).

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A quantitative and qualitative analysis of the landscape structure is essential to analyse of the patterns of landuse change. Thematic land-use and land-cover maps generated allow us to quantify characteristics such landscape heterogeneity (Baldwin etal., 2004) and landscape fragmentation (Benedek et al., 2011; Gao & Li, 2011; Sudhira et al., 2004). Spatio-temporal data (Remote Sensing (RS) data) with Geographic Information System (GIS) are helpful in data acquisition and analysis of LULC changes and for qualitative and quantitative results to understand the changes (Ramachandra et al., 2012; Sudhira et al., 2003).

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This communication analyses the growth pattern of a developing city in Karnataka State, India. The region has large neighborhood of various classes with diverse landscape patterns. The objectives of the study are (a) to understand the land cover and land use dynamics using temporal remote sensing data, b) quantify urban growth , (b) to understand the urban growth patterns in different locations using gradients and (d) to assess the pattern of growth over past two decades using spatial metrics over gradient.

STUDY AREA

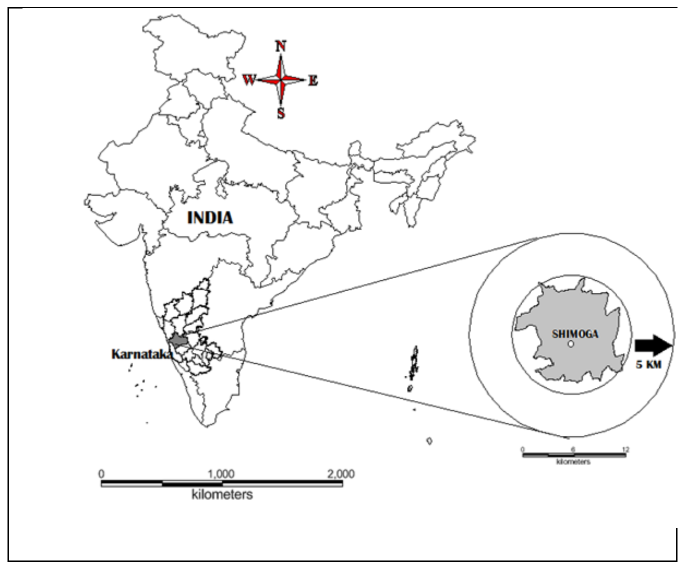

Figure 1: Study area considered for the analysis

Shimoga district is located at 13 43’N 75 15’ E and 14 08’N and 75 44’E in the central part of the state of Karnataka, India. It lies on the banks of the Tunga River. The climate is tropical wet and dry and temperature ranges between 37oC (Max) to 23.2o C (Min). The district receives an average rainfall of 1813 mm. Shimoga encompasses an area of 8477 sq. km. Shimoga district is divided into 2 Sub-divisions and 7 Taluks. The Sagar Sub-division comprises the taluks of Sagar, Shikaripura, Sorab and Hosanagara while the Shimoga Sub-division comprises the taluks of Shimoga, Bhadravathi and Thirthahalli. District Headquarters of Shimoga is located in Shimoga. Shimoga district has a population of 16.43 lakh (as per 2001 Census), with population density of 194 per sq. km.

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Agriculture and animal husbandry are the major contributors to the economy of Shimoga district. The Shimoga city having a radius of 7km is considered for the analysis and a buffer of 5 km is considered in order to account for peri-urban growth and to visualise likely urbanising regions during the next decade.

II. Materials and Methods

Urban dynamics was analysed using temporal remote sensing data of the period 1992 to 2010. The time series spatial data acquired from Landsat Series Thematic mapper (28.5m) sensors for the period 1992 to 2010 were downloaded from public domain (http://glcf.umiacs.umd.edu/data). Survey of India (SOI) toposheets of 1:50000 and 1:250000 scales were used to generate base layers of city boundary, etc. City map with ward boundaries were digitized from the city administration map. Population data was collected from the Directorate of Census Operations, Bangalore region (http://censuskarnataka.gov.in). Table I lists the data used in the current analysis. 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 toposheet and Google earth (http://earth.google.com, http://bhuvan.nrsc.gov.in).

DATA	Year	Purpose
Landsat Series Thematic mapper (28.5m) and Enhanced Thematic Mapper sensors	1992, 1999, 2005	Landcover and Land use analysis
IRS LISS III (23.5m)	2010	Landcover 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

Table I: Materials used in the analysis

III. Data Analysis

i. Preprocessing:

The remote sensing data corresponding to the study region were downloaded, geo-referenced, rectified and cropped pertaining to the administrative boundary with 5 km buffer. Landsat ETM+ bands of 2010 were corrected for the SLC-off by using image enhancement techniques, followed by nearest-neighbour interpolation.

ii. Land Cover Analysis:

Among different land cover indices, NDVI - Normalised Difference Vegetation Index was found appropriate NDVI was computed to understand the changes of land cover . NDVI is the most common measurement used for measuring vegetation cover. I t ranges from values -1 to +1. Very low values of NDVI (-0.1 and below) correspond to barren areas of rock, sand, or Urban builtup. Zero indicates the water cover. Moderate values represent low density of vegetation (0.1 to 0.3), while high values indicate vegetation (0.6 to 0.8).

iii. Land use analysis:

The method involves i) generation of False Colour Composite (FCC) of remote sensing data (bands – green, red and NIR). This helped in locating heterogeneous patches in the landscape ii) selection of training polygons (these correspond to heterogeneous patches in FCC) covering 15% of the study area and uniformly distributed over the entire study area, iii) loading these training polygons co-ordinates into pre-calibrated GPS, vi) collection of the corresponding attribute data (land use types) for these polygons from the field . GPS helped in locating respective training polygons in the field, iv) supplementing this information with Google Earth v) 60% of the training data has been used for classification, while the balance is used for validation or accuracy assessment.

Land use classification of Landsat satellite data was done using supervised pattern classifier - Gaussian maximum likelihood algorithm based on various classification decisions using probability and cost functions (Duda et al., 2000). Mean and covariance matrix are computed using estimate of maximum likelihood estimator.

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Land Use was computed using the temporal data through open source GIS: GRASS - Geographic Resource Analysis Support System (www.ces.iisc.ernet.in/grass). Four major types of land use classes considered were built-up, vegetation, cultivation area (since major portion is under cultivation), and water body. 60% of the derived signatures (training polygons) were used for classification and the rest for validation. Recent remote sensing data (2010) was classified using the collected training samples. For earlier time data, training polygon along with attribute details were compiled from the historical published topographic maps, vegetation maps, revenue maps, etc. Median filter of 3X3 was applied to the classification-derived maps to reduce the effect of "salt & pepper" noise produced by the classification procedure. Statistical assessment of classifier performance based on the performance of spectral classification considering reference pixels is done which include computation of kappa (κ) statistics and overall (producer's and user's) accuracies.

iv. Density Gradient Analysis:

Further the classified image is then divided into four zones based on directions considering the central pixel (Central Business district) as Northwest (NW), Northeast (NE), Southwest (SW) and Southeast (SE) respectively. The growth of the urban areas was monitored in each zone separately through the computation of urban density for different periods.

v. Division of four zones to concentric circles and computation of spatial metrics:

Each zone was further divided into incrementing concentric circles of 1km radius from the center of the city. The built up density in each circle is monitored overtime using time series analysis. Landscape metrics were computed for each circle, zone wise using classified land use data at the landscape level with the help of FRAGSTATS (McGarigal and Marks, 1995). Table II details the spatial metrics considered for the analysis of urban dynamics at local levels.

vi. Computation of Shannon's Entropy:

To determine whether the growth of urban areas was compact or divergent the Shannon's entropy (Yeh and Liu, 2001; Li and Yeh, 2004; Lata et al., 2001; Sudhira et al., 2004; Pathan et al., 2007; Ramachandra et al.,2012) was computed direction wise for the study region. Shannon's entropy (Hn) given in equation 1, provide insights to the degree of spatial concentration or dispersion of geographical variables among 'n' concentric circles across Zones.

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

Where Pi is the proportion of the built-up in the ith concentric circle. As per Shannon's Entropy, if the distribution is maximally concentrated the lowest value zero will be obtained. Conversely, if it evenly distribution the value would be closer to log n indicating dispersed growth or sprawl.

V. RESULTS

i. Land cover analysis:

NDVI was calculated using r.mapcalc in GRASS, open source GIS and results are depicted in figure 2 and Table III. The analysis reveals that there was reduction in the vegetation cover from 89% to 66% during the past two decades in the study region.

Class / Years	Vegetation in %	Non-Vegetation in %
1992	89.35	10.65
1999	78.92	21.08
2005	74.83	25.16
2010	66.72	33.28

Table III: Results of land cover analysis

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Sl No	Indicators	Formula	Range
1	Largest Patch Index (proportion of built up)	$LPI = \frac{\sum_{i=1}^{n} max(a_i)}{A}$ a_i = area (m^2) of patch i A= total landscape area	$0 \leq LPI \leq 1$
2	Number of Urban Patches	$NPU = n$ NP equals the number of patches in the landscape.	NPU>0, without limit.
3	Patch Density	f(sample area) = (Patch Number/Area) * 1000000	PD>0,without limit
4.	Normalized Landscape Shape Index	$NLSI = \frac{\sum_{i=1}^{i=N} \frac{p_i}{s_i}}{N}$ • s_i and p_i: Area and perimeter of patch i, • N : total number of patches.	$0 \leq NLSI < 1$
5.	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.	$-1 \leq CLUMPY \leq 1$

6.	Aggregation index	$$AI=\left[\sum_{i=1}^{m}\left(\frac{g_{ii}}{\max\rightarrow g_{ii}}\right)P_i\right](100)$$	1≤AI≤100
7	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.	0≤ IJI ≤100
8.	Percentage of Like Adjacencies (PLADJ)	$$PLADJ=\left(\frac{g_{ii}}{\sum_{k=1}^{m}g_{ik})}\right)(100)$$ 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.	0<=PLADJ<=100
9.	Proportion of Landscape (PLAND)	$$PLAND = P_I = (\sum_{J=1}^{n} a_{ij}/_{A})$$ P_i = proportion of the landscape occupied by patch type (class) i. a_{ij} = area (m^2) of patch ij. A = total landscape area (m^2).	0 < PLAND ≤ 100
10	Area Weighted Mean Fractal Dimension Index (FRAC_AM)	$$FRAC = {}^{2ln(0.25\ p_{IJ})}/_{ln\ am_{ij}}$$ pij = perimeter (m) of patch ij. amij = area weighted mean (m2) of patch ij.	1 ≤ FRAC_AM ≤ 2

Table II: Landscape metrics calculated for the study region

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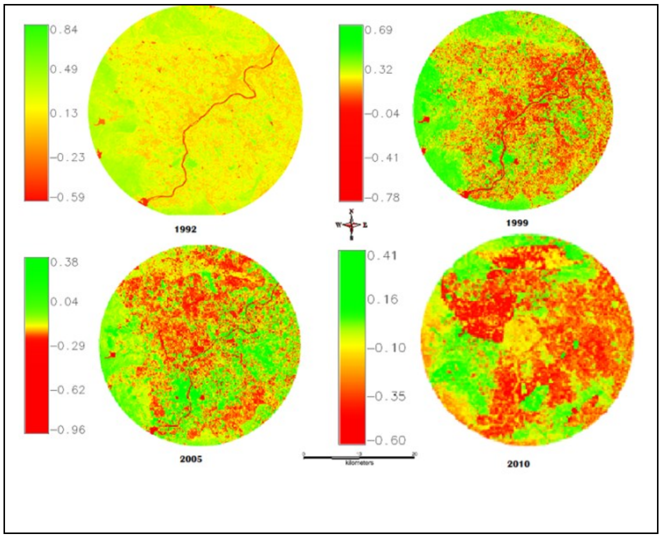

Figure 2: Temporal Land cover dynamics

ii. Land use analysis:

Land-use analysis was performed using using the function i.maxlik (in GRASS) based on supervised classifier based on Gaussian maximum likelihood algorithm. Temporal land use is given in figure 3 and the statistics of category-wise land uses are for 5 time period is given in Table IV. Urban category has increased from 13% (1992) to 33% (2010), which is about 253 times during the last two decades. Notable factor is that the Cultivation which is the major land use in the study region has increased to a small extent. Vegetation had decreased drastically over last two decades from 30% (1992) to about 6% (2010). The results of the overall accuracy for each classification map were 90% (1992), 90.33% (1999), 92.45% (2005) and 94.12% (2010). Kappa values were 0.84 (1992), 0.85 (1999), 0.9 (2005) and 0.91 (for 2010).

Class / Years	Urban %	Vegetation %	Water %	Cultivation %
1992	13.58	30.94	1.52	53.95
1999	25.32	24.82	1.51	48.35
2005	28.16	10.09	1.12	60.62
2010	33.56	5.52	1.2	59.72

Table IV: Results of Land use analysis

iii. Shannon's Entropy:

Shannon entropy was calculated to understand the state of urbanization direction wise in the study region (either fragmented or clumped) and are given in Table V. The analysis show of sprawl in the North West, while significant growth was observed in North East, South East and South west but fragmented due to presence of cultivable land in these regions.

	NE	NW	SE	SW
1992	0.23	0.24	0.18	0.25
1999	0.39	0.41	0.34	0.36
2005	0.4	0.45	0.38	0.43
2010	0.43	0.7	0.42	0.47
Reference value	1.079 (Log(12))			

Table V: Results of Shannon's entropy

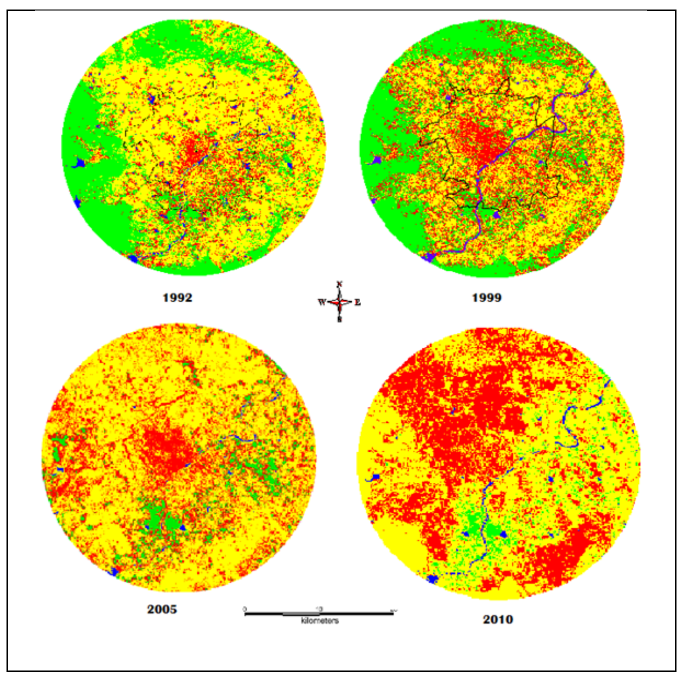

Figure 3: Results of Land use analysis

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iv. Landscape Metrics

Spatial metrics were computed using Fragstat (McGarigal and Marks, 1995) to understand the level of urban dynamics and are listed in table II. FRAGSTAT requires details such as rows and columns that were obtained using g.region –p. Class properties file was created using the ascii text format as per the land use classes. The output of the land use for the gradients corresponding to 1km gradients was considered in 16 bit binary format and the spatial metrics were calculated direction wise for each gradient. Results of the analysis indicate of clumped growth at the center of the city and are in the verge of forming a single class patch. Compared to this, outskirts or peri-urban regions are fragmented or sprawl with different classes in the neighborhood. Metric results are quantitatively described next.

Proportion of Landscape (PLAND) and Largest Patch Index (LPI): PLAND is one of the metrics that's calculated on the properties of the landscape. Pland approaches 0 when the land use class is rare in the landscape and the value will reach 100 when the entire landscape consists of a single patch type; intermediate values representing the degree of clumping or fragmentation. LPI = 0 when largest patch of the patch type becomes increasingly smaller as in the comparision of the landscape. LPI = 1 when when largest patch comprise 100% of the landscape (Wu et al., 2002, 2004). Results of the analysis of the PLAND metric is given in Figure 4a. Results reveal of phenomenal increase in urban area over the past decade . Outskirts neighborhood have large variability in land use classes but form single patches in 2010 especially in the north west and south west directions. The core area though clumped with urban class has lower PLAND due to the presence of water and cultivation categories as major land uses.

LPI (figure 4b) indicates that the landcape is aggregating to form single patches in almost all directions and gradients. Fragmented outskirts are also now on the verge of forming a single patch, and core center is almost constant except in North east and south east directions as it has also water class which is comparatively a large patch .

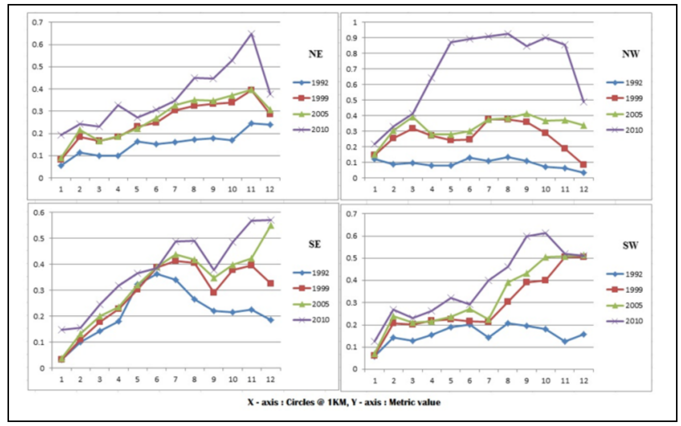

Figure 4a: Pland metric calculated for the study region

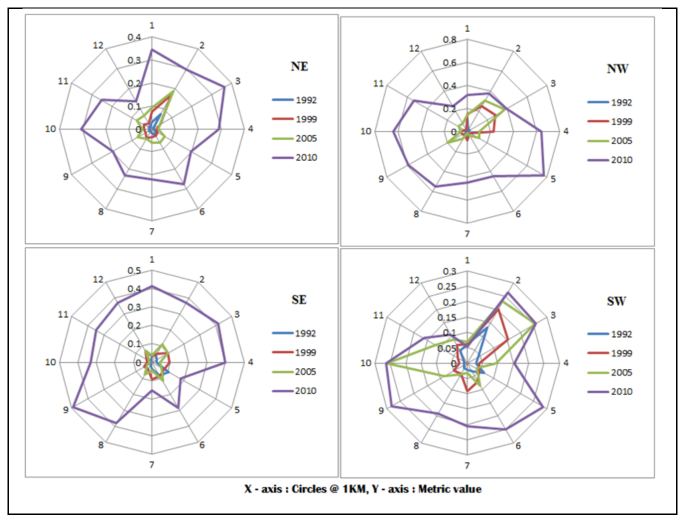

Figure 4b: Largest Patch Index

Number of Urban Patches (NP): NP reflects the extent of fragmentation (Baldwin et al., 2004, Turner et al., 1989) of a particular class in the landscape. Higher the value more the fragmentation, Lower values is indicative of clumped patch or patches forming a single class. Figure 4c illustrates that center of the city is in the verge of clumping especially accelerated in 2005 and 2010, while the outskirts remain fragmented and are highly fragmented during 2005 and 2010in North east, south east and south west directions. North west zone is losing its vegetation and cultivation class and this zone is highly fragmented in the outskirts during 2005 but is now in the verge of forming a single built up class.

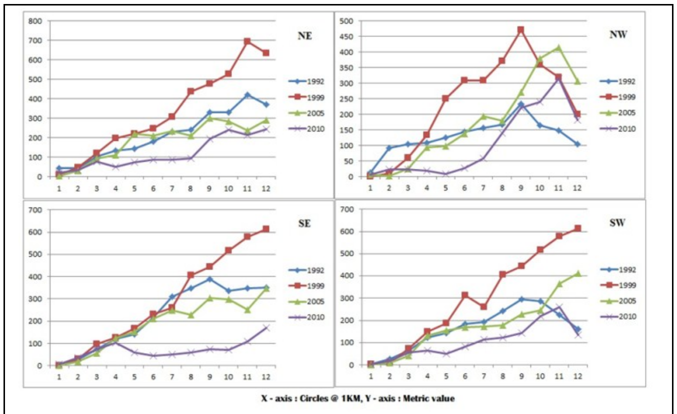

Figure 4c: Number of urban patches

Normalized Landscape Shape Index (NLSI): NLSI calculates the value based on particular class rather than landscape and is equal to zero when the landscape consists of single square or maximally compact almost square, its value increases when the patch types becomes increasingly disaggregated and is 1 when the patch type is maximally disaggregated. The results (Figure 4d) indicate that the urban area is almost clumped in all direction and all gradients especially in north east and west direction. It shows a small degree of fragmentation in the buffer regions in south west and south east direction. The core area is in the process of becoming maximally square in all directions.

Patch Density (PD): PD refers to number of patches per unit considered. This index is computed using a raster data with4 neighbor algorithm. Patch density increases with a greater number of patches within a reference area. As seen before the fragmentation is large in the buffer regions and hence the patch density is high in the buffer region as compared to the core area. Patch density increased with number of patches increasing in mid-90's further continued till 2005. During the years 2005- 2010 patch density considerably decreased as number of patches decreased and hence indicated the process of clumping. Figure 4e explains the patch density at patch level.

Aggregation index (AI) and Clumpiness Index (Clumpy): AI and Clumpy are two measures of degree of fragmentation of the landscape. AI equals zero when the patches are maximally disaggregated and equals 100 when the patches are maximally aggregated into a single compact patch (Cushman et al., 2008, Bailey et al., 2007) and Clumpy equals 0 when the patches are distributed randomly, and approaches 1 when the patch type is maximally aggregated. Results of AI (Figure 4f) are indicative of the clumpedness of the patches at the outskirts and buffer region and are fragmented in the central core. Clumpy (Figure 4f) also indicates the same as it is rather a proportion it also is indicative that the central core is fragmented, But in the process of clumping to form a single patch.

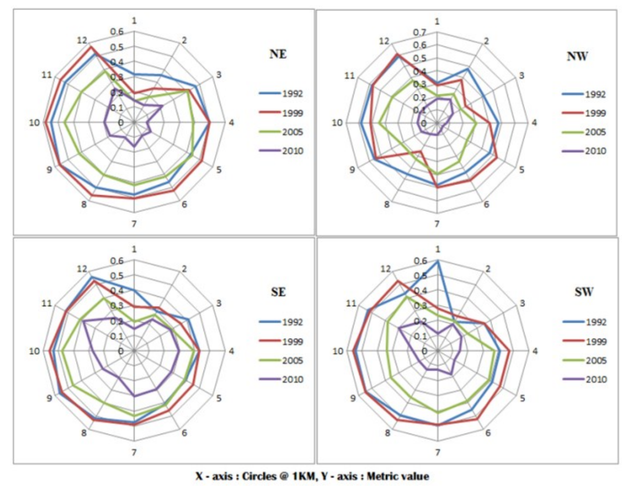

Figure 4d: NLSI index

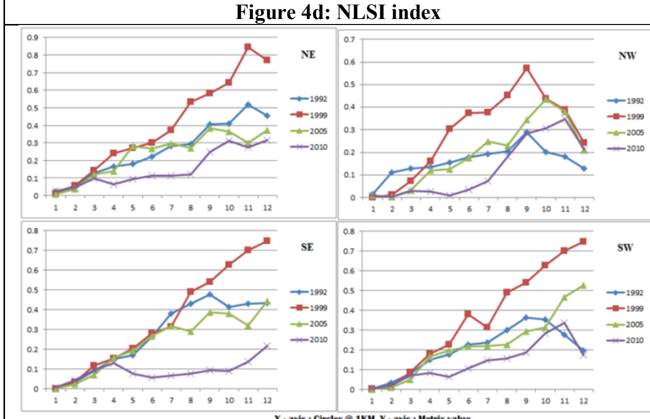

Figure 4e: Patch Density

Percentage of Like Adjacencies (PLADJ): PLADJ is the percentage of cell adjacencies involving the corresponding patch type that are like adjacencies. Cell adjacencies are tallied using the double-count method in which pixel order is preserved, at least for all internal adjacencies. equals 0 when the patch types are maximally disaggregated and

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there are no like adjacencies. PLADJ is 100 when all patch types are maximally and the landscape contains a border comprised entirely of the same class. The results (Figure 4h) indicate that the adjacencies are quite low in the core area as it has different patch types. Whereas high adjacencies are found in certain buffer zones of north west and south east directions. We can observe that the patches in 1998 and 2005 have disaggregation whereas in 2010 all patches are becoming aggregates.

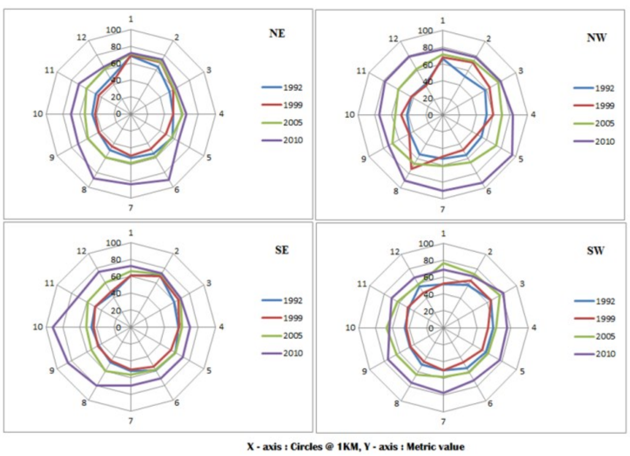

Figure 4f: Aggregation index

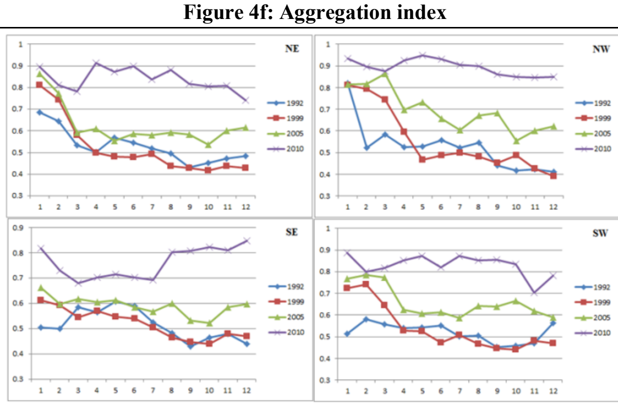

Figure 4g: Clumpiness index

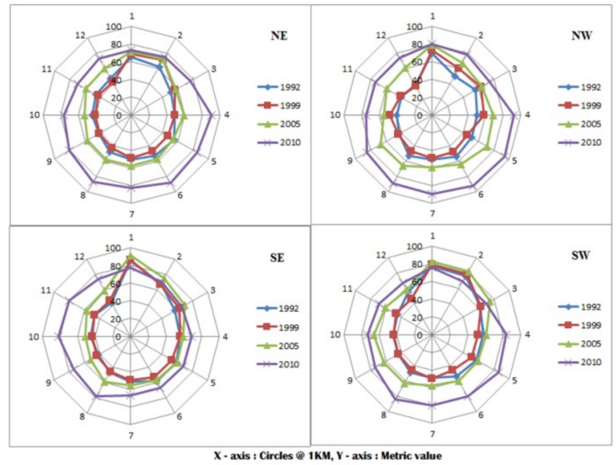

Figure 4h: Percentage of Land adjacency

Interspersion and Juxtaposition (IJI): Interspersion and Juxtaposition (Bailey et al., 2007) 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. Analysis on the study region indicates (Figure 4i) that near the core the values are near zero indicating adjacencies are uneven whereas in the outskirts and buffer zones values are relatively higher indicating that they are relatively adjacent and clumped

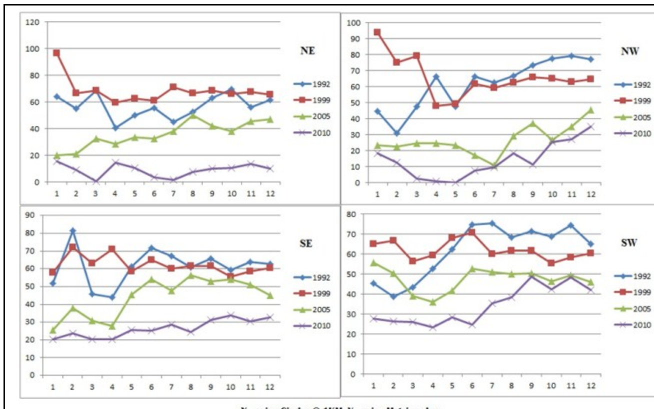

Figure 4i: IJI index

VI. CONCLUSION

A combination of qualitative and quantitative analyses of spatial temporal land use analyses, fragmentation analysis and characterisation of urbanization process through spatial metrics direction wise for each gradients were adopted for an improved understanding of urbanisation processes in the tier II city, Shimoga, Karnataka, India. Land cover analysis reveals that there was reduction in the vegetation cover from 89% to 66% during the past two decades in the study region.

Land use analysis reveals of increase in urban category from 13% (1992) to 33% (2010), which is about 253 times during the last two decades. Notable factor is that the Cultivation which is the major land use in the study region has increased to a small extent. Vegetation had decreased drastically over last two decades from 30% (1992) to about 6% (2010).

Spatial analysis revealed that land use in the outskirts is fragmented during 1998 – 2005. The process of clumping to form a single patch is noticed in the core area during 2005-2010 while in the urban fringe, it has been more contiguous and more disorganized in the form of leap frog growth. Presence of water bodies in the heart of the city is the reason for core area not getting aggregated. Shannon's entropy showed that there was urban sprawl in the outskirts necessitating immediate policy measures to provide infrastructure and basic amenities. Landscape metrics conform of the urban sprawl in the buffer zone, whereas the core area had mix of classes and as we go from the center towards administrative boundary the urban density intensifies. Although Shimoga does show a high degree of infill development that is evident from the reduction of fragmented land. Governmental agencies need to visualize possible growth poles for an effective policy intervention. . Any efforts to do so, however, must take into account the multitude of social, environmental and biophysical realities that will continue to shape the region's future. Physical urban growth in the region will undoubtedly continue, but it is required that the city planners and developers of Shimoga take a note of the situation and plan for further developmental urban activities in a sound, flexible and sustainable way.

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