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Understanding urban sprawl dynamics of Gulbarga - Tier II city in Karnataka through spatio-temporal data and spatial metrics

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ABSTRACT

Rapid urbanization coupled with burgeoning population, economic disparity and prevalence of infectious disease necessitate mitigation strategies in the context of environmental challenges and the sustainability of healthy natural resources. During the past decade, Tier II cities in Karnataka have been witnessing dramatic changes in land cover 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. This communication aims to quantify and analyze the spatial–temporal pattern of urbanization process of a tier II city – Gulbarga, Karnataka State, India using Remote Sensing (RS) data and spatial metrics. The results show that during the past decade (2000 - 2010), Gulbarga has experienced spatial expansion of urban area. The urban land use has increased from 1% to 22% in past 4 decades. Temporal remote sensing data with spatial metrics helped in understanding spatial patterns of urban sprawl. Spatial metrics indicate a clumped and aggregated growth at the city and sprawl at the outskirts. Computation of Shannon's entropy, spatial metrics with the gradient approach helped in bridging the knowledge gap between present and past land use. This knowledge helps the administrators and planners to visualize the urban growth to provide basic amenities.

Keywords: Urbanisation, sprawl, Tier II cities, Remote sensing data, Geospatial analysis

1. Introduction

Urbanisation is the physical growth of urban areas as a result of rural migration and even towns or suburban concentration transforming into cities. It occurs as governmental efforts to improve opportunities for jobs, education, housing and transportation. Unplanned urbanisation has serious impacts on the local ecology and on the sustenance of natural resources (Ramachandra et al., 2012). The process of urbanisation and its impacts on natural resources is a universal phenomenon taking place in most parts of India. All Cities in India have been experiencing this bewildering phenomenon involving large scale land use changes with globalisation. Urbanisation is an irreversible process involving changes in vast expanse of land cover and local ecology with the progressive concentration of human population. Rapidly urbanizing landscapes with high population density often face severe crisis due to inadequate infrastructure and lack of basic amenities (Bharath et al., 2012). The urban population in India is growing at about 2.3% per annum while the global urban population has increased from 13% (220 million in 1900) to 49% (3.2 billion, in 2005) and is projected to escalate to 60% (4.9 billion) by 2030 (Ramachandra and Kumar, 2008). The increase in urban population and changes in the land use is mainly due to migration from other areas. As per census 2011 there are 48 urban agglomerations in India, which are referred as Mega cities or Tier I with population of more than one million. Earlier studies suggest that Tier 1 cities due to burgeoning population and lack of proper urban planning have reached the saturation level evident from lack of basic amenities, over congestion due to inadequate infrastructure, higher amount of pollutants in the environment, contamination of water, scarcity of water and electricity, increasing crime rates, etc. (Sudhira et al., 2003, Ramachandra et al., 2012).. In this context, there is a need to plan Tier II cities (population less than 1 million) in India to ensure these cities do not face the serious infrastructure an environmental problems as Tier I cities. Tier II cities offer humongous scope in meeting the demand of urban population. Development of tier II cities entails the provision of basic infrastructure (like roads, air and rail connectivity), adequate social infrastructure (such as educational institutions, hospitals, etc.) along with other facilities. Spatio temporal patterns of land use and land cover (LULC) based on the temporal remote sensing data would aid in understanding and visualization of spatial patterns of urban growth. This would also help in identifying the probable pockets of intense urbanization and its effects such as sprawl, etc.

Urban sprawl refers to excessive unusual growth near the periphery of the city boundary or in the places where there is the absence of planning and availability of basic amenities. Cities need to grow in a planned and phased manner, and ensure a balance between proportion of growth and available resources. However rapid unplanned growth exerts pressure on the natural resources. This unplanned growth is called as Urban sprawl or sprawl. The urban sprawl involves disorganized and unattractive expansion of an urban area into the adjoining boundaries (Ramachandra et al., 2012). Remotely sensed satellite data having a good spatial and spectral resolution acquired over frequent time interval is the most widely used tool (Singh, 1989; Hall et al., 1991; Bharath H A. et al., 2012) to assess the changes in the urbanizing landscape over time and consequent sprawl (if happening). Unifying landscape structural ecology with remote sensing and other geospatial techniques can help in analysing and detecting the temporal changes occurring in larger areas more effectively through quantified landscape patterns (Crews-Meyer, 2002; Sudhira et al., 2003; Ramachandra et al., 2012). Quantification of landscape patterns allows to link spatial patterns with underlying ecological processes to some extent (O'Neill et al., 1988; Bhatta, 2010a; Bhatta et al., 2010b; Müller et al., 2010) and in understanding the relationship between urban growth and mobility (Zhao et al., 2011). Quantification of patterns and process helps in understanding the landscape dynamics s (Crews-Meyer, 2002; Bender, 2003), monitoring (Lausch and Herzog, 1999), management and planning (Kim and Pauleit, 2007; Lin et al., 2007). Spatial metrics have been widely used to study dynamic pattern with the underlying social, economic and political processes of urbanization (Yu and Ng, 2007; Jenerette and Potere, 2010). Applications of landscape metrics include landscape ecology (number of patches, mean patch size, total edge, total edge, mean shape), geographical applications by taking advantage of the properties of these metrics (Gibert and Marre, 2011; Rossi and Halder, 2010; Ramachandra et al., 2012; Bharath H. A et al., 2012). These studies also confirmed that Spatio-temporal data along with landscape metrics would help in understanding and evaluating the spatio temporal patterns of landscape dynamics required for appropriate management measures.

This communication is based on the analysis of urbanization pattern in a Tier II city, Gulbarga. Main objectives of the study includes (a) quantification of temporal urban growth in Gulbarga city with 5 km buffer, b) vegetation analysis, c) understanding local growth variation using gradient approach and (c) model the growth using spatial metrics to understand its dynamics . These information support policy interventions in urban planning and natural resource conservation.

2. Study Area

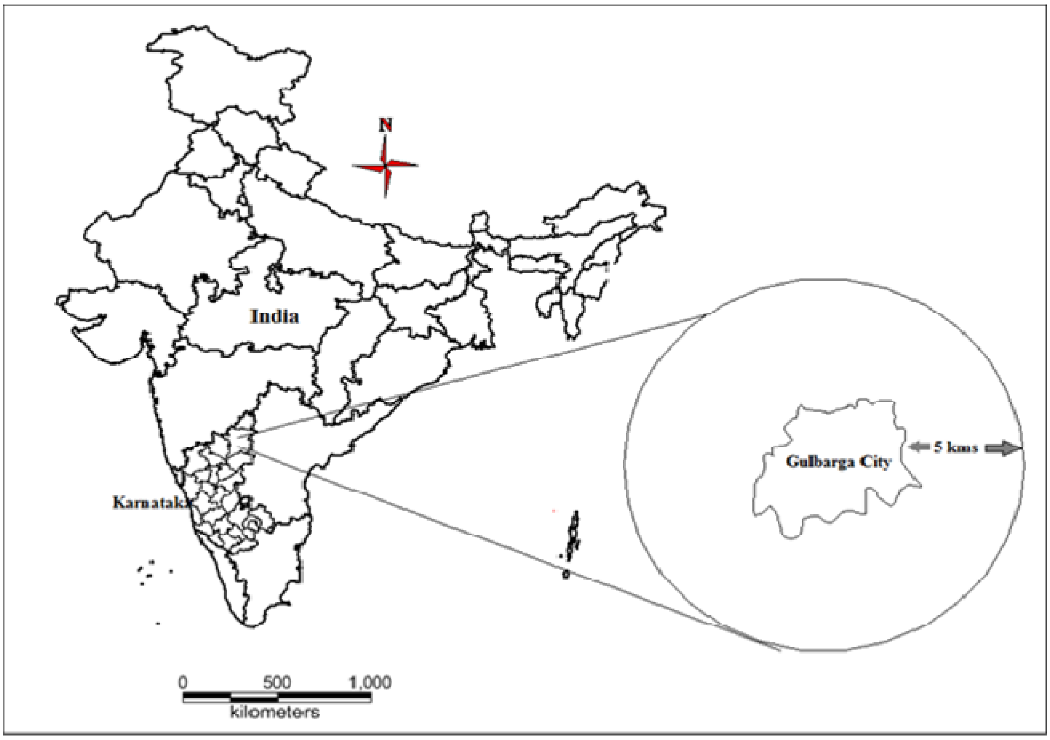

Figure 1: Study Area: Gulbarga

Gulbarga was known as 'Kalburgi' means "rose petals" in poetic Persian. Gulbarga district is located in the Northern part of the state and lies between latitude $17^{O}10'$ and $17^{O}45'$ N and longitude 76^{O} 10' and 77^{O} 45'E. This is a biggest district in Karnataka State covering 8.49% of the area and 5.9% of State's population. It is bounded by Bijapur district (of Karnataka) and Sholapur district (of Maharashtra), in the west by Bidar district (of Karnataka) and Osmanabad district (of Maharashtra) on the north and by Raichur district of Karnataka in the south. It is one of the three districts that were transferred from Hyderabad State to Karnataka state at the time of re-organization of the state in 1956. Gulbarga is basically an agriculture dominated District with crops such as Tur, Jowar, Bajra, Paddy, Sugarcane and Cotton. District receives and annual rainfall of 839 mm. Gulbarga city with 5 km Buffer region is considered for the analysis. Gulbarga city has an area of 64.00 Sq. km with 55 Wards and an Population of 5.3lakhs (Census 2001) and is governed by Gulbarga Mahanagara Palike

3. Materials

The time series spatial data acquired from Landsat Series Thematic mapper (28.5m) sensors for the period 1973 to 2002 were downloaded from public domain (http://glcf.umiacs.umd.edu/data). IRS LISS III (24 m) data coinciding with the field investigation dates were procured from National Remote Sensing Centre (www.nrsc.gov.in), Hyderabad.

Table 1: Materials used in analysis

DATA	Year	Purpose
Landsat Series TM (28.5m) and ETM	1973,1992, 2002	Landcover and Land use analysis
IRS LISS III (24m)	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

Survey of India (SOI) topo-sheets of 1:50000 and 1:250000 scales were used to generate base layers of city boundary, etc. Table1 lists the data used in the current analysis. Ground control points to register and geo-correct remote sensing data were collected using handheld pre-calibrated GPS (Global Positioning System), Survey of India Toposheet and Google earth (http://earth.google.com, http://bhuvan.nrsc.gov.in). Table1 lists the data used in the current analysis

3.1 Method

A stepwise normative gradient approach was adopted to understand the dynamics city. Which includes (i) first step to derive land use and land cover (ii) a zonal-gradient approach of 4 zones and 1km radius gradients to understand the pattern of growth during the past 4 decades.(iii)understanding the change in the land use dynamics using Landscape metrics analysis. Various stages in the data analysis are:

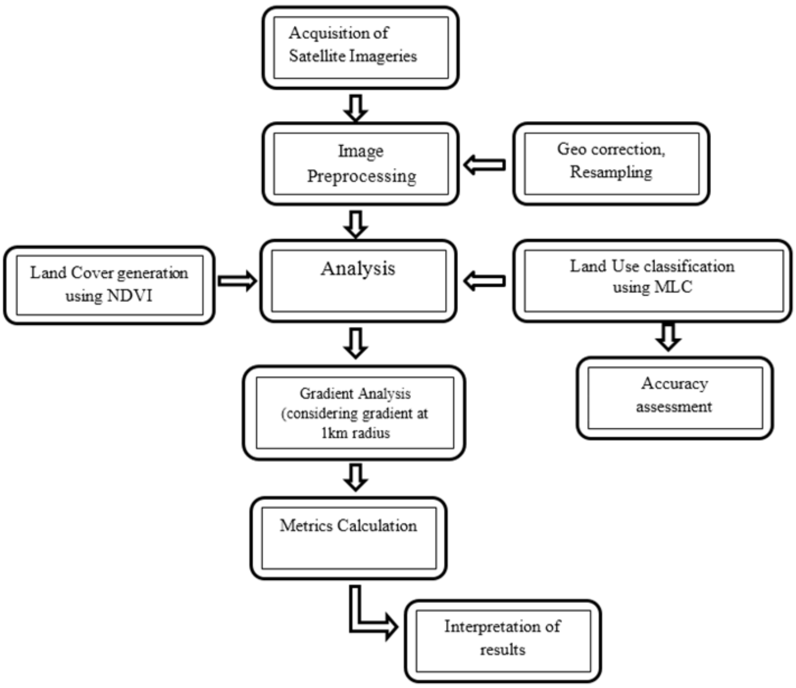

Figure 2: Procedure to understand the changes in spatial pattern and its dynamics

3.1.1 Preprocessing

The remote sensing data of landsat were downloaded from GLCF (Global Land Cover Facility) and IRS LISS III data were obtained from NRSC, Hyderabad. The data obtained were geo-referenced, rectified and cropped pertaining to the study area. The Landsat satellites have a spatial resolution of 28.5 m x 28.5 m (nominal resolution) were resampled to uniform 24 m for intra temporal comparisons.

3.1.2 Vegetation Cover Analysis

Vegetation cover analysis was performed using the index Normalized Difference Vegetation index (NDVI) was computed for all the years to understand the change in the temporal dynamics of the vegetation cover in the study region. NDVI value ranges from values -1 to +1, where -0.1 and below indicate soil or barren areas of rock, sand, or urban built-up. NDVI of zero indicates the water cover. Moderate values represent low density vegetation (0.1 to 0.3) and higher values indicate thick canopy vegetation (0.6 to 0.8).

3.1.3 Land use analysis

Further to investigate the different changes in the landscape land use analysis was performed. Categories included are as listed in Table 2, were classified with the training data (field data) using Gaussian maximum likelihood supervised classifier. This analysis includes generation of False Colour Composite (bands – green, red and NIR), which basically helps in visualizing the different heterogeneous patches. Further using the training data Polygons were digitized corresponding to the heterogeneous patches covering about 40% of the study region and uniformly distributed over the study region. These training polygons were loaded in pre-calibrated GPS (Global position System). Attribute data (land use types) were collected from the field with the help of GPS corresponding to these polygons. In addition to this, polygons were digitized from Google earth (www.googleearth.com) and Bhuvan (bhuvan.nrsc.gov.in). These polygons were overlaid on FCC to supplement the training data for classifying landsat data.

Gaussian maximum likelihood classifier (GMLC) is applied to classify the data using the training data. GMLC uses various classification decisions using probability and cost functions (Duda et al., 2000) and is proved superior compared to other techniques. Mean and covariance matrix are computed using estimate of maximum likelihood estimator. Estimations of temporal land uses were done through open source GIS (Geographic Information System) - GRASS (Geographic Resource Analysis Support System, http://ces.iisc.ernet.in/grass). 70% of field data were used for classifying the data and the balance 30% were used in validation and accuracy assessment. Thematic layers were generated of classifies data corresponding to four land use categories. Evaluation of the performance of classifiers is done through accuracy assessment techniques of testing the statistical significance of a difference, comparison of kappa coefficients and proportion of correctly allocated classes through computation of confusion matrix. These are most commonly used to demonstrate the effectiveness of the classifiers (Congalton, 1983; Congalton 1991).

Table 2: Land use categories

Land use Class	Land uses included in the class
Urban	This category includes residential area, industrial area, and all paved surfaces and mixed pixels having built up area.
Water bodies	Tanks, Lakes, Reservoirs.
Vegetation	Forest.
Cultivation	Croplands, Nurseries, Rocky area.

Further each zone was divided into concentric circle of incrementing radius of 1 km (figure 3) from the center of the city for visualising the changes at neighborhood levels. This also helped in identifying the causal factors and the degree of urbanization (in response to the economic, social and political forces) at local levels and visualizing the forms of urban sprawl. The temporal built up density in each circle is monitored through time series analysis.

Figure 3: Google earth representation of the study region along with the gradients

3.1.4 Urban sprawl analysis

Direction-wise Shannon's entropy (H_n) is computed (equation 1) to understand the extent of growth: compact or divergent (Lata et al., 2001, Sudhira et al., 2004). This provides an insight into the development (clumped or disaggregated) with respect to the geographical parameters across 'n' concentric regions in the respective zones.

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

Where Pi is the proportion of the built-up in the i^{th} concentric circle and n is the number of circles/local regions in the particular direction. Shannon's Entropy values ranges from zero (maximally concentrated) to log n (dispersed growth).

3.1 5 Spatial pattern analysis

Landscape metrics provide quantitative description of the composition and configuration of urban landscape. These metrics were computed for each circle, zonewise using classified landuse data at the landscape level with the help of FRAGSTATS (McGarigal & Marks, 1995). Urban dynamics is characterised by 7 prominent spatial metrics chosen based on complexity, and density criteria. The metrics include the patch area, shape, epoch/contagion/ dispersion and are listed in Table 3.

Table 3: Landscape metrics analysed

	Indicators	Range		Indicators	Range
1	Number of Urban Patches (NPU)	NPU>0, without limit.	5	Clumpiness	-1≤ CLUMPY ≤1.
2	Patch density(PD)	PD>0	6	Percentage of Like Adjacencies (PLADJ)	0<=PLADJ<=100
3	Normalized Landscape Shape Index (NLSI)	0≤NLSI<1	7	Aggregation index(AI)	1≤AI≤100
4	Landscape Shape Index (LSI)	LSI>1, Without Limit	8	Cohesion	0≤cohesion<100

4. Results and discussion

4.1 Land use Land Cover analysis

4.1.1 Vegetation cover analysis

Vegetation cover of the study area assessed through NDVI (Figure 4) shows that area under vegetation has declined by about 19%. Temporal NDVI values are listed in Table 4, which shows that there has been a substantial increase in the area other than the vegetation.

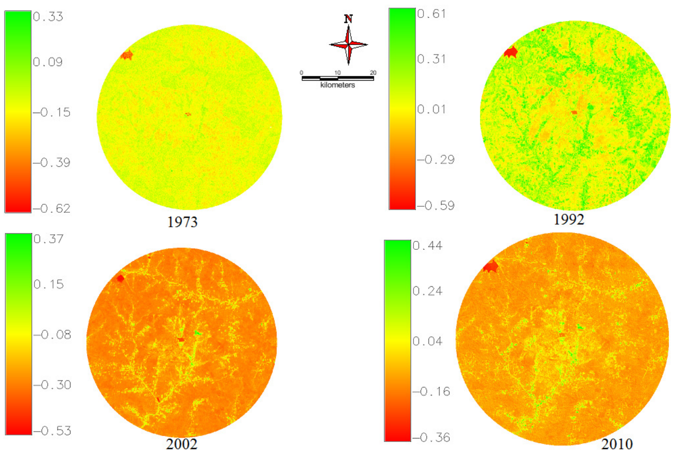

Figure 4: Temporal Land cover changes during 1973 – 2009;

Table 4: Temporal Land cover

Year	Vegetation %	Non vegetation %
1973	98.01	1.99
1992	94.72	5.28
2002	91.33	8.67
2010	79.41	20.57

4.1.2 Land use analysis

Land use assessed for the period 1973 to 2010 using Gaussian maximum likelihood classifier is listed table 5 and the same is depicted in figure 5. The overall accuracy of the classification Ranges from 73.23% (1973) to 94.32% (2010). Kappa statistics and overall accuracy was calculated and is as listed in Table 6. There has been a significant increase in built-up area during the last decade evident from 21% increase in urban area. Other category also had an enormous decrease in the land use. Consequent to these, vegetation cover has declined during the past four decades.

Table 5: Temporal land use details for Gulbarga

Land use / Year	Urban	Vegetation	Water	Cultivation and others
1973	1.08	1.01	0.34	97.17
1992	2.62	1.54	0.40	95.44
2002	7.22	0.55	0.23	92.01
2010	22.52	0.49	0.39	76.60

Table 6: Kappa statistics and overall accuracy

Year	Kappa coefficient	Overall accuracy (%)
1973	0.72	73.23
1989	0.86	89.69
1999	0.82	81.47
2009	0.93	94.32

4.1.3 Urban sprawl analysis

Shannon entropy computed using temporal data are listed in table 7. Gulbarga is experiencing the sprawl in all directions as entropy values are closer to the threshold value (log (10) = 1). Lower entropy values of 0.018 (SW), 0.023 (SE) during 70’s shows an aggregated growth.

However, the region show a tendency of dispersed growth during post 2000 with higher entropy values 0.268 (NE), 0.212 (NW) in 2010. Shannon's entropy values of recent time indicate of minimal but fragmented/dispersed urban growth in the region.

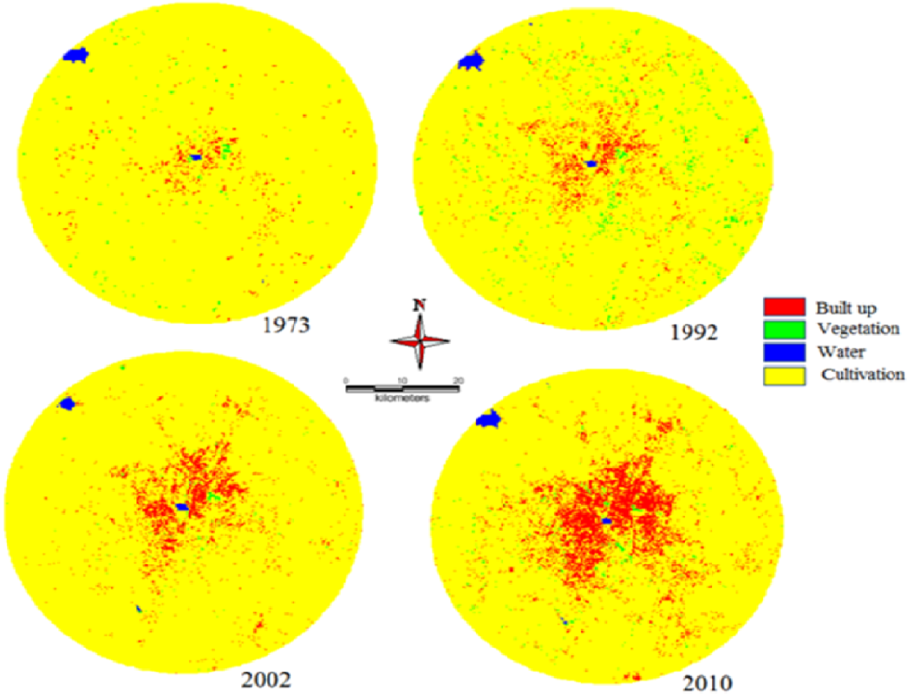

Figure 5: Classification output of Gulbarga

Table 7: Shannon Entropy Index

	NE	NW	SE	SW
2010	0.268	0.212	0.193	0.141
2002	0.139	0.112	0.091	0.098
1992	0.086	0.065	0.046	0.055
1973	0.067	0.034	0.023	0.018

4.1.4 Spatial patterns of urbanisation

Further to understand the spatial pattern of urbanization and the dynamical growth, eight landscape level metrics were computed zonewise for each circle. These metrics are discussed below: Number of Urban Patch (Np) is a landscape metric indicates the level of fragmentation and ranges from 0 (fragment) to 100 (clumpiness). Figure 6a illustrates of the urban growth evident from the increase in number of patches in 1992 and 2002 whereas in 2010 the patches have decreased indicating aggregation or clumped growth, while outskirts and boundary area (5th circle onwards) is showing a fragmented growth. Clumped patches at center are more prominent in NE and SE directions. Outskirts are fragmented more in NE and SE directions indicative of higher sprawl in the region.

NOTE: X-axis represents gradients and Y-axis value of the metrics

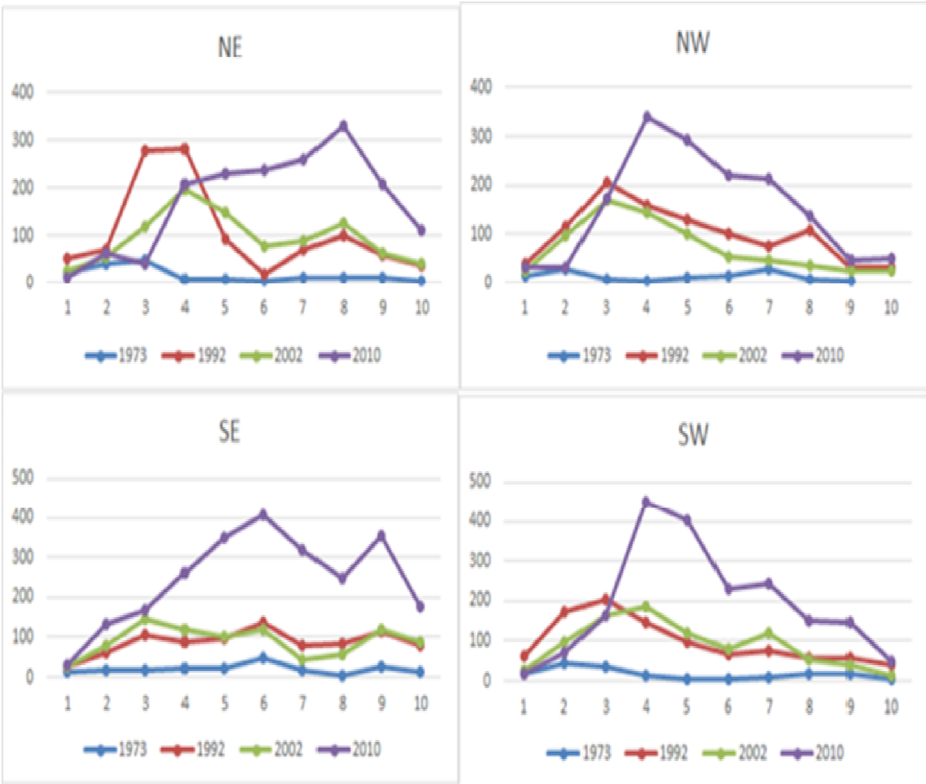

Figure 6a: Number of urban patches (zone, circlewise); Fig 6b: Patch density – zone, circle wise

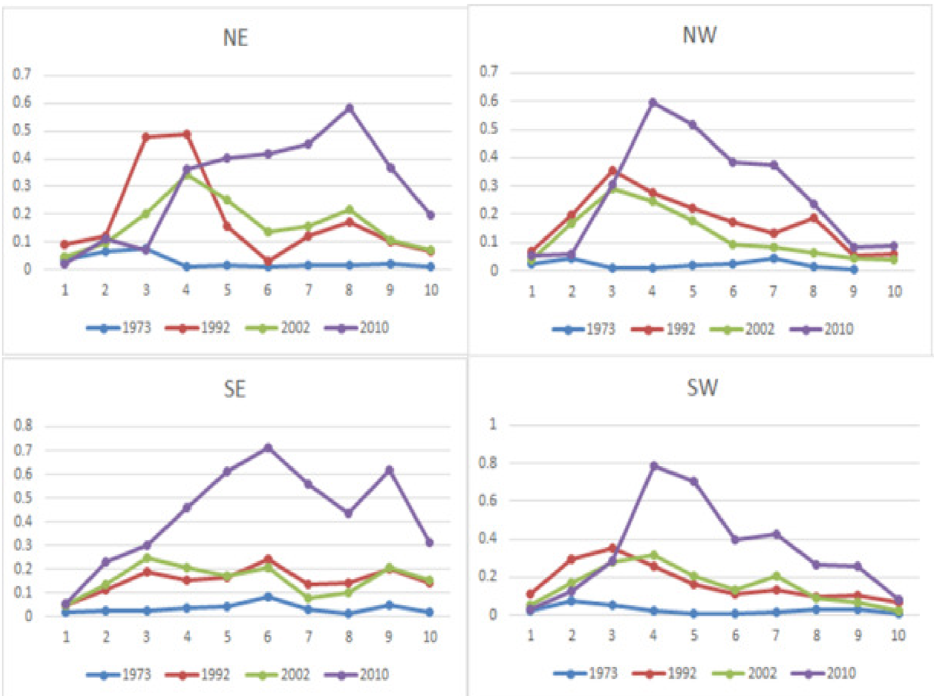

Figure 6b: Patch density – zone, circle wise

The patch density (Figure 6b) is calculated on a raster data, using a 4 neighbor algorithm. Patch density increases with a greater number of patches within a reference area. Patch density was higher in 1992 in all directions and gradients due to small urban patches. This remarkably increased in 2002 in the outskirts which are an indication of sprawl in 2002, subsequently increasing in 2010. PD is low at centre indicating the clumped growth, which was in accordance with number of patches.

Landscape Shape Index (LSI): LSI equals to 1 when the landscape consists of a single square or maximally compact (i.e., almost square) patch of the corresponding type and LSI increases without limit as the patch type becomes more disaggregated. Figure 6c indicates of lower LSI values in 1973 due to minimal concentrated urban areas at the center. The city has been experiencing dispersed growth in all direction and circles since 1990's. In 2010 it shows a aggregating trend at the centre as the value is close to 1, whereas it is very high in the outskirts indicating the peri urban development.

Normalized Landscape Shape Index (NLSI): NLSI is 0 when the landscape consists of Single Square or maximally compact almost square, it increases as patch types becomes increasingly disaggregated and is 1 when the patch type is maximally disaggregated. Results (Figure 6d) indicates that the landscape in 2010 had a highly fragmented urban class in the buffer region and is aggregated class in the center, conforming to the other landscape metrics. Clumpiness index equals zero when the patches are distributed randomly, and approaches 1 when the patch type is maximally aggregated. Aggregation index equals 0 when the patches are maximally disaggregated and equals 100 when the patches are maximally aggregated into a single compact patch.

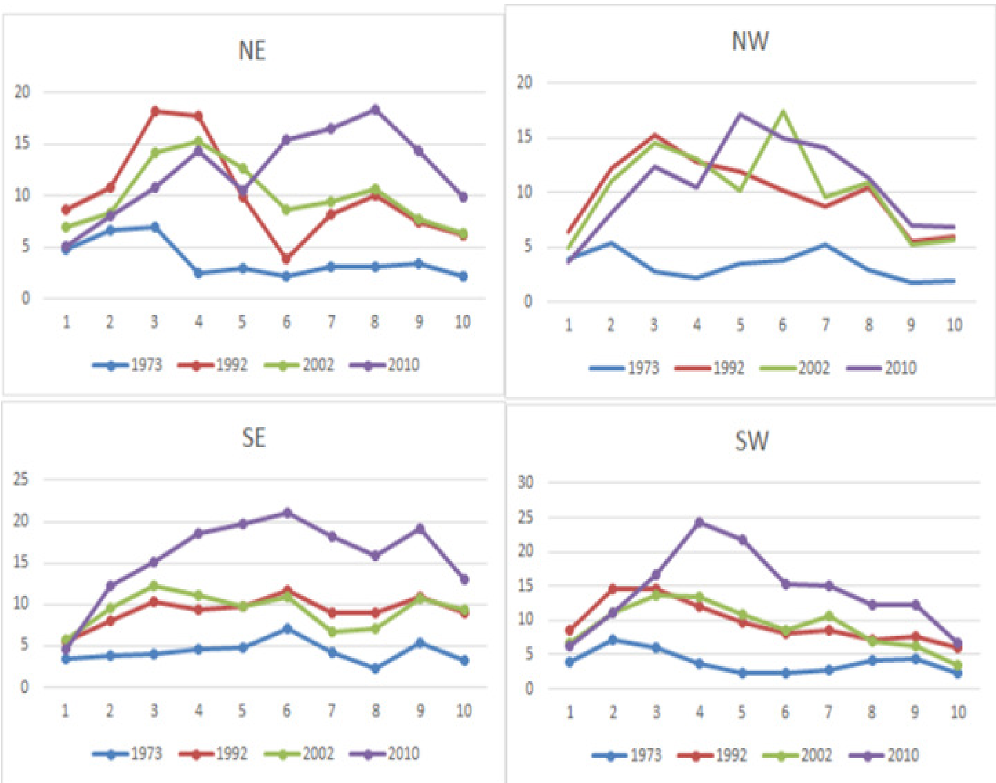

Figure 6c: Landscape Shape index – zone andcirclewise

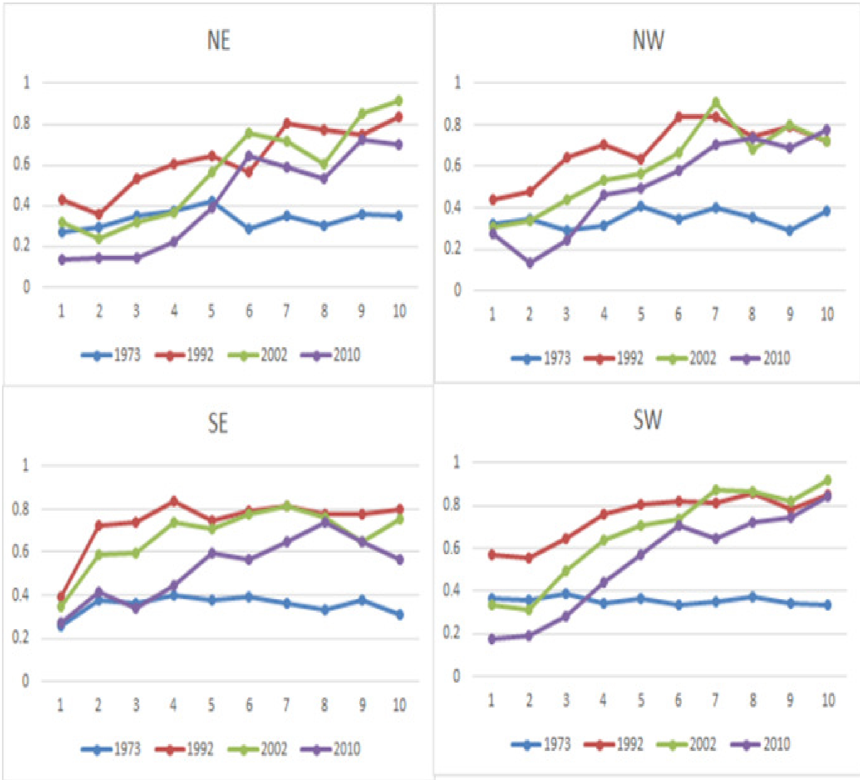

Figure 6d: Normalised Landscape Shape index – zone and circlewise

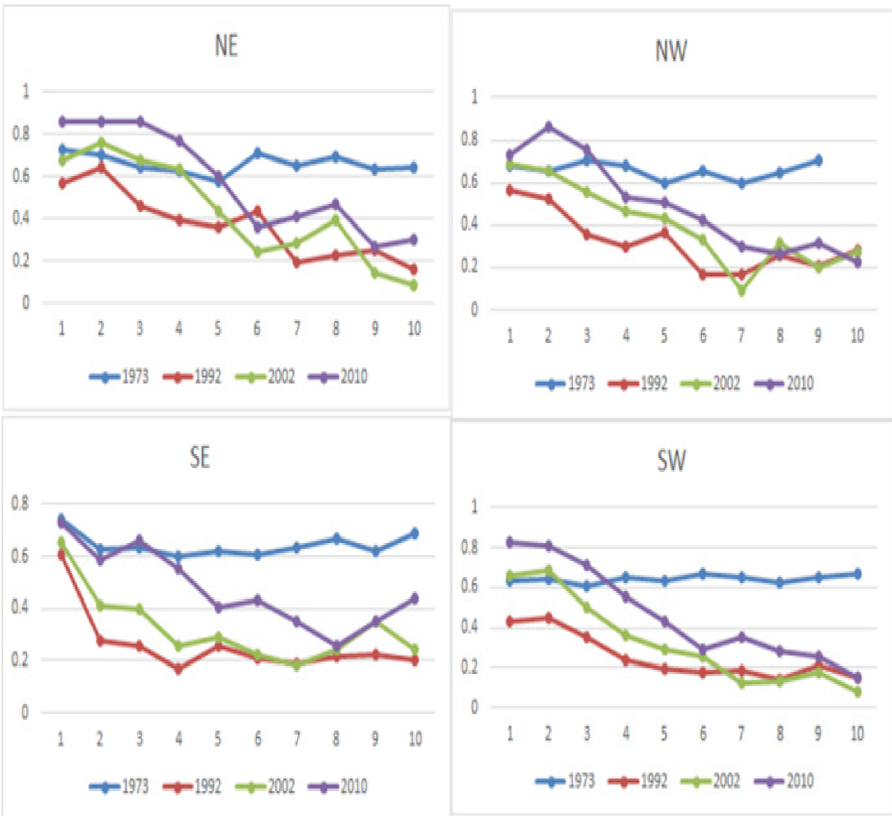

Figure 6e: Clumpiness – zonewise, circle wise;

Figure 6f: Aggregation-zone and circle wise

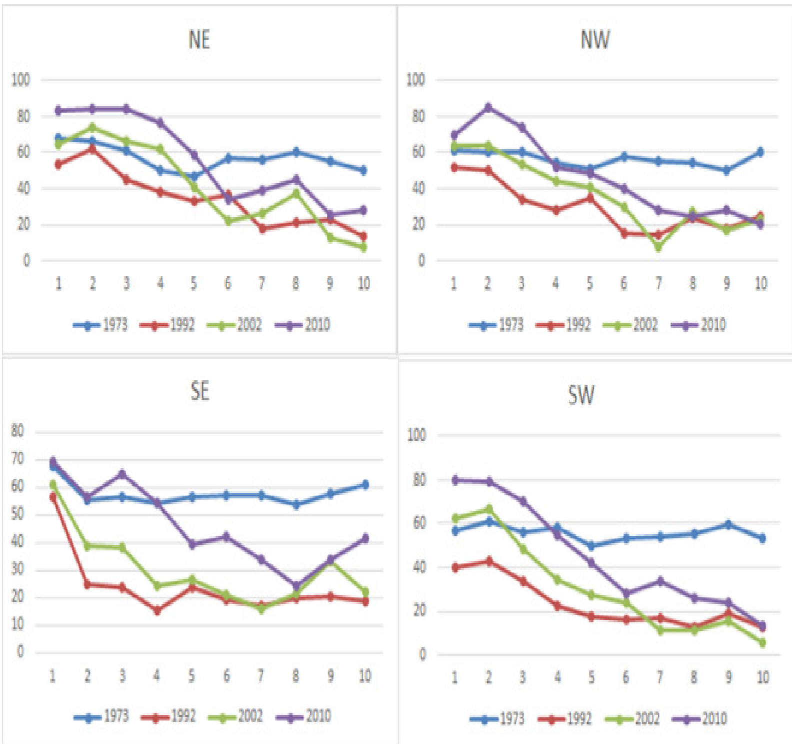

Figure 6g: Zone and circle wise – Pladj

Percentage of Like Adjacencies (Pladj) is the percentage of cell adjacencies involving the corresponding patch type those are like adjacent. Cell adjacencies are tallied using the *double-count* method in which pixel order is preserved, at least for all internal adjacencies.

This metrics also indicates (Figure 6g) the city center is getting more and more clumped and the adjacent patches of urban are much closer and are forming a single patch in 2010 and outskirts are relatively sharing different internal adjacencies are the patches are not immediately adjacent which is also indicative of sprawl. Patch cohesion index measures the physical connectedness of the corresponding patch type. This is sensitive to the aggregation of the focal class below the percolation threshold. Patch cohesion increases as the patch type becomes more clumped or aggregated in its distribution; hence, more physically connected. Above the percolation threshold, patch cohesion is not sensitive to patch configuration. Figure 6h indicate of physical connectedness of the urban patch with the higher cohesion value (in 2010). Lower values in 1973 illustrate that the patches were rare in the landscape.

Figure 6h: Cohesion Index

5. Conclusion

Karnataka government's initiative and focus to develop the major tier II cities such as Gulbarga in order to decongest the burgeoning Tier 1 city, Bangalore, has posed challenges to the district planners to accommodate the developmental activities at a higher speed while ensuring sustainability of natural resources. Availability of temporal spatial data has aided in monitoring the temporal land use dynamics. Spatial metrics in conjunction with the density gradient approach have been effective in capturing the patterns of urbanization at local levels. The techniques would aid as decision-support tools for unraveling the impacts of classical urban sprawl patterns in Gulbarga. A set of spatial metrics describing the morphology of unplanned areas have been extracted along with temporal land uses. The extracted indices have indicated the areas of high likelihood of 'unplanned growth' considering the three dimensions (size/density/pattern).

Land use assessed for the period 1973 to 2010 using Gaussian maximum likelihood classifier highlight that there has been a significant increase (22%) in urban area, with consequent reduction in vegetation cover. Shannon entropy computed using temporal data illustrates that Gulbarga city is showing the signs of sprawl in all directions with the gradual increase of entropy value. Spatial metrics at landscape level reveal that the landscape had a highly fragmented urban class and started clumping to form a single square in in 2002 especially in NE and NW direction in all circle and few inner circles in SE and SW directions, conforming to the other landscape metrics.

The urban pattern highlights the need for policy interventions for integrated urban planning considering land use, mobility and the sustainability of natural resources. This would help in appropriate mitigation measures in addressing traffic congestion, escalation in infrastructure costs, reduction of environment quality and social interactions. These techniques help to visualise the growth pattern and aid decision makers, stakeholders and planners in providing appropriate infrastructure and creating urban boundaries with the prior knowledge of thresholds, which support smart growth.

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