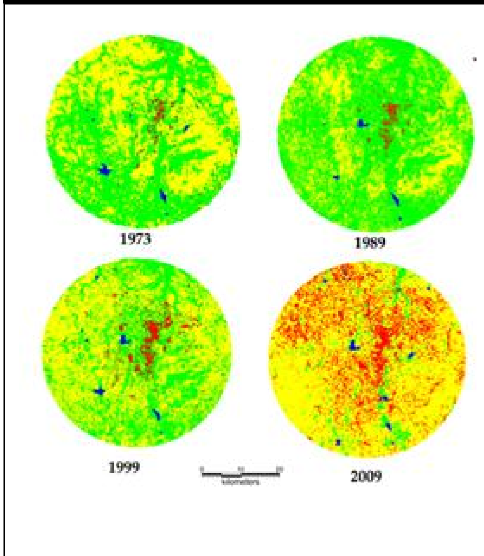
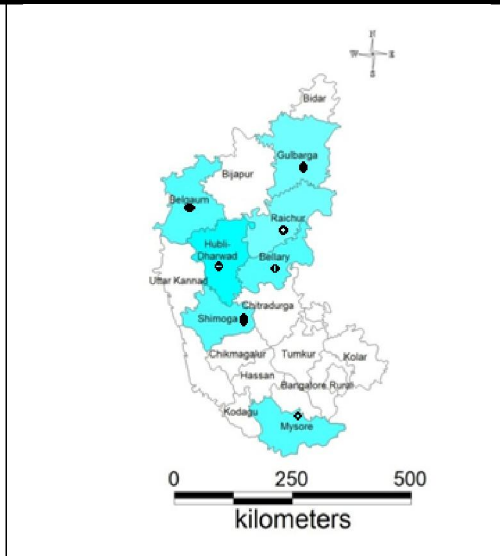
URBAN TRAJECTORY IN METROPOLITAN AND MEGALOPOLIS REGIONS OF KARNATAKA, INDIA

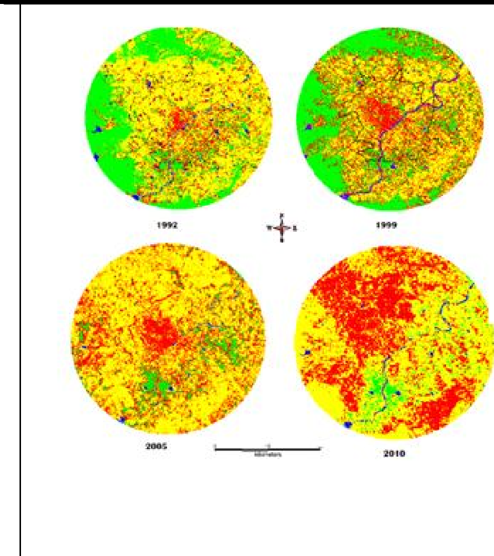
T V Ramachandra | **Bharath H. Aithal**



Mysore



Karnataka



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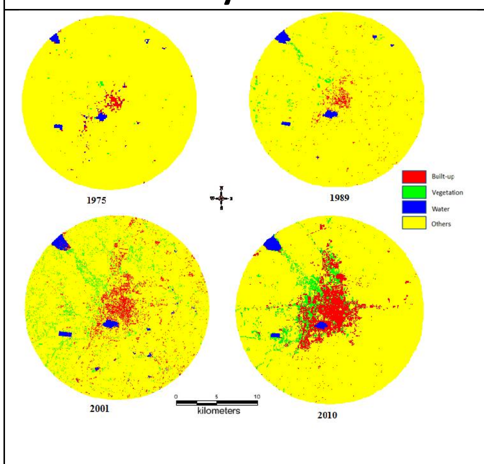

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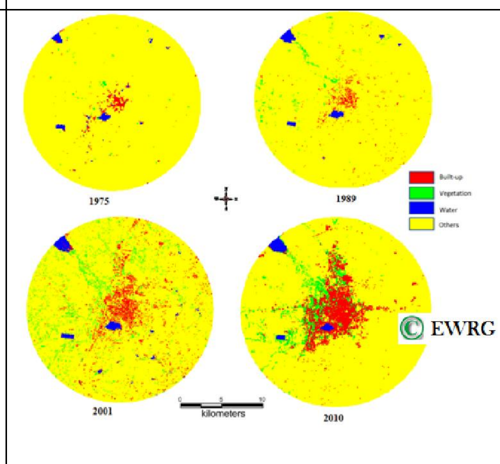

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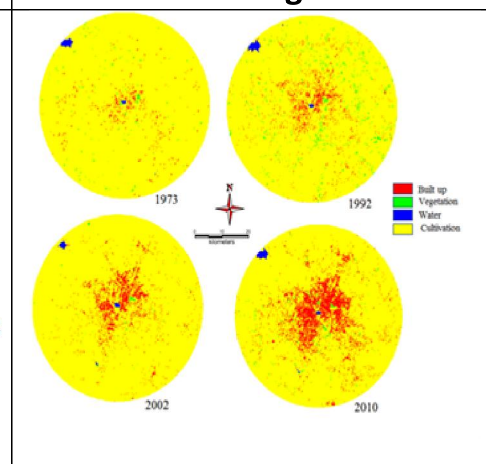

Gulbarga

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URBAN TRAJECTORY IN METROPOLITAN AND MEGALOPOLIS REGIONS OF KARNATAKA, INDIA

Abstract: Rapid irreversible changes in land cover in recent days are due to unplanned urban planning in a region. Urban growth is driven by burgeoning population and has been accompanied with the mismanagement of natural resources. Urbanization subsequent to opening up of Indian markets in early ninety's show dominant changes in land use during the last two decades. Human-induced land use changes are the prime drivers of the global environmental changes. Urban regions in India are experiencing the faster rates of urban dominance, while peri-urban areas are experiencing sprawl. Megalopolis regions (Tier II cities) in India are undergoing land cover changes in recent times and need to be planned to minimize the impacts of unplanned urbanisation. This report focuses on seven Megalopolis regions (tier II cities), chosen based on population. Mysore, Shimoga, Hubli, Dharwad, Raichur, Belgaum, Gulbarga and Bellary are the rapidly urbanizing regions of Karnataka, India. In this study, an integrated approach of remote sensing and spatial metrics with gradient analysis was used to identify the trends of urban land changes with a minimum buffer of 3 km buffer from the city boundary has been studied (based on availability of data), which help in the implementation of location specific mitigation measures. Results indicated a significant increase of urban built-up area during the last four decades. Landscape metrics indicates the coalescence of urban areas has occurred in almost all these regions. Urban growth has been clumped at the center with simple shapes and dispersed growth in the boundary region and the peri-urban regions with convoluted shapes.

***Keywords* -** Land cover, land use, Landscape Metrics, Urbanisation, Urban Sprawl, Remote sensing, Tier II, Karnataka, India

1. Introduction

Urbanization is a process that involves a complex set of processes that are influenced by economic, demographic, social, cultural, technological, and environmental aspects that is a result due to an increase in the population of a territory/area, an increasing density of population within urban settlements. Urbanization involves process that is irreversible and leads to most dominant land use transformation. India is a place where urban areas have experienced a high rate of growth over the last Decade. Demographic processes of immigration and migration, as well as natural population growth, are important determinants of urbanization. Karnataka being one of the major hub for livelihood of various groups of working population has its share in the growing urban area. Geoinformatics through spatio-temporal tools can aid city planners to measure, monitor, and understand urban sprawl processes. Patterns and processes of globalization and consequent urbanization are the factors influencing contemporary land use trends and also posing challenges for sustainable land uses (Currit ei al., 2009). Analysis of landscape patterns and dynamics has become the primary objectives of landscape, geographical and ecological studies in recent times. Urban Sprawl refers to the areas in the outskirts or in the periphery where there occurs a dispersed growth and hence leading to changes in Land use and Land cover of these regions (Ramachandra and Kumar, 2009). Multi temporal remote sensing data available since 1970 at regular intervals helps in analyzing and understanding the agents of temporal changes. By understanding the Dynamics of these changes it can help in various monitoring activities such as better planning, improved facilities to the sprawl areas, resource management etc.

Previous studies (Sudhira et al., 2004; Priyadarshini et al., 2010; Aninditha et al., 2010; Bharath et al., 2010, Bharath et al., 2012), show that the tier 1 cities have reached the threshold of urbanization. Hence, the demand for urban area has shifted towards Tier two cities for urban development. Tier two cities are to be managed and planned properly in order to avoid haphazard growth with urban Sprawl. Hence, there is a need to study urban pattern in tier two cities. Spatial data available temporal scale helps to monitor urban dynamics accurately and efficiently. Temporal remote sensing data obtained from sensors mounted on satellites helps in providing information on spatial and temporal aspects of landscape. This helps in inventorying and mapping land cover (LC) changes due to urbanization. Mapping landscapes on temporal scale provide an opportunity to monitor the changes, which is important for natural resource management and sustainable planning activities. In this context, “Density Gradient” with the time series spatial data analysis is potentially useful in measuring urban development (Torrens and Alberti, 2000). Through spatial metrics, which are the measures for analyses of spatial pattern of LC patches or entire landscape helps in providing understanding of heterogeneous characteristics of urban area and also the impact of urban development in that area and on the surrounding environment (Jenerette, 2001; Yu and Ng, 2007). This work combines land use analyses, environmental change and analyses of alternative pathways for sustainable development. The analyses will directly address crosscutting issues at the interface between policy and science.

2.0 Objective

Analysis of patterns, and process of urbanisation in Tier II cities of Karnataka is the primary goal of this research. This helps regional planners in visualisation of urban growth, land cover planning , etc., which help in evolving effective natural resources management strategies.

3.0 Study Area

Karnataka is one of the largest states of South India. The state covers an area of 191,976 square kilometres or 5.83% of the total geographical area of India. It is the eighth largest Indian state by area, the ninth largest by population and comprises 30 districts. According to Population census of 2011, the Population of Karnataka is 61.09 million which 52.73 million in 2001. The Population of Karnataka has increased by 15.6% in 2011 from 2001 and comparatively increased by 17.20% in 2001 as compared to census of India in 1991. Karnataka lies between the Latitudes : 14° 49' 37.15"N to 13° 18' 39.29"N, Longitude:76° 56' 37.1"E to 77° 28' 15.66"E The study area considered are Tier two cities of Karnataka which have a population of 2 lakhs - 8 lakhs, namely Mysore, Shimoga, Hubli- Dharwad, Belgaum, Bellary, Raichur, Gulbarga (Figure 1).

Figure 1: Study Area - Tier II Cities in Karnataka

4.0 Approach

Measuring urban sustainability is a multi-dimensional issue, while urban quality and patterns provide useful information on the state of urban sustainability, urban flows are also crucial to guide sustainable urban planning for improving the understanding of how urban sustainability performance is interacted with its activities and lifestyles. One direction in studying urban flows is to examine urban impact on the environment through ecological footprints by analysing the flows of natural resources that support urban metabolism. This helps to allow a conservative measurement of human impacts by measuring the biologically productive land and sea areas which are required to maintain the biotic resource consumptions and compensate carbon emissions for a given population. Tier II cities in Karnataka have been chosen for implementing the proposed study.

Temporal land use changes refer to dynamic changes that the land/geographical area has undergone with time, which can be effectively analysed using the satellite data (ex: Landsat data) and classifying it using supervised pattern classifiers based on Gaussian maximum likelihood estimation using maximum likelihood estimation with the best estimates maximising the probability of the pixels falling into one of the classes using the open source program of Geographic Resources Analysis Support System http://ces.iisc.ernet.in/grass). The study regions were analyzed by considering a buffer and dividing the region based on directions and using the effective concentric ring approach. The complexity of a dynamic phenomenon of urban sprawl pattern has been done through the computation of sprawl indicator metrics.

i. **Greater Bangalore:** Greater Bangalore is the administrative, cultural, commercial, industrial, and knowledge capital of the state of Karnataka, India with an area of 741 sq. km. and lies between the latitude 12°39'00'' to 13°13'00'' N and longitude 77°22'00'' to 77°52'00'' E. Bangalore city administrative jurisdiction was redefined in the year 2006 by merging the existing area of Bangalore city spatial limits with 8 neighbouring Urban Local Bodies (ULBs) and 111 Villages of Bangalore Urban District. Bangalore has grown spatially more than ten times since 1949 (~69 square kilometres to 716 square kilometres) and is the fifth largest metropolis in India currently with a population of about 7 million (Ramachandra and Kumar, 2008; 2010, Sudhira et al., 2007). Bangalore city population has increased enormously from 65,37,124 (in 2001) to 95,88,910 (in 2011), accounting for 46.68 % growth in a decade. Population density has increased from as 10732 (in 2001) to 13392 (in 2011) persons per sq. km. The per capita GDP of Bangalore is about $2066, which is considerably low with limited expansion to balance both environmental and economic needs.

ii. **Mysore:** Mysore is the second largest city in the state of Karnataka, India. This Vibrant royal city of South, with a large area of heritage sites, has hit the fast track of urbanization off late, altering the landscape that will in the coming years go beyond recognition. With the government planning to develop this area under various Projects which has invited the surge of investors to invest heavily in this heritage city, especially the IT Companies. The City has been growing and in demand and is expected to generate at least 60,000 new jobs during the next few years, which means its demographic and geographic profile is also set to alter with these changes, bringing in a touch of cosmopolitan culture.

iii. **Shimoga**: Shimoga is located in 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 23.2ºC (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. 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.

iv. **Hubli-Dharwad:** Hubli - Dharwad are twin cities in Indian state of Karnataka. Hubli-Dharwad is the second-largest urbanized centres in Karnataka. The twin cities have a common governance and are governed by Hubli - Dharwad Municipal Corporation (HDMC) with a corporation governing area of 202.3Sq km. The population of the Twin cities is about 1 million (Census 2011). Hubli is basically a commercial and industrial centre with various commercial establishments. Dharwad is an educational and administrative centre with numerous colleges, universities and government offices. Hubli - District encompasses an area of 4263 sq. kms.

v. **Gulbarga**: Gulbarga was known as 'Kalburgi' means "rose petals" in poetic Persian. 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.

vi. **Raichur:** Raichur district is one of major district in northern Karnataka, India, having 5 taluks and 37 hobli's and 120 hamlets, with an area of 8386 sq. km. and a population density of 181 persons per sq. km (2001). Raichur is drought prone, and it falls in the northeast dry agro climatic zone. The normal annual rainfall of the district is 621 mm. The average temperature is 35^0 C. Krishna and the Tungabhadra are two water sources which cater to the needs of drinking water supply to Raichur city. Raichur is famous for its rice mills which exports high quality rice and has a production of pure cotton.

vii. **Bellary:** Bellary city is situated in the Karnataka State and has a jurisdiction over an area of 82 Sq. Kms. Population of about 0.4 million as per 2011 census (provisional).Bordering Bellary on the west, state of Andhra Pradesh on the East, Chitradurga and Davangere on the south. Temperature ranges from 25^0c to 45^0c. Mean Annual Rainfall is about 700mm. The city has a huge spread of industrial activity and is one of the major centres in production of clothing in the country.

viii. **Belgaum**: Belgaum City (Figure1) geographically located in the North Western Part of Karnataka State, with a gross area of 38013.27 hectares. The city has about 58 Wards, with population of 488292 (2011 Census Provisional) and Population Density of 84.21 persons per hectare, the population in the region has a decadal increase of 7.31%. BUDA (Belgaum Urban Development Authority) formed during 1988 is responsible for Layout and Town planning in Belgaum. BUDA consists of local planning area of 182 sq.km including the Belgaum city corporation, 26 surrounding villages and area coming under conurbation limit under BUDA since 1988 about 19 townships have been developed (belgaumuda.org). Temperature varies from as low as 18 degrees in winter to 40 degrees during summer, city receives annual average rainfall of 1418 mm. Soils in the region consist of shallow to very deep black soils, red loamy soils, lateritic soils etc.

5.0 Results: Land use Land Cover analysis:

5.1 Mysore: Vegetation cover of the study area assessed through NDVI (Figure 2a), shows that area under vegetation has declined to 9.24% (2009) from 51.09% (1973). Temporal NDVI values are listed in Table 1.

Land use analysis: Land use assessed for the period 1973 to 2009 using Gaussian maximum likelihood classifier is listed Table 2a and the same is depicted in figure 2b. The overall accuracy of the classification ranges from 75% (1973), 79% (1989), 83% (1999) to 88% (2009) respectively. Kappa statistics and overall accuracy was calculated and is as listed in Table 2b. There has been a significant increase in built-up area during the last decade evident from 514% increase in urban area. Other category also had an enormous increase and covers 166 % of the land use. Consequent to these, vegetation cover has declined drastically during the past four decades. The water spread area has increased due to the commissioning of waste water treatment plants (ex. Vidyaranyapura, Rayankere, Kesare) during late 90's and early 2000.

Year	Vegetation		Non vegetation	
	%	Ha	%	Ha
1973	51.09	10255.554	48.81	9583.83
1989	57.58	34921.69	42.42	8529.8
1999	44.65	8978.2	55.35	11129.77
2009	09.24	1857.92	90.76	19625.41

Table 1: Temporal Land cover details.

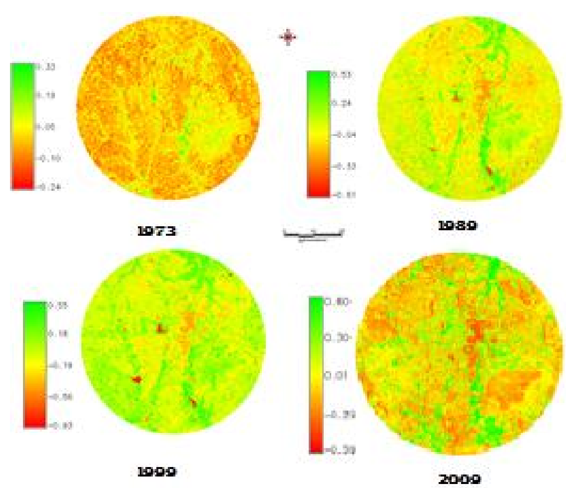

Figure 2a: Temporal Land cover changes during 1973 – 2009

Land use / Year	Urban	Vegetation	Water	Others
1973	222.93	10705.68	124.47	9054.99
1989	229.41	13242.51	78.75	6557.4
1999	730.8	8360.1	117.9	10899.2
2009	3757.489	1159.336	142.58	15050.5
Total (Land in ha)		20108.91		

Table 2a: Temporal land use details for Mysore

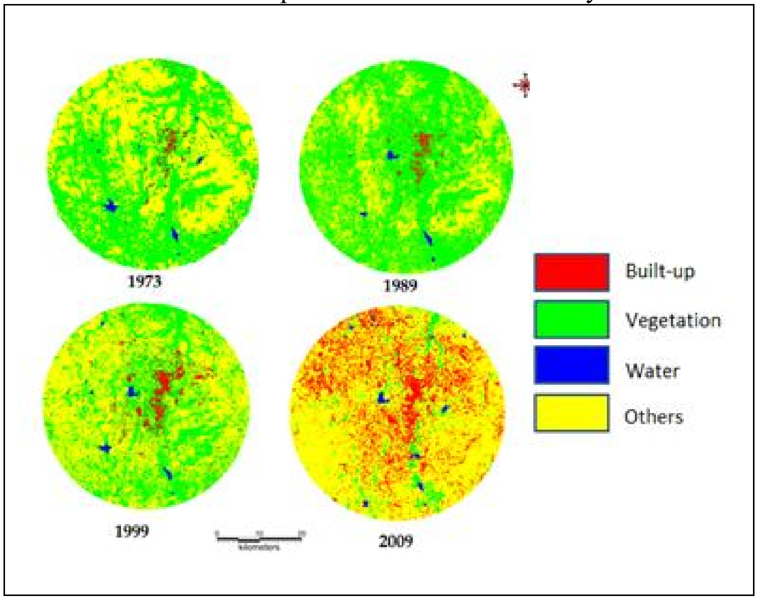

Figure 2b: Classification output of Mysore

Year	Kappa coefficient	Overall accuracy (%)
1973	0.76	75.04
1989	0.72	79.52
1999	0.82	78.46
2009	0.86	84.58

Table 2b: Kappa statistics and overall accuracy

5.2 Shimoga: NDVI was calculated using r.mapcalc in GRASS, open source GIS and results are depicted in figure 3a and Table 3a. 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 3a: Results of land cover analysis

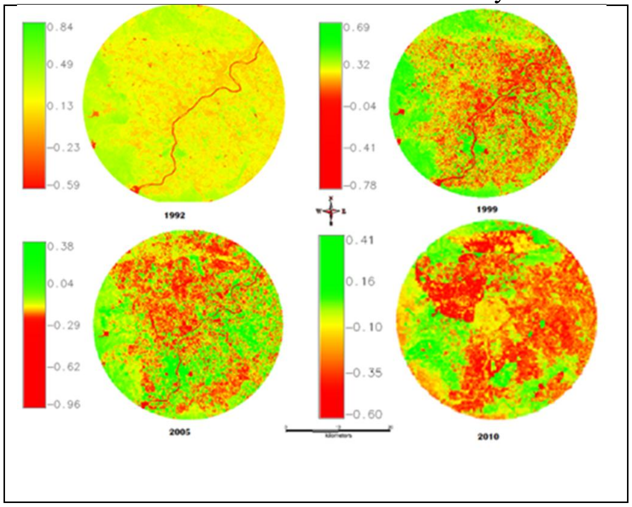

Figure 3a: Results of Land cover analysis

Land use analysis: Temporal land use is given in figure 3b and the statistics of category-wise land uses are for 5 time period is given in table 3b. 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 3b: Results of Land use analysis

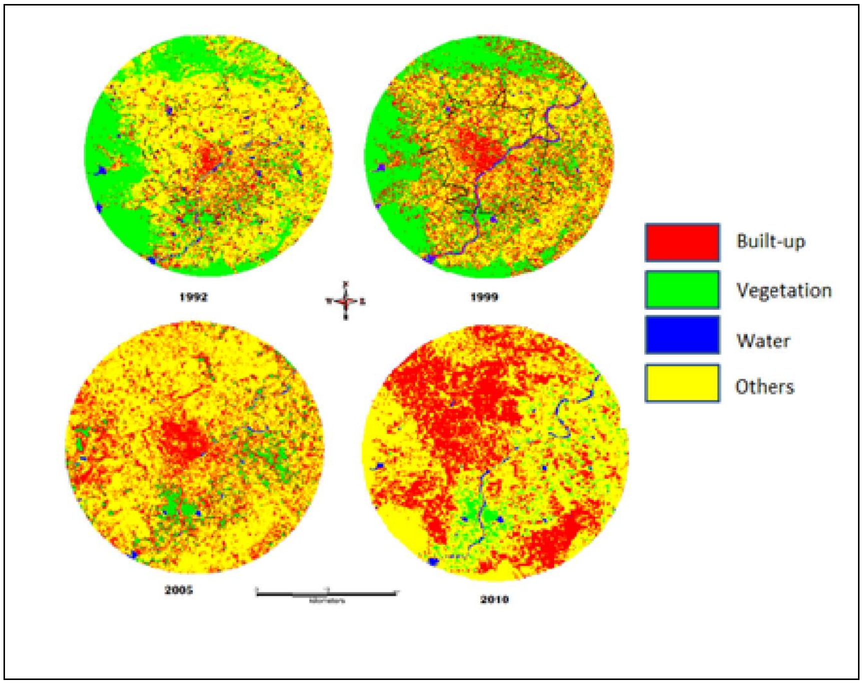

Figure 3b: Results of Land use analysis

5.3 **Hubli –Dharwad**: Both Hubli and Dharwad dominated by cultivable land area has a huge green area which includes both Green cover and cultivation. Vegetation cover of the study area assessed through NDVI (Figure 4a), shows that area under vegetation has declined from 97% (1989) to 78% (2010) in Hubli and from 98% (1989) to 86% (2010) in Dharwad. Temporal NDVI values are listed in Table 4a.

Land use analysis: Land use assessed for the period 1973 to 2009 using Gaussian maximum likelihood classifier is listed Table 4b and the same is depicted in figure 4b. The overall accuracy of the classification ranges from 76% (1989), 83% (2000), 81% (2005) to 94% (2010) respectively. Kappa statistics and overall accuracy was calculated and is as listed in Table 4c. There has been a significant increase in built-up area during the last decade evident from table 4c. Other category covers major portion of the land use. Consequent to these, there has been a slight decrease of vegetation cover especially in the Dharwad region during the past three decades.

Year	Hubli - Vegetation	Hubli - Non-Vegetation	Dharwad - vegetation	Dharwad - Non -vegetation
1989	97.0	3.0	98.12	1.88
2000	94.35	5.65	96.48	3.52
2005	89.73	10.27	92.21	7.79
2010	78.31	21.69	86.43	13.57

Table 4a: Temporal Land cover details (%).

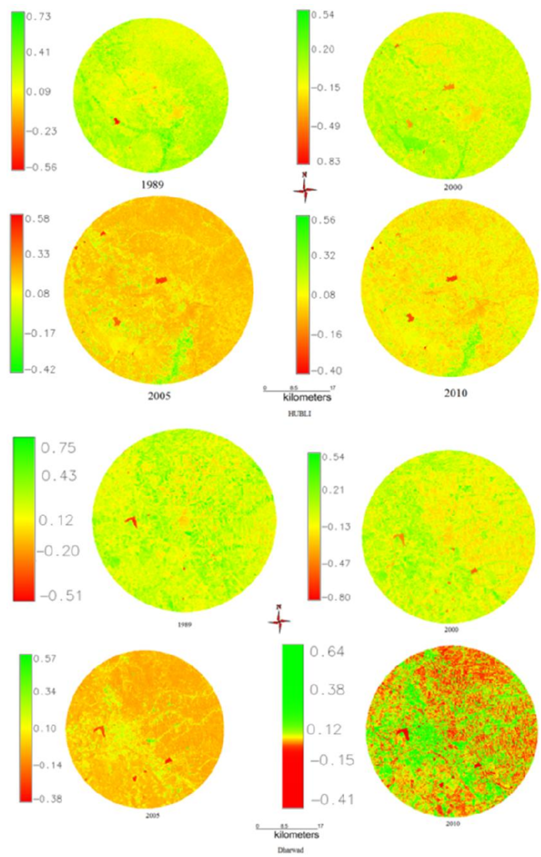

Figure 4a: Temporal Land cover changes during Past three Decades Hubli and Dharwad.

Land use -Hubli				
Year	Urban	Vegetation	Water	Others
1989	1.08	0.22	0.64	98.06
2000	2.25	0.45	0.98	96.31
2005	9.85	0.71	0.74	88.70
2010	14.62	0.42	0.65	84.30

Table 4b: Temporal land use details for Hubli

Land use - Dharwad	Urban	Vegetation	Water	Others
Year				
1989	0.62	1.43	0.51	97.45
2000	1.93	1.41	1.13	95.52
2005	3.75	1.29	0.25	94.71
2010	6.47	0.69	0.47	92.36

Table 4b: Temporal land use details for Dharwad

Year	Kappa coefficient	Overall accuracy (%)
1989	0.82	76.34
2000	0.89	83.54
2005	0.83	81.62
2010	0.91	94.86

Table 4c: Kappa statistics and overall accuracy

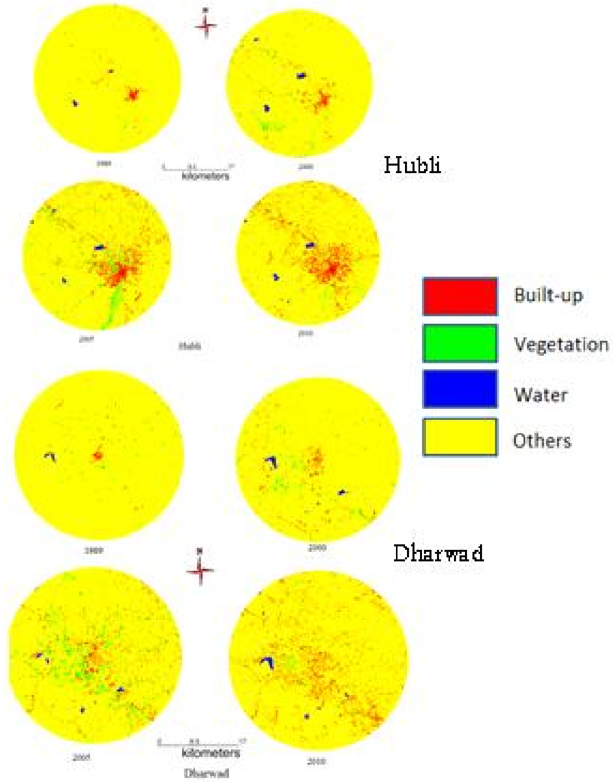

Figure 4b: Classification output of Hubli & Dharwad

5.4 Gulbarga: Land use Land Cover analysis - Vegetation cover analysis: Vegetation cover of the study area assessed through NDVI (Figure 5a) shows that area under vegetation has declined by about 19%. Temporal NDVI values are listed in Table 5a, which shows that there has been a substantial increase in the area other than the vegetation.

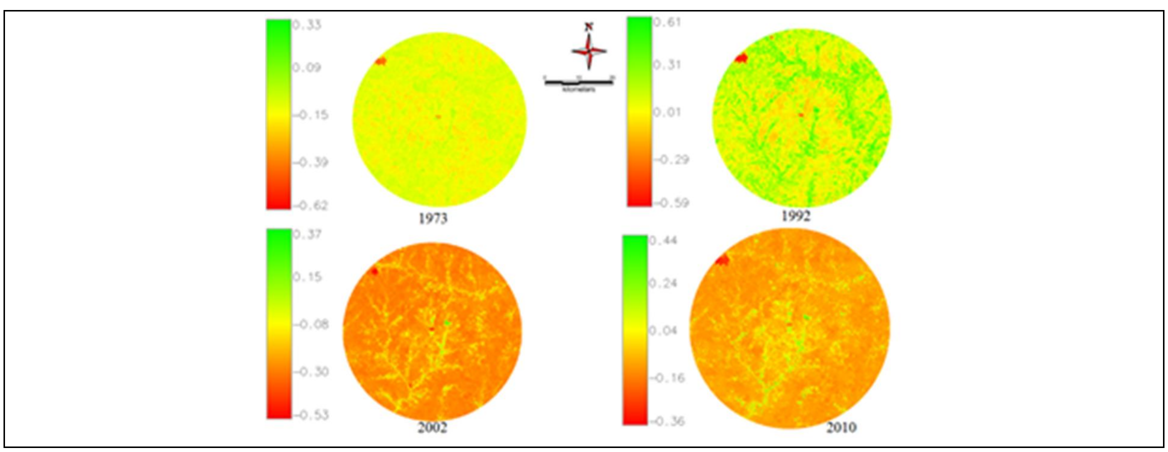

Figure 5a: Temporal Land cover changes during 1973 – 2009;

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

Table 5a: Temporal Land cover details

Land use analysis: Land use assessed for the period 1973 to 2010 using Gaussian maximum likelihood classifier is listed Table 5b and the same is depicted in figure 5b. 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 5c. 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.

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 5b: Temporal land use details for Gulbarga

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

Table 5c: Kappa statistics and overall accuracy

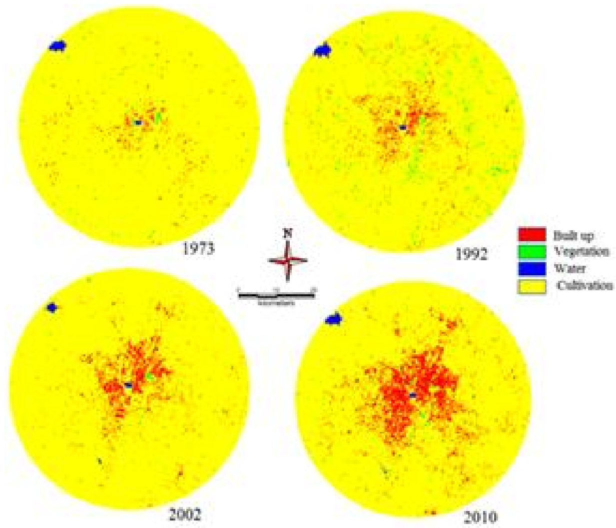

Figure 5b: Classification output of Gulbarga:

5.5 Raichur: Vegetation cover analysis - Vegetation cover of the study area assessed through NDVI (Figure 6a), shows that area under vegetation has declined by about 19%. Temporal NDVI values are listed in Table 6a. Which shows that there has been a substantial increase in the Non Vegetative area. There has been an increase from 3 % to 17 percent this tells us that there has been staggering growth of impervious cover in the region, which is also indicated by decrease in vegetative cover.

Land use analysis: Land use assessed for the period 1973 to 2010 using Gaussian maximum likelihood classifier is listed Table 6b and the same is depicted in figure 6b. The overall accuracy of the classification Ranges from 69.28 % (1973) to 88.12 % (2010). Kappa statistics and overall accuracy was calculated and is as listed in Table 6c. There has been a significant increase in built-up area during the last decade evident from 590% increase in urban area which was 1.44% in 1975 has grown to 8.51% considering buffer area. Other category also had an enormous decrease in the land use. Consequent to these, cultivable area has come down drastically.

Year	Vegetation %	Non vegetation %
1975	96.32	3.68
1989	92.18	7.82
2001	89.36	10.64
2010	82.48	17.52

Table 6a: Temporal Land cover details.

Figure 6a: Temporal Land cover changes during 1973 – 2010

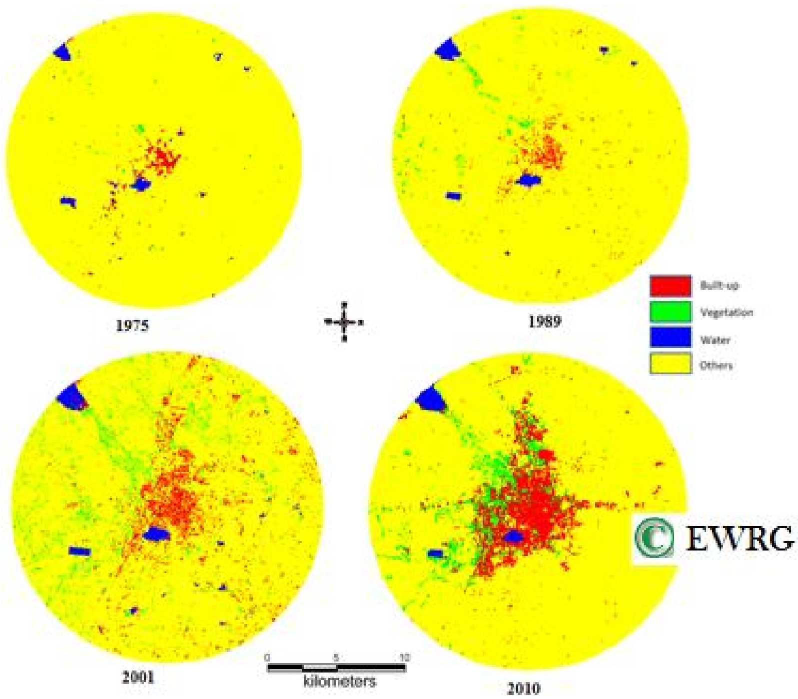

Figure 6b:Classification output of Raichur

Land use Year	Urban	Vegetation	Water	Cultivation and others
2010	8.51	4.81	0.97	85.71
2002	5.21	3.58	1.36	89.85
1992	2.48	0.91	1.04	95.57
1973	1.44	1.62	0.88	96.16

Table 6b: Temporal land use details for Raichur

Year	Kappa coefficient	Overall accuracy (%)
1973	0.69	69.28
1989	0.83	81.69
1999	0.83	84.53
2009	0.89	88.12

Table 6c: Kappa statistics and overall accuracy

5.6 Bellary: Land use Land Cover analysis- Land cover analysis: Vegetation cover of the study area assessed through the computation of NDVI (Figure 7a). Since as discussed earlier the NDVI values indicate the status of vegetation versus Non vegetation, here vegetation indication all the reflectance's which have higher values in Near IR region (Cultivation, vegetation etc.). The area under vegetation in 1973 is 57.53% which indicates that total of cultivable and vegetative area, since the open soil was higher in the region. During 1973-2001 there was an increase in cultivable area in these region which showed that vegetation increase in 2001, 2005 and 2010. To understand the vegetation status and cultivation status further and to assess the urban growth land use investigation was carried out. Temporal NDVI values are listed in Table 7a.

Year	Vegetation %	Non-Vegetation %
1973	57.51	42.47
2001	94.87	5.13
2005	94.8	5.2
2010	93.7	6.27

Table 7a: Temporal Land cover details.

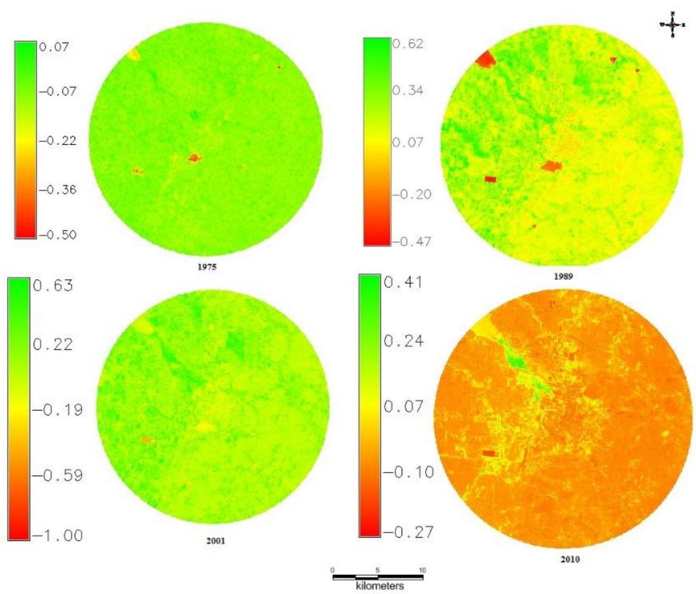

Figure 7a: Temporal Land cover changes during Past three Decades

Land use analysis: Land use assessed for the period 1973 to 2010 using Gaussian maximum likelihood classifier is listed Table 7b and the results is as depicted in figure 7b. The overall accuracy of the classification ranges from 78% (1973), 86% (2001), 84% (2005) to 89% (2010) respectively. Kappa statistics and overall accuracy was calculated and is as listed in Table 7c. There has been a significant increase in built-up area during the last decade evident from table V. There has been a decrease of vegetation cover in the region during the past four decades. Significant increase in other class and the urban class was observed.

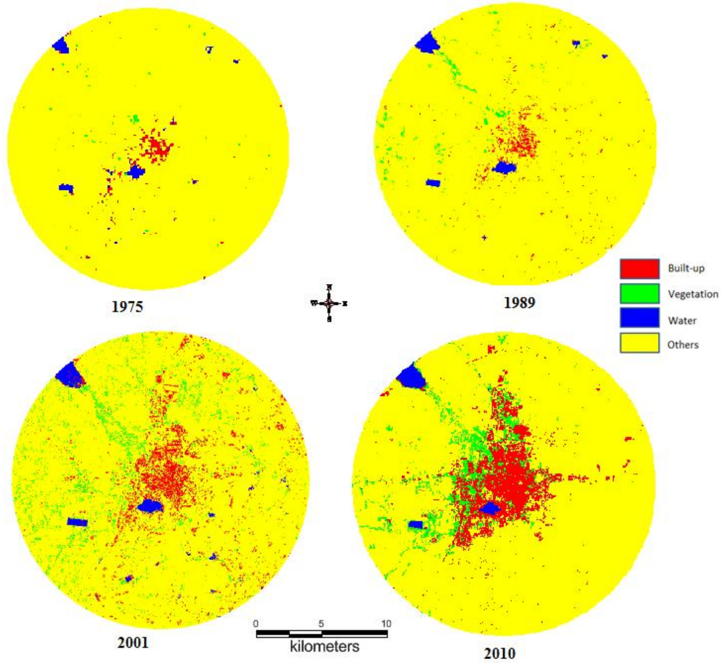

Figure 7b:Classification output of Bellary

Land use / Year	Urban	Vegetation	Water	Cultivation and others
2010	7.42	0.48	2.04	90.07
2005	4.23	0.92	4.73	90.12
2001	2.64	0.41	2.01	94.94
1973	2.12	4.61	2.35	90.92

Table 7b: Temporal land use details for Bellary

Year	Kappa coefficient	Overall accuracy (%)
1973	0.69	78.32
2001	0.84	86.94
2005	0.82	84.53
2010	0.86	89.69

Table 7c: Kappa statistics and overall accuracy

5.7 **Belgaum**: Land Cover Analysis - To understand the ration of vegetation and non-vegetation as primary analysis various land cover indices were analysed. NDVI index proved to provide insights to understand the vegetation cover. NDVI was calculated for all the years for which data is considered, the results of the analysis are shown in Figure 8a and are as tabulated in Table 8a. The results indicate that the vegetation in the study region decreased for 98.8% in 1989 to 91.74% in 2012. Further this necessitated understanding the land use temporally in order to understand the status of various land use.

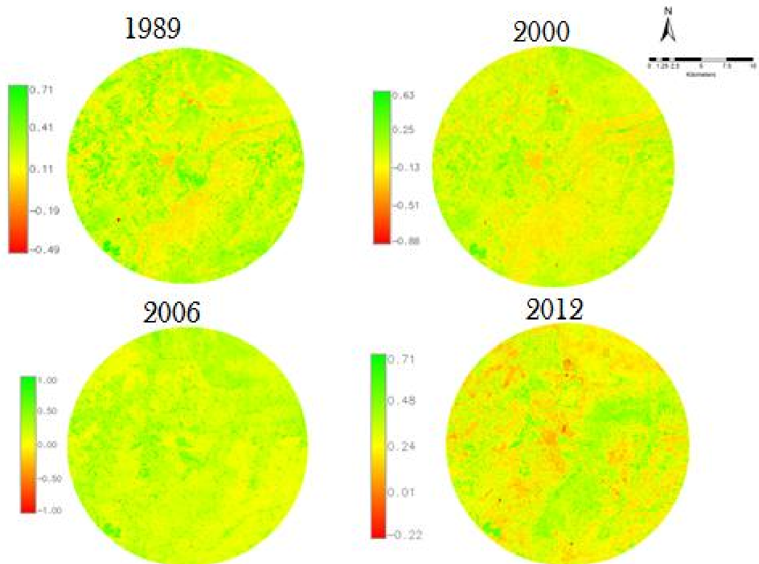

Figure 8a: Land Cover Classification

Year	Vegetation	Non Vegetation
1989	98.8%	1.2%
2000	98.41%	1.59%
2006	96.35%	3.65%
2012	91.74 %	8.26 %

Table 8a. Land cover analysis

Land Use Analysis: The spatio temporal land use changes between years 1989 to 2006 were analysed using maximum likelihood Classifier, the results of the analysis are as shown in figure 8b and the temporal land use is as tabulated in listed in Table 8b. The results of the analysis indicate that the urban impervious land use has increased from 0.31 % in 1989 to 6.74% in 2012; vegetation decreased from 4.62% in 1989 to 2.44% in 2012, Water category remained fairly constant.

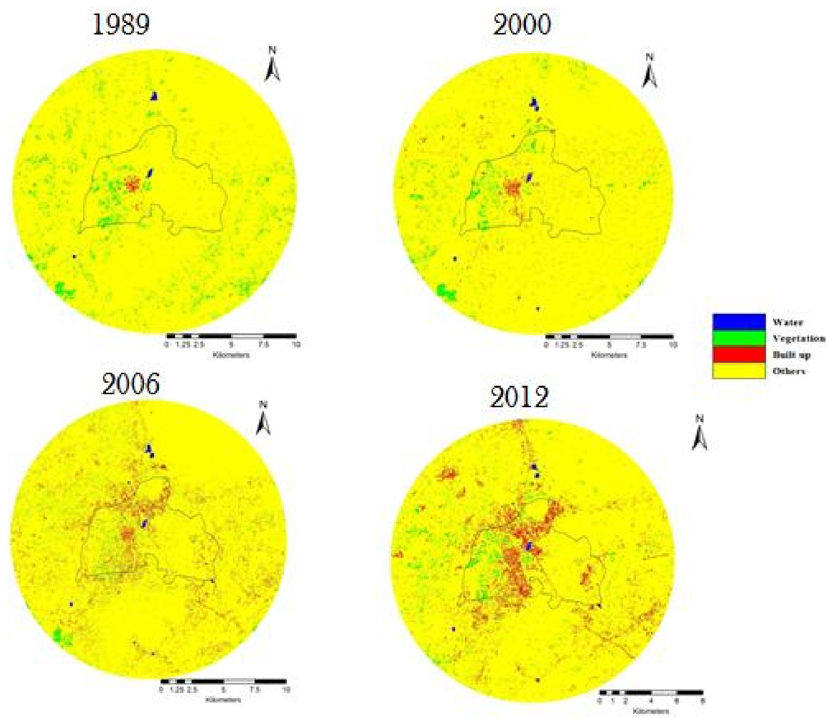

Figure 8b. Land Use Classification

Year	1989		2000		2006		2012	
Land use	%	Area(Ha)	%	Area(Ha)	%	Area(Ha)	%	Area(Ha)
Water	0.14	53.24	0.33	125.49	0.23	87.47	0.24	92.03
Vegetation	4.62	1756.92	2.58	981.14	2.33	886.07	2.44	928.73
Built up	0.31	117.89	1.17	444.93	4.81	1829.17	6.74	2190.15
Others	94.9	36089.11	95.92	36477.00	92.93	35339.95	91.58	34904.41
Total Area in Hectares : 38028.57								

Table 8b. Land Use analysis

Year	Overall Accuracy	Kappa Value
1989	94.85	0.87
2000	92.73	0.83
2006	93.64	0.92
2012	93.12	0.93

Table 8c: Kappa Statistics and Accuracy Assessment

6.0 Urban Sprawl Analysis – Computation of Shannon Entropy:

6.1 Mysore: Shannon entropy computed using temporal data are listed in table 9a. Mysore is experiencing the sprawl in all directions as entropy values are closer to the threshold value (log (8) = 0.9). Lower entropy values of 0.007 (NW), 0.008 (SW) during 70's shows an aggregated growth as most of urbanization were concentrated at city centre. However, the region experienced dispersed growth in 90's reaching higher values of 0.452 (NE), 0.441 (NW) in 2009 during post 2000's. The entropy computed for the city (without buffer regions) shows the sprawl phenomenon at outskirts. However, entropy values are comparatively lower when buffer region is considered. Shannon's entropy values of recent time confirms of minimal fragmented dispersed urban growth in the city. This also illustrates and establishes the influence of drivers of urbanization in various directions.

	NE	NW	SE	SW
2009	0.452	0.441	0.346	0.305
1999	0.139	0.043	0.0711	0.050
1992	0.060	0.010	0.0292	0.007
1973	0.067	0.007	0.0265	0.008

Table 9a: Shannon Entropy for Mysore

6.2 Shimoga: 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 9b. 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 9b: Results of Shannon's entropy: Shimoga

6.3 Hubli-Dharwad: Shannon entropy computed using temporal data are listed in Table 9c. Hubli-Dharwad is experiencing the sprawl in all directions as entropy values inching closer to the threshold value (for Hubli: log (12) = 1.07 For Dharwad: log(7) = 0.845). Lower entropy values of 0.02 (NW), 0.011 (SW) during late 80's shows an aggregated growth as most of urbanization were concentrated at city center. However, the region experienced dispersed growth in 90's reaching higher values of 0.36 (NE), 0.49 (SE) in 2010 during post 2000's. The entropy computed for the city (without buffer regions) shows the sprawl phenomenon at outskirts. However, entropy values are comparatively lower when buffer region is considered. Shannon's entropy values of recent time confirms of minimal fragmented dispersed urban growth in the city. This also illustrates and establishes the influence of drivers of urbanization in various directions.

Hubli	NE	NW	SE	SW	Dharwad	NE	NW	SE	SW
1989	0.027	0.02	0.055	0.011	1989	0.011	0.013	0.008	0.006
2000	0.029	0.053	0.102	0.042	2000	0.016	0.023	0.014	0.018
2005	0.146	0.09	0.21	0.059	2005	0.08	0.086	0.09	0.0745
2010	0.369	0.134	0.49	0.128	2010	0.168	0.164	0.213	0.216

Table 9c: Shannon Entropy Index

6.4 Gulbarga: Shannon entropy computed using temporal data are listed in Table 9d. Mysore 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.

	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

Table 9d: Shannon Entropy Index

6.5 Raichur: The entropy is calculated considering 7 gradients in 4 directions and are listed in table 9e. The reference value is taken as Log (7) which is 0.77 and the computed Shannon's entropy values closer to this, indicates of sprawl. Increasing entropy values from 1973 to 2010 shows the tendency of dispersed growth of built-up area in the city with respect to 4 directions as we move towards the outskirts and this phenomenon is most prominent in SE and SW directions.

	NE	NW	SE	SW
2010	0.135	0.146	0.168	0.194
2002	0.078	0.083	0.084	0.097
1992	0.023	0.026	0.026	0.027
1973	0.01	0.006	0.007	0.005

Table 9e: Shannon Entropy Index

6.6 Bellary: The entropy is calculated considering 10 gradients in 4 directions and are listed in table 9f. The reference value is taken as Log (10) which is 1 and the computed Shannon's entropy values are inching closer to the threshold value, indicating tendency of sprawl. Increasing entropy values from 1973 to 2010 shows the tendency of dispersed growth of built-up area in the city with respect to 4 directions as we move towards the outskirts and this phenomenon is most prominent in SE and NE directions.

	NE	NW	SE	SW
2010	0.37	0.32	0.389	0.33
2005	0.23	0.25	0.26	0.24
2001	0.1	0.09	0.12	0.14
1973	0.04	0.03	0.08	0.06

Table 9f: Shannon Entropy Index

6.7 Belgaum: The threshold limit of Shannon's Entropy is log11 (1.04139). The results indicated that though Belgaum considering the buffer region has effect of urban sprawl considering the values of 1980 and 2012, and the effect is gaining strength temporally considering the threshold value of 1.041

	NE	NW	SE	SW
1989	0.005967	0.019111	0.003412	0.008811
2000	0.028393	0.054622	0.017126	0.033461
2006	0.079145	0.14097	0.108442	0.113038
2012	0.086431	0.165239	0.115427	0.137098

Table 9g: Shannon's Entropy Analysis

7.0 Spatial patterns of urbanisation: In order to understand the spatial pattern of urbanization, eleven landscape level metrics were computed zone wise for each circle. These metrics are discussed below:

7.1 Mysore: Number of Urban Patch (Np) is a landscape metric indicates the level of fragmentation and ranges from 0 (fragment) to 100 (clumpiness). Figure 10a illustrates that the city is becoming clumped patch at the center, while outskirts are relatively fragmented. Clumped patches are more prominent in NE and NW directions and patches is agglomerating to a single urban patch. Largest patch index (Fig 10b) highlights that the city's landscape is fragmented in all direction (in 1973) due to heterogeneous landscapes, transformed a homogeneous single patch in 2009.The patch sizes given in figure 8c highlights that there were small urban patches in all directions (till 1999) and the increase in the LPI values implies increased urban patches during 2009 in the NE and SW. Higher values at the center indicates the aggregation at the center and in the verge of forming a single urban patch largest patches were found in NE and SW direction (2009).

The patch density (Fig 10c) is calculated on a raster map, using a 4 neighbour algorithm. Patch density increases with a greater number of patches within a reference area. Patch density was higher in 1973 as the number of patches is higher in all directions and gradients due to presence of diverse land use, which remarkably increased post 1989(NW) and subsequently reduced in 1999, indicating the sprawl in the region in in early 90's and started to clump during 2009, which was even confirmed by 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. Results (Fig 10d) indicate that there were low LSI values in 1973 as there was minimal urban areas which were aggregated at the centre. Since 1990's the city has been experiencing dispersed growth in all direction and circles, towards 2009 it shows a aggregating trend as the value reaches 1.

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 4e indicate of physical connectedness of the urban patch with the higher cohesion value (in 2009). Lower values in 1973 illustrate that the patches were rare in the landscape (Fig. 10e).

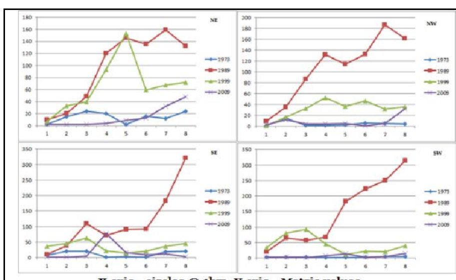

Fig 10a: Number of patches (zonewise, circlewise)

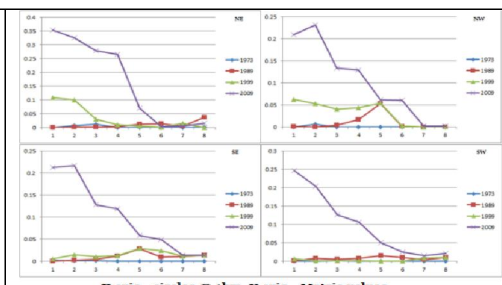

Fig 10b: Largest Patch – zonewise, circlewise

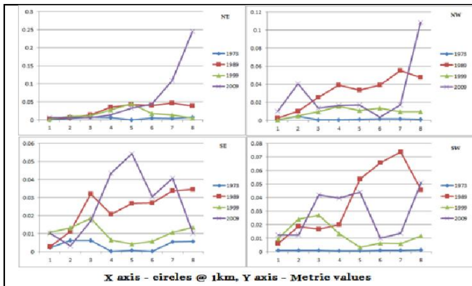

Fig 10c: Patch density – zonewise, circle wise

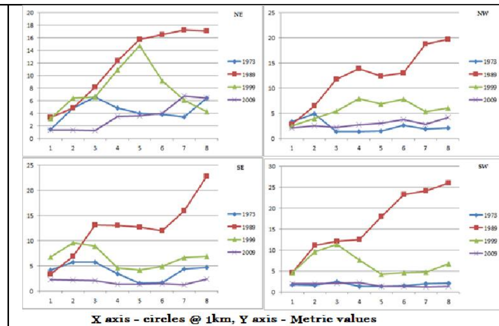

Figure 10d: Zonewise and circle wise LSI

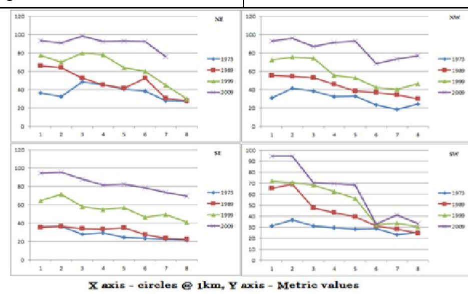

Figure 10e: Cohesion Index

7.2 Shimoga: Number of Patches (NP) NP reflects the extent of fragmentation 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. The results (figure 11a) show that center is in the verge of clumping especially accelerated in 2005 and 2010, while the outskirts remain fragmented and are highly fragmented during 2005 and 2010 in 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.

Largest patch index: LPI (figure 11b) 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 .

Patch Density (PD): PD refers to number of patches per unit considered. This index is computed using a raster data with4 neighbour 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 11c explains the patch density at patch level.

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 11d) 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.

Interspersion and Juxtaposition (IJI): Interspersion and Juxtaposition approaches 0 when the distribution of adjacencies among unique patch types becomes increasingly uneven. IJI is equal to 100 when all the patch types are equally adjacent to all other patch types. Analysis on the study region indicates (Figure 11e) 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

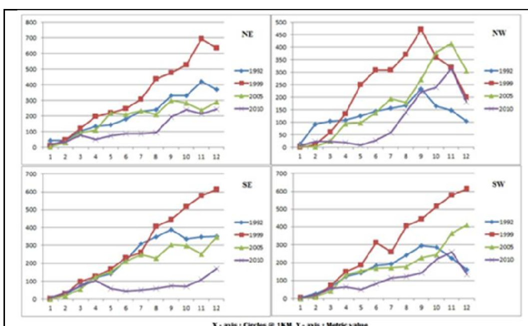

Fig 11a: Number of patches (zonewise, circlewise)

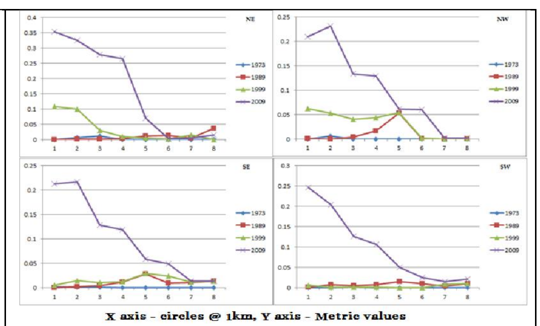

Fig 11b: Largest Patch – zonewise, circlewise

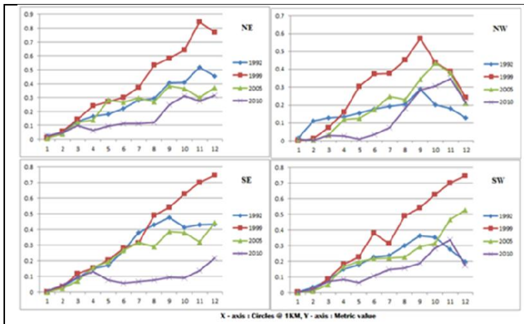

Fig 11c: Patch density – zonewise, circle wise

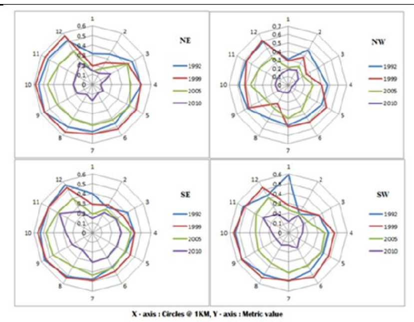

Figure 11d: Zonewise and circle wise NLSI

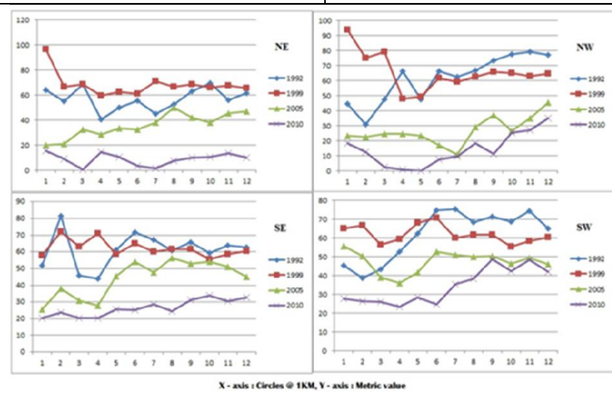

Figure 11e: IJI Index

7.3 Hubli-Dharwad: Figure 12a illustrates that the Hubli city is forming patched that are clumped at the center but is relatively disaggregated at the outskirts, but compared to the year 2005, 2010 results is indicative of clumped urban patch in the city and is directive of forming a single urban patch. Clumped patches are more prominent in NE and SW directions and patches is agglomerating to a single urban patch. The case with Dharwad is different as in case it has started to disaggregate in 2010, until 2010 there were less no of urban patches in the city, which have increased in 2010, which is indicative of sprawled growth in the city.

Patch density (Fig 12b) is calculated on a raster map, using a 4 neighbor algorithm. Patch density increases with a greater number of patches within a reference area. Patch density in Hubli and Dharwad was higher in 2005 as the number of patches is higher in all directions and gradients due to increase in the urban built area, which remarkably increased post 1989(SW, NE) and subsequently reduced in 2010, indicating the sprawl in the region in in early 90's and started to clump during 2010. The patch density is quite high in the outskirts also in both the cities.

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. Results (Fig 12c) indicate that there were low LSI values in 1989 as there was minimal urban areas in both Hubli and Dharwad which were mainly aggregated at the center. Since late 1990's both the city has been experiencing dispersed growth in all direction and circles and Hubli reached the peak of dispersed growth during 2005, towards 2010 it shows a aggregating trend in Hubli, whereas In Dharwad it is showing an dispersed growth.

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 explains the adjacencies of urban patches that the city center is getting more and more clumped with similar class (Urban) and outskirts are relatively sharing different internal adjacencies. Hubli city shows more adjacent clumped growth, whereas Dharwad shows more disaggregated growth (Fig. 12d).

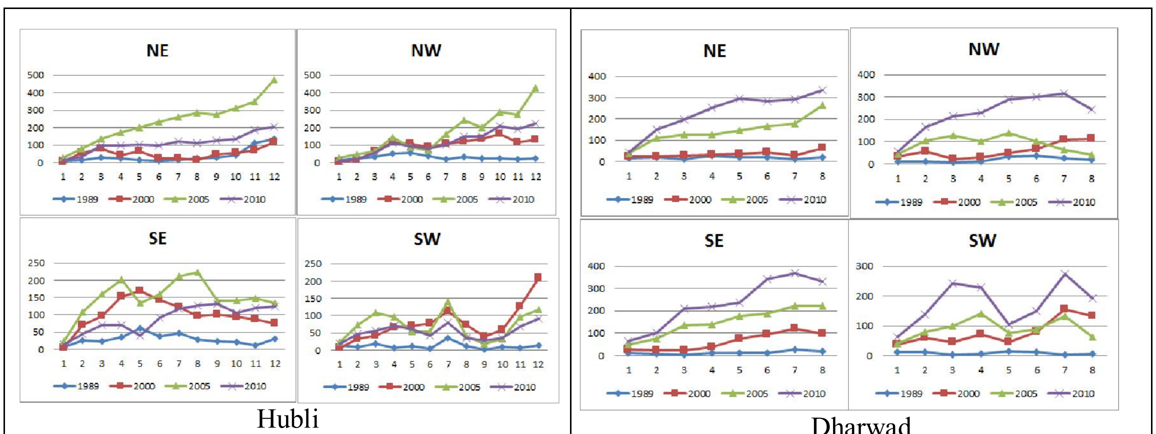

Figure 12a: Number of urban patches (Directionwise, circlewise)

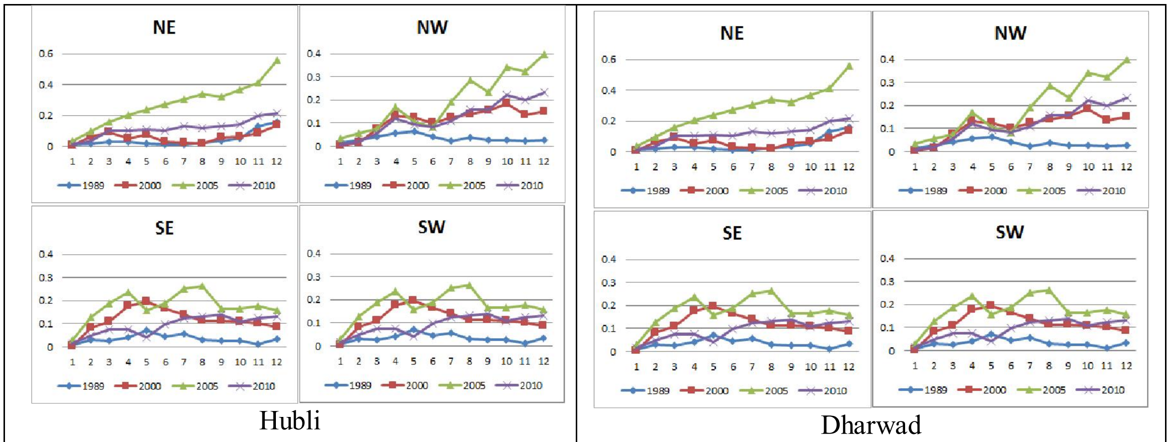

Figure 12b: Patch Density (Directionwise, circlewise)

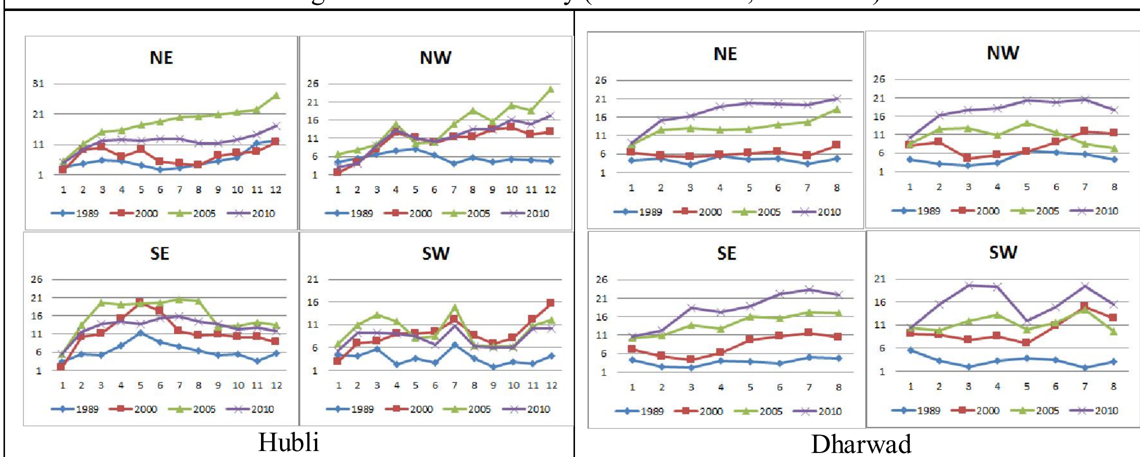

Figure 12c: Landscape Shape Index (Directionwise, circlewise)

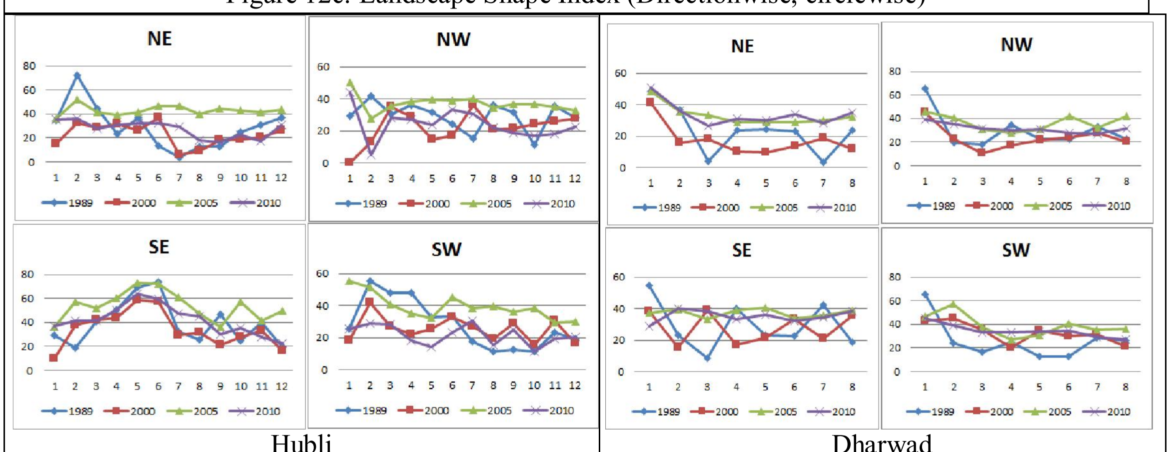

Figure 12d: Percentage of Like Adjacencies (Direction wise, circle wise)

7.4 Gulbarga: Number of patches: Figure 13a 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.

The patch density (Figure 13b) is calculated on a raster data, using a 4 neighbour 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 (fig 13c).

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 13d 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.

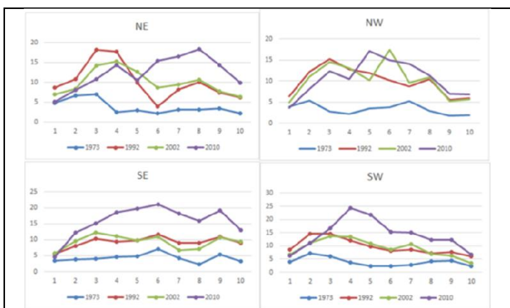

Fig 13a: Number of urban patches (zonewise, circlewise)

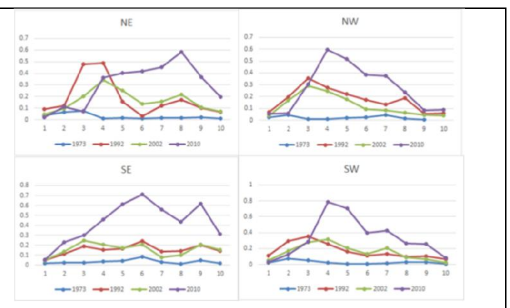

Fig 13b: Patch density – zonewise, circle wise

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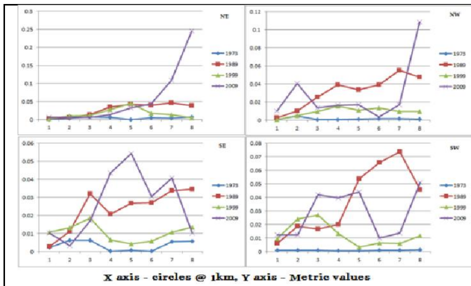
<td>
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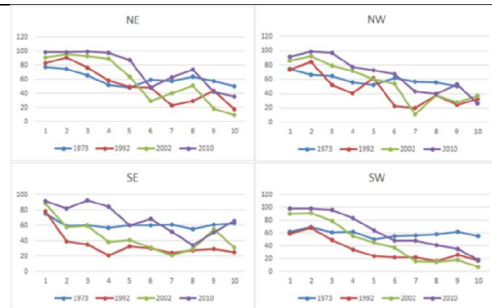
<td>
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<td>Fig 13c: Patch density – zonewise, circle wise</td>
<td>Figure 13d: Zonewise and circle wise Patch cohesion</td>
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7.5 Raichur: Number of patches: Figure 14a illustrates the temporal dynamics of number of patches. Urban patches are less at the center in 1970's as the growth was concentrated in central pockets. There was a gradual increase in the number of patches in 80's and further in 2001, but these patches are forming a single patch during 2010 indicative that the urban area is getting clumped as a single patch at the center, but in the buffer regions there has been a tremendous increase in 2001. Clumped patches at center are more prominent in NE and SE directions and patches is agglomerating to a single urban patch.

The patch density (Fig 14b) is calculated on a raster map, using a 4 neighbor algorithm. Patch density increases with a greater number of patches within a reference area. Patch density was higher in 1989 and 2001 as the number of patches is higher at the in all directions. Ensity declined at the central gradients in 2010. In the outskirts the patch density has increased in early 2000's which is indicative of sprawl in the region and PD is low at center indicating the clumped growth during late 2000's, 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. Results (Fig 14c) indicate that there were low LSI values in 1973 as there were minimal urban areas and were concentrated in the center. Since 1990's the city has been experiencing dispersed growth in all direction and circles, towards 2010 it shows a aggregating trend at the center as the value is close to 1, whereas it is very high in the outskirts indicating the peri urban development.

Patch cohesion index measures the physical connectedness of the corresponding patch type. Figure 14d 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.

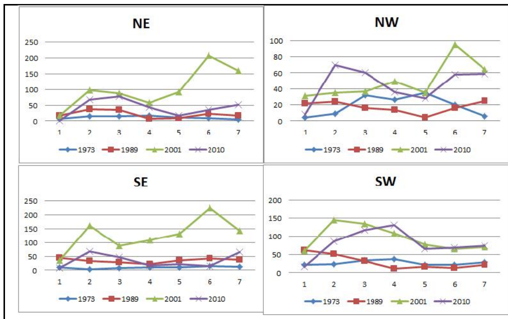

Fig 14a: Number of patches index (zonewise, circlewise)

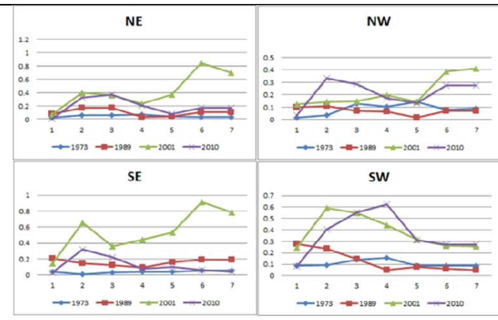

Fig 14b: Patch density – zonewise, circle wise

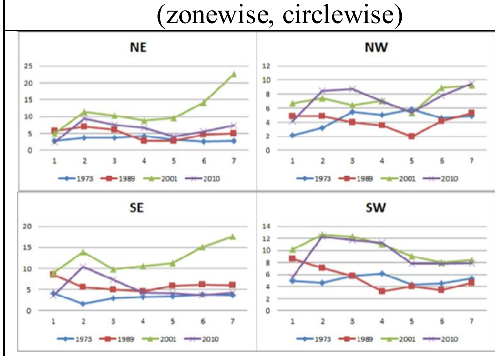

Fig 14c: Landscape shape index – zonewise, circle wise

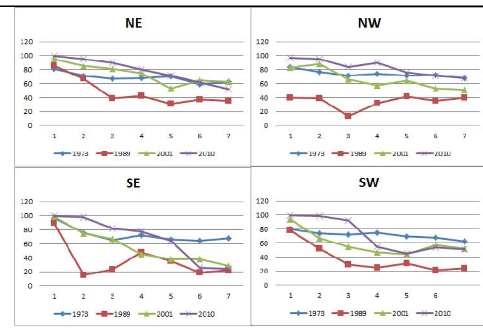

Figure 14d: Zonewise and circle wise Patch cohesion

7.6 Bellary: Number of Urban Patch (Np) is a landscape metric indicates the level of fragmentation and ranges from 0 (fragment) to 100 (clumpiness). Figure 15a illustrates the temporal dynamics of number of patches. Increased number of patches indicates the land fragmentation and decreasing of increased patches indicates the fragmented landscape forming a single land use patch. As observed from the figure, urban patches are least in the landscape in 1970's as the growth was concentrated on at the city center. In 2000's Bellary city saw a gradual increase in the number of patches, which can be understood as features of fragmented landscape, further in 2010, these patches are increasingly forming a single patch at the center during 2010 indicative that the urban area forming a single clump patch destroying all other land uses, but the case in the buffer regions has been indicative of higher fragmentation during the latter years. Clumped patches at center are more prominent in NE and SE directions and patches are agglomerating to a single urban patch.

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. Results (Fig 15b) indicate that there were low LSI values in 1973 as there were minimal urban areas and were concentrated in the center. Since 2001 the city has been experiencing dispersed growth in all direction and in every gradient, towards 2010 it shows aggregating urban land use at the center forming a simple shaped single patch as the value is close to 1, whereas, the values of LSI are very high in the outskirts indicating a complex shaped growth with also is indicative of fragmented landscape in the buffer zone.

Largest Patch Index (LPI): This metric reveals information about the largest patches in the Landscape and its native existence. Urban patch again counted as a largest patch in 2010 in the central area of Bellary, whereas the buffer zones had a mixture of other patches. Figure 15c is illustrative of results of this analysis.

Patch cohesion index measures the physical connectedness of the corresponding patch type. Figure 15d describes the results of the analysis of physical connectedness of the urban patch with the higher cohesion value (in 2010) indicating that the urban count is higher in the considered study region. Lower values in 1973 illustrate that the urban patches were rare in the landscape.

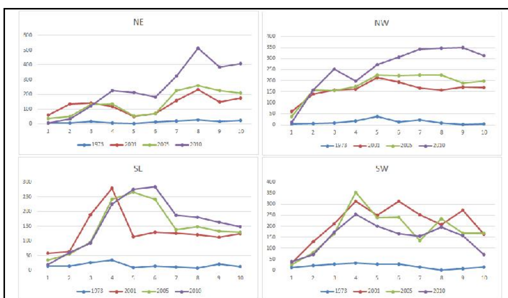

Fig 14a: Number of patches index (zonewise, circlewise)

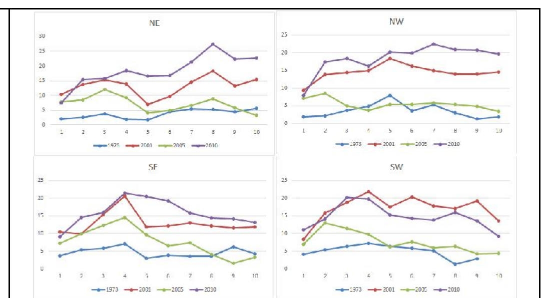

Fig 14b: Landscape shape index – zonewise, circle wise

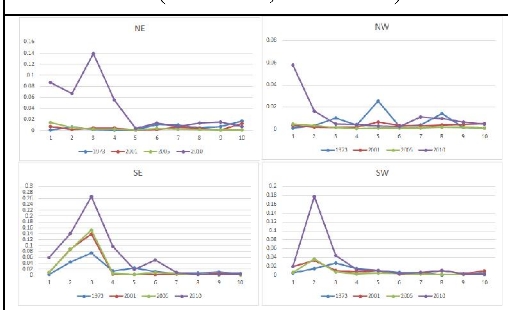

Fig 14c: Landscape patch index – zonewise, circle wise

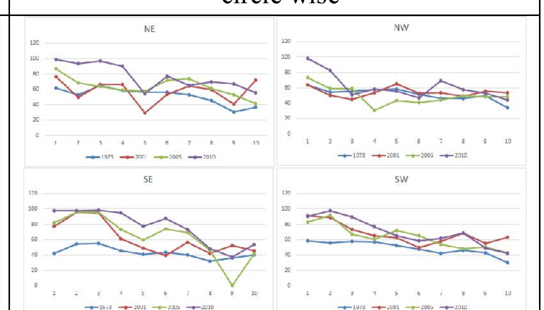

Figure 14d: Zonewise and circle wise Patch cohesion

7.7 Belgaum: Number of Patches (NP): NP is a type of metric describes the growth of particular patches wither in a aggregated or fragmented patch growth in the region and also explains the underlying urbanization process. Number of Patch is always equal to or greater 1, NP = 1 indicates that there is only 1 patch of a particular class, showing aggregated growth, larger values of NP indicate fragmented growth. The results indicate that there has been an extensive growth of urban patches in all directions post 2000, which have increased specially in the buffer zones, which indicate the growth of sprawl area as fragments represented in figure 15a.

Patch Density (PD): PD is a landscape metric which is quite similar to number of patches but gives density about the landscape in analysis, The values vary from 0 to 1, 0 indicating a single homogenous patch, whereas values towards 1 indicates fragmented growth as the patches increase the patch density increases. The results as observed that from the figure 15b below, the landscape under study is becoming fragmented towards the outskirts, but at the core of the city, clumped patches are prominent in all directions specially post 2000. In 2012, this substantially decreased in almost all directions mainly due to patches getting clumped and forming a single patch.

Landscape Shape Index (LSI): LSI provides a measure of class aggregation or clumpiness depending on the shape of the class in analysis, when the value of LSI is 1, this indicates clumped growth, the increasing values of LSI indicates aggregation. Figure 15c represents the results of LSI. The results of metric puts out a fact that in 2012 landscape class shapes are becoming more complex indicative of fragmented growth, with comparison of simple shape in 1980's a clumped growth

Cohesion measures the physical connectivity between adjacent patches; the cohesion value 0 indicates disaggregation and no inter connectivity between patches and higher value indicates clumped and connectivity between patches. Value higher post 2000 tells us that the fragmented landscape if forming a single clumped patch.in almost all gradients and zones (Figure 15d).

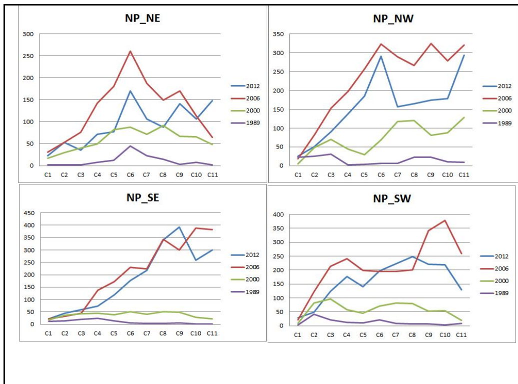

Fig 15a: Number of patches index (zonewise, circlewise)

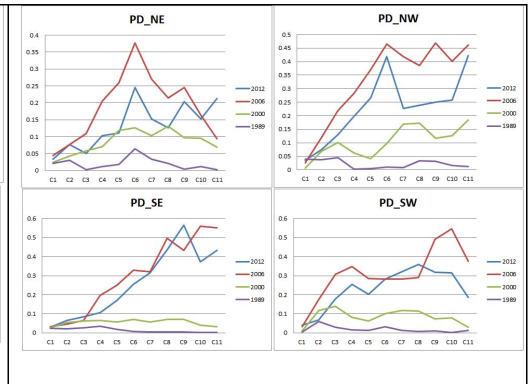

Fig 15b: Patch density – zonewise, circle wise

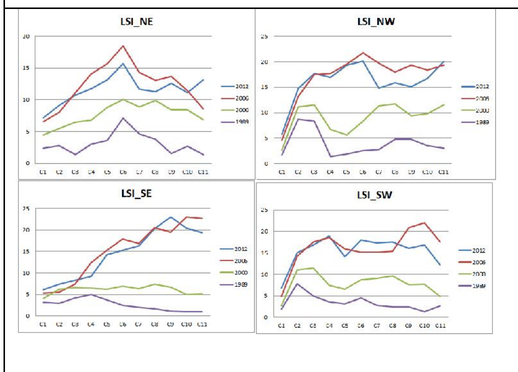

Fig 15c: Landscape shape index – zonewise, circle wise

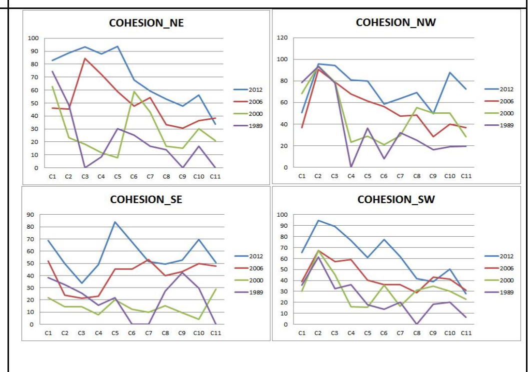

Figure 15d: Zonewise and circle wise Patch cohesion

8.0 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 cities, Megalopolis of Karnataka, India. Land cover analysis reveals that there was reduction in the vegetation cover during the past two decades in the study regions.

Land use analysis reveals of increase in urban category increased in last two decades. Spatial analysis revealed that land use in the outskirts is fragmented. 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. 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 all these cities take a note of the situation and plan for further developmental urban activities in a sound, flexible and sustainable way.

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References

1. Currit, N., Easterling, W. 2009. Globalization and population drivers of rural-urban land-use change in Chihauhua, Mexico. Land Use Policy, 26, 535–544.
2. Ramachandra, T. V., Kumar, U., 2009. Land surface temperature with land cover dynamics: multi-resolution, spatio-temporal data analysis of Greater Bangalore, International Journal of Geoinformatics, 5 (3), 43-53
3. Torrens, P., Alberti, M., 2000. Measuring sprawl. CASA working paper series 27. UCL. http://www.casa.ucl.ac.uk/publications/workingpapers.asp
4. Yu, X. J., Ng, C.N., 2007. Spatial and temporal dynamics of urban sprawl along two urban-rural transects: a case study of Guangzhou, China. Landsc. Urban Plann. 79, 96–109.
5. Jenerette, G.D., Wu, J., 2001. Analysis and simulation of land-use change in the Central Arizona – Phoenix region, USA. Landsc. Ecol. 16, 611–626.
6. Sudhira, H.S., Ramachandra, T.V., and Jagadish, K.S., 2004. Urban sprawl: metrics, dynamics and modelling using G1S. Int. J Applied Earth Observation and Geoinformation, 5, 29-39.
7. Bharath.H.Aithal, Sannadurgappa D. and Ramachandra. T.V., 2012, Insights to Urban Dynamics through Landscape Spatial Pattern Analysis, Journal of Applied Earth Observation and Geoinformation, 18: 329-343.
8. Bharath.H.Aithal, D.Sannadurgappa and Ramachandra. T.V., 2010. Urban growth monitoring through spatio-temporal analysis, In proceedings Lake 2010: Wetlands, Biodiversity and Climate change, 22-24 Dec 2010, Satish Dhawan Auditorium, Indian Institute of Science, Bangalore.
9. Anindita Dasgupta, Uttam Kumar and Ramachandra. T.V., 2010. Urban growth monitoring through spatio-temporal analysis, In proceedings Lake 2010: Wetlands, Biodiversity and Climate change, 22-24 Dec 2010, Satish Dhawan Auditorium, Indian Institute of Science, Bangalore.
10. Priyadarshini J Shetty, Shashikala V and Ramachandra. T.V., 2010. Urban Footprint Dynamics in Indian Metropolis, In proceedings Lake 2010: Wetlands, Biodiversity and Climate change, 18-20 oct 2010, Satish Dhawan Auditorium, Indian Institute of Science, Bangalore.

Publications

1. Ramachandra T V, Bharath H Aithal and Durgappa D S, 2012. Insights to urban dynamics through landscape spatial pattern analysis, Int. J Applied Earth Observation and Geoinformation, 18; 329-343, http://dx.doi.org/10.1016/j.jag.2012.03.005.
2. Ramachandra TV and Bharath H Aithal, 2013. Understanding urban sprawl dynamics of Gulbarga - Tier II city in Karnataka through spatio-temporal data and spatial metrics, International journal of Geomatics and Geosciences, 3(3), 388-404
3. Ramachandra. T V and Bharath H Aithal, 2012. Spatio temporal patterns of urban growth in Bellary, Tier II City of Karnataka State, India, International Journal of Emerging Technologies in Computational and Applied Sciences, 3(2), 201-212.
4. Ramachandra. T V and Bharath H Aithal, 2012. Spatio-Temporal Dynamics of Urbanising Landscape in Twin Cities in Karnataka, India, International Journal of Artificial Intelligence and Mechatronics, 1(5), 87-98.
5. Ramachandra T V and Bharath H Aithal, 2012, Spatio-temporal dynamics of landscape dynamics in Shimoga, Tier II city, Karnataka State, India, International Journal of Emerging Technology and Advanced Engineering, 2(9):563-576,
6. Ramachandra T V, Bharath H. Aithal and Sreekantha S, 2012 (invited). Spatial metrics based landscape structure and dynamics assessment for an emerging Indian megapolis, International Journal of Advanced Research in Artificial Intelligence, 1(1): Pp 49-57.
7. Bharath H Aithal, Bharath Settur, Sanna Durgappa D, Ramachandra T V, 2012. Empirical patterns of the influence of Spatial Resolution of Remote Sensing Data on Landscape Metrics, International Journal of Engineering Research and Applications (IJERA), 2(3):767-775.
8. Bharath H Aithal, Bharath Setturu, Sreekantha S, Sanna Durgappa D and Ramachandra T. V., (2012), Spatial patterns of urbanization in Mysore: Emerging Tier II City in Karnataka, Proceedings of National Remote Sensing Users Meet, NRSC, Hyderabad, India, 16-17 February, 2012.
9. Bharath H Aithal and Ramachandra T. V., (2012), Spatial Pattern analysis of two urbanising Tier II cities in Karnataka using open source GIS - GRASS, Proceedings OSGEO-INDIA: FOSS4G 2012- FIRST NATIONAL CONFERENCE "Open Source Geospatial Resources to Spearhead Development and Growth" 25-27th October 2012, IIIT Hyderabad.
10. Bharath H Aithal, Sanna durgappa D and Ramachandra T V, 2012. Status of wetlands in urbanising Tier II cities of Karnataka, In proceedings Lake 2012: Lake 2012: National Conference on Conservation and Management of Wetland Ecosystems, 06-08, Nov 2012, School of Environmental Sciences, Mahatma Gandhi University, Kottayam, Kerala.
11. Vinay S, Bharath H Aithal and Ramachandra T V, 2012. Spatio Temporal dynamics of Raichur City, In proceedings Lake 2012: National Conference on Conservation and Management of Wetland Ecosystems,

06-08, Nov 2012, School of Environmental Sciences, Mahatma Gandhi University, Kottayam, Kerala

12. Bharath H Aithal, Sreekantha S, Sanna Durgappa D and Ramachandra T V, (2012), Spatial patterns of urbanization in an emerging Tier II City, Mysore, Proceedings of Samanway 2012, Indian Institute of Science, Bangalore, India, 03-04 March, 2012.
13. Bharath Setturu, Bharath H Aithal and Ramachandra T V, 2012. Peri-Urban to Urban Landscape Patterns Elucidation through Spatial Metrics, International Journal of Engineering Research and Development. 2(12), 58-81.
15. Bharath H Aithal, Vinay S, and Ramachandra T V, 2013, Comprehension of temporal land use dynamics in urbanising landscape, Proceedings of National Remote Sensing Users Meet, NRSC, Hyderabad, India, 21-22 February, 2013.
16. Bharath H Aithal, Bharath Setturu, Sanna Durgappa D and Ramachandra T V, (2012), Effectiveness of landscape Spatial Metrics with reference to the Spatial Resolutions of Remote Sensing Data, In India Conference on Geo-spatial Technologies & Applications 2012, IIT Bombay, Mumbai, India, 12-14 April, 2012.
17. Ramachandra T V, Bharath H Aithal, 2013, Urbanisation and Sprawl in the Tier II City: Metrics, Dynamics and Modelling Using Spatio-Temporal Data, International Journal of Remote Sensing Applications, 3(2), 66-75.
18. Ramachandra T V, Bharath H Aithal, Vinay S, 2013, Land Use Land Cover Dynamics in a Rapidly Urbanising Landscape, SCIT Journal, 13, 1-14.
19. Bharath. H. Aithal and Ramachandra. T.V., 2013. Measuring urban sprawl in Tier II cities of Karnataka, India, In Proceedings IEEE Global Humanitarian Technology Conference: South Asia Satellite (IEEE-GHTC-SAS), 2013, Techno Park, Trivandrum, Kerala, India, 23-24 Aug. 2013.
20. Bharath H Aithal, Vinay S and Ramachandra T V, 2013, Prediction of Land use dynamics in the rapidly urbanising landscape using land change modeller. In proceedings Fourth International Joint Conference on Advances in Engineering and Technology, AET 2013, December 13-14, NCR Delhi, India.
21. Bharath H Aithal, Vinay S and Ramachandra T V, Modelling and Simulation of Urbanization in Greater Bangalore. In proceedings of National Geospatial Data Infrastructure 2013, November 29-30, IIT Bombay, Mumbai, India
22. Ramachandra T V, Bharath H Aithal, Vinay S, Uttam Kumar, Joshi N V and Venugopal Rao, 2013, Modelling Urbanisation pattern, In proceedings of the 30th Annual In-House Symposium on Space Science and Technology, ISRO-IISc Space Technology Cell, Indian Institute of Science, Bangalore, India, 7-8 November, 2010.

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Insights to urban dynamics through landscape spatial pattern analysis

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ABSTRACT

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. Main objective of this research is to quantify the urban dynamics using temporal remote sensing data with the help of well-established landscape metrics. Bangalore being one of the rapidly urbanising landscapes in India has been chosen for this investigation. Complex process of urban sprawl was modelled using spatio temporal analysis. Land use analyses show 584% growth in built-up area during the last four decades with the decline of vegetation by 66% and water bodies by 74%. Analyses of the temporal data reveals an increase in urban built up area of 342.83% (during 1973–1992), 129.56% (during 1992–1999), 106.7% (1999–2002), 114.51% (2002–2006) and 126.19% from 2006 to 2010. The Study area was divided into four zones and each zone is further divided into 17 concentric circles of 1 km incrementing radius to understand the patterns and extent of the urbanisation at local levels. The urban density gradient illustrates radial pattern of urbanisation for the period 1973–2010. Bangalore grew radially from 1973 to 2010 indicating that the urbanisation is intensifying from the central core and has reached the periphery of the Greater Bangalore. Shannon's entropy, alpha and beta population densities were computed to understand the level of urbanisation at local levels. Shannon's entropy values of recent time confirms dispersed haphazard urban growth in the city, particularly in the outskirts of the city. This also illustrates the extent of influence of drivers of urbanisation in various directions. Landscape metrics provided in depth knowledge about the sprawl. Principal component analysis helped in prioritizing the metrics for detailed analyses. The results clearly indicates that whole landscape is aggregating to a large patch in 2010 as compared to earlier years which was dominated by several small patches. The large scale conversion of small patches to large single patch can be seen from 2006 to 2010. In the year 2010 patches are maximally aggregated indicating that the city is becoming more compact and more urbanised in recent years. Bangalore was the most sought after destination for its climatic condition and the availability of various facilities (land availability, economy, political factors) compared to other cities. The growth into a single urban patch can be attributed to rapid urbanisation coupled with the industrialisation. Monitoring of growth through landscape metrics helps to maintain and manage the natural resources.

1. Introduction

Urbanisation and Urban Sprawl: Urbanisation is a dynamic process involving changes in vast expanse of land cover with the progressive concentration of human population. The process entails switch from spread out pattern of human settlements to compact growth in urban centres. Rapidly urbanising landscapes attains inordinately large population size leading to gradual collapse in the urban services evident from the basic problems in housing, slum, lack of treated water supply, inadequate infrastructure, higher pollution levels, poor quality of life, etc. Urbanisation is a product of demographic explosion and poverty induced rural-urban migration. Globalisation, liberalization, privatization are the agents fuelling urbanisation in most parts of India. However, unplanned urbanisation coupled with the lack of holistic approaches, is leading to lack of infrastructure and basic amenities.

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Hence proper urban planning with operational, developmental and restorative strategies is required to ensure the sustainable management of natural resources.

Urban dynamics involving large scale changes in the land use depend on (i) nature of land use and (ii) the level of spatial accumulation. Nature of land use depends on the activities that are taking place in the region while the level of spatial accumulation depends on the intensity and concentration. Central areas have a high level of spatial accumulation of urban land use (as in the CBD: Central Business District), while peripheral areas have lower levels of accumulation. Most economic, social or cultural activities imply a multitude of functions, such as production, consumption and distribution. These functions take place at specific locations depending on the nature of activities – industries, institutions, etc.

Unplanned growth would involve radical land use conversion of forests, surface water bodies, etc. with the irretrievable loss of ground prospects (Pathan et al., 1989, 1991, 1993, 2004). The process of urbanisation could be either in the form of townships or unplanned or organic. Many organic towns in India are now influencing large-scale infrastructure development, etc. Due to the impetus from the National government through development schemes such as JNNURM (Jawaharlal Nehru National Urban Renewal Mission), etc. The focus is on the fast track development through an efficient infrastructure and delivery mechanisms, community participation, etc.

The urban population in India is growing at about 2.3% per annum with the global urban population increasing 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; World Urbanisation Prospects, 2005). The increase in urban population in response to the growth in urban areas is mainly due to migration. There are 48 urban agglomerations/cities having a population of more than one million in India (in 2011).

Urbanisation often leads to the dispersed haphazard development in the outskirts, which is often referred as sprawl. Thus urban sprawl is a consequence of social and economic development of a certain region under certain circumstances. This phenomenon is also defined as an uncontrolled, scattered suburban development that depletes local resources due to large scale land use changes involving the conversion of open spaces (water bodies, parks, etc.) while increasing carbon footprint through the spurt in anthropogenic activities and congestion in the city (Peiser, 2001; Ramachandra and Kumar, 2009). Urban sprawl increasingly has become a major issue facing many metropolitan areas. Due to lack of visualization of sprawl a priori, these regions are devoid of any infrastructure and basic amenities (like supply of treated water, electricity, sanitation facilities). Also these regions are normally left out in all government surveys (even in national population census), as this cannot be grouped under either urban or rural area. Understanding this kind of growth is very crucial in order to provide basic amenities and more importantly the sustainable management of local natural resources through decentralized regional planning.

Urban sprawl has been captured indirectly through socioeconomic indicators such as population growth, employment opportunity, number of commercial establishments, etc. (Brueckner, 2000; Lucy and Philips, 2001). However, these techniques cannot effectively identify the impacts of urban sprawl in a spatial context. In this context, availability of spatial data at regular interval through space-borne remote sensors are helpful in effectively detecting and monitoring rapid land use changes (e.g., Chen et al., 2000; Epstein et al., 2002; Ji et al., 2001; Lo and Yang, 2002; Dietzel et al., 2005). Urban sprawl is characterised based on various indicators such as growth, social, aesthetic, decentralisation, accessibility, density, open space, dynamics, costs, benefits, etc. (Bhatta, 2009a,b, 2010). Further, Galster et al. (2001), has identified parameters such as density, continuity, concentration, clustering, centrality, nuclearity, proximity and mixed uses for quantifying sprawl. Urbanisation and sprawl analysis would help the regional planners and decision makers to visualize growth patterns and plan to facilitate various infrastructure facilities. In the context of rapid urban growth, development should be planned and properly monitored to maintain internal equilibrium through sustainable management of natural resources. Internal equilibrium refers to the urban system and its dynamics evolving harmony and thus internally limiting impacts on the natural environment consequent to various economic activities with the enhanced growth of population, infra-structure, services, pollution, waste, etc. (Barredo and Demicheli, 2003). Due to globalisation process, the cities and towns in India are experiencing rapid urbanisation consequently lacking appropriate infrastructure and basic amenities. Thus understanding the urban dynamics considering social and economic changes is a major challenge. The social and economic dynamics trigger the change processes in urban places of different sizes ranging from large metropolises, cities and small towns. In this context, the

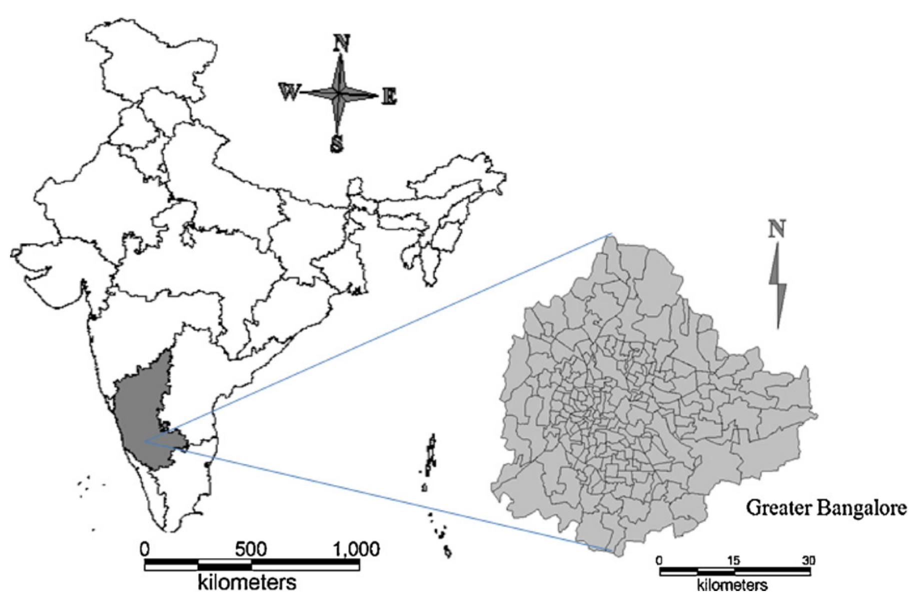


Fig. 1. Study area: Greater Bangalore.

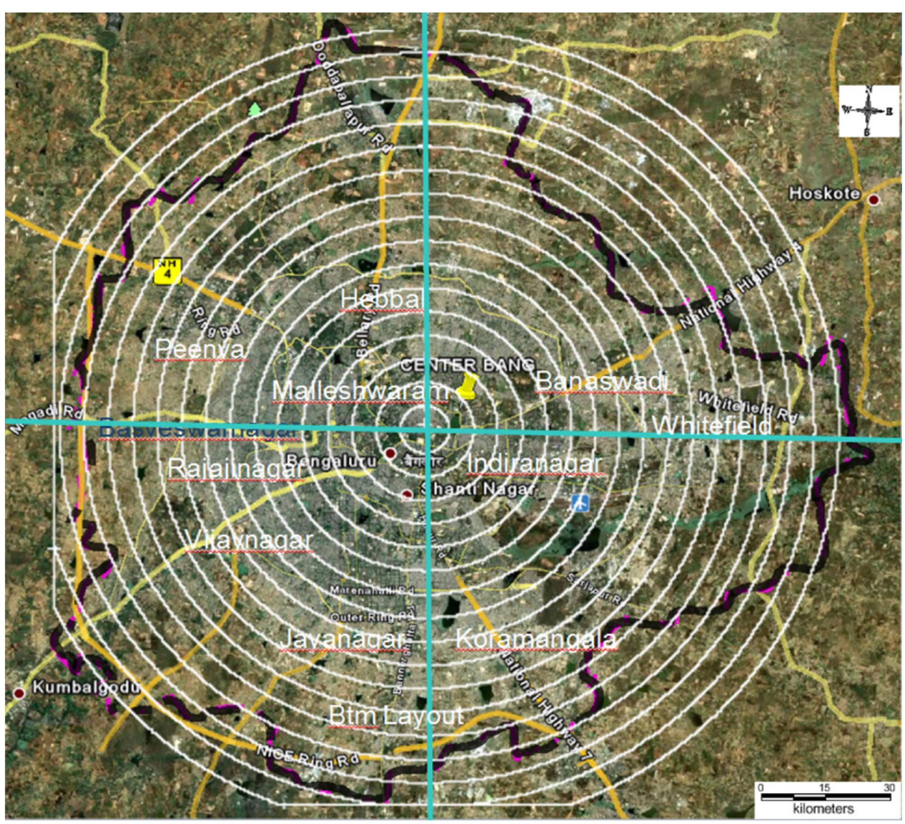
Table 1
Materials used in the analysis.

Data	Year	Purpose
Landsat Series Multispectral sensor (57.5 m)	1973	Land use analysis
Landsat Series Thematic mapper (28.5 m) and enhanced thematic mapper sensors	1992, 1999, 2002, 2006, 2010	Land use analysis
Survey of India (SOI) toposheets of 1:50,000 and 1:250,000 scales		Boundary and base layers
Census data	2001	Population density ward-wise

analysis of urban dynamics entails capturing and analyzing the process of changes spatially and temporally (Sudhira et al., 2004; Tian et al., 2005; Yu and Ng, 2007).

Land use Analysis and Gradient approach: The basic information about the current and historical land cover and land use plays a major role in urban planning and management (Zhang et al., 2002). Land-cover essentially indicates the feature present on the land surface (Janssen, 2000; Lillesand and Kiefer, 2002; Sudhira et al., 2004). Land use relates to human activity/economic activity on piece of land under consideration (Janssen, 2000; Lillesand and Kiefer, 2002; Sudhira et al., 2004). This analysis provides various uses of land as urban, agriculture, forest, plantation, etc., specified as per USGS classification system (http://landcover.usgs.gov/pdf/anderson.pdf) and National Remote Sensing Centre, India (http://www.nrsc.gov.in). Mapping landscapes on temporal scale provide an opportunity to monitor the changes, which is important for natural resource management and sustainable planning activities. In this regard, "Density Gradient metrics" with the time series spatial data analysis are potentially useful in measuring urbanisation and sprawl (Torrens and Alberti, 2000). Density gradient metrics include sprawl density gradient, Shannon's entropy, alpha and beta population densities, etc. This paper presents temporal land use analysis for rapidly urbanising Bangalore and density gradient metrics have been computed to evaluate and monitor urban dynamics. Landscape dynamics have been unraveled from temporally discrete data (remote sensing data) through spatial metrics (Crews-Meyer, 2002). Landscape metrics (longitudinal data) integrated with the conventional change detection techniques would help in monitoring land use changes (Rainis, 2003). This has been demonstrated through the application in many regions (Kienast, 1993; Luque et al., 1994; Simpson et al., 1994; Thibault and Zipperer, 1994; Hulshoff, 1995; Medley et al., 1995; Zheng et al., 1997; Palang et al., 1998; Sachs et al., 1998; Pan et al., 1999; Lausch and Herzog, 1999).

Further, landscape metrics were computed to quantify the patterns of urban dynamics, which helps in quantifying spatial patterns of various land cover features in the region (McGarigal and Marks, 1995) and has been used effectively to capture urban dynamics similar to the applications in landscape ecology (Gustafson, 1998; Turner et al., 2001) for describing ecological relationships such as connectivity and adjacency of habitat reservoirs (Geri et al., 2010; Jim and Chen, 2009). Herold et al. (2002, 2003) quantifies urban land use dynamics using remote sensing data and landscape metrics in conjunction with the spatial modelling of urban growth. Angel et al. (2007) have considered five metrics for measuring the sprawl and five attributes for characterizing the type of sprawl. Spatial metrics were used for effective characterisation of the sprawl by quantifying landscape attributes (shape, complexity,



Source: Google earth

Fig. 2. Division of the study area into concentric circles of incrementing radius of 1 km.

Table 2
Prioritised landscape metrics.

	Indicators	Type of metrics and formula	Range	Significance/description
1	Number of urban patches	Patch metrics NPU = n NP equals the number of patches in the landscape	NPU > 0, without limit	Higher the value more the fragmentation
2	Perimeter Area Weighted Mean Ratio. PARA_AM	*Edge metrics* PARA _AM = P_{ij}/A_{ij} P_{ij} = perimeter of patch ij A_{ij} = area weighted mean of patch ij $\mathrm{AM} = \sum_{j=1}^{n} x_{ij} \left[\left(\frac{a_{ij}}{\sum_{j=1}^{a} a_{ij}} \right) \right]$	≥0, without limit	PARA AM is a measure of the amount of ‘edge’ for a landscape or class. PARA AM value increases with increasing patch shape complexity
3	Landscape Shape Index (LSI)	Shape Metrics LSI $= \frac{e_i}{\min e_i}$ e_i = total length of edge (or perimeter) of class i in terms of number of cell surfaces; includes all landscape boundary and background edge segments involving class i. min e_i = minimum total length of edge (or perimeter) of class i in terms of number of cell surfaces (see below)	LSI > 1, without limit	LSI = 1 when the landscape is a single square or maximally compact patch; LSI increases without limit as the patch type becomes more disaggregated
4.	Clumpiness	Compactness/contagion/dispersion metrics $\mathrm{CLUMPY} = \begin{bmatrix} \frac{G_i - P_i}{P_i} & \text{for} \quad G_i < P_i \& P_i < 5, \text{ else} \\ \frac{G_i - P_i}{1 - P_i} & \end{bmatrix}$ $G_i = \left(\frac{g_{ii}}{\sum_{k=1}^{m} g_{ii}} - \min e_i \right)$ 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≤ CLUMPY ≤1	It equals 0 when the patches are distributed randomly, and approaches 1 when the patch type is maximally aggregated
5.	Aggregation index	Compactness/contagion/dispersion metrics $AI = \left[\sum_{i=1}^{m} \left(\frac{g_{ii}}{\max \to g_{ii}} \right) P_i \right] \times 100$ g_{ii} = number of like adjacencies (joins) between pixels of patch type (class) i based on the single count method. max-g_{ii} = maximum number of like adjacencies (joins) between pixels of patch type class i based on single count method. P_i = 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.
6.	Interspersion and Juxtaposition	Compactness/contagion/dispersion metrics $\mathrm{IJI} = \frac{-\sum_{i=1}^{m} \sum_{k=i+1}^{m} [(e_{ik}/E) \ln(e_{ik}/E)]}{\ln(0.5[m(m-1)])} \times 100$ 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	IJI is used to measure patch adjacency. IJI approach 0 when distribution of adjacencies among unique patch types becomes increasingly uneven; is equal to 100 when all patch types are equally adjacent to all other patch types

etc.). Jiang et al. (2007) used 13 geospatial indices for measuring the sprawl in Beijing and proposed an urban Sprawl Index combining all indices. This approach reduces computation and interpretation time and effort. However, this approach requires extensive data such as population, GDP, land-use maps, floor-area ratio, maps of roadways/highways, urban city center spatial maps, etc. This confirms that landscape metrics aid as important mathematical tool for characterising urban sprawl efficiently. Population data along with geospatial indices help to characterise the sprawl (Ji et al., 2006) as population is one of the causal factor driving land use changes. These studies confirm that spatio-temporal data along with landscape metrics, population metrics and urban modelling would help in understanding and evaluating the spatio temporal patterns of urban dynamics.

2. Objective

The objective of this study is to understand the urbanisation and urban sprawl process in a rapidly urbanising landscape, through spatial techniques involving temporal remote sensing data, geographic information system with spatial metrics. This involved (i) temporal analysis of land use pattern, (ii) exploring interconnection and effectiveness of population indices, Shannon's entropy for quantifying and understanding urbanisation and (iii) understanding the spatial patterns of urbanisation at landscape level through metrics.

3. Study area

The study has been carried out for a rapidly urbanising region in India. Greater Bangalore is the administrative, cultural, commercial, industrial, and knowledge capital of the state of Karnataka, India with an area of 741 sq km and lies between the latitude 12°39′00″ to 13°13′00″N and longitude 77°22′00″ to 77°52′00″E. Bangalore city administrative jurisdiction was redefined in the year 2006 by merging the existing area of Bangalore city spatial limits with 8 neighbouring Urban Local Bodies (ULBs) and 111 Villages of Bangalore Urban District. Bangalore has grown spatially more

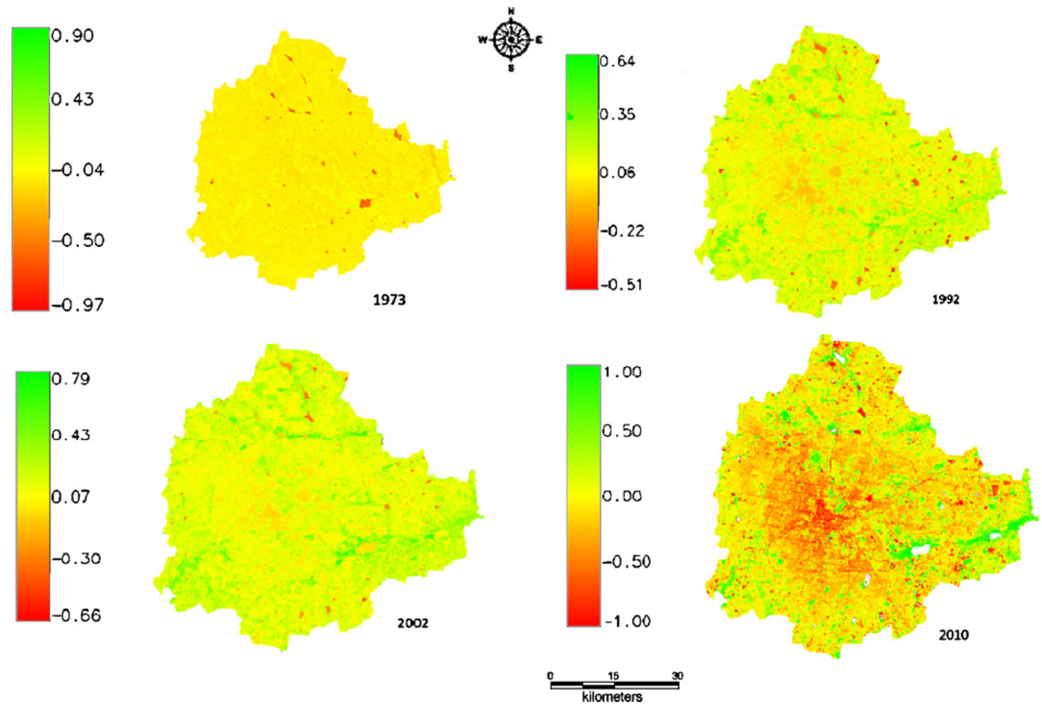


Fig. 3. Land cover changes from 1973 to 2010.

than ten times since 1949 (~69–716 square kilometres) and is the fifth largest metropolis in India currently with a population of about 7 million (Ramachandra and Kumar, 2008, 2010; Sudhira et al., 2007). Bangalore city population has increased enormously from 6,537,124 (in 2001) to 9,588,910 (in 2011), accounting for 46.68% growth in a decade. Population density has increased from as 10,732 (in 2001) to 13,392 (in 2011) persons per sq. km. The per capita GDP of Bangalore is about $2066, which is considerably low with limited expansion to balance both environmental and economic needs (Fig. 1).

4. Material and methods

Urban dynamics was analysed using temporal remote sensing data of the period 1973–2010. The time series spatial data acquired from Landsat Series Multispectral sensor (57.5 m), Thematic mapper and enhanced thematic mapper plus (28.5 m) sensors for the period 1973–2010 were downloaded from public domain (http://glcf.umiacs.umd.edu/data). Survey of India (SOI) toposheets of 1:50,000 and 1:250,000 scales were used to generate base layers of city boundary, etc. City map with ward boundaries were digitized from the BBMP (Bruhat Bangalore Mahanagara Palike) map. Population data was collected from the Directorate of Census Operations, Bangalore region (http://censuskarnataka.gov.in). Table 1 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, Google earth, Bhuvan (http://earth.google.com, http://bhuvan.nrsc.gov.in).

5. Data analysis involved

5.1. Pre-processing

The remote sensing data obtained were geo-referenced, rectified and cropped pertaining to the study area. Geo-registration of remote sensing data (Landsat data) has been done using ground control points collected from the field using pre calibrated GPS (Global Positioning System) and also from known points (such as road intersections, etc.) collected from geo-referenced topographic maps published by the Survey of India. The Landsat satellite 1973 images have a spatial resolution of 57.5 m × 57.5 m (nominal resolution) were resampled to 28.5 m comparable to the 1989–2010 data which are 28.5 m × 28.5 m (nominal resolution). Landsat ETM+ bands of 2010 were corrected for the SLC-off by using image enhancement techniques, followed by nearest-neighbour interpolation.

5.2. Vegetation cover analysis

Normalised Difference Vegetation Index (NDVI) was computed to understand the changes in the vegetation cover during the study

Table 3
Temporal land use dynamics.

Class→	Urban		Vegetation		Water		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
1999	24163	35.37	31272	45.77	1542	2.26	11346	16.61
2002	25782	37.75	26453	38.72	1263	1.84	14825	21.69
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

period. NDVI is the most common measurement used for measuring vegetation cover. It ranges from values −1 to +1. Very low values of NDVI (−0.1 and below) correspond to soil or barren areas of rock, sand, or urban builtup. Zero indicates the water cover. Moderate values represent low-density vegetation (0.1–0.3), while high values indicate thick canopy vegetation (0.6–0.8).

5.3. 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 and (v) 60% of the training data has been used for classification, while the balance is used for validation or accuracy assessment.

Land use analysis was carried out using supervised pattern classifier – Gaussian maximum likelihood algorithm. This has been proved superior classifier as it uses various classification decisions using probability and cost functions (Duda et al., 2000). Mean and covariance matrix are computed using estimate of maximum likelihood estimator. Accuracy assessment to evaluate the performance of classifiers (Mitrakis et al., 2008; Ngigi et al., 2008; Gao and Liu, 2008), was done with the help of field data by testing the statistical significance of a difference, computation of kappa coefficients (Congalton et al., 1983; Sha et al., 2008) and proportion of correctly allocated cases (Gao and Liu, 2008). Recent remote sensing data (2010) was classified using the collected training samples. 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. For earlier time data, training polygon along with attribute details were compiled from the historical published topographic maps, vegetation maps, revenue maps, etc.

Table 4
Kappa values and overall accuracy.

Year	Kappa coefficient	Overall accuracy (%)
1973	0.88	72
1992	0.63	77
1999	0.82	76
2002	0.77	80
2006	0.89	75
2010	0.74	78

Table 5
Shannon entropy.

	NE	NW	SE	SW
1973	0.173	0.217	0.126	0.179
1992	0.433	0.509	0.399	0.498
1999	0.504	0.658	0.435	0.607
2002	0.546	0.637	0.447	0.636
2006	0.65	0.649	0.610	0.695
2010	0.771	0.812	0.640	0.778

Application of maximum likelihood classification method resulted in accuracy of 76% in all the datasets. Land use was computed using the temporal data through open source program GRASS – Geographic Resource Analysis Support System (http://grass.fbk.eu/). Land use categories include (i) area under vegetation (parks, botanical gardens, grass lands such as golf field), (ii) built up (buildings, roads or any paved surface, (iii) water bodies (lakes/tanks, sewage treatment tanks), and (iv) others (open area such as play grounds, quarry regions, etc.).

5.4. Density gradient analysis

Urbanisation pattern has not been uniform in all directions. To understand the pattern of growth *vis-a-vis* agents, the region has been divided into 4 zones based on directions – Northwest (NW), Northeast (NE), Southwest (SW) and Southeast (SE), respectively (Fig. 2) based on the Central pixel (Central Business district). The growth of the urban areas in respective zones was monitored through the computation of urban density for different periods.

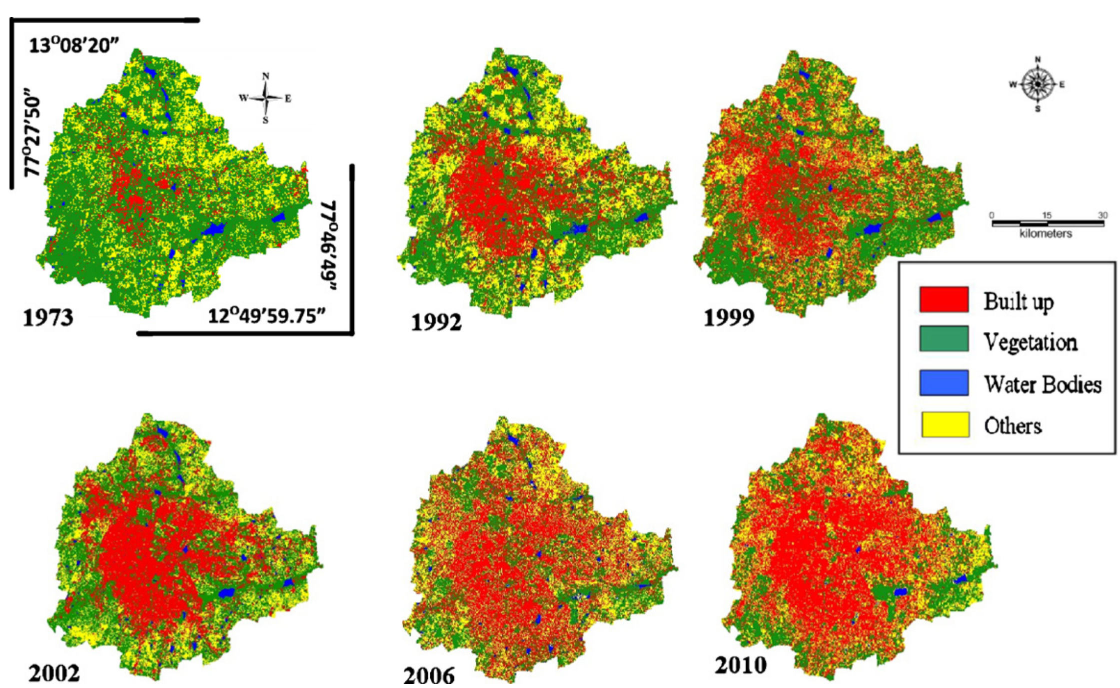


Fig. 4. Land use changes in Greater Bangalore.

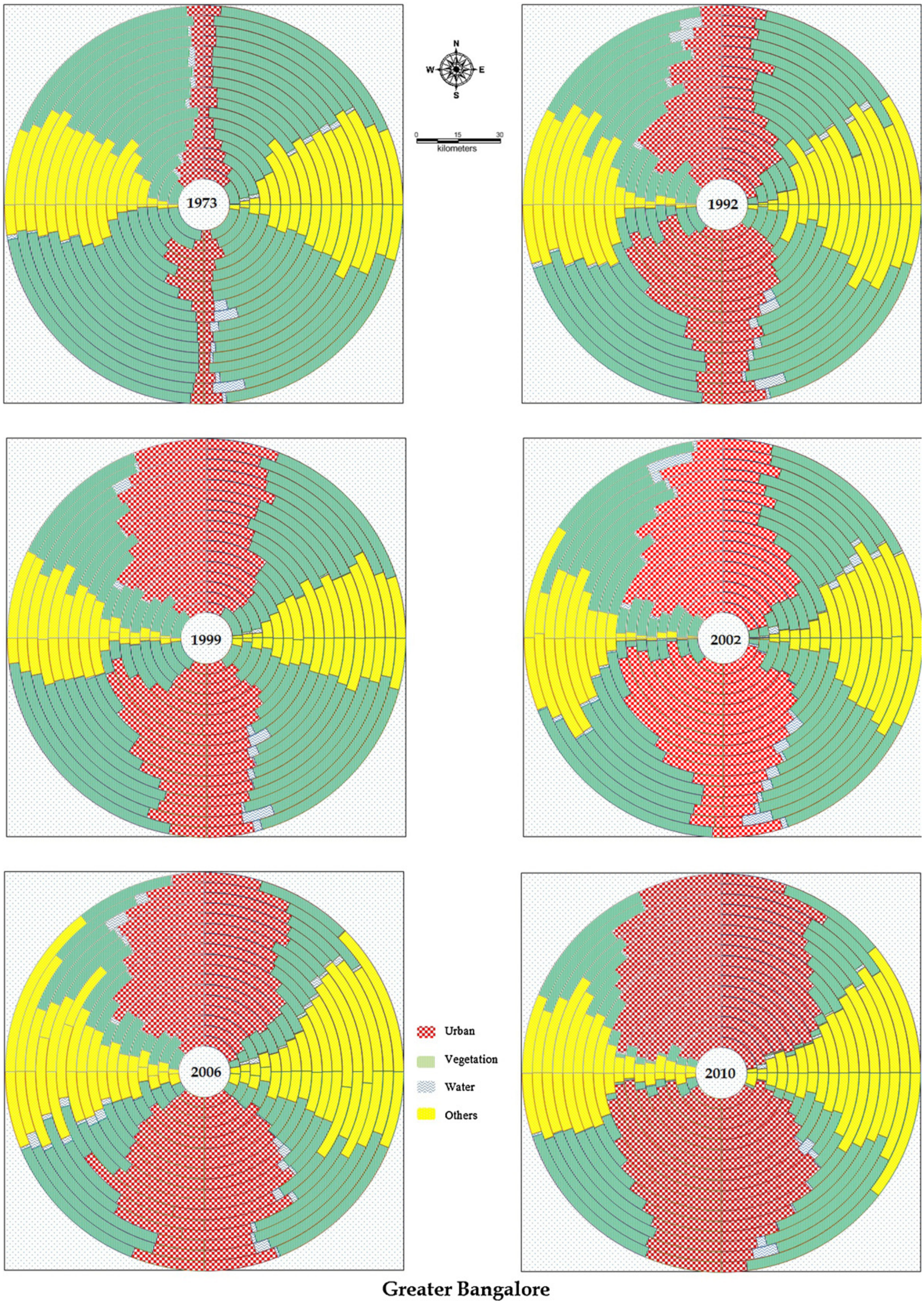


Fig. 5. Zone-wise and Gradient-wise temporal land use.

5.5. Division of these zones to concentric circles and computation of metrics

Further each zone was divided into concentric circle of incrementing radius of 1 km from the centre of the city (Fig. 2), that would help in visualizing and understanding the agents responsible for changes at local level. These regions are comparable to the administrative wards ranging from 67 to 1935 hectares. This helps in identifying the causal factors and locations experiencing various levels (sprawl, compact growth, etc.) of urbanisation in response to the economic, social and political forces. This approach (zones, concentric circles) also helps in visualizing the forms of urban sprawl (low density, ribbon, leaf-frog development). The built up density in each circle is monitored overtime using time series analysis.

5.6. 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., 2004) was computed for each zones. Shannon's entropy (H_n) given in Eq. (1), provides the degree of spatial concentration or dispersion of geographical variables among 'n' concentric circles across Zones.

$$H_n = -\sum_{i=1}^{n} \mathrm{Pi}\log(Pi) \tag{1}$$

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 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 $\log n$.

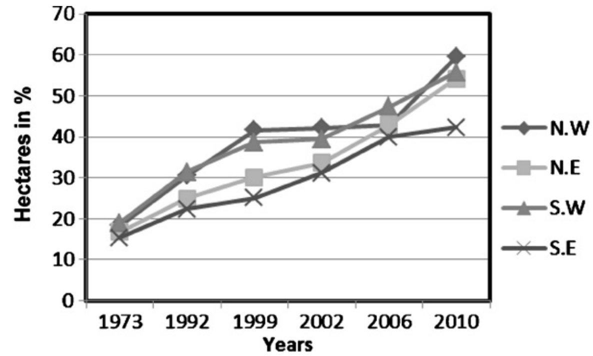


Fig. 6. Built up density across years from 1973 to 2010.

5.7. Computation of alpha and beta population density

Alpha and beta population densities were calculated for each circle with respect to zones. Alpha population density is the ratio of total population in a region to the total builtup area, while Beta population density is the ratio of total population to the total

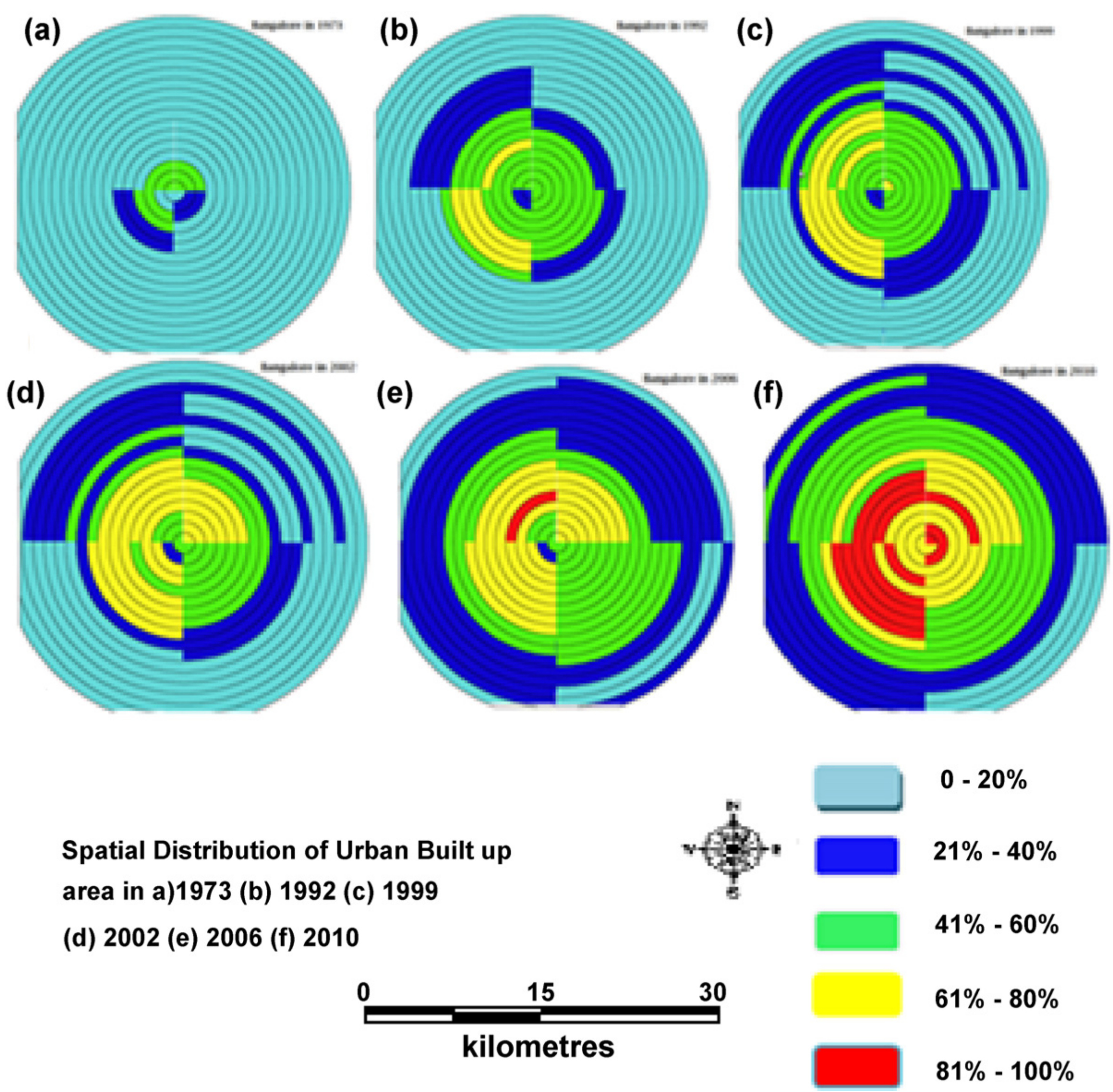


Fig. 7. Gradient analysis of Greater Bangalore- Builtup density circlewise and zonewise.

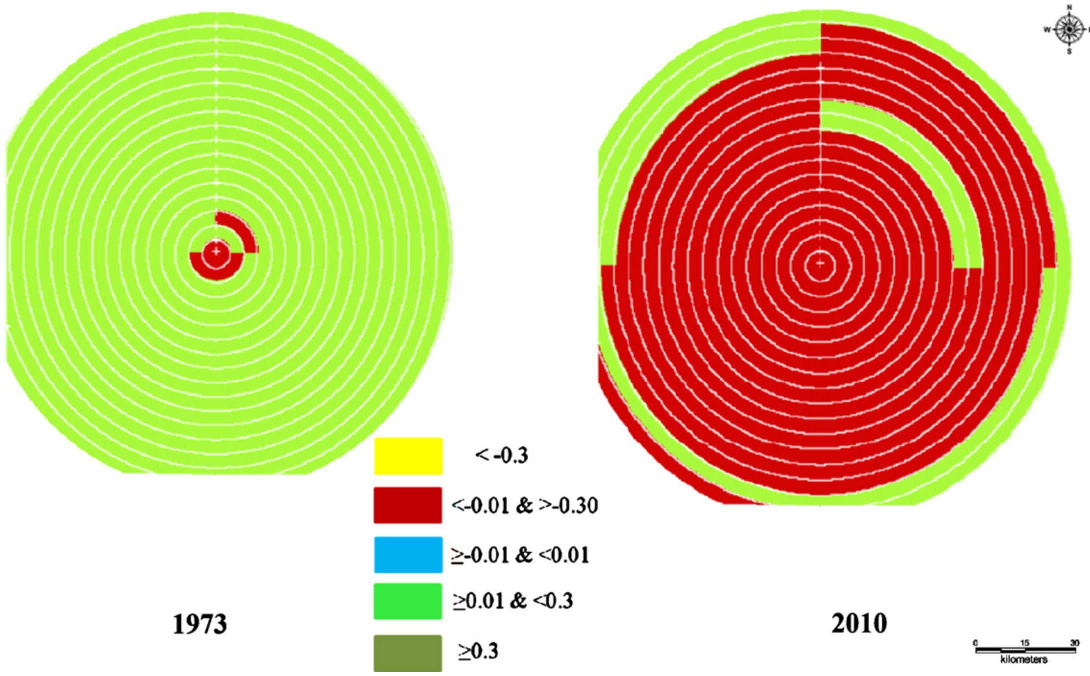


Fig. 8. NDVI gradients – circlewise and zone wise.

geographical area. These metrics have been often used as the indicators of urbanisation and urban sprawl and are given by:

$$\alpha\,\text{density} = \frac{\text{total population}}{\text{total built up}} \tag{2}$$

$$\beta\,\text{density} = \frac{\text{total population}}{\text{total geographic area}} \tag{3}$$

5.8. Gradient analysis of NDVI images of 1973 and 2010

The NDVI gradient was generated to visualize the vegetation cover changes in the specific pockets of the study area.

5.9. Calculation of landscape metrics

Landscape metrics provide quantitative description of the composition and configuration of urban landscape. 21 spatial metrics chosen based on complexity, centrality and density criteria (Huang et al., 2007) to characterize urban dynamics, were computed zone-wise for each circle using classified land use data at the landscape level with the help of FRAGSTATS (McGarigal and Marks, 1995). The metrics include the patch area (built up (total land area), Percentage of Landscape (PLAND), Largest Patch Index (percentage of landscape), number of urban patches, patch density, perimeter-area fractal dimension (PAFRAC), Landscape Division Index (DIVISION)), edge/border (edge density, area weighted mean patch fractal dimension (AWMPFD), perimeter area weighted mean ratio (PARA_AM), mean patch fractal dimension (MPFD), total edge (TE), shape (NLSI – Normalized Landscape Shape Index), Landscape Shape Index (LSI)), epoch/contagion/dispersion (Clumpiness, percentage of like adjacencies (PLADJ), total core area (TCA), ENND coefficient of variation, Aggregation Index, interspersion and juxtaposition). These metrics were computed for each region and principal component analysis was done to prioritise metrics for further detailed analysis.

5.10. Principal component analysis

Principal component analysis (PCA) is a multivariate statistical analysis that aids in identifying the patterns of the data while reducing multiple dimensions. PCA through Eigen analysis transforms a number of (possibly) correlated variables into a (smaller) number of uncorrelated variables called principal components. The first principal component accounts for as much of the variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible (Wang, 2009). PCA helped in prioritizing six landscape metrics based on the relative contributions of each metrics in the principal components with maximum variability (Table 2).

6. Results and discussion

Vegetation cover of the study area was analysed through NDVI. Fig. 3 illustrates that area under vegetation has declined from 72% (488 sq. km in 1973) to 21% (145 sq. km in 2010).

6.1. Land use analysis

a. Land use analysis for the period 1973 to 2010 has been done using Gaussian maximum likelihood classifier and the temporal land use details are given in Table 3. Fig. 4 provides the land use in the region during the study period. Overall accuracy of the classification was 72% (1973), 77% (1992), 76% (1999), 80% (2002), 75% (2006) and 78% (2010) respectively. There has been a 584% growth in built-up area during the last four decades with the decline of vegetation by 66% and water bodies by 74%. Analyses of the temporal data reveals an increase in urban built up area of 342.83% (during 1973–1992), 129.56% (during 1992–1999), 106.7% (1999–2002), 114.51% (2002–2006) and 126.19% from 2006 to 2010. Fig. 5 illustrates the zone-wise temporal land use changes at local levels. Table 4 lists kappa statistics and overall accuracy.
b. Urban density is computed for the period 1973–2010 and is depicted in Fig. 6, which illustrates that there has been a linear

Table 6
Alpha and beta density in each region – zone wise, circle wise.

Radius	North east		North west		South east		South west	
	Alpha	Beta	Alpha	Beta	Alpha	Beta	Alpha	Beta
1	1526.57	1385.38	704.71	496.05	3390.82	2437.32	3218.51	2196.83
2	333.99	288.58	371.00	280.41	983.51	857.04	851.23	555.33
3	527.99	399.83	612.02	353.50	904.02	701.47	469.19	369.67
4	446.99	343.51	360.72	286.39	602.14	441.66	308.47	262.52
5	152.43	122.74	255.11	226.72	323.07	243.02	236.56	188.26
6	123.16	94.91	370.22	324.12	306.48	203.54	58.57	51.12
7	73.65	57.96	254.49	207.29	54.77	32.64	77.07	73.09
8	38.16	27.80	71.54	62.38	57.22	30.52	61.85	57.29
9	44.99	29.54	92.73	69.97	51.74	26.00	37.60	31.90
10	48.43	25.22	93.51	55.75	33.31	17.44	25.99	16.61
11	50.32	23.77	100.55	56.56	22.69	11.63	35.90	18.75
12	42.34	17.92	67.36	34.36	27.12	11.29	25.52	10.86
13	59.87	22.20	40.87	17.71	30.66	9.44	35.59	11.92
14	54.10	18.38	24.51	9.91	24.16	5.35	19.77	5.49
15	60.81	20.73	21.48	8.98	19.52	3.50	26.41	6.56
16	62.17	23.79	46.81	12.83	16.92	2.96	66.19	17.35
17	16.54	24.76	53.30	14.58	16.45	2.02	41.40	10.36

growth in almost all directions (except NW direction, which show stagnation during 1999–2006). Developments in various fronts with the consequent increasing demand for housing have urbanised these regions evident from the drastic increase in the urban density during the last two decades. In order to understand the level of urbanisation and quantification at local level, each zone is further divided into concentric circles.

6.2. Density gradient analysis

Study area was divided into concentric incrementing circles of 1 km radius (with respect to centroid or central business district). The urban density gradient given in Fig. 7 for the period 1973–2010, illustrates radial pattern of urbanisation and concentrated closer to the central business district and the growth was minimal in 1973. Bangalore grew intensely in the NW and SW zones in 1992 due to the policy of industrialization consequent to the globalisation. The industrial layouts came up in NW and housing colonies in SW and urban sprawl was noticed in others parts of the Bangalore. This phenomenon intensified due to impetus to IT and BT sectors in SE and NE during post 2000. Subsequent to this, relaxation of FAR (floor area ratio) in mid-2005, lead to the spurt in residential sectors, paved way for large-scale conversion of land leading to intense urbanisation in many localities. This also led to the compact growth at central core areas of Bangalore and sprawl at outskirts which are deprived of basic amenities. The analysis showed that Bangalore grew radially from 1973 to 2010 indicating that the urbanisation has intensified from the city centre and reached the periphery of Greater Bangalore. Gradients of NDVI given in Fig. 8 further corroborate this trend. Shannon entropy, alpha and beta population densities were computed to understand the level of urbanisation at local levels.

6.3. Calculation of Shannon's entropy, alpha and beta densities

Shannon entropy was calculated for the years 1973, 1992, 1999, 2002, 2006, 2010 listed in Table 5. The value of entropy ranges from zero to $\log(n)$. Lower entropy values indicate aggregated or compact development. Higher the value or closer to $\log(n)$ indicates the sprawl or dispersed or sparse development. Grater

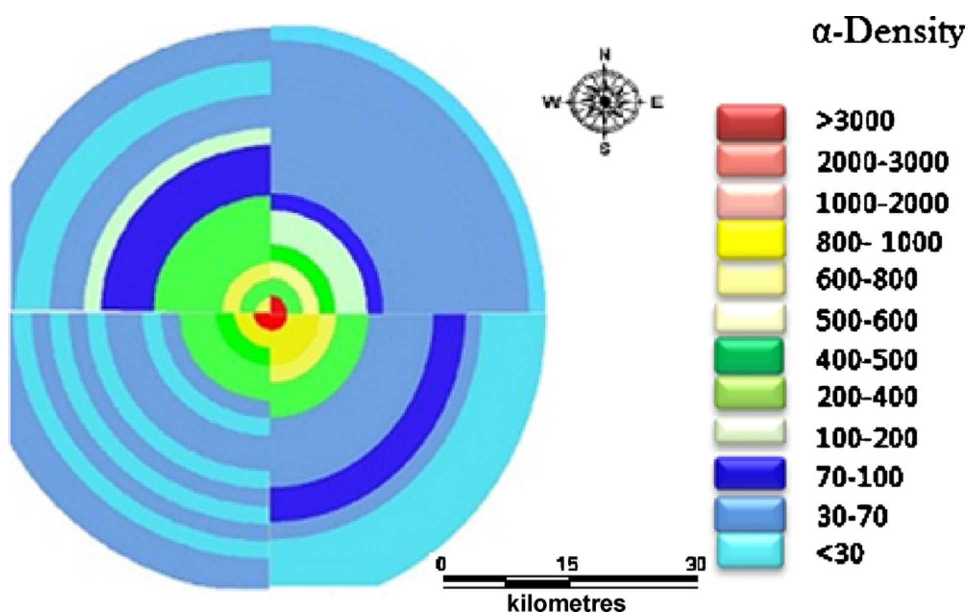


Fig. 9. Alpha density– zonewise for each local regions.

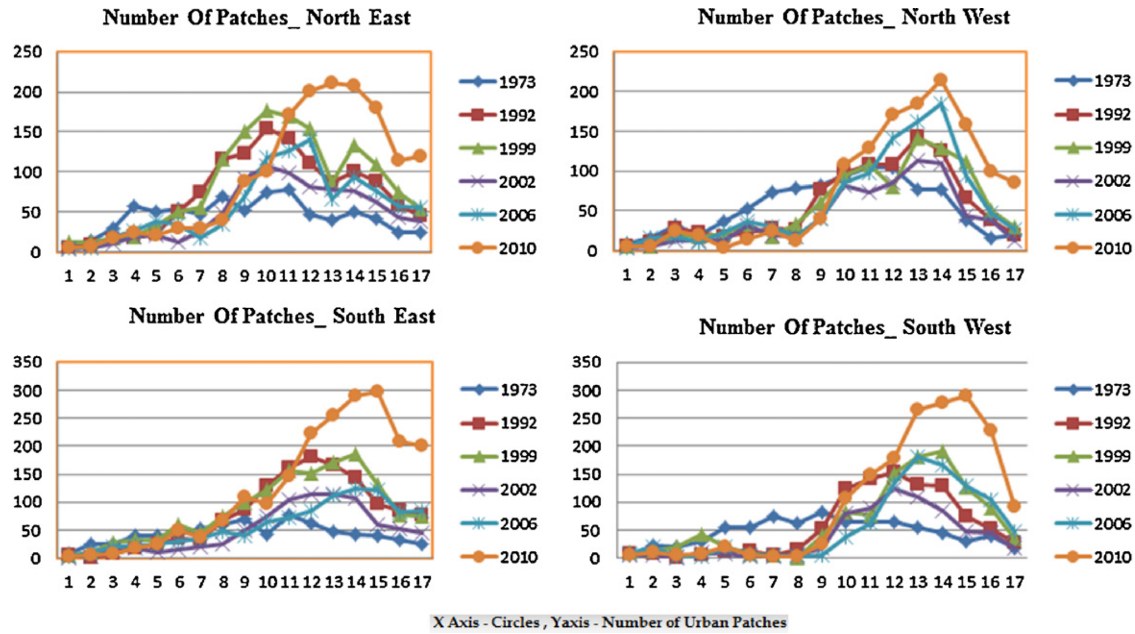


Fig. 10. Number of patches – direction-wise/circle-wise.

Bangalore grew and has almost reached the threshold of growth ($\log(n) = \log(17) = 1.23$) in all directions. Lower entropy values of 0.126 (SE), 0.173 (NE), 0.170 (SW) and 0.217 (NW) during 1970s show aggregated growth. However, the dispersed growth is noticed at outskirts in 1990s and post 2000s (0.64 (SE), 0.771 (NE), 0.812 (NW) and 0.778 (SW)).

Shannon's entropy values of recent time confirm dispersed haphazard urban growth in the city, particularly in city outskirts. This also illustrates the extent of influence of drivers of urbanisation in various directions. In order to understand this phenomenon, alpha and beta population densities were computed.

Table 6 lists alpha and beta densities zone-wise for each circle. These indices (both alpha and beta densities) indicate that there has been intense growth in the centre of the city and SE, SW and NE core central area has reached the threshold of urbanisation.

Gradients of alpha and beta densities is given in Fig. 9, illustrates urban intensification in the urban centre and sprawl is also evident NW and SW regions.

6.4. Landscape metrics

Landscape metrics were computed circle-wise for each zones. Percentage of Landscape (PLAND) indicates that the Greater Bangalore is increasingly urbanised as we move from the centre of the city towards the periphery. This parameter showed similar trends in all directions. It varied from 0.043 to 0.084 in NE during 1973. This has changed in 2010, and varies from 7.16 to 75.93. NW also shows a maximum value of 87.77 in 2010. Largest patch index indicate that the city landscape is fragmented in all direction during 1973 due to heterogeneous landscapes. However, this has aggregated

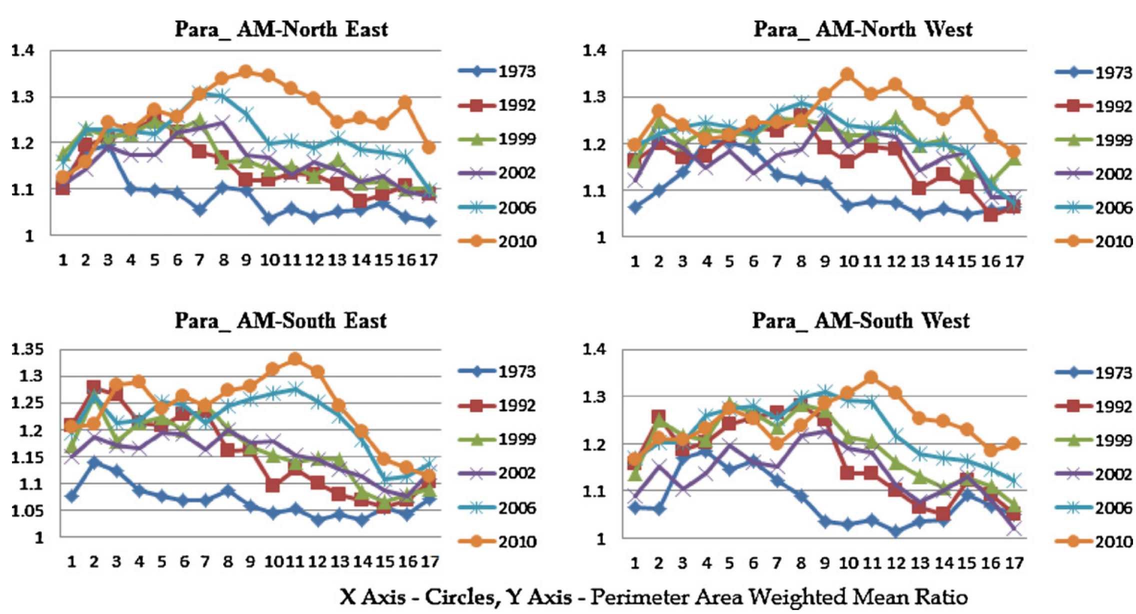


Fig. 11. PARA_AM – direction-wise/circle-wise.

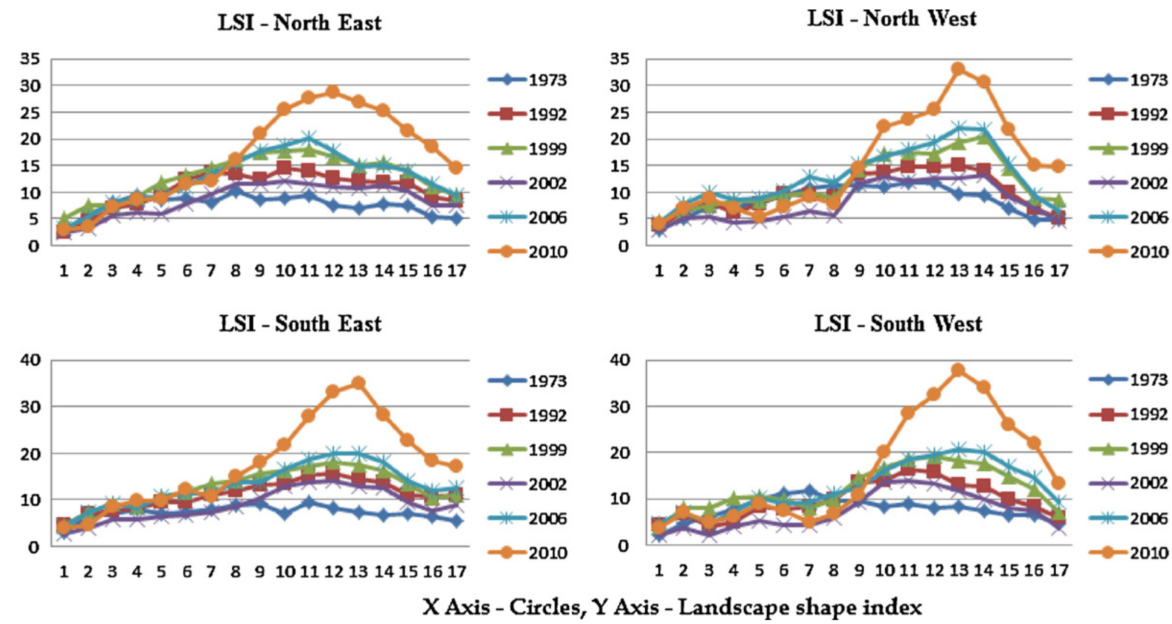


Fig. 12. LSI – direction-wise/circle-wise.

to a single patch in 2010, indicating homogenisation of landscape. The patch sizes were relatively small in all directions till 2002 with higher values in SW and NE. In 2006 and 2010, patches reached threshold in all directions except NW which showed a slower trend. Largest patches are in SW and NE direction (2010). The patch density was higher in 1973 in all directions due to heterogeneous land uses, which increased in 2002 and subsequently reduced in 2010, indicating the sprawl in early 2000s and aggregation in 2010. PAFRAC had lower values (1.383) in 1973 and maximum of 1.684 (2010) which demonstrates circular patterns in the growth evident from the gradient. Lower edge density was in 1973, increased drastically to relatively higher value 2.5 (in 2010). Clumpiness index, Aggregation index, Interspersion and Juxtaposition Index highlights that the centre of the city is more compact in 2010 with more clumpiness in NW and SW directions. Area weighted Euclidean mean nearest neighbour distance is measure of patch context to quantify patch isolation. Higher v values in 1973 gradually decrease by 2002 in all directions and circles. This is similar to patch density dynamics and can be attributed to industrialization and consequent increase in the housing sector. Analyses confirm that the development of industrial zones and housing blocks in NW and SW in post 1990s, in NE and SE during post 2000 are mainly due to policy decision of either setting up industries or boost to IT and BT sectors and consequent housing, infrastructure and transportation

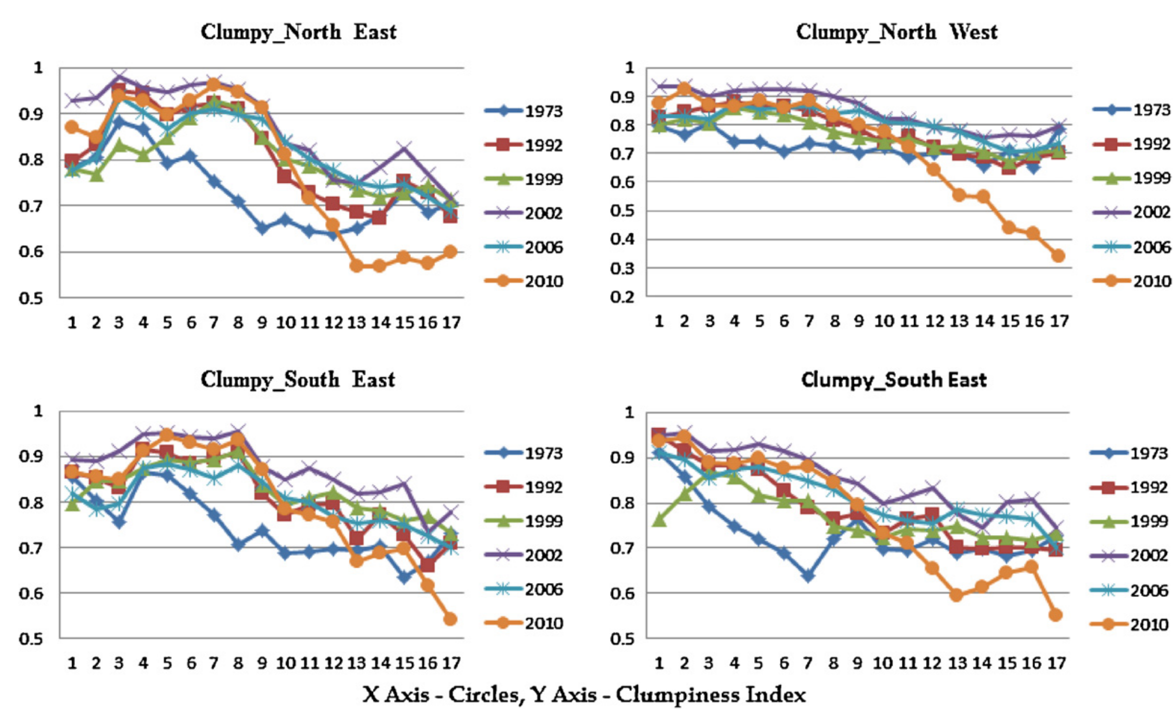


Fig. 13. Clumpiness Index – direction-wise/circle-wise.

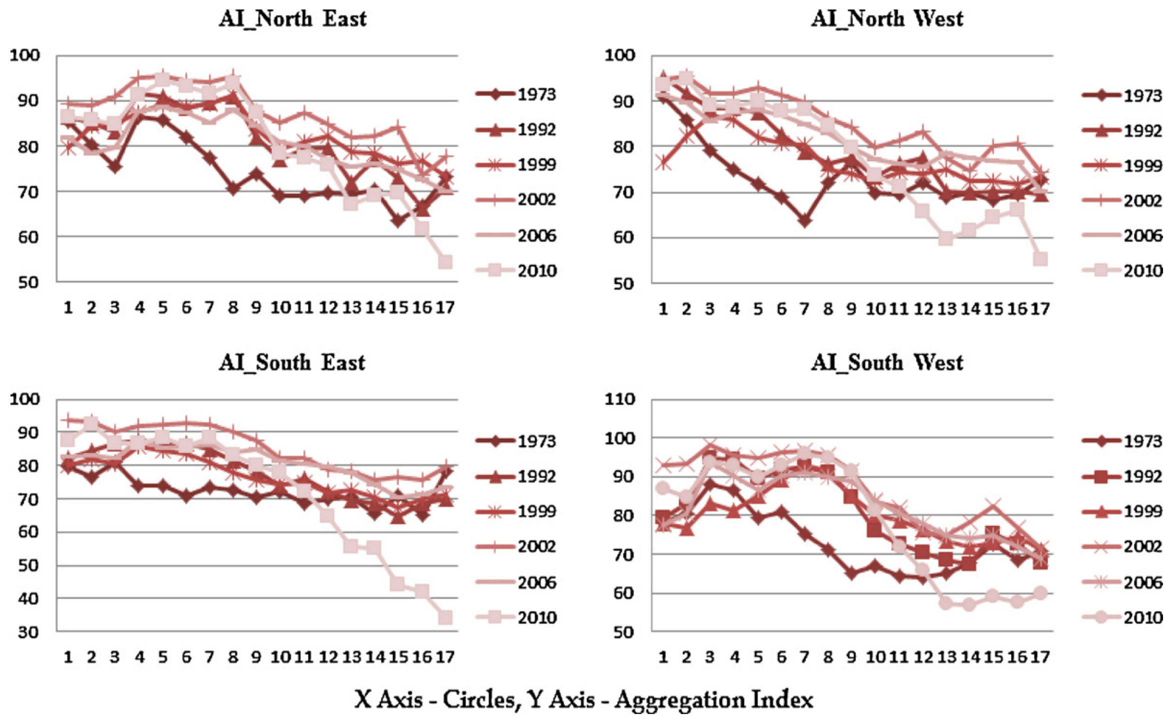


Fig. 14. Aggregation Index – direction-wise/circle-wise.

facilities. PCA was performed with 21 metrics computed zonewise for each circle. This helped in prioritising the metrics (Table 2) while removing redundant metrics for understanding the urbanisation, which are discussed next.

i. Number of urban patches has steadily decreased in the inner core circles from 1973 to 2010, which indicates aggregation. A sharp increase in the urban patches in the periphery (outer rings) from 25 to 120 indicates of numerous small urban patches pointing to the urban sprawl. Urban sprawl is thus effectively visualized by this index, evident with SW, SE and NE zones in Fig. 10. The outer circle having on an average 120 urban patches compared to 5 in inner circles.
ii. Perimeter area weighted mean ratio (PAWMR) reflects the patch shape complexity and is given in Fig. 11. The values closer to zero in the inner circles indicate the simple shape, whereas the outer circles show the increasing trends in all directions. This highlights an enhanced rate of anthropogenic interventions and hence the process of Sprawl.
iii. Landscape shape index indicates the complexity of shape, close to zero indicates maximally compact (at city centre) and higher values in outer circles indicate disaggregated growth in 2010

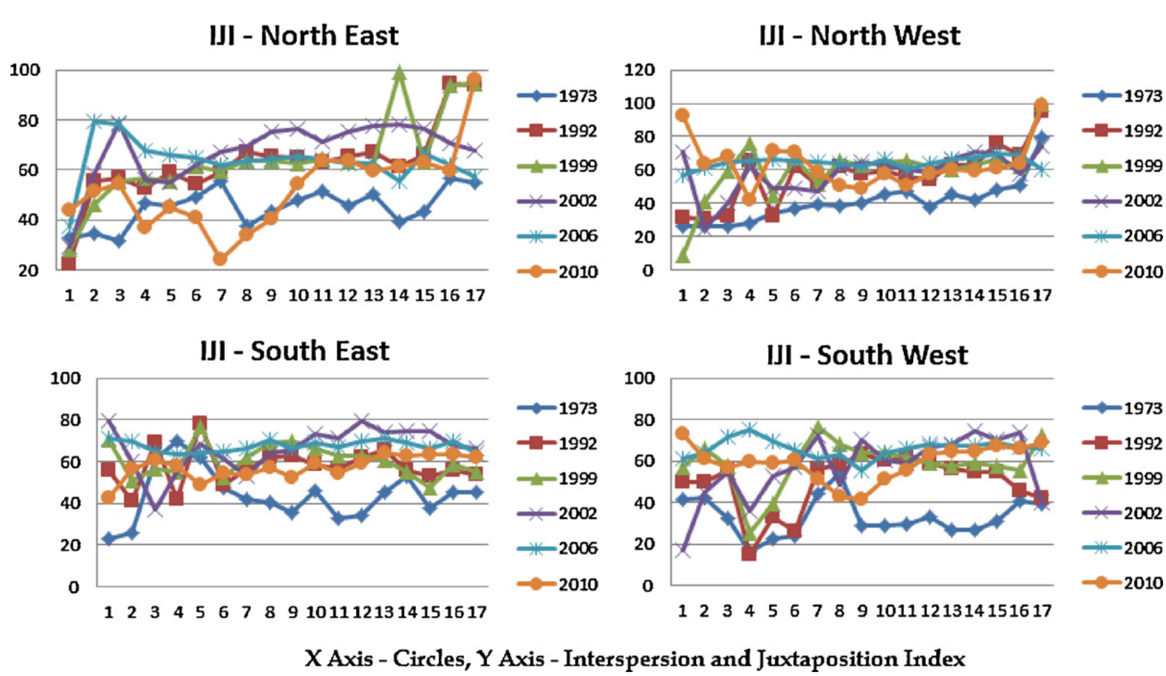


Fig. 15. Interspersion and Juxtaposition – direction-wise/circle-wise.

(Fig. 12). The trend of sprawl at city outskirts as well as at the centre was noticed till 1980s. However, post 1980s values indicate of compactness at city centre, while outer rings show disaggregated growth.

iv. Clumpiness index represents the similar trend of compact growth at the center of the city which gradually decreases towards outer rings indicating the urban agglomeration at centre and phenomena of sprawl at the outskirts in 2010 (Fig. 13). This phenomenon is very prominent in Northeast and Southwest direction.

v. Aggregation Index indicated that the patches are maximally aggregated in 2010 while it was more dispersed in 1973, indicating that city is getting more and more compact (Fig. 14).

vi. Interspersion and Juxtaposition Index was very high as high as 94 in all directions which indicate that the urban area is becoming a single patch and a compact growth towards 2010 (Fig. 15). All these metrics point towards compact growth in the region, due to intense urbanisation. Concentrated growth in a region has telling influences on natural resources (disappearance of open spaces – parks and water bodies), traffic congestion, enhanced pollution levels and also changes in local climate (Ramachandra and Kumar, 2009, 2010)

The discussion highlights that the development during 1992–2002 was phenomenal in NW, SW due to Industrial development (Rajajinagar Industrial estate, Peenya industrial estate, etc.) and consequent spurt in housing colonies in the nearby localities. The urban growth picked up in NE and SE (Whitefield, Electronic city, etc.) during post 2000 due to State's encouraging policy to information technology and biotechnology sectors and also setting up International airport.

7. Conclusion

Urban dynamics of rapidly urbanising landscape – Bangalore has been analysed to understand historical perspective of land use changes, spatial patterns and impacts of the changes. The analysis of changes in the vegetation cover shows a decline from 72% (488 sq. km in 1973) to 21% (145 sq. km in 2010) during the last four decades in Bangalore.

Land use analyses show that there has been a 584% growth in built-up area during the last four decades with the decline of vegetation by 66% and water bodies by 74%. Temporal analyses of greater Bangalore reveals an increase in urban built up area by 342.83% (during 1973–1992), 129.56% (during 1992–1999), 106.7% (1999–2002), 114.51% (2002–2006) and 126.19% from 2006 to 2010. Urban growth pattern of Greater Bangalore has been done in four directions through landscape metrics and gradient analysis across six time periods. The urban density gradient illustrates radial pattern of urbanisation during 1973–2010 indicating of intense urbanisation at central core and sprawl at outskirts, which conform with Shanon's entropy, alpha and beta population densities. Landscape metrics further highlight of compact growth in the region.

Gradients of alpha and beta densities illustrate urban intensification in the center and sprawl in NW and SW regions. Landscape metrics point towards compact growth in the region, due to intense urbanisation in 2000. The analysis confirms that the nature of land use depended on the activities while the level of spatial accumulation depended on the intensity and concentration of urban builtup. Central areas have a high level of spatial accumulation and corresponding land uses, such as in the CBD, while peripheral areas have lower levels of accumulation. Unplanned concentrated growth or intensified developmental activities in a region has telling influences on natural resources (disappearance of open spaces – parks and water bodies), traffic congestion, enhanced pollution levels and also changes in the local climate.

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References

Angel, S., Parent, J., Civco, D., 2007. Urban sprawl metrics: an analysis of global urban expansion using GIS. In: Proceedings of ASPRS 2007 Annual Conference, Tampa, Florida May 7–11, URL: http://clear.uconn.edu/publications/research/tech_papers/Angel_et_al_ASPRS2007.pdf.

Barredo, J.I., Demicheli, L., 2003. Urban sustainability in developing countries mega cities, modeling and predicting future urban growth in lagos. Cities 20 (5), 297–310.

Bhatta, B., 2009a. Analysis of urban growth pattern using remote sensing and GIS: a case study of Kolkata, India. International Journal of Remote Sensing 30 (18), 4733–4746.

Bhatta, B., 2009b. Modeling of urban growth boundary using geoinformatics. International Journal of Digital Earth 2 (4), 359–381.

Bhatta, B., 2010. Analysis of Urban Growth and Sprawl from Remote Sensing Data. Springer-Verlag, Berlin, Heidelberg.

Brueckner, J.K., 2000. Urban sprawl: diagnosis and remedies. International Regional Science Review 23 (2), 160–171.

Chen, S., Zeng, S., Xie, C., 2000. Remote sensing and GIS for urban growth analysis in China. Photogrammetric Engineering and Remote Sensing 66 (5), 593–598.

Congalton, R.G., Oderwald, R.G., Mead, R.A., 1983. Assessing landsat classification accuracy using discrete multivariate analysis statistical techniques. Photogrammetric Engineering and Remote Sensing 49, 1671–1678.

Crews-Meyer, K.A., 2002. Characterizing landscape dynamism using paneled-pattern metrics. Photogrammetric Engineering and Remote Sensing 68 (10), 1031–1040.

Dietzel, C., Herold, M., Hemphell, J.J., Clarke, K.C., 2005. Spatio-temporal dynamics in California's central valley: empirical links to urban theory. International Journal of Geographic Information Science 19 (2), 175–195.

Duda, R.O., Hart, P.E., Stork, D.G., 2000. Pattern Classification, A, 2nd ed. Wiley-Interscience Publication, ISBN 9814-12-602-0.

Epstein, J., Payne, K., Kramer, E., 2002. Techniques for mapping suburban sprawl. Photogrammetric Engineering and Remote Sensing 63 (9), 913–918.

Galster, G., Hanson, R., Ratclfee, M.R., 2001. Wrestling sprawl to the ground: defining and measuring an elusive concept. Housing Policy Debate 12 (4), 681–717.

Gao., Liu, Y., 2008. Mapping land degradation from space: a comparative study of landsat ETM+ and ASTER data. International Journal of Remote Sensing 29, 4029–4043.

Geri, F., Amici, V., Rocchini, D., 2010. Human activity impact on hetrogenity of a mediterranean landscape. Applied Geography 30 (3), 370–379.

Gustafson, E.J., 1998. Quantifying landscape spatial pattern: what is the state of the art? Ecosystems 1, 143–156.

Herold, M., Goldstein, N.C., Clarke, K.C., 2003. The spatiotemporal form of urban growth: measurement analysis and modeling. Remote Sensing of the Environment 86, 286–302.

Herold, M., Scepan, J., Clarke, K.C., 2002. The use of remote sensing and landscape-metrics to describe structures and changes in urban land uses. Environment and Planning 34, 1443–1458.

Huang, J., Lu, X., Sellers, J., 2007. A Global comparative analysis of urban form: applying spatial metrics and remote sensing. Landscape and Urban Planning 82 (4), 184–197.

Hulshoff, R.M., 1995. Landscape indices describing a Dutch landscape. Landscape Ecology 10 (2), 101–111.

Janssen, L.L.E., 2000. Principles of Remote Sensing, 1st ed. The international institute for Aerospace Survey and Earth Science(ITC), ISBN 90-61-64-183-7:132-133.

Ji, C.Y., Lin, P., Li, X., Liu, Q., Sun, D., Wang, S., 2001. Monitoring urban expansion with remote sensing in China. International Journal of Remote Sensing 22 (8), 1441–1455.

Ji, W., Ma, J., Twibell, R.W., Underhill, K., 2006. Characterizing urban sprawl using multi-stage remote sensing images and landscape metrics. Computers, Environment and Urban Systems 30, 861–879.

Jiang, F., Liu, S., Yuan, H., Zhang, Q., 2007. Measuring urban sprawl in Beijing with geo-spatial indices. Journal of Geographical Sciences 17, 469–478.

Jim, C.Y., Chen, W.Y., 2009. Diversity and distribution of landscape trees in the compact Asian city of Taipei. Applied Geography 29 (4), 577–587.

Kienast, F., 1993. Analysis of historic landscape patterns with a Geographical Information System – a methodological outline. Landscape Ecology 8 (2), 101–118.

Lata, K.M., Sankar Rao, C.H., Krishna Prasad, V., Badrinath, K.V.S., Raghavaswamy, 2001. Measuring urban sprawl: a case study of Hyderabad. GISdevelopment 5 (12), 26–29.

Lausch, A., Herzog, F., 1999. Applicability of landscape metrics for the monitoring of landscape change: issues of scale, resolution and interpretability. In: Paper presented at the International Conference, St. Petersburg, Russia.

Li, X., Yeh, A.G.O., 2004. Analyzing spatial restructuring of land use patterns in a fast growing region remote sensing and GIS. Landscape and Urban Planning 69, 335–354.

Lillesand, T.M., Kiefer, R.W., 2002. Remote Sensing and Image Interpretation, 4th ed. John Wiley and Sons, ISBN 9971-51-427-3, pp. 215–216.

Lo, C.P., Yang, X., 2002. Drivers of land-use/land-cover changes and dynamic modelling for the Atlanta, Georgia Metropolitan Area. Photogrammetric Engineering and Remote Sensing 68 (10), 1062–1073.

Lucy, w., Philips, D., 2001. Suburbs and the Census: Patterns of Growth and Decline, Survey Series. Brookings Institution, Centre on Urban and Metropolitan Policy, Washington, DC.

Luque, S.S., Lathrop, R.G., Bognar, J.A., 1994. Temporal and spatial changes in an area of the New Jersey Pine landscape. Landscape and Ecology 9 (4), 287–300.

McGarigal, K., Marks, B.J., 1995. FRAGSTATS: spatial pattern analysis program for quantifying landscape structure. USDA Forest Service General Technical Report PNW-351.

Medley, K.E., Okey, B.W., Barrett, G.W., Lucas, M.F., Renwick, W.H., 1995. Landscape change with agricultural intensification in a rural watershed, southwestern Ohio, U.S.A. Landscape and Ecology 10 (3), 161–176.

Mitrakis, N.E., Topalogou, C.A., Alexandridis, T.K., Theocharis, J.B., Zalidis, G.C., 2008. A novel self organising neuro-fuzzy multilayered classifier for land cover classification of a VHR image. International Journal of Remote Sensing 29, 4061–4087.

Ngigi, T.G., Tateishi, R., Shalaby, A., Soliman, N., Ghar, M., 2008. Comparison of a new classifier, the mix unmix classifier, with conventional hard and soft classifiers. International Journal of Remote Sensing 29, 4111–4128.

Palang, H., Mander, Ü., Luud, A., 1998. Landscape diversity changes in Estonia. Landscape and Urban Planning 41, 163–169.

Pan, D., Domon, G., de Blois, S., Bouchard, A., 1999. Temporal (1958–1993) and spatial patterns of land use changes in Haut–Saint–Laurent (Quebec, Canada) and their relation to landscape physical attributes'. Landscape and Ecology 14, 35–52.

Pathan, S.K., Patel, J.G., Bhanderi, R.J., Ajai, Kulshrestha, Goyal, V.P., Banarjee, D.L., Marthe, S., Nagar, V.K., Katare, V., 2004. Urban planning with specific rel;erence to master plan of lndore city using RS and GIS techniques. In: Proc. of GSDI-7 International Conference on Spatial Data Infrastructure for Sustainable Development, Bangalore from February 2 to 6.

Pathan, S.K., Sampat Kumar, D., Mukund, Rao., Sastry, S.V.C., 1993. Urban growth trend analysis using GIS techniques – a case study of the Bombay metropolitan region. International Journal of Remote Sensing 14 (17), 3169–3179.

Pathan, S.K., Shukla, V.K., Patel, R.G., Mehta, K.S., 1991. Urban land use mapping – a case study of Ahmedabad city and its environs. Journal of the Indian Society of Remote Sensing 19 (2), 12, 95- I.

Pathan, S.K., Jothimani, P., Pendharkar, S.P., Sampat Kumar, D., 1989. Urban land use mapping and zoning of Bombay metropolitan region using remote sensing data. Journal of the Indian Society of Remote Sensing 17 (3), 11–22.

Peiser, R., 2001. Decomposing urban sprawl. Town Planning Review 72 (3), 275–298.

Rainis, R., 2003. Application of GIS and landscape metrics in monitoring urban land use change. In: Hashim, N.M., Rainis, R. (Eds.), Urban Ecosystem Studies in Malaysia: A Study of Change. , pp. 267–278.

Ramachandra, T.V., Kumar, U., 2008. Wetlands of greater Bangalore, India: automatic delineation through pattern classifiers. Electronic Green Journal (26), Spring 2008 ISSN: 1076-7975.

Ramachandra, T.V., Kumar, U., 2009. Land surface temperature with land cover dynamics: multi-resolution, spatio-temporal data analysis of greater Bangalore. International Journal of Geoinformatics 5 (3), 43–53.

Ramachandra, T.V., Kumar, U., 2010. Greater Bangalore: emerging heat island. GIS for Development 14 (1), 86–104, http://www.gisdevelopment.net/application/urban/sprawl/Greater-Bangalore-Emerging-Urban-Heat-Island.htm.

Sachs, D.L., Sollins, P., Cohen, W.B., 1998. Detecting landscape changes in the interior of British Columbia from 1975 to 1992 using satellite imagery. Canadian Journal of Forest Research 28, 23–36.

Sha, Z., Bai, Y., Xie, Y., Yu, M., Zhang, L., 2008. Using a hybrid fuzzy classifier (HFC) to map typical grassland vegetation in Xilin River Basin, Inner Mongolia, China. International Journal of Remote Sensing 29, 2317–2337.

Simpson, J.W., Boerner, R.E.J., DeMers, M.N., Berns, L.A., 1994. Forty-eight years of landscape change on two contiguous Ohio landscapes. Landscape and Ecology 9 (4), 261–270.

Sudhira, H.S., Ramachandra, T.V., Bala Subramanya, M.H., 2007. City Profile: Bangalore. Cities l24 (4), 379–390.

Sudhira, H.S., Ramachandra, T.V., Jagadish, K.S., 2004. Urban sprawl: metrics dynamics and modelling using G1S. International Journal of Applied Earth Observation and Geoinformation 5, 29–39.

Thibault, P.A., Zipperer, W.C., 1994. Temporal changes of wetlands within an urbanizing agricultural landscape. Lands and Urban Planning 28, 245–251.

Tian, G., Liu, J., Xie, Y., Yang, Z., Zhuang, D., Niu, Z., 2005. Analysis of spatio temporal dynamic pattern and driving forces of urbanland in China in 1990 using TM images and GIS. Cities 22 (6), 400–410.

Torrens P.M., Alberti M., 2000. Measuring sprawl. Working Paper No. 27, Centre for Advanced Spatial Analysis, University College, London.

Turner, M.G., Gardner, R.H., O'Neill, R.V., 2001. Landscape Ecology in Theory and Practice: Pattern and Process. Springer, New York.

Wang, F., 2009. Factor analysis and principal-components analysis. International Encyclopedia of Human Geography, doi:10.1016/B978-008044910-4.00434-X.

World Urbanisation Prospects, 2005. Revision, Population, Division. Department of Economic and Social Affairs, UN.

Yeh, A.G.O., Liu, X., 2001. Measurement and Monitoring of urban sprawl in a Rapidly growing region using Entropy. Photogrammetric Engineering and Remote Sensing 67 (I), 83–90.

Yu, X.J., Ng, C.N., 2007. Landscape and urban planning. Spatio and temporal dynamics of urban sprawl along two urban–rural transects: a case study of Guamgzhou. China 79, 96–109.

Zhang, Q., Wang, J., Peng, X., Gang, R., Shi, P., 2002. Urban built-up land change detection with road density and spectral information from multi-temporal Landsat TM data. International Journal of Remote Sensing 23 (15), 3057–3078.

Zheng, D., Wallin, D.O., Hao, Z., 1997. Rates and patterns of landscape change between 1972 and 1988 in the Changbai Mountain area of China and North Korea. Landscape and Ecology 12, 241–254.

Spatial Metrics based Landscape Structure and Dynamics Assessment for an emerging Indian Megalopolis

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***Abstract*—Human-induced land use changes are considered the prime agents of the global environmental changes. Urbanisation and associated growth patterns (urban sprawl) are characteristic of spatial temporal changes that take place at regional levels. Unplanned urbanization and consequent impacts on natural resources including basic amenities has necessitated the investigations of spatial patterns of urbanization. A comprehensive assessment using quantitative methods and methodological understanding using rigorous methods is required to understand the patterns of change that occur as human processes transform the landscapes to help regional land use planners to easily identify, understand the necessary requirement. Tier II cities in India are undergoing rapid changes in recent times and need to be planned to minimize the impacts of unplanned urbanisation. Mysore is one of the rapidly urbanizing traditional regions of Karnataka, India. In this study, an integrated approach of remote sensing and spatial metrics with gradient analysis was used to identify the trends of urban land changes. The spatial and temporal dynamic pattern of the urbanization process of the megalopolis region considering the spatial data for the five decades with 3 km buffer from the city boundary has been studied, which help in the implementation of location specific mitigation measures.**

The time series of gradient analysis through landscape metrics helped in describing, quantifying and monitoring the spatial configuration of urbanization at landscape levels. Results indicated a significant increase of urban built-up area during the last four decades. Landscape metrics indicates the coalescence of urban areas occurred during the rapid urban growth from 2000 to 2009 indicating the clumped growth at the center with simple shapes and dispersed growth in the boundary region with convoluted shapes.

Keywords-Landscape Metrics; Urbanisation; Urban Sprawl; Remote sensing; Geoinformatics; Mysore City, India.

I. INTRODUCTION

Patterns and processes of globalization and consequent urbanization are the factors influencing contemporary land use trends and also posing challenges for sustainable land uses [9]. Analysis of landscape patterns and dynamics has become the primary objectives of landscape, geographical and ecological studies in recent times. Landscape changes involving large scale deforestation are the primary drivers of the climate change [52], [11] earth dynamics [51]. The spatial patterns of landscape transformation through time are undoubtedly related to changes in land uses [41].Landscape changes are diverse but very often influenced by regional policies [6]. The main driving factors for global environmental changes are been identified as agriculture intensification [17], [19], urbanisation [40] in the context of local policies[24,30,34]. The socio-economic impacts are often determinants of the type of land use within a given region, which in turn affect environmental issues [32], [35]. In order to address these urbanization challenges without compromising the environment values and their local sustainance, land use planning and necessary supporting data are crucial, especially to developing countries under severe environmental and demographic strains [12].

Urbanization is a irreversible process involving changes in vast expanse of land cover with the progressive concentration of human population. Urbanising landscapes will invariably have high population density that might lead to lack of infrastructure and provision of basic facilities. The urban population in India is growing at about 2.3% per annum with the global urban population increasing 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 [42]. Population of Mysore is 1 million as per census 2001 compared to 0.653 million (1991).

The increase in urban population is in response to the growth in urban areas due to migration from either rural area or other cities. There are 48 urban agglomerations (Mega cities, Tier I) having a population of more than one million in India (in 2011). Tier 1 cities have reached the saturation level evident from lack of basic amenities, traffic bottlenecks, higher concentrations of pollutants, higher crime rates due to burgeoning population. In this context, well planned Tier 2 cities offer humongous potential with the scope for meeting the basic amenities required. This 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. Modeling and visualization of urban growth based on the historical spatio-temporal data would help in identifying the probable regions of intense urbanization and sprawl.

Urban sprawl implies a sharp imbalance between urban spatial expansion and the underlying population growth [5]. Sprawl of human settlements is a major driving force of land use and land cover changes [3], [16] with detrimental impacts on natural resources and local ecology. Sprawl process entails the growth of the urban area from the urban center towards the periphery of the city municipal jurisdiction. These small pockets in the outskirts lack basic amenities like supply of treated water, electricity and sanitation facilities. Sprawl is associated with high negative impacts and especially the increasing dependency for basic amenities [50], the need for more infrastructure [5], the loss of agricultural and natural land, higher energy consumption, the degradation of peri-urban ecosystems etc., [23], [25], [27]. Understanding the sprawl over past few decades is crucial for the regional administration to handle the population growth and provide basic amenities while ensuring the sustainable management of local natural resources.

The information about the current and historical land cover/land use plays a major role for urban planning and management [54]. Mapping landscapes on temporal scale provide an opportunity to monitor the changes, which is important for natural resource management and sustainable planning activities. In this context, “Density Gradient” with the time series spatial data analysis is potentially useful in measuring urban development [50]. This article presents the temporal land use analysis and adopts the density gradient approach to evaluate and monitor landscape dynamics and further explains the landscape pattern through use of landscape metrics.

Knowledge of the spatio-temporal pattern of the urbanization is important to understand the size and functional changes in the landscape. Spatial metrics were computed to quantify the patterns of urban dynamics, that aid in understanding spatial patterns of various land cover features in the region [33]. Quantifying the landscape pattern and its change is essential for monitoring and assessing the urbanization process and its ecological consequences [31], [20], [27], [46]. Spatial metrics have been widely used to study the structure, dynamic pattern with the underlying social, economic and political processes of urbanization [21], [22], [45], [53]. This has provided useful information for implementing holistic approaches in the regional land-use planning [48]. [1] reviews the spatial characteristics of metropolitan growth including analysis [2], [4], [14], [28] the study of urban landscapes. Applications of landscape metrics include landscape ecology (number of patches, mean patch size, total edge, total edge and mean shape), geographical applications by taking advantage of the properties of these metrics [15], [39], [44] and measurement of ecological sustainability [43].

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.

According to the City Development Plan (CDP), a 20-year vision document for Mysore, there has been a 70% increase in the city’s spatial extent since 2001, resulting in the higher degree of sprawl at outskirts. Objectives of this study are to understand and interpret the evolving landscape dynamics through temporal analysis of land use land cover pattern taking 3km buffer, through spatial metrics.

II. Study Area

Mysore city in Karnataka is one of the tier II cities and the cultural capital of India with a hub of industrial activities. It is designated as the 2nd capital of Karnataka. Mysore city is 128 sq. km in area and is one of the most preferred destinations for industries including IT hubs other than Bangalore.It is a main trading centre of silk and sandalwood. Mysore district is bounded by Mandya to the northeast, Chamrajnagar to the southeast, Kerala state to the south, Kodagu to the west, and Hassan to the north. It has an area of 128.42 km² and a population of about 1 million (2001 census). The district lies in the southern Deccan plateau, within the watershed region of Kaveri River, which flows through the northern and eastern parts of the district.

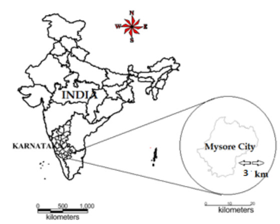


Figure 1. Study Area: Mysore city and 3 km buffer

III. Materials Used

DATA	Year	Purpose
Landsat Series MSS(57.5m)	1973	Landcover and Land use analysis
Landsat Series TM (28.5m) and ETM	1989, 1999,	Landcover and Land use analysis
IRS p6: Liss-4 MX data (5.6m)	2009	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 Analysis

IV. Method

A two-step approach was adopted to chart the direction of the City’s development, which includes (i) a normative approach to understand the land use and (ii) a gradient approach of 1km radius to understand the pattern of growth during the past 4 decades. Various stages in the data analysis are:

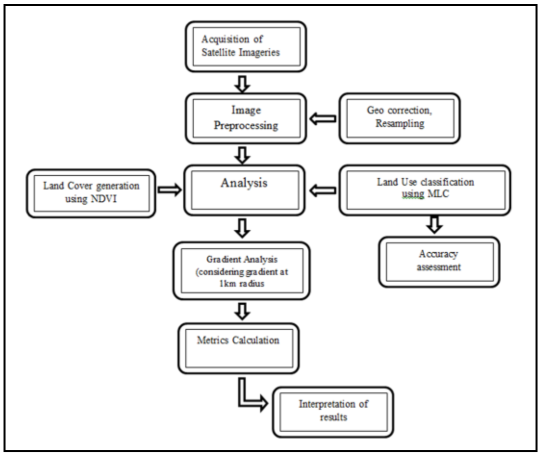


Figure 2. Procedure followed to understand the spatial pattern of landscape change

A. *Preprocessing*

The remote sensing data obtained were geo-referenced, rectified and cropped pertaining to the study area. The Landsat satellite 1973 images have a spatial resolution of 57.5 m x 57.5 m (nominal resolution) and 1989 - 1999 data of 28.5 m x 28.5 m (nominal resolution) were resampled to uniform 30 m for intra temporal comparisons. Latest data of IRS P6 of spatial resolution 5.6 m was procured from NRSC, Hyderabad (http://www.nrsc.gov.in).

Vegetation Cover Analysis: Normalized Difference Vegetation index (NDVI) was computed to understand the temporal dynamics of the vegetation cover. NDVI value ranges from values -1 to +1, where -0.1 and below indicate soil or barren areas of rock, sand, or urban buildup. 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).

B. *Land use analysis*

Land use categories listed in Table 2 were classified with the training data (field data) using Gaussian maximum likelihood supervised classier. The analysis included generation of False Color Composite (bands – green, red and NIR), which helped in identifying heterogeneous area. 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-calbrated 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), which were used for classifying latest IRS P6 data. 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 [10] 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 satellite data and the balance 30% were used in validation and accuracy assessment. Thematic layers were generated of classified data corresponding to four land use categories.

Evaluation of the performance of classifiers [36], [37], [13] is done through accuracy assessment techniques of testing the statistical significance of a difference, comparison of kappa coefficients [8], [47] and proportion of correctly allocated classes [12] through computation of confusion matrix. These are most commonly used to demonstrate the effectiveness of the classifiers [8], [7], [29].

Further each zone was divided into concentric circle of incrementing radii of 1 km (figure 2) 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.

TABLE I. a 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, Cropland, nurseries.
Others	Rocks, quarry pits, open ground at building sites, kaccha roads.

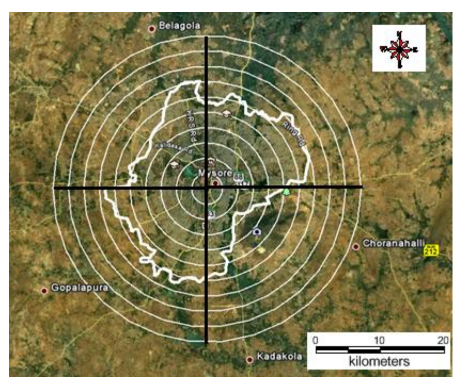


Figure 3. Google earth representation of the study region

C. *Urban sprawl analysis*

Direction-wise Shannon's entropy (Hn) is computed (equation 1) to understand the extent of growth: compact or divergent [26], [49], [38]. This provides an insight into the development (clumped or disaggregated) with respect to the geographical parameters across 'n' concentric regions in the respective zones.

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

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).

D. 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 [34].

Urban dynamics is characterised by 11 spatial metrics chosen based on complexity, centrality and density criteria. The metrics include the patch area, edge/border, shape, epoch/contagion/ dispersion and are listed in Table II.

V. RESULTS & DISCUSSION

1) Land use Land Cover analysis:

a) Vegetation cover analysis: Vegetation cover of the study area assessed through NDVI (Figure 3), shows that area under vegetation has declined to 9.24% (2009) from 51.09% (1973). Temporal NDVI values are listed in Table III.

b) Land use analysis: Land use assessed for the period 1973 to 2009 using Gaussian maximum likelihood classifier is listed Table IV and the same is depicted in figure 4. The overall accuracy of the classification ranges from 75% (1973), 79% (1989), 83% (1999) to 88% (2009) respectively. Kappa statistics and overall accuracy was calculated and is as listed in Table V.

c) There has been a significant increase in built-up area during the last decade evident from 514% increase in urban area. Other category also had an enormous increase and covers 166 % of the land use. Consequent to these, vegetation cover has declined drastically during the past four decades. The water spread area has increased due to the commissioning of waste water treatment plants (ex. Vidyaranyapura, Rayankere, Kesare) during late 90's and early 2000.

Year	Vegetation		Non vegetation	
	%	Ha	%	Ha
1973	51.09	10255.554	48.81	9583.83
1989	57.58	34921.69	42.42	8529.8
1999	44.65	8978.2	55.35	11129.77
2009	09.24	1857.92	90.76	19625.41

TABLE II. TEMPORAL LAND COVER DETAILS.

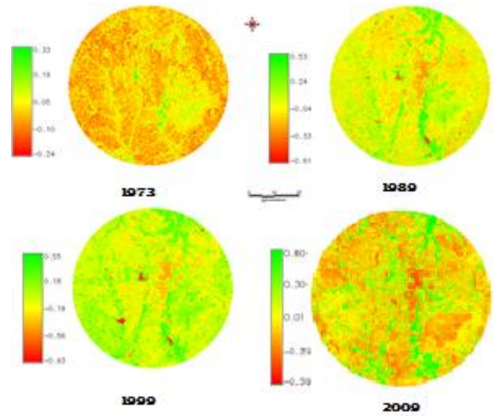


Figure 4. Temporal Land cover changes during 1973 – 2009

2) Built up Density Gradient Analysis: Built up density was minimal and the value ranges from 0.026 (considering 3km buffer) to 0.036 (without considering 3km buffer) in the North east direction (in 1973). The federal government's policy in 1990's to develop tier 2 cities led to the increase in urban area. There was a sharp growth in the region in almost all direction from 1999 till 2009, maximum value reaching 0.216 in the NE direction (considering 3km buffer) and 0.42 (without considering the buffer). This can be attributed to development of this region with the IT & BT industry which were earlier confined to Bangalore.

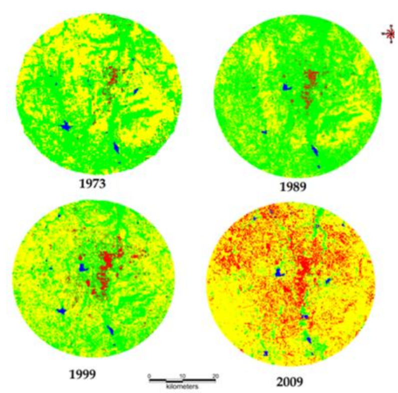


Figure 5. Classification output of Mysore

Land use / Year	Urban	Vegetation	Water	Others
1973	222.93	10705.68	124.47	9054.99
1989	229.41	13242.51	78.75	6557.4
1999	730.8	8360.1	117.9	10899.2
2009	3757.489	1159.336	142.58	15050.5
Total (Land in ha)		20108.91		

TABLE III. TEMPORAL LAND USE DETAILS FOR MYSORE

	Indicators	Formula	Range
	Category : Patch area metrics		
1	Largest Patch Index(Percentage of landscape)(LPI)	$LPI = \frac{\max_{j=1}^{n}(a_{ij})}{A}(100)$ a $_{ij}$ = area (m^2) of patch ij A= total landscape area	$0 \leq LPI \leq 100$
2	Number of Urban Patches (NPU)	$NPU = n$ NP equals the number of patches in the landscape.	NPU>0, without limit.
3	Patch density(PD)	f(sample area) = (Patch Number/Area) * 1000000	PD>0
4	Perimeter-Area Fractal Dimension (PAFRAC)	$\frac{2}{\frac{\left[N\sum_{i=1}^{m}\sum_{j=1}^{n}(\ln P_{ij}.\ln a_{ij})\right]-\left[\left(\sum_{i=1}^{m}\sum_{j=1}^{n}\ln p_{ij}\right)\left(\sum_{i=1}^{m}\sum_{j=1}^{n}\ln a_{ij}\right)\right]}{\left(N\sum_{i=1}^{m}\sum_{j=1}^{n}\ln p_{ij}^{2}\right)-\left(\sum_{i=1}^{m}\sum_{j=1}^{n}\ln p_{ij}\right)}}$ Perimeter-Area Fractal Dimension a_{ij} = area (m^2) of patch ij. p_{ij}=perimeter (m) of patch ij. N= total number of patches in the landscape	$1 \leq PAFRAC \leq 2$
	Category : Shape metrics		
5	Normalized Landscape Shape Index (NLSI)	$NLSI = \frac{\sum_{i=1}^{i=N}\frac{p_i}{s_i}}{N}$ Where s_i and p_i are the area and perimeter of patch i, and N is the total number of patches.	$0 \leq NLSI < 1$
6	Landscape Shape Index (LSI)	$LSI = e_i / \min e_i$ e_i =total length of edge (or perimeter) of class i in terms of number of cell surfaces; includes all landscape boundary and background edge segments involving class i. min e_i=minimum total length of edge (or perimeter) of class i in terms of number of cell surfaces.	LSI>1, Without Limit
	Category: Compactness/ contagion / dispersion metrics		
7	Clumpiness	$CLUMPY = \left[\begin{array}{l}\frac{G_i - P_i}{P_i}\ for G_i < P_i \,\&\, P_i < 5, else \\ \frac{G_i - P_i}{1 - P_i}\end{array}\right]$ $G_i = \left(\frac{g_{ii}}{\left(\sum_{k=1}^{m} g_{ik}\right) - \min e_i}\right)$ g_{ii} =number of like adjacencies between pixels of patch type g_{ik} =number of adjacencies between pixels of patch types i and k. P_i =proportion of the landscape occupied by patch type (class) i.	$-1 \leq CLUMPY \leq 1$.
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 g_{ik} = number of adjacencies between pixels of patch types i and k	0<=PLADJ<=100
9	Cohesion	$Cohesion = \left[1 - \frac{\sum_{j=1}^{n} p_{ij}}{\sum_{j=1}^{n} p_{IJ}\sqrt[2]{a_{ij}}}\right]\left[1 - \frac{1}{\sqrt[2]{A}}\right]^{-1} * 100$	$0 \leq cohesion < 100$

10	Aggregation index(AI)	$$AI = \left[\sum_{i=1}^{m} \left(\frac{g_{ii}}{\max \rightarrow g_{ii}} \right) P_i \right] (100)$$ g_{ii} =number of like adjacencies between pixels of patch type P_i= proportion of landscape comprised of patch type.	1≤AI≤100
11	Interspersion and Juxtaposition(IJI)	$$IJI = \frac{-\sum_{i=1}^{m}\sum_{k=i+1}^{m}\left[\left(\frac{e_{ik}}{E}\right).\ln\left(\frac{e_{ik}}{E}\right)\right]}{\ln\left(0.5[m(m-1)]\right)}(100)$$ e_{ik} = total length (m) of edge between patch types E = total length (m) of edge in landscape, excluding background m = number of patch types (classes) present in the landscape.	0≤ IJI ≤100

TABLE IV. SPATIAL LANDSCAPE INDICES

TABLE V.

Year	Kappa coefficient	Overall accuracy (%)
1973	0.76	75.04
1989	0.72	79.52
1999	0.82	78.46
2009	0.86	84.58

TABLE VI. KAPPA STATISTICS AND OVERALL ACCURACY

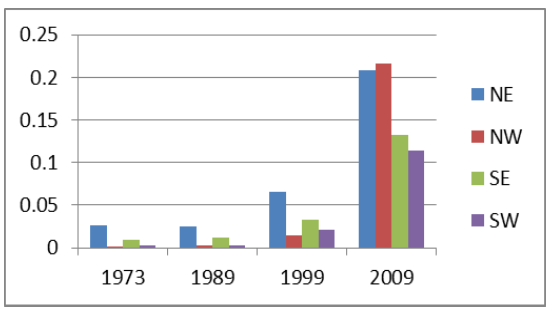


Figure 6. Urban density analysis of Mysore

3) Urban sprawl analysis: Shannon entropy computed using temporal data are listed in Table VI. Mysore is experiencing the sprawl in all directions as entropy values are closer to the threshold value (log (8) = 0.9). Lower entropy values of 0.007 (NW), 0.008 (SW) during 70's shows an aggregated growth as most of urbanization were concentrated at city centre. However, the region experienced dispersed growth in 90's reaching higher values of 0.452 (NE), 0.441 (NW) in 2009 during post 2000's.

The entropy computed for the city (without buffer regions) shows the sprawl phenomenon at outskirts. However, entropy values are comparatively lower when buffer region is considered. Shannon's entropy values of recent time confirms of minimal fragmented dispersed urban growth in the city. This also illustrates and establishes the influence of drivers of urbanization in various directions.

	NE	NW	SE	SW
2009	0.452	0.441	0.346	0.305
1999	0.139	0.043	0.0711	0.050
1992	0.060	0.010	0.0292	0.007
1973	0.067	0.007	0.0265	0.008

TABLE VII. SHANNON ENTROPY INDEX

4) Spatial patterns of urbanisation: In order to understand the spatial pattern of urbanization, eleven 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).

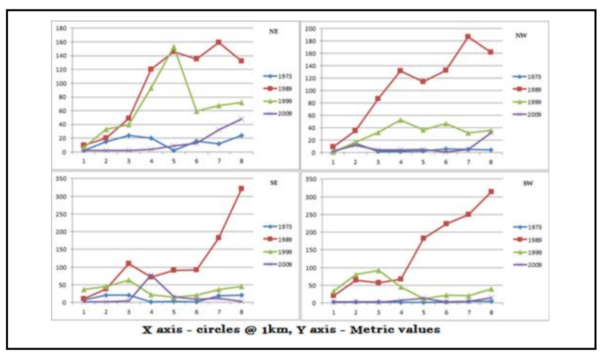


Figure 8.a Number of urban patches (zonewise, circlewise)

Figure 8a illustrates that the city is becoming clumped patch at the center, while outskirts are relatively fragmented. Clumped patches are more prominent in NE and NW directions and patches is agglomerating to a single urban patch. Largest patch index (Fig 8b) highlights that the city's landscape is fragmented in all direction (in 1973) due to heterogeneous landscapes, transformed a homogeneous single patch in 2009.The patch sizes given in figure 8c highlights that there were small urban patches in all directions (till 1999) and the increase in the LPI values implies increased urban patches during 2009 in the NE and SW. Higher values at the center indicates the aggregation at the center and in the verge of forming a single urban patch largest patches were found in NE and SW direction (2009).

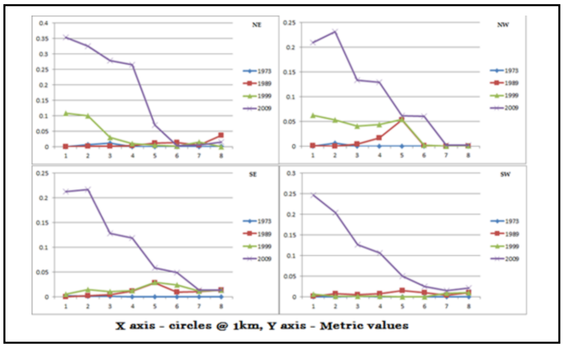


Figure 8.b Largest Patch – zonewise, circlewise

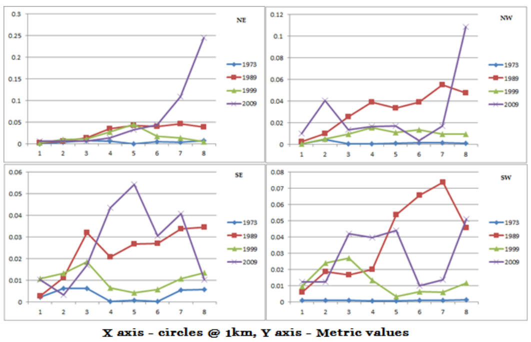


Figure 8.c Patch density – zonewise, circle wise

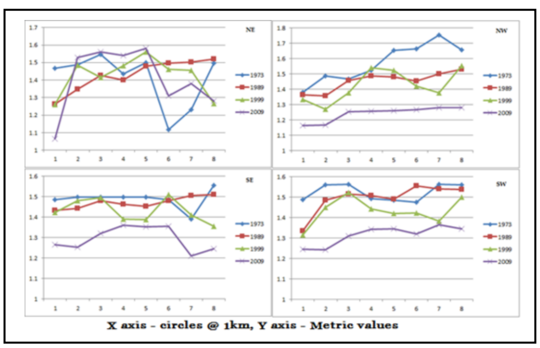


Figure 8.d PAFRAC – zonewise, circle wise

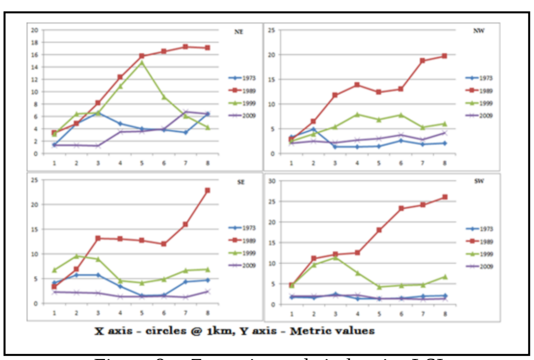


Figure 8.e Zonewise and circle wise LSI

The patch density (Fig 8c) is calculated on a raster map, using a 4 neighbor algorithm. Patch density increases with a greater number of patches within a reference area. Patch density was higher in 1973 as the number of patches is higher in all directions and gradients due to presence of diverse land use, which remarkably increased post 1989(NW) and subsequently reduced in 1999, indicating the sprawl in the region in in early 90's and started to clump during 2009, which was even confirmed by number of patches.

PAFRAC approaches 1 for shapes with very simple perimeters such as squares (indicating clumping of specific classes), and approaches 2 for shapes with highly convoluted, perimeters. PAFRAC requires patches to vary in size. Results (Fig 8d) indicate of dispersed development during 70's and 80's as PAFRAC highly convoluted. The value approaches 1 in 1990's and 2000's indicating aggregation leading to clumped region of urban land use.

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. Results (Fig 8e) indicate that there were low LSI values in 1973 as there was minimal urban areas which were aggregated at the centre. Since 1990's the city has been experiencing dispersed growth in all direction and circles, towards 2009 it shows a aggregating trend as the value reaches 1.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 (Fig 8f) indicates that the landscape had a highly fragmented urban class, which became further fragmented during 80's and started clumping to form a single square in late 90's especially in NE and NW direction in all circle and few inner circles in SE and SW directions, conforming with the other landscape metrics.

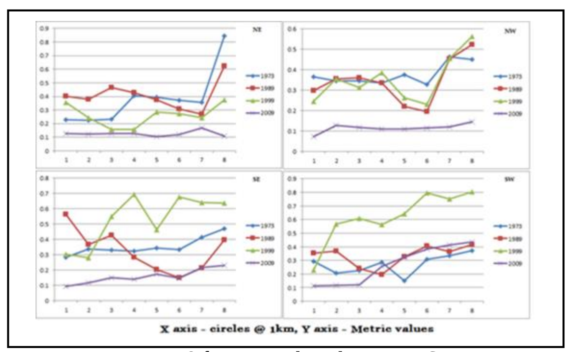


Figure 8.f Zone and circlewise NLSI

Clumpiness index equals 0 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. IJI approaches 0 when distribution of adjacencies among unique patch types becomes increasingly uneven; is equal to 100 when all patch types are equally adjacent to all other patch types.

Clumpiness index, Aggregation index, Interspersion and Juxtaposition Index highlights that the center of the city is more compact in 2009 with more clumpiness and aggregation in NW and NE directions. In 1973 the results indicate that there were a small number of urban patches existing in all direction and in every circle and due to which disaggregation is more. Post 1999 and in 2009 it is observed that large urban patches are located closely almost forming a single patch especially at the center and in NW direction in different gradients (Fig 8g, Fig 8h and Fig 8i).

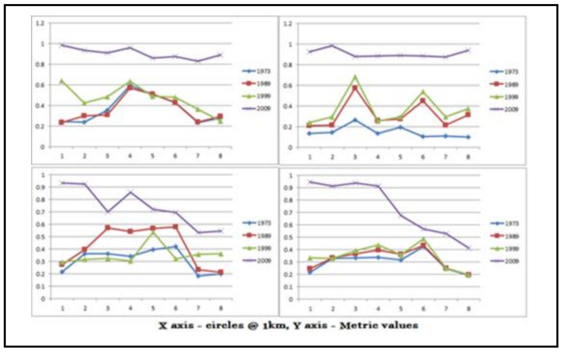
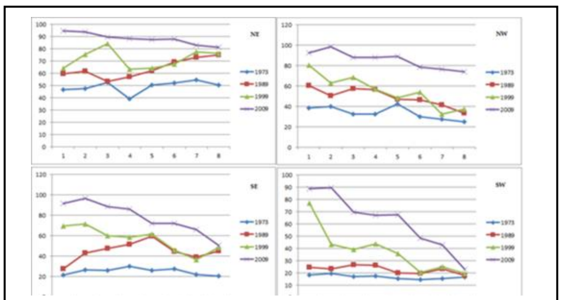


Figure 8.g Clumpiness – zonewise, circle wise



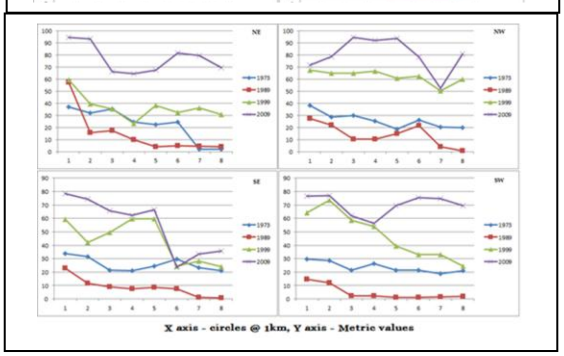


Figure 8.i Zone and circle wise - IJI

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 the city center is getting more and more clumped with similar class (Urban) and outskirts are relatively sharing different internal adjacencies.

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 [18]. Figure 8k indicate of physical connectedness of the urban patch with the higher cohesion value (in 2009). Lower values in 1973 illustrate that the patches were rare in the landscape.

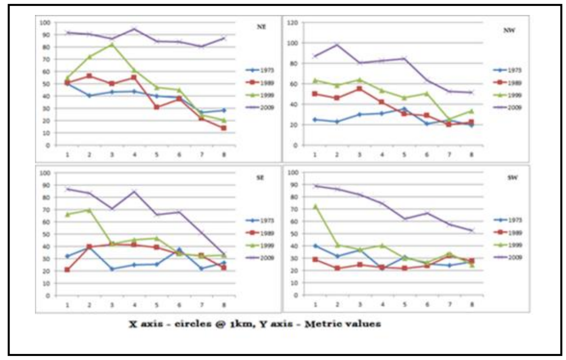


Figure 8.j Zone and circlewise Pladj

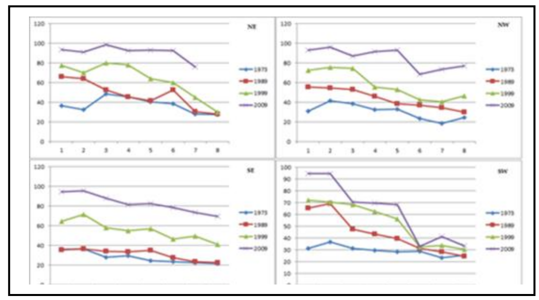


Figure 8.k Cohesion Index

VI. CONCLUSION

Karnataka government's current focus to develop tier 2 cities in order to decongest major cities, has posed a challenge as unplanned developmental activities is leading to urban sprawl impinging basic amenities to the common man in the outskirts. Availability of spatial data since 1970's has aided in 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 Mysore. 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 'unplannedness' considering the three dimensions (size/density/pattern).

Land use assessed for the period 1973 to 2009 using Gaussian maximum likelihood classifier highlight that there has been a significant increase (514%) in urban area, with consequent reduction in vegetation cover. Built up density was minimal and the value ranges from 0.026 (considering 3km buffer) to 0.036 (without considering 3km buffer) in the North east direction (in 1973). Shannon entropy computed using temporal data illustrates that Mysore city is experiencing the sprawl in all directions as entropy values are closer to the threshold. Spatial metrics at landscape level reveal that the landscape had a highly fragmented urban class and started clumping to form a single square in late 90's especially in NE and NW direction in all circle and few inner circles in SE and SW directions, conforming to the other landscape metrics.

Local urban and rural planners need to put forward effective implementable adaptive plans to improve basic amenities in the sprawl localities. Temporal land use analysis along with urban density gradient across four directions has helped in visualizing the growth along with the cultural and industrial evolution.

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REFERENCES

[1] F. Aguilera, R. Talavera. (2009). “Valoración de escenarios futuros a través de la conectividad del Paisaje (Future scenarios assessment through landscape connectivity).” Observatorio Medioambiental 12, pp. 17–36. (in Spanish, abstract version in English)

[2] M. Alberti, P. Waddell. (2000). “An integrated urban development and ecological simulation model.” Int. Assess. 1, pp. 215–227.

[3] N. Batisani, B. Yarnal. (2009). “Urban expansion in Centre County, Pennsylvania: Spatial dynamics and landscape transformations. Applied Geography.” 29(2), pp. 235–249.

[4] S. Berling-Wolf, J. Wu. (2004). “Modelling urban landscape dynamics: a case study in Phoenix, USA.” Urban Ecosyst. 7, pp. 215–240.

[5] J. Brueckner. (2001). “Urban Sprawl: Lessons from Urban Economics,” Unpublished Manuscript, (Department of Economics and Institute of Government and Public Affairs, University of Illinois at Urbana-Champaign, 2000).

[6] M.S. Calvo-Iglesias, U. Fra-Paleo, R.A. Dias-Varela, (2008). “Changes in farming system and population as drivers of land cover and landscape dynamics: the case of enclosed and semi openfield systems in Northern Galicia (Spain)”. Landscape & Urban Plan. 90, pp. 168–177.

[7] R. G. Congalton, (1991). “A review of assessing the accuracy of classifications of remotely sensed data”. Remote Sensing of Environment, 37, pp. 35-46.

[8] R. G. Congalton, R. G. Oderwald, & R. A. Mead, (1983). “Assessing Landsat classification accuracy using discrete multivariate analysis statistical techniques.” Photogrammetric Engineering and Remote Sensing, 49, pp. 1671-1678.

[9] N. Currit, W. Easterling, (2009). “Globalization and population drivers of rural-urban land-use change in Chihauhua, Mexico.” Land Use Policy, 26, pp. 535–544.

[10] R.O. Duda, P.E. Hart, D.G. Stork, (2000), “Pattern Classification.” A Wiley-Interscience Publication, Second Edition, ISBN 9814-12-602-0.

[11] A. Firmino, (1999). “Agriculture and landscape in Portugal”. Landscape and Urban Planning. 46, pp. 83–91.

[12] Food and Agriculture Organization, (1995). “Planning for Sustainable Use of Land Resources: Towards a New Approach.” Land and Water Development Division, Rome.

[13] Y. Gao, Liu, (2008). “Mapping land degradation from space: A comparative study of Landsat ETM+ and ASTER data.” International Journal of Remote Sensing, 29, pp. 4029–4043.

[14] J. Geoghegan, L.A. Wainger, N.E. Bockstael, (1997). “Spatial landscape índices in a hedonic framework: an ecological economics analysis using GIS.” Ecol. Econ. 23, pp. 251–264.

[15] K. Gibert, M. Sànchez-Marrè, (2011). “Outcomes from the iEMSs data mining in the environmental sciences work shop series.” Environmental Modelling & Software, 26 (7), pp. 983 -985.

[16] C. E. Gonzalez-Abraham, V. C. Radeloff, R. B. Hammer, T. J. Hawbaker, S. I. Stewart, & M. K. Clayton, (2007). “Building patterns and landscape fragmentation in northern Wisconsin, USA.” Landscape Ecology, 22, pp. 217–230.

[17] B.H. Green, (1990). “Agricultural intensification and the loss of habitat, species and anemity in British grasslands: a review of historical change and assessment of future prospects.” Grass Forage Sci. 45, pp. 365-372.

[18] E.J. Gustafson, (1998). “Quantifying landscape spatial pattern: what is the state of the art?,” Ecosystems 1, pp.143–156.

[19] W.B. Harms, A.H.F. Stottelder, W. Vos. (1984). “Effects of intensification of agriculture on nature and landscape in the netherlands.” Ekologia (CSSR) 3, pp. 281-304.

[20] M. Herold, J. Scepan, K.C. Clarke, (2002). “The use of remote sensing and landscape metrics to describe structures and changes in urban land uses.” Environ. Plann. A 34, pp.1443–1458.

[21] G.D.Jenerette, D. Potere. (2010). “Global analysis and simulation of land-use change associated with urbanization.” Landsc. Ecol. 25 (5), pp. 657–670.

[22] G.D. Jenerette, J. Wu, (2001). “Analysis and simulation of land-use change in the Central Arizona – Phoenix region, USA.” Landsc. Ecol. 16, pp. 611–626.

[23] M. Johnson, (2001). “Environmental impacts of urban sprawl: a survey of the literature and proposed research agenda.” Environment and Planning A, 33, pp. 717-735.

[24] J. Kubes, (1994). “Bohemian agricultural landscape and villages, 1950 and 1990: Landuse, landcover and other characteristics.” Ekologia (Bratislava) 13, pp. 187-l98.

[25] A. Lagarias, 2011. “Land use planning for sustainable development in periurban ecosystems: the case of Lake Koroneia in Thessaloniki, Greece. “In Proceedings of the 2nd international exergy, life cycle assessment and sustainability workshop & symposium, ELCAS 2, Nisyros, Greece.

[26] K.M., Lata, C.H.S. Rao, V.K. Prasad, K.V.S. Badarianth, V. Raghavasamy, (2001). Measuring Urban sprawl A case study of Hyderabad, gis@development, 5(12), pp. 26-29.

[27] Y. Li, S. Zhao, K. Zhao, P. Xie, J. Fang, (2006). “Land-cover changes in an urban lake watershed in a mega-city, central China.” Environmental Monitoring and Assessment, 115, pp. 349-359.

[28] X. Li, Q. Yang, X. Liu, (2008). “Discovering and evaluating urban signatures for simulating compact development using cellular automata.” Landsc. Urban Plann. 86, pp. 177–186.

[29] T. M. Lillesand, R. W. Kiefer, (2005). “Remote sensing and image interpretation.” New York: John Wiley & Sons.

[30] Z. Lipsky, (1992). “Landscape structure changes in the Czech rural landscape.” In: Cultural aspects of landscape. 2nd Int. Con., 1992. IALE, pp. 80-86.

[31] M. Luck, J.G. Wu, (2002). “A gradient analysis of urban landscape pattern: a case study from the Phoenix metropolitan region, Arizona, USA.” Landsc. Ecol. 17, pp. 327–339.

[32] U. Mander, H. Palang, (1994). “Change on landscape structure in Estonia during the Soviet period.” GeoJournal 33, pp.55–62.

[33] K. McGarigal, B. J. Marks, 1995. “FRAGSTATS: spatial pattern analysis program for quantifying landscape structure.” USDA Forest Service General Technical Report PNW-351. www.umass.edu/landeco/research/fragstats/fragstats.html.

[34] J.H.A. Meeus, (1993). “The transformation of agricultural landscapes in Western Europe.” The Science of the Total Environment 129. pp. 171-190.

[35] A. Melluma, (1994). “Metamorphoses of Latvian landscapes during fifty years of Soviet rule.” GeoJournal 33, pp. 55–62

[36] N. E. Mitrakis, C. A. Topalogou, T. K. Alexandridis, J. B. Theocharis, G. C. Zalidis, (2008). “A novel self organising neuro-fuzzy multilayered classifier for land cover classification of a VHR image.” International Journal of Remote Sensing, 29, pp. 4061− 4087.

[37] T. G. Ngigi, R. Tateishi, A. Shalaby, N. Soliman, , M. Ghar, (2008). “Comparison of a new classifier, The mix unmix classifier, with conventional hard and soft classifiers.” International Journal of Remote Sensing, 29, pp. 4111 −4128.

[38] S.K. Pathan, J G. Patel, R.J. Bhanderi. Ajai, Kulshrestha, V.P. Goyal, D.L. Banarjee. S. Marthe, V.K. Nagar, V. Katare, (2004). “Urban planning with specific reference to master plan of lndore city using RS and GIS techniques.” Proc. of GSDI-7 International Conference on

Spatial Data Infrastructure tbr Sustainable Development, held at Bangalore from Feb, 2-6, 2004.

[39] M. Pereira dos Santos Silva, G. Camara , M. Sobral I. Escada, R.C. Modesto de Souza, (2008). "Remote sensing image mining: detecting agents of land-use change in tropical forest areas." International Journal of Remote Sensing 29 (16), pp. 4803-4822.

[40] M. Phipps, J. Baudry, F. Burel, (1986). "Dynamique de I'organisation ecologique d'un paysage rural: Modalites de la desorganisation dans une zone peri-urbaine." C.R. Acad. SC. Paris. 303. pp.263-268.

[41] C. Potter, M. Lobley, (1996). "Unbroken threads? Succession and its effects on family farms in Britain." Sociologia Ruralis 36, pp. 286–306.

[42] T. V. Ramachandra, U. Kumar, (2008). "Wetlands of Greater Bangalore, India: Automatic Delineation through Pattern Classifiers." Electronic Green Journal, Issue 26, Spring 2008 ISSN: 1076-7975.

[43] C. Renetzedera, S. Schindlera, J. Peterseila, M.A. Prinza, S. Mücherc, T. Wrbka, (2010). "Can we measure ecological sustainability? Landscape pattern as an indicator for naturalness and land use intensity at regional, national and European level." Ecol. Indic. 10, pp. 39–48.

[44] J.P. Rossi, I. van Halder, (2010). "Towards indicators of butterfly biodiversity based on a multiscale landscape description." Ecol. Indic. 10, pp. 452–458.

[45] A. Schneider, K.C. Seto, D. Webster, (2005). "Urban growth in Chengdu, Western China: application of remote sensing to assess planning and policy outcomes." Environ. Plann. B 32 (3), pp. 323–345.

[46] K.C. Seto, M. Fragkias, (2005). "Quantifying spatiotemporal patterns of urban land-use change in four cities of China with time series landscape metrics." Landsc. Ecol. 20, pp. 871–888.

[47] Z. Sha, Y. Bai, Y. Xie, M. Yu, L. Zhang, (2008). "Using a hybrid fuzzy classifier (HFC) to map typical grassland vegetation in Xilin River Basin, Inner Mongolia, China." International Journal of Remote Sensing, 29, pp. 2317–2337.

[48] T. Simoniello, M.T. Carone, R. Coppola, A. Grippa, M. Lanfredi, M. Liberti, M. Macchiato, (2006). "Preliminary study to monitor land degradation phenomena through landscape metrics. In: 2nd Workshop of the EARSeL SIG on Land Use and Land Cover." Center for Remote Sensing of Land Surfaces, Bonn, pp. 408 - 414.

[49] H.S. Sudhira, T.V. Ramachandra, K.S. Jagadish, (2004). "Urban sprawl: metrics, dynamics and modelling using G1S." Int. J Applied Earth Observation and Geoinformation,' 5, pp. 29-39.

[50] P. Torrens, M. Alberti, (2000). "Measuring sprawl. CASA working paper series 27." UCL. http://www.casa.ucl.ac.uk/publications/workingpapers.asp.

[51] P. M. Vitousek, (1994). "Beyond global warming: ecology and global change." Ecology 75, pp. 1861-1876.

[52] R. Wood, J. Handley, (2001). "Landscape dynamics and the management of change." Landscape Research, 26 (1), pp. 45-54.

[53] X. J. Yu, C.N. Ng, (2007). "Spatial and temporal dynamics of urban sprawl along two urban-rural transects: a case study of Guangzhou, China." Landsc. Urban Plann. 79, pp. 96–109.

[54] Q. Zhang, J. Wang, X. Peng, R. Gang, P. Shi, (2002). "Urban built-up land change detection with road density and spectral information from multi- temporal Landsat TM data." Int. J. Remote Sensing, 23(15), pp. 3057-3078.

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Empirical patterns of the influence of Spatial Resolution of Remote Sensing Data on Landscape Metrics

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ABSTRACT

Landscape metrics are quantitative spatial measures that aid in the landscape spatial pattern analysis. Understanding the role and capability of spatial metrics with the remote sensing data of various spatial resolutions for quantifying landscape patterns is crucial in assessing the potential of spatial metrics. The objective of this communication is to analyse the role of the landscape metrics using multi-resolution (spatial) remote sensing data for quantifying landscape patterns. Sensitivity and effectiveness in quantifying the spatial pattern components were analyzed considering part of Greater Bangalore as a sample space with 13 widely used landscape spatial metrics with the data from various sensors of differing resolutions for the month of January. The results indicate that all except three (cohesion, connect and shape) of the landscape metrics, were significantly dependent on the spatial resolution of the remote sensing data. This emphasises the consideration of appropriate spatial resolution while analyzing spatial patterns of the landscape, which provides a base for proper use of landscape metrics in the planning and management.

Keywords - Landscape, Spatial Metrics, Spatial Resolution, Remote Sensing data, Image Processing, Fragstat software.

1. INTRODUCTION

Landscape metrics based on category, patch, and class representations developed in late 80's are quantitative spatial measures of landscape pattern exhibiting variations in spatial characteristics ([1], [2], [3], [4], [5]). These metrics interpret and quantify geometric properties of a landscape and have been extensively used in landscape ecology [3]. These metrics are now finding their practical applications in the regional planning ([6], [7], [8], [9]) and monitoring ([10], [11], [12], [13], [14], [15]) of landscapes. Spatial characteristics of a landscape [1] are quantified as numeric through metrics and are interpreted, compared with the various ground data and investigating it further for diverse landscape. However, these exercises are without considering the spatial resolution and its effect in quantification of metrics. Spatial metrics bring out the pattern of change in a particular landscape and needs to be understood considering all aspects to understand the process ([16], [17]) as spatial metrics behave differently with different pattern of landscape [3]. Uuemaa et al., 2009 provides an account of spatial metrics and their relationships in the landscape planning and other activities.

Landscape metrics have been increasingly applied in understanding landscape dynamics with adequate explanations of the underlying processes. Aggregation Index, cohesion index, etc. are new indices being evaluated and considered [19] and exploration is in progress to apply these metrics for various purposes to link with the current scenarios. DPSIR (Driving force–pressure–state–impacts–response) approach [9] was used to evaluate the land use changes and related environmental impacts that have occurred in recent decades by integrating the analytical and operational approaches with help of metrics to pursue sustainable management. Peng et al., [20] evaluated the effectiveness of landscape metrics in quantifying spatial patterns of 36 simulated landscapes as sample space through 23 widely used landscape metrics with the application of the multivariate linear regression analysis. The results highlight that metrics are effective in quantifying several components of spatial patterns.

Li et al., [21] examined landscape metrics based on its functions as landscape and class level metrics. 19 landscape level metrics and 17 class level metrics have been tried using five data sets and establish the factors that describe landscape dynamics. The resolution and scale are the two crucial factors considered in the landscape analysis, which are being explored among many factors ([22], [10], [23], [24], [25], [26]; [27]). The analysis of effectiveness of spatial resolution on various landscape fragmentation indices, state that spatial resolution, might have a role in analysing and understanding landscape patterns [28]. The integrity of the analysis of landscape depends on the selection of appropriate spatial metrics, the resolution of spatial data apart from careful interpretation of the results([29], [21]).This communication analyses the role of the spatial resolution in quantifying the real world scenario.

2. Objective

The objective of the study is to understand the role of spatial resolution while assessing landscape dynamics through spatial metrics and the effectiveness of the landscape metrics in supporting landscape planning and management decisions

3. Study area

The influence of spatial resolution in assessing the landscape dynamics through spatial metrics has been done considering multi-resolution remote sensing data for the sample space - northern region of Greater Bangalore. Greater Bangalore is the capital city of the state of Karnataka, India and the hub of administrative, cultural, commercial, industrial, and knowledge activities. The spatial extent of Greater Bangalore is about 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. It is the fifth largest metropolis in India currently with a population of about 8 million [30, 31]. The Sample space chosen for the study lies in the northern part of Greater Bangalore with representative fractions of all land use types. Bangalore has witnessed rapid urbanization during 1990-2010 which has brought on fundamental land use change. The conversions between urban land, vegetation and water were the major change types in the region.

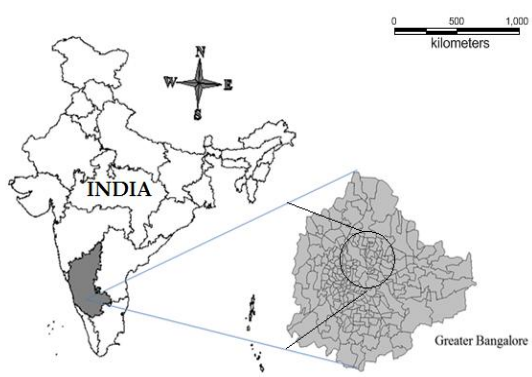


Fig. 1. Study Area: Greater Bangalore.

4. Material and Methods

Analysis was carried out using the multi-resolution remote sensing data acquired during January 2010. Multi-resolution remote sensing data includes Ikonos (4 m), Landsat Series Enhanced Thematic mapper (28.5 m) sensor, IRS P6 LISS III sensor (5.8 m) and Modis data (500 m). Landsat data of Thematic mapper (28.5m) sensors for 2010 was downloaded from public domain (http://glcf.umiacs.umd.edu/data). MODIS data "MOD 02 Level-1B Calibrated Geolocation Data Set" were downloaded from EOS Data Gateway (http://edcimswww.cr.usgs.gov/pub/imswelcome). IRS P6 LISS-III data was purchased from the National Remote Sensing Centre, Hyderabad (www.nrsc.gov.in). Geoeye Foundation provided Ikonos (4 m) data for academic use. Base layers such as city boundary, etc. were digitized with a negligible error count of 0.001from the city map (procured from BBMP: Bruhat Bangalore Mahanagara Palike), cadastral revenue maps (1:6000), Survey of India (SOI) toposheets (1:25000, 1:50000 and 1:250000 scales). Ground control points to register, geo-correct remote sensing data and Verify the output were collected using handheld pre-calibrated GPS (Global Positioning System), Survey of India Toposheet, Bhuvan and Google earth (http://bhuvan.nrsc.gov.in; http://earth.google.com).

DATA	Year	Purpose
Landsat Series Multispectral sensor (57.5m)	1973	Land use analysis
Landsat Series Thematic mapper (28.5m) and Enhanced Thematic Mapper sensors	1992, 1999, 2002, 2006, 2010	Land use analysis
Survey of India (SOI) toposheets of 1:50000 and 1:250000 scales		Boundary and base layers.

Table 1: Materials used in the analysis.

5. Analysis:

5.1 Preprocessing: The remote sensing data obtained were geo-referenced, 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.

5.2 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 of the data, while the balance is used for validation or accuracy assessment.

Land use classification was carried out using supervised pattern classifier - Gaussian maximum likelihood algorithm. This classifier is superior as it uses various classification decisions using probability and cost functions (Duda et al., 2000). Mean and covariance matrix are computed using estimate of maximum likelihood estimator. Land use was computed using the temporal data through open source program GRASS - Geographic Resource Analysis Support System (http://wgbis.ces.iisc.ernet.in/grass/index.php). Four major types of land use classes were considered: built-up area, forestland, open area, and water body. Application of this method resulted in accuracy of about 88% using Landsat data, 91% accuracy using IRS-P6 data, 94% accuracy using Ikonos data and 74% using Modis data. For the purpose of accuracy assessment, a confusion matrix was calculated.

5.3 Landscape Metrics: Landscape metrics were computed for each of chosen multi-resolution data - MODIS data (500 m) was resampled to 250 m and 100 m. Landsat resampled to 30 m and 15m, Ikonosof 4m resampled to 3m 2m and 1m respectively. The resampled data were considered for further analysis. Classified land use data (data and also for resampled data) was converted to ASCII format and metrics at the landscape level were computed with FRAGSTATS [32]. Fragstat is open-source software that can be freely downloaded (http://www.umass.edu/landeco/research/fragstats/fragstats.html). The spatial metrics include the patch area, edge/border, shape, compact/contagion/ dispersion and are listed in Appendix 1.

6. Results and Discussion

Land use analysis: Land use analysis using Gaussian Maximum Likelihood Classifier was done for multi-resolution data (MODIS, Landsat, IRS P6 and Ikonos) and the results are presented in Table 2 and figure 4. Overall accuracy of the classification was 88% using Landsat data, 91% accuracy using IRS-P6 data and 74% using Modis data respectively.

Class →	Urban	Vegetation	Water	Others
Year ↓	Ha	Ha	Ha	Ha
1973	5448	46639	2324	13903
1992	18650	31579	1790	16303
1999	24163	31272	1542	11346
2002	25782	26453	1263	14825
2006	29535	19696	1073	18017
2010	37266	16031	617	14565

Table 3.a. Temporal Land use dynamics in Hectares

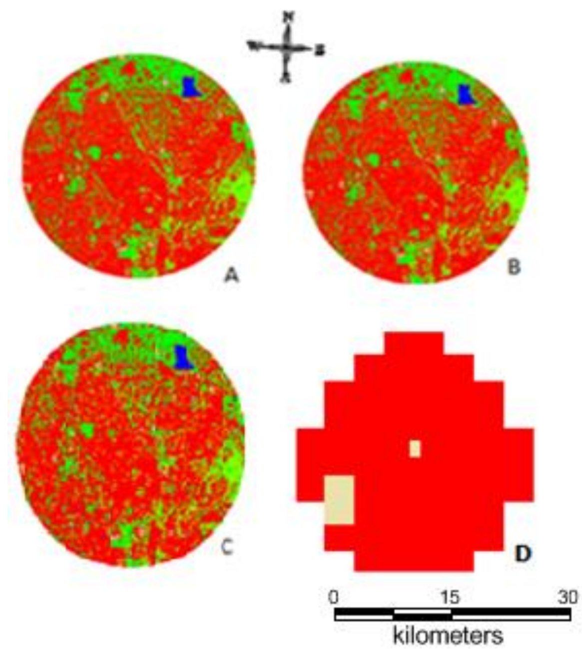


Figure 2: Land use statistics a). Ikonos 4m, b).IRS-P6 5 m, c). Landsat-30m, d). Modis-500m.

Class → Year ↓	Urban %	Vegetation %	Water %	Others %
1973	7.97	68.27	3.40	20.35
1992	27.30	46.22	2.60	23.86
1999	35.37	45.77	2.26	16.61
2002	37.75	38.72	1.84	21.69
2006	43.23	28.83	1.57	26.37
2010	54.42	23.41	0.90	21.27

Table 3.b. Temporal Land use dynamics in %

Landscape Metrics: Landscape metrics were computed for varied resolution of data for sample space in Greater Bangalore. The data was classified into 4 land use categories in a heterogeneous landscape, Urban category was considered for further analysis as the landscape is rapidly urbanizing and constitute a dominant class. Table 3 lists the quantified values of each metrics across resolutions of multi-resolution data.

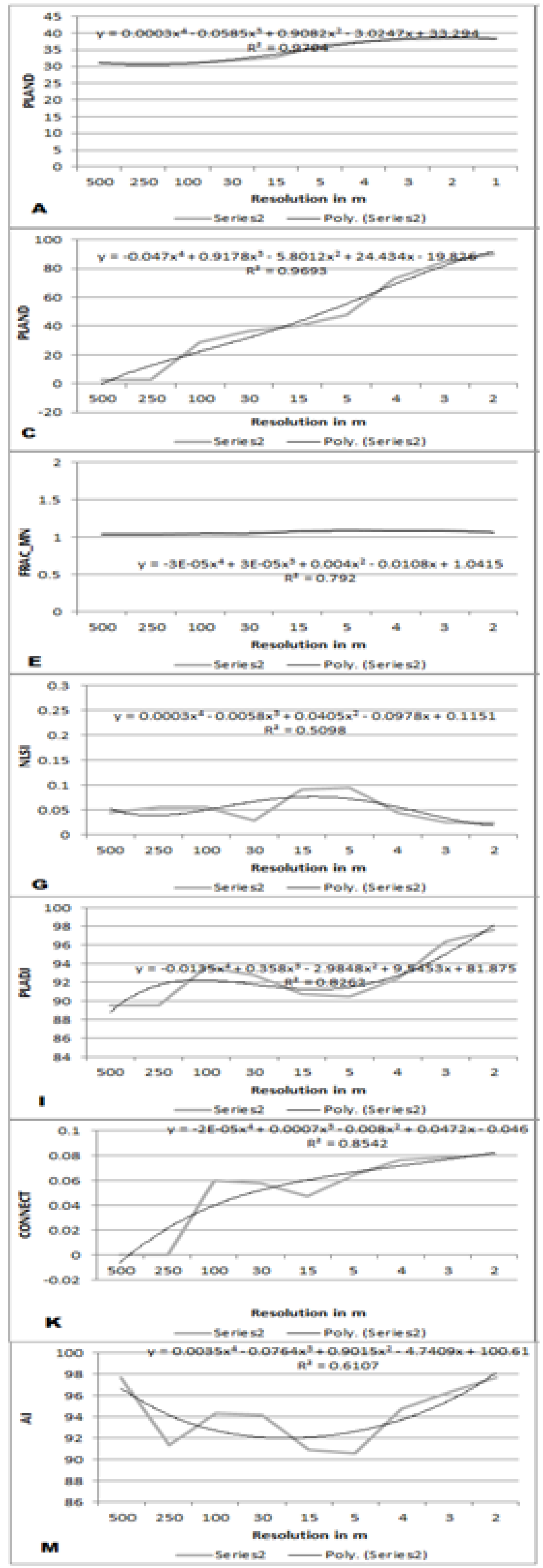
Percentage of Landscape (PLAND) and Number of Patches (NP) as tabulated in table 3, Indicates the level of fragmentation. The results highlight the dependence on spatial resolutions evident from the refinement of values with finer spatial resolutions. PLAND indicates that the urban patches in this region is becoming a single patch. Figure 3a highlight the correlation of PLAND with the resolutions (r = 0.97). Number of Patches (NP) indicates that smaller patches aggregating to form a cluster of the urban surface. Figure 3b indicates that better spatial resolution reveals large number of smaller patches and as the resolution becomes finer the number of patch metrics becomes precise.

Largest patch index (LPI) indicate that the landscape is in the process of aggregation to a single patch indicating homogenisation of landscape. This metrics is not dependent on resolutions as in quantifies the largest patch and almost accurately in all resolutions as illustrated in figure 3c.

The Patch density (PD) indicates the densification of a particular patch. Figure 3d indicates of improved performance with finer resolution. This was verified with the ground truth data and validation of the classified land use data with spatial metrics along with the resolutions of the data.

Fractal dimension index (FRAC) indicates complexity of the shape, while FRAC_MN and FRAC_AM which indicates complexity of shape around the mean and with respect to area weighted mean (AM) which has very high values indicating complex geometry. Moderate and high resolution images were able to quantify these accurately (Figure 3e).

Clumpiness index (Clumpy), Aggregation index (AI), Interspersion and Juxtaposition Index (IJI) highlights the occurrence of same patch in the neighborhood. Clumpiness and aggregation indexes mainly highlight the nature of development of a particular class in the neighborhood. Clumpiness value of 1 indicates that the particular class is highly clumped in that region. Aggregation value close to 100 indicates the same. If the value of IJI is not obtained it means to say that the patch types distinctly pound is less than three. All resolution output for all these metrics indicates that higher or better resolution is necessary to obtain appropriate result. Figure 3f, 3g and 3h corresponding to these spatial metrics indicate of improved results with the improvements in the spatial resolution.



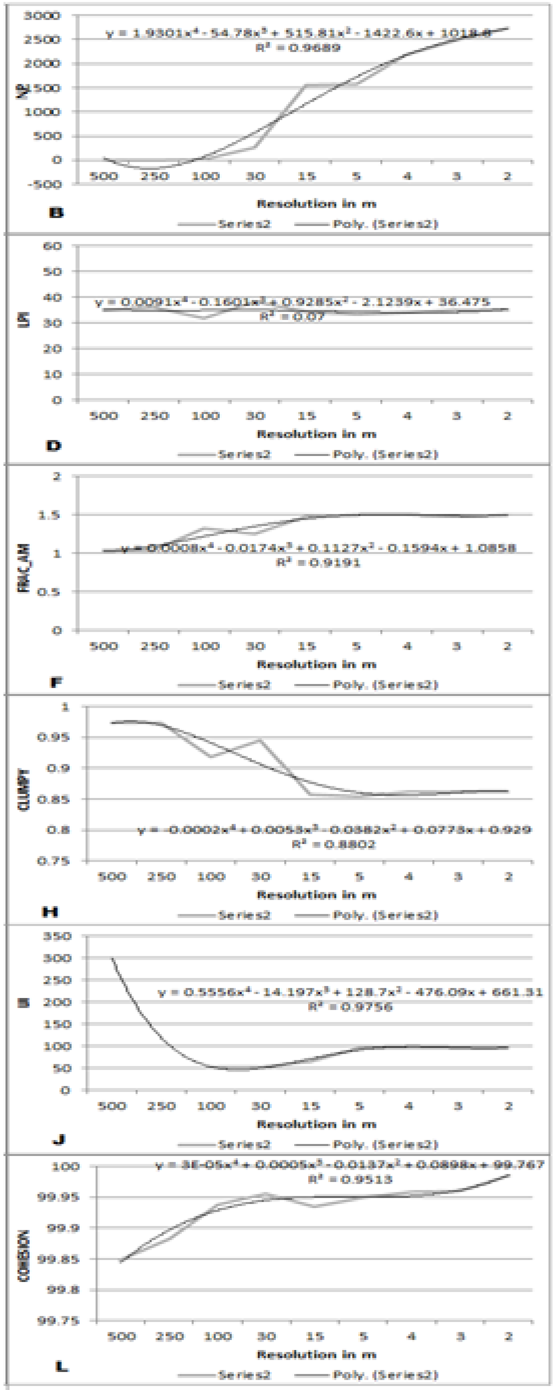


Figure 3: Correlation of spatial Matrices with resolutions of the data

Cohesion and Connect metrics measures the physical connectedness of the patches. It increases with increase in aggregation of among the patch type. Cohesion value of 100 indicates the clumpiness or connectedness of the patch values close to 0 indicates *highly unconnected fragmented landscape. Earlier as* indicated the aggregation level in the considered image is quite high hence the cohesion values should be on its higher side. Connect value of 0 indicates that the considered area is becoming a single patch and the values close to 100 indicates that every patch is highly connected and there are small fragmented patches. Figure 3i and 3j indicate that these metrics are independent of resolutions used and gives almost similar results.

Percentage of Like Adjacencies (PLADJ) calculated for the adjacency matrix indicates the frequency of different pairs of patch types occurring, measuring the degree of aggregation of the focal patch type. The values close to 0 indicates maximally dispersed pattern and values close to 100 indicates maximally contagious. Figure 3k highlight of dependence on spatial resolutions as lower resolution images fails to give an appropriate result.

Normalized Landscape Shape Index (NLSI) indicates the shape of the landscape. Values close to 0 indicates that the landscape under study has simple shape means to say it is further aggregating to become a single patch. Values close to 1 indicates that the landscape has a complex shape. Figure 3l highlight that the regions are becoming a single patch of the simple size and independent of resolutions.

7. Conclusion

The study tested the behaviour and credibility of various landscape metrics for discriminating various landscape patterns and properties across various spatial resolutions. It reveals that the spatial resolution of the remote sensing data plays an important role in the landscape analysis. Exploration of landscape structure to understand the different landscape patterns for the analysis of composition reveal the dependency on spatial resolution of the data. The results reveal that landscape metrics based on patch (NP, PLADJ, AGGREGATION, IJI, CLUMPINESS) are sensitive to spatial resolution whereas metrics that are based on shape and neighbourhood (Cohesion, Connect, NLSI) are not sensitive and behave similarly across all resolutions. Comparison of the landscape metrics of various resolutions provides explicit knowledge of their sensitivity. Variations in landscape metrics with different spatial resolutions decide the effectiveness of the approach through spatial metrics used to analyze the landscape dynamics. Landscape metrics are apt indicators of land use development and environmental status and there is a need to incorporate these indices in spatial environment monitoring and information systems to achieve sustainable management of the natural resources.

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References:

[1] M. Herold, H. Couclelis, and K.. C. Clarke. The role of spatial metrics in the analysis and modeling of urban land use change. *Computers, Environment and Urban Systems, 29(14), 2005, 369-399.*

[2] W. Acevedo, T. W. Foresman, and J. T. Buchanan,. Origins and philosophy of building a temporal database to examine human transformation processes. *Proceedings, ASPRS/ACSM annual convention and exhibition, Baltimore, MD, 1996, April 22–24.*

[3] X. Li, S, H. He, R. Bu, Q. Wen, Yu. Chang, Y. Hu, Y. Li. The Adequacy of different landscape metrics for various landscape patterns. *Pattern Recognition, 38, 2005, 2626-2638.*

[4] B.J. Goodwin, Is landscape connectivity a dependent or independent variable? *Landscape Ecology. 18 (7), 2003, 687–699.*

[5] K.C. Seto, M. Fragkias. Quantifying spatiotemporal patterns of urban land-use change in four cities of China with time series landscape metrics. *Landscape Ecology, 20, 2005, 871–888*.

[6] A. Botequilha, Leitao., Jack, Ahern. Applying landscape ecological concepts and metrics in sustainable landscape planning, *Landscape and Urban Planning 59, 2002.65-93*.

[7] M. Herold, N.C. Goldstein, K.C. Clarke. The spatiotemporal form of urban growth: measurement, analysis and modeling. *Remote Sensing Environment, 86, 2003, 286–302.*

[8] R.S. De Groot. Function-analysis and valuation as a tool to assess land use conflicts in planning for sustainable, multi-functional landscapes. *Landscape Urban Planning., 75 (3–4), 2006, 175–186.*

[9] L. Benini, V. Bandini, D. Marazza, A. Contin. Assessment of land use changes through an indicator-based approach: a case study from the Lamone River basin in Northern Italy. *Ecological Indicators, 10, 2010, 4–14.*

[10] A. Lausch, F.Herzog. Applicability of landscape metrics for the monitoring of landscape change: issues of scale, resolution and interpretability, *Ecological Indicators, 2(1), 2002, 3-15.*

[11] Heinz Center. Landscape Pattern Indicators for the Nation: A Report from the Heinz Center's Landscape Pattern Task Group, Washington, DC, 2008. (The H. John Heinz III Center for Science, Economics and the Environment). *http://www.heinzctr.org/Major_Reports.html*.

[12] B.C. Meyer, R. Grabaum. MULBO. Model framework for multicriteria landscape assessment and optimisation. A support system for spatial land use decisions. *Landscape Res., 33(2), 2008, 155–179*.

[13] L.M. Valenzuela, F. Aguilera, J.A. Soria, E. Molero. Designing and assessing of development scenarios for metropolitan patterns, M. Paegelow, M.T. Camacho (Editors), *Modelling Environmental Dynamics, Springer-Verlag, Berlín, 2008, 337–362*.

[14] I. Sante, A. M. Garcia, D. Miranda, R.Crescente. Cellular automata models for the simulation of real-world urban processes: a review and analysis. *Landsc. Urban Plann., 96, 2010, 108–122.*

[15] P. Isabel, C. Mario, Pereira, S. Luis,. Remote sensing based indicators of changes in a mountain rural landscape of Northeast Portugal. *Applied Geography, 31(3), 2011, 871-880.*

[16] M.G. Turner, R.H. Gardner, R.V. O'Neill. Landscape ecology in theory and practice: *Pattern and process, Springer, New York, 2001*.

[17] T.V. De Voorde, W. Jacquet, F. Canters. Mapping form and function in urban areas: An approach based on urban metrics and continuous impervious surface data, Landscape and Urban Planning, *102(3), 2011, 143-155*.

[18] E. Uuemaa, M. Antrop, J. Roosaare, R. Marja, and Ü. Mander. Landscape Metrics and Indices: An Overview of Their Use in Landscape Research, *Living Reviews in Landscape Research, 3(1), 2009, lrlr-2009-1.*

[19] H.S. He, B. DeZonia, D.J. Mladenoff. An aggregation index (AI) to quantify spatial patterns of landscapes, *Landscape Ecol. 15 (7), 2000, 591–601*.

[20] J. Peng, Y. Wang, Y. Zhang, J. Wu, W. Li, Y. Li. Evaluating the effectiveness of landscape metrics in quantifying spatial, *Ecological Indicators, 10(2). 2010, 217-223.*

[21] H. Li, J. Wu. Use and misuse of landscape indices. *Landsc. Ecol., 19, 2004, 389–399*.

[22] J.A. Wiens. Spatial scaling in ecology, *Functional Ecology, 3(4), 1989, 385–397.*

[23] D.J.B. Baldwin, K. Weaver, F. Schnekenburger, A.H. Perera.. Sensitivity of landscape pattern indices to input data characteristics on real landcapes: Implications for their use in natural disturbances emulation, *Landscape Ecology, 19(3), 2004, 255–271.*

[24] R.C. Corry. Characterizing fine-scale patterns of alternative agricultural landscapes with landscape pattern indices, *Landscape Ecology, 20(5), 2005, 591–608.*

[25] O. Bastian, R. Kronert, Z. Lipsky. Landscape diagnosis on different space and time scales—a challenge for landscape planning. *Landscape Ecol., 21 (3), 2006, 359–374.*

[26] G. Castilla, K. Larkin, J. Linke, G. Hay. The impact of thematic resolution on the patch-mosaic model of natural landscapes, *Landscape Ecology, 24(1), 2009, 15–23.*
[27] J.F. Mas, Y. Gao, J.A.N. Pacheco. Sensitivity of landscape pattern metrics to classification approaches, *Forest Ecology and Management, 259(7), 2010, 1215–1224.*
[28] S. Saura, J. Martínez-Millán. Landscape patterns simulation with a modified random clusters method, *Landscape Ecol. 15(7), 2000, 661–678.*
[29] M.G. Turner, R.H. Gardner, and R.V. O'Neill. Landscape Ecology in Theory and Practice: *Pattern and Process, New York; Berlin (Springer), 2nd edn, 2003.*
[30] T. V. Ramachandra, U. Kumar, Wetlands of Greater Bangalore, India: Automatic Delineation through Pattern Classifiers. *Electronic Green Journal, Issue 26, Spring 2008* .
[31] T.V. Ramachandra, A.H. Bharath and D.S. Durgappa. Insights to urban dynamics through landscape spatial pattern analysis, *Int. J Applied Earth Observation and Geoinformation, 18, 2012,329-343,* http://dx.doi.org/10.1016/j.jag.2012.03.005.
[32] K. McGarigal and B. J. Marks. FRAGSTATS: spatial pattern analysis program for quantifying landscape structure. *USDA Forest Service General Technical Report PNW-351, 1995.*

Appendix 1

	Indicators	**Formula**	**Range**	**Significance/ Description**
		Category : Patch area metrics		
1 .	Percentage of Landscape (PLAND)	$$PLAND = P_i = \frac{\sum_{j=1}^{n} a_{ij}}{A}(100)$$ 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	PLAND is 0 when patch type (class) becomes increasingly rare in the landscape. PLAND = 100 with single patch type;
2 .	Largest Patch Index(Percentage of landscape)	$$LPI = \frac{\max_{j=1}^{n}(a_{ij})}{A}(100)$$ a_{ij} = area (m^2) of patch ij A= total landscape area	0 ≤ LPI≤100	LPI = 0 when largest patch of the patch type becomes increasingly smaller. LPI = 100 when the entire landscape consists of a single patch
3 .	Number of Urban Patches	$$NPU = N$$ NP equals the number of patches in the landscape.	NPU>0, without limit.	Higher the value more the fragmentation
4 .	Patch Density	F (sample area) = (Patch Number/Area) * 1000000	PD>0,without limit	Patch density increases with a greater number of patches within a reference area.
	Category : Edge/border metrics			

5.	Area weighted mean patch fractal dimension (AWMPFD)	$$AWMPFD = \frac{\sum_{i=1}^{i=N} 2\ln 0.25\, p_i / \ln S_i}{N} \times \frac{S}{\sum_{i=1}^{i=N}}$$ Where s_i and p_i are the area and perimeter of patch i, and N is the total number of patches	1≤AWMPFD ≤2	AWMPFD is 1 for shapes with very simple perimeters, such as circles or squares, and approaches 2 for shapes with highly convoluted perimeter
6.	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	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
7.	Mean Patch Fractal Dimension (MPFD)	$$MPFD = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}\left(\frac{2\ln(0.25\,pij)}{\ln aij}\right)}{N}$$ pij = perimeter of patch ij aij= area weighted mean of patch ij N = total number of patches in the landscape	1<=MPFD<2	Shape Complexity. MPFD approaches one for shapes with simple perimeters and approaches two when shapes are more complex.
Category : Shape metrics				
8.	NLSI(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.	0≤NLSI<1	NLSI = 0 when the landscape consists of single square or maximally compact almost square and is 1 when the patch type is maximally disaggregated
Category: Compactness/ contagion / dispersion metrics				
9.	Clumpiness	$$CLUMPY = \begin{bmatrix} \frac{G_i - P_i}{P_i}\ for G_i < P_i \,\&\, P_i < 5, else \\ \frac{G_i - P_i}{1 - P_i} \end{bmatrix}$$	-1≤ CLUMPY ≤1 .	It equals 0 when the patches are distributed randomly, and approaches 1 when the patch type is maximally aggregated

		$$G_{i=}\left(\frac{g_{ii}}{\left(\sum_{k=1}^{m} g_{ik}\right)-\min e_i}\right)$$ 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.	Aggregation index	$$AI=\left[\sum_{i=1}^{m}\left(\frac{g_{ii}}{\max \rightarrow g_{ii}}\right)P_i\right](100)$$ max-g_{ii} = maximum number of like adjacencies (joins) between pixels of patch type class i based on single count method. P_i= 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.
11.	Interspersion and Juxtaposition	$$IJI=\frac{-\sum_{i=1}^{m}\sum_{k=i+1}^{m}\left[\left(\frac{e_{ik}}{E}\right).\ln\left(\frac{e_{ik}}{E}\right)\right]}{\ln\left(0.5\left[m(m-1)\right]\right)}(10($$ 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.	0≤ IJI ≤100	IJI is a measure of patch adjacency. IJI approach 0 when distribution of adjacencies among unique patch types becomes uneven; is equal to 100 when all patch types are equally adjacent to all other patch types.
12.	Cohesion	$$COHESION=\left[1-\frac{\sum_{j=1}^{n} p_{ij}}{\sum_{j=1}^{n} p_{ij}\sqrt{a_{ij}}}\right]\left[1-\frac{1}{\sqrt{A}}\right]^{-1}.(100$$	0≤cohesion<100	*Patch cohesion index* measures the physical connectedness of the corresponding patch type.
13.	Built up Area	------	>0	Total built-up land (in ha)

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Peri-Urban to Urban Landscape Patterns Elucidation through Spatial Metrics

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Abstract—Elucidation of urban land use dynamics with the quantification and pattern analysis of spatial metrics is gaining significant importance in recent times. Rapid unplanned urbanisation has telling impacts on natural resources, local ecology and infrastructure. Analysing spatio-temporal characteristics of urban landscapes through remote sensing data and landscape metrics will help in evolving appropriate strategies for integrated regional planning and sustainable management of natural resources. Temporal remote sensing data provides an opportunity to identify, quantify spatio-temporal changes. This helps in the implementation of location specific mitigation measures to minimize the impacts. This Communication focuses on spatio temporal patterns of the land use dynamics of Bangalore. Analysis was carried out radially from the city center using temporal remote sensing data acquired through space-borne sensors. Greater Bangalore with 10 kilometer buffer is considered in order to take into account spatial changes in the gradient of peri-urban to urban regions. The region has been divided into eight zones based on directions. Further, these zones are divided into 13 circles each of 2 km radius (Bangalore administrative region: 741 square kilometer being 16 km radius with 10 kilometer buffer), Landscape metrics was computed for each circle in each zone, which helped in understanding spatio-temporal patterns and associated dynamics of the landscape at local levels. PCA and CCA analysis were carried out that helped in prioritising metrics for understanding the interrelationships of spatial patterns while eliminating redundancy of numerous indices in the landscape level analysis. The analysis reveals there has been a growth of 28.47 % in urban area of Bangalore metropolitan region (including 10 kilometer buffer) during 1973 to 2010. Landscape metrics analysis reveals compact growth at the center and sprawl in the peri-urban regions.

Keywords—Urban, Landscape metrics, Shannon entropy, UII, GRASS.

I. INTRODUCTION

Urbanisation is a dynamic process refers to the growth of urban population resulting in land use land cover (LULC) changes, being experienced by most of the developing nations. Recent projections indicate that the world population living in urban areas will reach 60 percentages by 2030 [1]. Urbanisation process involves changes in LULC, socioeconomic aspects including population density. Urban land use entails interactions of urban economic activities with environment, which further leads to expansion. The rapid and uncontrolled growth of the urbanising cities brings numerous changes in the structure and hence the functioning of landscape [2]. Urban form reveals the relationship between a city with its surroundings as well as the impact of human actions on the local environment within and around a city [3]. This necessitates planning at various stages to manage the urban growth while addressing economic development with the environment goals. Multi Resolution remote sensing data acquired through sensors mounted on Earth Observation Satellites (EOS) provides a synoptic and repetitive coverage of large areas through time. It is now possible to monitor and analyze urban expansion and land use changes in a timely and cost-effective way due to improvements in spatial, spectral, temporal and radiometric resolutions with analytical techniques [4]. However, there are technical challenges in retrieving accurate information of urban expansions with rapid land use changes. A major challenge in urban remote sensing data analysis is caused by the high heterogeneity and complexity of the urban environment in terms of its spatial and spectral characteristics. A successful implementation of remote sensing technique requires adequate consideration and understanding of these specific urban landscape characteristics in order to explore the capabilities and limitation of remote sensing data and to develop appropriate image analysis techniques [5]. Recently there has been an increased interest in the application of spatial metrics techniques in urban environment because of their capability in revealing the spatial component in landscape structure with the dynamics of ecology and growth process [6-9]. The analysis of temporal landscape structure would aid in accounting spatial implications of ecological processes [10]. Many spatial landscape properties can be quantified by using a set of metrics [5], [11-14]. In this context, spatial metrics are a very valuable tool for planners in understanding and accurately characterising urban processes and their consequences [5],[10], [15]. Spatial metrics have aided in landscape monitoring, including landscape changes [16-18], assessing impacts of management decisions and human activities [19-21].A variety of landscape metrics have been proposed to characterize the spatial configuration of individual landscape class or the whole landscape base [22-25]. Compared to the other change detection techniques, the landscape metrics techniques are advantageous in capturing inherent spatial structure of landscape pattern and biophysical characteristics of these spatial dynamic [26]. Furthermore, spatial metrics have the potential for detailed analyses of thespatio-temporal patterns of urban change, and the interpretation and assessment of urbanisation process.

Land use dynamics detection using remote sensing data

Remote sensing data aids in detecting and analysing temporal changes occurring in the landscape. Availability of digital data offers cost effective solutions to map and monitor large areas. Remote sensing methods have been widely applied in mapping land surface features in urban areas [27]. Satellite based remote sensing offers a tremendous advantage over historical maps or air photos, as it provides consistent observations over a large geographical area, revealing explicit patterns of land cover and land use. It presents a synoptic view of the landscape at low cost [28]. Remote sensing also provides high-resolution datasets that are used to assess spatial structure and pattern through spatial metrics.

Landscape metrics analysis for landscape change detection

Landscape metrics or spatial metrics is based on the geometric properties of the landscape elements, are indicators widely used to measure several aspects of the landscape structure and spatial pattern, and their variation in space and time [12]. A variety of landscape metrics have been proposed to characterize the spatial configuration for the individual landscape class or the whole landscape. Scaling functions of the images describes the variations of different landscape pattern metrics with spatial resolutions [29-31]. Patch size and patch shape metrics have been widely used to assess patch fragmentation both at small and large scales [26]. Patch shape index acts as an indicator, which correlates with the basicparameter of individual patch, such as the area, perimeter, or perimeter–area ratio. However, these indices fail in reflecting the spatial location of patches within the landscape [25]. Heterogeneity based indices proposed subsequently aid in quantifying the spatial structures and organization within the landscape which was not quantified by patch shape index. Similarly, the proximity indices quantify the spatial context of patches in relation to their neighbors [32]. For example, the nearest-neighbor distance index distinguishes isolated distributions of small patches from the complex cluster configuration of larger patches [33]. Thus patch-based and heterogeneity-based indices highlight two aspects of spatial patterns, which are complement to each other. As landscape patterns possess both homogeneous and heterogeneous attributes, it is necessary to adopt both groups of indices for analysing spatial patterns of heterogeneous landscapes [34]. This illustrates that multi-resolution remote sensing data with spatial metrics provide more spatially consistent and detailed information about urban structures with the temporal changes, while allowing the improved representations for better understanding of heterogeneous characteristics of urban areas. This helps in assessing the impacts of unplanned developmental activities on the surrounding ecosystems.

II. OBJECTIVES

Main objective of the study is to quantify urbanisation process. This involved,

a. Quantitative assessment of the spatio-temporal dynamics of urbanising landscape.
b. Analysis of urbanisation process through spatial metrics.

III. STUDY AREA

Greater Bangalore with an area of 741 square kilometers and with an altitude of 949 meters above sea level is the administrative capital of Karnataka State, India is located in the Deccan Plateau to the south-eastern part of Karnataka. It lies between the latitudes 12°39’00’’ to 13°13’00’’N and longitude 77°22’00’’ to 77°52’00’’E,. To account for rural-urban gradient, 10 kilometer circular buffer has been considered from the Bangalore administrative (http://www.bbmp.gov.in/) boundary by considering the centroid as City Business District (CBD).

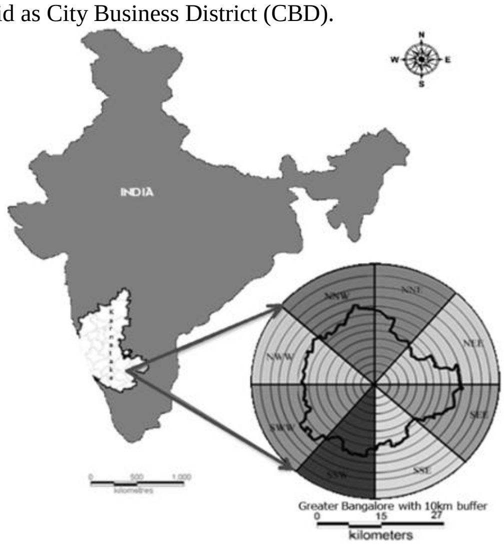

Fig.1 Study area

Bangalore was founded in the year 1537 by then ruler Kempe Gowda and has eventually evolved into economic hub of Karnataka. Bangalore is accessible by air, road, and rail. The city is well-known for its diverse culture, and history. Greenery with salubrious climate has attracted a large number of investors and migrants from other parts of the country as well as from overseas. Bangalore has grown ten folds spatially from 69 (1949) to 741 square kilometer [35]. Bangalore has been witnessing rapid urbanisation since 1990’s, which has resulted in fundamental land use changes. 632% increase in built-up has resulted in the loss of 76% vegetation and 78% water bodies during the last four decades. These large scale landscape changes has influenced the local climate and has aided in regular floods, Bangalore has been experiencing changes in the temperature leading to urban heat islands [36].

IV. MATERIALS

Remote sensing data

Multi-resolution remote sensing data of Landsat (a series of earth resource scanning satellites launched by the USA) satellite for the period 1973 to 2010 has been used. The time series of Landsat Series Multispectral sensor (57.5 meter) of 1973, Thematic mapper (28.5 meter) sensors for the years 1992 and 1999, Enhanced Thematic Mapper Plus (30 meter) of 2003, 2008 and 2010, were downloaded from public domain USGS (http://glovis.usgs.gov/) and GLCF (http://glcf.umiacs.umd.edu/data). Survey of India (SOI) topo-sheets 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 BBMP (Bruhat Bangalore Mahanagara Palike) map. Ground control points to register and geo-correct remote sensing data were collected using pre-calibrated handheld GPS (Global Positioning System) and Google earth (http://earth.google.com).

V. METHOD

Figure 2 outlines the method adopted for analysing multi-resolution remote sensing data. Landsat data acquired were geo-corrected with the help of known ground control points (GCP's) collected from the Survey of India topo-sheets and Global Positioning System (GPS). ETM+ data was corrected for SLC-off defect. Geo corrected data is then resampled to 30 meter in order to maintain a common resolution across all the data sets.

The data was classified into four land use categories - urban, vegetation, water bodies and others (open space, barren land, etc) with the help of training data using supervised classifier – Gaussian maximum likelihood classifier (GMLC). This preserves the basic land use characteristics through statistical classification techniques using a number of well-distributed training pixels. ***Grass GIS***(http://wgbis.ces.iisc.ernet.in/grass/index.php), free and open source software with robust support of processing both vector and raster data has been used for this analysis. Possible errors during spectral classification are assessed by a set of reference pixels. Based on the reference pixels, statistical assessmentof classifier performance including confusion matrix, kappa (κ) statistics and producer's and user's accuracies were calculated. These accuracies relate solely to the performance of spectral classification.Infill, linear, clustered, expansion, scattered are considered as different growth types in this study. Infill development is usually referred as compact development. Infill development converts vacant or unutilized urban land into higher density development. Infill is means of accommodating the growth within urban area's geographical extent. Growth of the urban is modeled by a fixed amount of changes for each time period referred as linear growth. The expansion of a community without concern for consequences and expanded around their peripheries that forms a new agglomeration termed as high expansion or clustered growth. Scattered development is a low density development, growth of urban area increases dramatically in short time span with new development activities in the periphery.

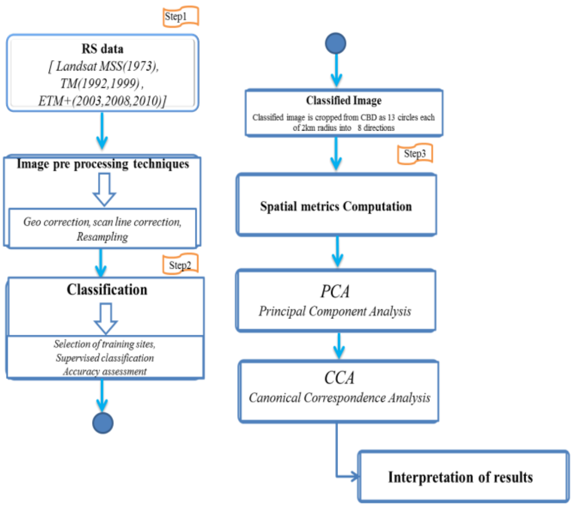

Fig. 2 Method tailed to understand urban landscape change

Analysis of urban sprawl

Urban sprawl refers to the disaggregated or dispersed growth at outskirts and these localities are devoid of basic amenities (drinking water, sanitation, etc.). This necessitates understanding sprawl process for effective regional planning. The location factors, such as distance to urban center and roads act as catalyst for urban sprawl. Shannon's entropy given in equation 1 has been used to measure the extent of urban sprawl with remote sensing data [37], [38]. Shannon's entropy was calculated across all directions to analyse the extent of urbanisation

$$Hn = -\sum Pi \log_e(Pi) \qquad \ldots\ldots\ldots \quad (1)$$

Where, P_i is the Proportion of the variable in the i^{th} zone and n is the total number of zones. This value ranges from 0 to log *n*, indicating very compact distribution for values closer to 0. The values closer to log *n* indicates that the distribution is much dispersed. Larger value (close to log n) indicates fragmented growth indicative of sprawl.

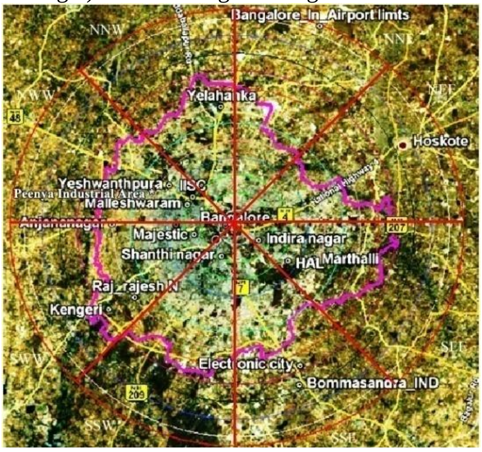

Fig. 3 Study area with important landmarks (source: Google Earth)

Analysis of spatial patterns of urbanisation - computation of Landscape metrics

The gradient based approach is adopted to explain the spatial patterns of urbanisation. The study region, given in Figure 1 was divided into eight zones based on the directions, which were further divided into concentric circles (13 circles) with incrementing radius of 2 kilometer. Landscape metrics were computed for each region to understand the landscape dynamics at local levels due to urbanisation.

A Spatio-temporal pattern of the landscape is understood through landscape metrics. These spatial metrics are a series of quantitative indices representing physical characteristics of the landscape mosaic. Table 1(Appendix I) lists the indicators that reflect the landscape's spatial and temporal changes [5], [16], [39], [40]. Thesemetrics are grouped into the five categories: Patch area metrics, Edge/border metrics, Shape metrics, Compactness/ contagion / dispersion metrics, Open Space metrics.

Analysis of land use expansion – computation of Urban Intensity Index (UII):

Urban Intensity Index (UII) is used to compare the intensity of land use expansion at different time periods. UII results in the normalization of the land area in various spatial units divided by the annual rate of expansion [41]. UII is the percentage of expansive area of urban land use in the total area and is given by 2.

UII = [(UAi,t+n –UAi,t)/n]*[100/TA] …… (2)

Where UA is urban area per year of spatial unit i, urban land use area of year t+n, land use of year t and TA resembles total land area;n represents the number of years.

VI. RESULTS AND DISCUSSION

Temporal land use changes are given in Table 2. Figures 4 and 5 depict the temporal dynamics during 1973 to 2010. This illustrates that the urban land (%) is increasing in all directions due to the policy decisions of industrialization and consequent housing requirements in the periphery. The urban growth is concentric at the center and dispersed growth in the periphery. Table 3 illustrates the accuracy assessment for the supervised classified images of 1973, 1992, 1999, 2003, 2008 and 2010 with an overall accuracy of 93.6%, 79.52%, 88.26%, 85.85%, 99.71%, and 82.73%.

Table 2 illustrates that the percentage of urban has increased from 1.87(1973) to 28.47% (2010) whereas the vegetation has decreased from 62.38 to 36.48%.

Table 2.a: **Temporal land use of Bangalore in %**

Land use Type→	**Urban**	**Vegetation**	**Water**	**Others**
Year	**%**	**%**	**%**	**%**
1973	1.87	62.38	3.31	32.45
1992	8.22	58.80	1.45	31.53
1999	16.06	41.47	1.11	41.35
2003	19.7	38.81	0.37	41.12
2008	24.94	38.27	0.53	36.25
2010	28.97	36.48	0.79	34.27

Table 2.b: Temporal land use of Bangalore in hectares

Land use →	**Urban**	**Vegetation**	**Water**	**Others**
Year	**Ha**	**Ha**	**Ha**	**Ha**
1973	3744.72	125116.74	6630.12	65091.6
1992	17314.11	123852.87	3063.69	66406.5
1999	32270.67	83321.65	2238.21	83083.05
2003	39576.06	77985.63	748.26	82611.18
2008	50115.96	76901.94	1065.42	72837.81
2010	57208.14	73286.46	1577.61	68848.92

Table 3: **Accuracy assessment**

Year	**Kappa coefficient**	**Overall accuracy (%)**
1973	0.88	93.6
1992	0.63	79.52
1999	0.82	88.26
2003	0.77	85.85
2008	0.99	99.71
2010	0.74	82.73

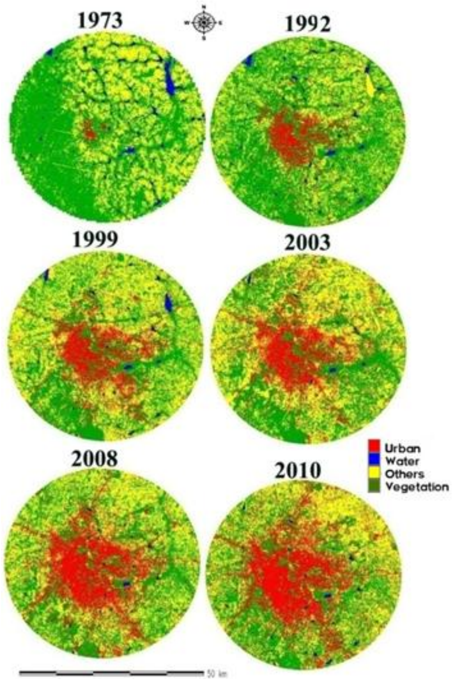

Fig. 4 Bangalore from 1973, 1992, 1999, 2003, 2008 and 2010

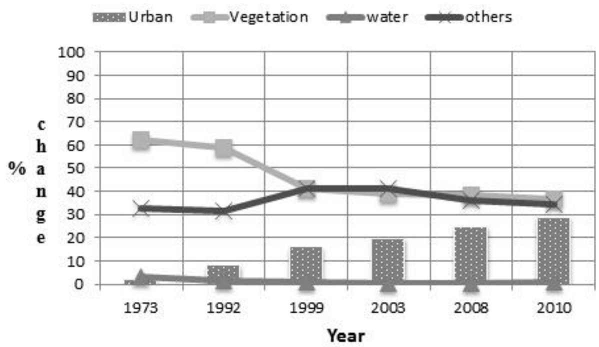

Fig. 5Land use dynamics for Bangalore from 1973 to 2010

Land use Dynamics of Bangalore from 1973-2010

Figure 6 (in Appendix II) explains the spatio temporal land use dynamics of Greater Bangalore with 10 kilometer buffer region for the period 1973to 2010. The built-up percentage (urban) in circle 1 is increasing (from 1973 to 2010) in all directions with the decline of vegetation. In 1973 built-up is high in NNE (25.37%), NWW (17.45%), NNW (43.25%) directions whereas in 2010 built-up has increased in NNE (79.02%), SSW (74.11%), NWW (76.89%), NNW (85.71%) directions due to compact growth of residential areas, commercial complex areas. I*nfilling* is observed in these regions during 1973 to 2010 due to conversion of open spaces and vegetated areas in to built-up. The urban land is increasing in all directions in Circle 2, due to more residential areas like Shanti nagar, Majestic, Seshadripuram etc., In 1973 built-up is high in SSW (11.33%), SWW (47.05%), NWW (18.96%) directions whereas in 2010 built-up has increased in NNE (90.00%), SSW (78.25%), SWW (78.30%) directions, declining the vegetation cover in the region. In 1973 built-up is high in SSW (39.94%), NWW (33.03%) directions in Circle 3 whereas in 2010 built-up has increased substantially in NNE (89.24%), SSW (71.06%), SWW (92.06%), NWW (83.73%), NNW (69.39%) directions, which in turn show decline of vegetation cover in the region. The urban land has increased in all directions due to increase in residential and commercial areas like Gandhi nagar, Guttahalli, Wilson Garden, KR Market, Kormangala (some of the IT industries are located in this region) etc. It has been observed *infilling* urban growth in the region due to more commercial/financial services/activities. Land use changes in the circle 4 during 1973 to 2010 indicate an increase of urban land in all directions due to dense residential areas like Malleswaram, Rajajinagar, Jayanagar, Yeshwanthpur and small scale industries estates like Rajaji nagar Industrial area, Yeshwanthpur Industrial suburb etc,. In the year 1973 built-up percentage is high in SEE (5.06%) and NWW (7.81%) directions whereas in 2010 built-up is more in NEE (77.06%), SSW (89.69%), SWW (92.39%), NWW (83.61%) directions, which in turn declining in the area of vegetation cover and water bodies in the region. In 1973, the area under built-up is less in all the direction in Circle 5 whereas in 2010, built-up has increased substantially in SSW (84.02%), SWW (93.01%), NWW (83.03%) directions, decreasing the vegetation cover.

The urban land has increased in all directions due to the increase in residential and commercial areas like Vijaynagar, Dasarahalli, Banshankari, Marthahalli, BTM layout and Bommanahalli industrial area (IT & BT industries) etc., in 1973 built-up in Circle 6 in NNW is 2.67% compared to all directions. In 2010 built-up has increased in SSW (68.12%), SWW (53.46%), NWW (66.90%) directions. The urban land is increasing in all directions due to more residential areas and commercial areas like Vidyaranyapuram, Jalahalli, Yelahanka satellite Town, HMT layout etc. Asia's biggest Industrial area- Peenya Industrial estate located in this region (SWW, NWW). Infilling (Peenya Industries) and high expansion (other areas) is observed in this region.

The urban land is increasing with respect to all the directions due to residential area development as in Yelahanka new town, White Field, Tunganagar, MEI housing colony and small scale industries. In 1973built-up in Circle 7 is very less, However, this has increased in 2010, in SSE (38.54%), SSW (37.72%), SWW (46.37%), NWW (63.71%) directions, which has resulted in the decline of vegetation cover and water bodies. In this region urban growth expansion due to manufacturing industrial activities is observed.

The built-up area is increasing all the directions from 1973 to 2010 in circle 8. Built-up direction wise are NNE (31.68%), SSE (32.90%), NWW (46.29%), NNW (32.29%) due to residential layouts and small scale industries.

The built-up area is increasing all the directions from 1973 to 2010. In 2010 Built-up area with respect to SSE (24.26%), SSW (21.26%), NWW (24.61%) directions has increased due to new residential areas of moderate density (Hoskote residential area) and industries (part of Bommasandra Industrial area). The built-up has increased from 1973 to 2010 in Circle 10. In 2010, Built-up has increased with respect to NNE (18.57%), SSE (22.46%), NWW (18.06%) directions due to small residential layouts, industries (part of Bommasandra Industrial area) of technical, transport and communication infrastructure. The built-up has increased in Circle 11 from 1973 to 2010 due to the land use changes from open spaces and land under vegetation to builtup. Small scale Industries near Anekal (SSE) is driving these changes. In 2010 Built-up percentage is high in NNE (16.48%), SSE (22.39%), NNW (13.35%) directions. Regions in Circle 12, in all directions have experienced the decline of water bodies and vegetation due to large scale small residential layouts and Jigani Industrial estate (located in SSE). The built-up has increased from 1973 to 2010, evident from the growth in SSE (22.09%), NNE (14.92%) and NEE (14.17%) directions during 2010.

Similar trend is observed in Circle 13 with the built up increase in SSE (21.43%), NNE (18.74%) directions due to small residential layouts, part of Jigani Industrial estate (SSE) and also residential complexes due to the proximity of Bengaluru International Airport (NNE).

Shannon's entropy

The entropy calculated with respect to 13 circles in 4 directions is listed in table 4. The reference value is taken as Log (13) which is 1.114 and the computed Shannon's entropy values closer to this, indicates of sprawl. Increasing entropy values from 1973 to 2010 shows dispersed growth of built-up area in the city with respect to 4 directions as we move towards the outskirts and this phenomenon is most prominent in SWW and NWW directions.

Table 4: **Shannon entropy**

Direction	NNE	NEE	SEE	SSE	SSW	SWW	NWW	NNW
1973	0.061	0.043	0.042	0.036	0.027	0.059	0.056	0.049
1992	0.159	0.122	0.142	0.165	0.186	0.2	0.219	0.146
1999	0.21	0.21	0.23	0.39	0.35	0.34	0.33	0.24
2003	0.3	0.25	0.27	0.33	0.36	0.4	0.45	0.37
2008	0.3	0.27	0.34	0.46	0.45	0.48	0.48	0.37
2010	0.46	0.32	0.38	0.5	0.5	0.5	0.54	0.44
Year	**Reference value: 1.114**							

Landscape metrics Analysis and interpretation

The entropy values show of compact growth in certain pockets and dispersed growth at outskirts. In order to understand the process of urbanisation, spatial metrics (Table 1 in Appendix I) were computed. Metrics computed at the class level are helpful for understanding of landscape development for each class. The analysis of landscape metrics provided an overall summary of landscape composition and configuration.

Figure 7 to 15 (Appendix III) describes Patch area metrics. Figure 7 reflects the direction-wise temporal built-up area, while Figure 8 explains percentage of built-up. These figures illustrate the inner circles (1, 2, 3, and 4) having the higher values indicates concentrated growth in the core areas especially in SWW and NWW regions. However, there has been intense growth in all zones and in all circles inside the boundary from 1973 to 2010 and which leading to spread near the boundary and 10 kilometer buffer. The values of urban intensification in certain pockets near periphery suggest the implications of IT sector after 90's (example: one such is the IT sector being established in the NEE & SEE regions). Patch indices (such as largest patch) is computed to understand the process of urbanisation as it provides an idea of aggregation or fragmented growth. Figure 9 and 10 shows largest patch index with respect to built-up (i.e. class level) and also with respect to the entire landscape.

In 1973, circle-3 of SWW direction has largest built-up patch, which is aggregating to form a single patch. In 2010 largest patches can be found in circle 4 to circle 12 indicating the process of urbanisation. In circle 12 with respect to all directions the largest patches are located due to new paved surfaces areas, among all NNW direction is having higher largest patch. Similar trend has been noticed for the largest patch with respect to whole landscape, which indicates of largest patch in SWW (circle 3) among one of the land use classes in 1973 and in NNE (circle 9) in 2010. In order to analyse the dimension of the urban patch and its growth intensity, Mean patch size (MPS) is computed, Results are as shown in Figure 11. MPS values are higher near the periphery in 1973 due to a single homogeneous patch. Whereas, it showed higher value near the center where urban patches were prominent and were less near periphery which indicated fragmented growth in the center in 2010.

Figure 12 shows number of patches (NP) of built-up area from 1973 to 2010. This is fragmentation based indices. Less NP in 1973 has increased in 2010 showing more fragmented patches which can be attributed to the sprawl at periphery (circle 6 to 13) with respect to all the directions. The more number of patches can be found in NNE direction of circle 6 and circle 12. The PD and NP indices are proportional to each other. Figure 13 shows patch density (PD) in built-up, which indicates lower values in 1973 and higher values in 2010 indicating fragmentation towards periphery. Figure 14 shows Patch area distribution coefficient of variation (PAD_CV) which indicates almost zero value (all patches in the landscape are the same size or there is only one patch) in 1973 with respect to all the directions in outer circles. This has been changed in 2010, with high PAD_CV indicating new different size patches in the landscape are present due to the intensified growth towards the outskirts with respect to all the directions. Figure 15 shows PAFRAC (Perimeter-Area Fractal Dimension) index from 1973 to 2010, which approaches 1 in all the directions, indicating of simple perimeters in the region.

Figure 16 to 20 (Appendix III) explains the Edge metrics to analyse the edge pattern of the landscape. Figure 16 shows Edge Density (ED), which shows an increase from circle 4 to 13 with respect to all directions from 1973 to 2010clarifies the landscape is having simple edges at center and becoming complex to the periphery due to large number of edges or fragments in the periphery. Figure 17 shows prominent AWMPFD in 2010 for the circle 4 in all directions. Circle 5 to Circle 8 in NNW approaches to value 2, which shows the shapes of the patches are having the convoluted perimeters. AWMPFD approaches to 1 for the shapes with simple perimeters, Perimeters that are simple indicate that there is homogeneous aggregation happening in this region. Perimeters that are complex shaped indicate the fragment that are being formed, which is most prominent in 2010.

Figure 18 shows PARA_AM, which illustrates fragmentation in the outer circles with higher values in all directions for all years and especially circle 11 of NNW direction has higher perimeter. Figure 19 and 20, shows MPFD (Mean Patch Fractal Dimension), covariance indicates that in 1973 the landscape with simple edges (almost square) has become complicated in 2010 with convoluted edges in all directions because of fragmentation and newly developing edges in the landscape.

Figure 21 to 23(Appendix III) explains the shape complexity of the landscape by the utility of shape metrics. NLSI (Normalized Landscape Shape Index) which explain shape complexity of simple (in 1973) to complex in 2010 as shown in Figure 21 with respect to all directions. Figure 22 and Figure 23 shows MSI (Mean Shape Index) and AWMSI (Area Weighted Mean Shape Index) indices, which explains in 1973 the shape of landscape is simple i.e. almost square and in 2010 due to irregular patches the shape has become more complex in all directions of the outer circles.

Figure 24 to 28 (Appendix III) describes the clumpiness of the landscape in terms of the urban pattern. Figure 24 shows Clumpy Index. City is more clumped/Aggregated in the center with respect to all directions but disaggregated towards periphery indicates small fragments or urban sprawl. Circles 1, 2, 3 are clearly portraits the intensified growth of the region in respective directions.

Figure 25 shows higher ENN_AM (Euclidean nearest neighbour distance Area weighted mean) for 1973 which has reduced in all directions from 1973 to 2010 due to intermediate urban patches. The new industries and other development activities from 1992 to 2010 especially lead to establish new urban patches which lead to reduction of nearest neighbor distance of urban patches.

Figure 26 shows ENN_CV (Euclidean nearest neighbour distance coefficient of variation) Index from 1973 to 2010, which is another form of ENN_AM, and is expressed in terms of percentage. ENN_CV value is decreasing due to more unique intermediate urban patches coming up in the region with new built-up areas. Figure 27 illustrates AI (Aggregation) Index, which is similar to Figure 24 (clumpy index).

Figure 28 shows IJI (Interspersion and Juxtaposition) which is a measure of patch adjacency IJI values are increasing due to decrease in the neighbouring urban patch distance in all the directions in 2010 which is indicative of patches/fragments becomes a single patch i.e. maximal interspersion and equally adjacent to all other patch types that are present in the landscape.

Figure 29 and 30(Appendix III) explains the open space indices, computed to assess the status of the landscape for accounting the open space and dominance of land use classes. Figure 29 shows Ratio of Open Space (ROS), which helps to understand the growth of urban region and its connected dynamics. ROS was higher in 1973 with respect to all the directions, especially in the periphery of 10 kilometerboundary. ROS decreases in the subsequent years and reaches dismal low values in 2010. Specifically, circles 1, 2, 3 , 4 shows the zero availability of open space indicating that the urban patch dominates the open area which causes limits spaces and congestion in the core urban area leading to the destruction of vegetation cover for construction purposes. This is also driving the migration from the city center towards periphery for new developmental activities. Figure 30 shows dominance index which increases considerably since 1973 and reaches considerably maximum value (in 2010) indicating that the urban category becoming the dominant land use in the landscape.

Finally, UII was calculated, which explains the growth rate at which the study area is urbanising temporally through years 1973 to 2010. The growth rate during 1973 to 1992 showed less intensification of urban whereas from 1992 to 2010 there has been a drastic increase. Table 5 explains the urban intensification temporally, revealing higher growth rates in NNE, NWW and NNW

Table 5: **UII with respect to the previous time period**

Direction		NNE	NEE	SEE	SSE	SSW	SWW	NWW	NNW
Year	**1973-1992**	0.26	0.19	0.26	0.33	0.45	0.45	0.51	0.26
	1992-1999	0.43	0.71	0.76	2.19	1.51	1.22	1.11	0.78
	1999-2003	1.36	0.06	0.62	0.04	0.33	1.18	2.25	2.17
	2003-2008	0.04	0.35	1.06	1.27	1.43	1.33	0.56	0.27
	2008-2010	6.1	1.66	1	1.29	2.05	0.96	2.61	2.35

Principal components analysis (PCA):

Principal component analysis (PCA) was carried out to reduce the number of dimensions in the data set while keeping best of the variance, and to identify the major independent dimensions of the landscape patterns [42], [43]. PCA is for reduction and interpretation of large multivariate data sets [44] with some underlying linear structure.PCA is adopted in landscape analysis to identify independent components of landscape structure, and cluster analysis to group the components and then calculated the universality, strength, and consistency of the identified landscape structure components [45]. PCA helped in prioritising representative spatial metrics that best reflect the landscape's temporal changes.

PCA has removed effect of landscape composition, and the resulting components that are the major independent dimensions of landscape configuration. Plot of principal components (PC's) in Figure 31 shows the combination of the categories with loadings. This contains the plotted component scores of each sample and the loading coefficients as eigenvectors. The largest percentage of variance was explained by metrics from PC1 and PC2. Principal component analysis illustrates the spatial pattern of patches. The combined PCA gives the most consistent metrics with high loadings across the landscape. The positive loadings explain the behaviour of fragmentation for respective circles and also compactness in some circles. These metrics are effective for discerning the patterns of urban growth at a landscape.

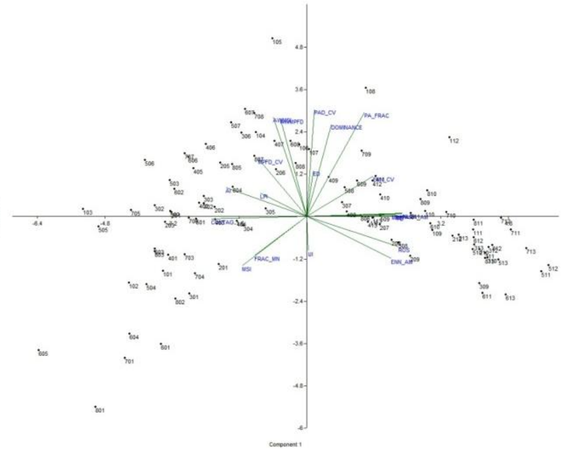

Fig. 31 PCA biplot of the first and second principal components. Dots correspond to the 104 samples (13circles for 8 directions) of spatial metrics

Computation of Canonical Correspondence Analysis (CCA):

Canonical Correspondence Analysis (CCA) an eigenvector ordination technique for multivariate direct gradient analysis [46-48] has been tried as CCA maximizes the correlation for summarising the joint variations in two sets of variables. An eigenvalue close to 1 will represent a high degree of correspondence and an eigenvalue close to zero will indicate very little correspondence. CCA is implemented considering the landscape metrics as variables with respect to 13 different circles in 8 directions and the outcome is given in figure 32. This illustrates spatial arrangement of the patches within the study area, explained by percentage variance in the respective landscape metrics. Axis 1 explains 93.23% of variance and axis 2 explains 7.09% variance. The plot shows the metrics which are the influence factors for each circle with respect to the each direction. The positive axis explains the fragmentation based indices and negative axis shows the compactness.

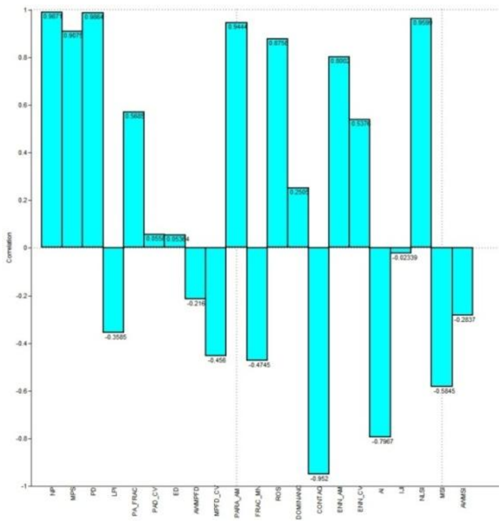

Fig. 31(a) PCA loadings with respect to each metrics

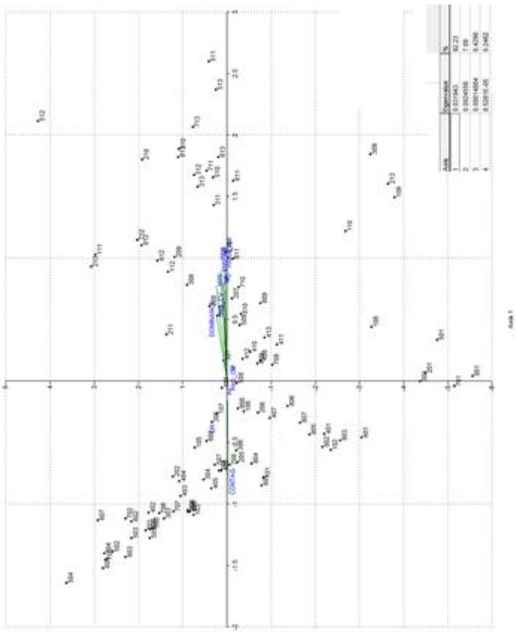

Fig. 32CCA plot of the first and second axes with % variance

VII. CONCLUSION

The peri urban to urban gradients analysis elucidated the changes in land use intensity due to the policy focus on setting up industries, leading to the increase in the population of urban and suburbs. The study shows that Bangalore is rapidly expanding with a significant increase in built-up area from 1.87% (1973) to 28.47% (2010), whereas the vegetation has decreased from 62.38% to 36.48% and also depletion of large water bodies and open spaces. Shannon entropy value is increasing from 1973 to 2010 and reaching towards the critical (reference) value highlights the sprawl. The present work demonstrates the usefulness of spatial metrics for metropolitan land use planning.

The study identified the potential utility of common landscape metrics for discriminating different patterns of the spatio–temporal land use change in response to the process of urbanisation. The landscape metrics number of patches (NP) and patch density PD showing the higher fragmentation of urban patches at periphery. Due to higher the value of number of patches (NP), mean patch size (MPS) value has come down ENN_AM showing the intermediate urban patches are developed. AI is showing the urban patches are disaggregated towards periphery. AWMSI showing the patches are becoming more irregular. The results shows urban patches are more clumped at the urban center, but fragmented towards the periphery due to newly developed urban patches at the edge. Intensified urbanisation is taking place continuously at a faster rate in outer areas, bringing more area under built-up (Urban) category as revealed by metrics (dispersed growth).

PCA was implemented to prioritize the landscape metrics useful for analysing urban dynamics. CCA was also done which brought out the critical relationships between metrics and hence proved as a very useful statistical tool to explain the higher contributors in a given set of landscape metrics. Finally, urban landscape planning design requires strengthening the structural connectivity of ecological landscapes to improve urban-ecological functional linkages. Spatial metrics and variables of urban land use form the basis for alternative representations of these factors in urban models. Such information at regional level will help decision makers in modifying the landscape in order to achieve a sustainable balance of resources.

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REFERENCES

[1]. United Nations Report 2008.http://www.un.org/millenniumgoals/reports.shtml.

[2]. Solon, J., 2009. Spatial context of urbanisation: Landscape pattern and 1950 and 1990 in the Warsaw metropolitan area, Poland. Landscape and Urban Planning doi:10.1016/j/landurbplan.2009.07.012.

[3]. Grimm Nancy B, Stanley H. Faeth, Nancy E. Golubiewski, Charles L. Redman, Jianguo Wu, XuemeiBai and John M. Briggs, 2008. Global change and the ecology of cities, Science319 (5864), 756–760.

[4]. Yang, L.M., Xian, G., Klaver, J.M., Deal, B., 2003. Urban land-cover change detec-tion through sub-pixel imperviousness mapping using remotely sensed data. Photogrammetry Engineering Remote Sensing. 69, 1003–1010.

[5]. Herold M, 2005. The role of spatial metrics in the analysis and modelling of urban land use change" Computer, Environ, and Urban Systems 29, 369–399.

[6]. McGarigal K., B. Marks, 1995. FRAGSTATS, spatial pattern analysis program for quantifying landscape structure. General Technical Report PNW-GTR-351. USDA, Forest service, Pacific, Northwest research station, Portland.

[7]. Luck, M., Wu, J., 2002. A gradient analysis of urban landscape pattern: a case study from the Phoenix metropolitan, Arizona, USA. Landsc. Ecol. 17, 327–339.

[8]. Dietzel, C., Herold, M., Hemphell, J.J., Clarke, K.C., 2005. Spatio-temporal dynamics in California's central valley: Empirical links to urban theory. Int. J. Geographic Information Science, 19(2), 175-195.

[9]. Porter Bolland, L., Ellis, E.A., Cholz, F.L., 2007. Land use dynamics and landscape history in La Monta˜ na, Campeche. Landscape and Urban Planning, 82,198–207.

[10]. Di Bari, J., 2007. Evaluation of five landscape-level metrics for measuring the effects of urbanisation on landscape structure: the case of Tucson, Arizona, USA. Landscape and Urban Planning. 79, 308–313.

[11]. McGarigal, K., S.A. Cushman, M.C. Neel, E. Ene, 2002. FRAGSTATS: Spatial Pattern Analysis Program for Categorical Maps. Computer software program produced by the authors at the University of Massachusetts, Amherst.

[12]. Li, H., Wu, J., 2004. Use and misuse of landscape indices. Landsc. Ecol. 19, 389–399.

[13]. Uuemaa, E., Antrop, M., Roosaare, J., Marja, R., Mander, U., 2009. Landscape metrics and indices: an overview of their use in landscape research. Living Rev. Landsc. Res. 3, http://www.livingreviews.org/lrlr-2009-1.

[14]. Herold, M., Goldstein, N.C., Clarke, K.C., 2003. The spatiotemporal form of urban growth: measurement, analysis and modeling. Remote Sens. Environ. 86, 286–302.

[15]. Kim, J., Ellis, C., 2009. Determining the effects of local development regulations on landscape structure: comparison of the woodlands and North Houston, TX. Landscape and Urban Planning. 92, 293–303.

[16]. Lausch A, F. Herzog, 2002. Applicability of landscape metrics for the monitoring of landscape change: issues of scale, resolution and interpretability/ Ecological Indicators 2, 3–15.

[17]. Petrov, L., Lavalle, C., Kasanko, M., 2009. Urban land use scenarios for a tourist region in Europe: applying the MOLAND model to Algarve, Portugal. Landscape and Urban Planning. 92, 10–23.

[18]. Ramachandra T.V., A.H. Bharath and D.S. Durgappa. Insights to urban dynamics through landscape spatial pattern analysis, Int. J Applied Earth Observation and Geoinformation, 18, 2012, 329- 43.

[19]. Geri, F., Amici, V., & Rocchini, D., 2010. Human activity impact on the heterogeneity of a Mediterranean landscape. Applied Geography. 30(3), 370-379.

[20]. Lin, Y., Han, G., Zhao, M., & Chang, S. X., 2010. Spatial vegetation patterns as early signs of desertification: a case study of a desert steppe in Inner Mongolia, China. Landscape Ecology. 10,1519-1527.

[21]. Proulx, R., &Fahrig, L., 2010. Detecting human -driven deviations from trajectories in landscape composition and configuration. Landscape Ecology, 10, 1479-14 87.

[22]. Patton, D.R., 1975. A diversity index for quantifying habitat "edge". Wildl. Soc. Bull. 3:171–173.

[23]. Forman, R.T.T., Gordron,M., 1986. Landscape Ecology. John Wiley & Sons, New York, ISBN 0-471-87037-4.

[24]. O'Neill, R.V., Krummel, J.R., Gardner, R.H., Sugihara, G., Jackson, B.L., DeAngelis, D.L.,Milne, B.T., Turner, M.G., Zygmunt, B., Christensen, S.W., Dale, V.H., Graham, R.L.,1988. Indices of landscape pattern. Landscape and Ecology. 1, 153–162.

[25]. Imbernon, J., Branthomme, A., 2001. Characterization of landscape patterns of deforestation in tropical rain forest. Int. J. Remote Sens. 22, 1753–1765.

[26]. Fuller, D.O., 2001. Forest fragmentation in Loudoun County, Virginia, USA evaluated with multi temporal Landsat imagery. Landsc. Ecol. 16, 627–642.

[27]. Haack, B. N., Guptill, S. C., Holz, R. K., Jampoler, S. M., Jensen, J. R., & Welch, R. A. (1997). Urban analysis and planning. In Philipson et al. (Eds.), Manual of photographic interpretation (2nd ed., p517–554).

[28]. Lillesand, T.M., Keifer, R.W. 1987. Remote sensing and Image interpretation, John Willey and Sons, NewYork.

[29]. Wu, J., Shen,W., Sun,W., Tueller, P.T., 2002. Empirical patterns of the effects of changing scale on landscape metrics. Landscape Ecology 17 (8), 761–782.

[30]. Yu, X., Ng, C., 2006. An integrated evaluation of landscape change using remote sensing and landscape metrics: a case study of Panyu, Guangzhou. International Journal of Remote Sensing 27 (6), 1075–1092.

[31]. Saura S, Castro S, 2007. Scaling functions for landscape pattern metrics derived from remotely sensed data: Are their sub pixel estimates really accurate? ISPRS Journal of Photogrammetry & Remote Sensing 62, 201–216.

[32]. Gustafson, E.J., 1998. Quantifying landscape spatial pattern: what is the state of the art? Ecosystems 1,143–156.

[33]. Turner, M.G., 1989. Landscape ecology: the effects of pattern on process. Ann. Rev.Ecolog. Syst. 20, 171–197.

[34]. Turner, M.G., Gardner, R.H., 1990. Quantitative method in landscape ecology: an introduction. Ecolog. Stud. 82, 3–14.

[35]. Ramachandra, T.V., and Kumar, U., 2008, Wetlands of Greater Bangalore, India: Automatic Delineation through Pattern Classifiers. Electronic Green Journal 26, Web URL: http://egj.lib.uidaho.edu/index.php/egj/article/view/3171.

[36]. Ramachandra, T.V., and Kumar, 2009. Urban Land surface temperature with land cover dynamics: multi-resolution, spatio-temporal data analysis of Greater Bangalore, International Journal of Geo informatics, 5(3), 43-53.

[37]. Yeh, A. G. O., & Li, X. 2001. Measurement and monitoring of urban sprawl in a rapidly growing region using entropy. Photogrammetric Engineering and Remote Sensing, 67(1), 83–90.

[38]. Sudhira, H. S., Ramachandra, T. V., &Jagdish, K. S., 2004. Urban sprawl: metrics, dynamics and modeling using GIS. International Journal of Applied Earth Observation and Geo information, 5, 29–39.

[39]. Aguilera, F., Luis Valenzuela M., Andre Botequilha-Leitao., 2011. Landscape metrics in the analysis of urban land uses patterns: A case study in a Spanish metropolitan area. Landscape and Urban Planning, 99, 3-4, 226-238.

[40]. Taubenbock H. M., Wegmann, A. Roth, H. Mehl, S. Dech, 2009. Urbanisation in India – Spatiotemporal analysis using remote sensing data Original Research Article Computers, Environment and Urban Systems, 33, 3, 179 - 188.

[41]. Dong W, Zhang XL, Wang B., Duan Z.L, 2007. Expansion of Urmqi urban area and its spatial differentiation, Science in China Series D: Earth Sciences 50,159-168.

[42]. Riitters, K.H., O'Neill, R.V., Hunsaker, C.T., Wickham, J.D., Yankee, D.H., Timmins, S.P., Jones, K.B., Jackson, B.L., 1995. A factor analysis of landscape pattern and structure metrics, Landscape Ecology, 10(1), 23-39.

[43]. Jackson, D.A., 1993. Stopping rules in principal components analysis: a comparison of heuristical and statistical approaches. Ecology, 74, 2204–2214.

[44]. Sabatier, R., Lebreton, J.D., Chessel, D., 1989. Principal component analysis with instrumental variables as a tool for modelling composition data, 341-352.

[45]. Samuel, A. C., McGarigal, k., Neel, M.C., 2008. Parsimony in landscape metrics: Strength, universality, and consistency Ecological Indicators, 8 (5), 691-703.

[46]. TerBraak, J.F.C., 1986. Canonical Correspondence Analysis: A new Eigenvector Technique for Multivariate Direct Gradient Analysis. Ecology, 67 (5), 1167-1179.

[47]. Retuerto, R., Carballeira, A., 1991. Defining phytoclimatic units in Galicia, Spain, by means of multivariate methods. Journal of Vegetation Science, 2, 699-710.

[48]. Palmer, M.W., 1993. Putting things in even better order – the advantages of canonical correspondence-analysis. Ecology, 74, 2215–2230.

Appendix I:

Table 1: Landscape metrics with significance

SL NO	INDICATORS	FORMULA	RANGE	SIGNIFICANCE/ DESCRIPTION
		Category : Patch area metrics		
1	**Built up (Total Land Area)**	------	>0	Total built-up land (in ha)
2	**Built up (Percentage of landscape)**	$BP = \frac{A_{builtup}}{A}(100)$ A $_{built-up}$ = total built-up area A= total landscape area	0<BP≤100	It represents the percentage of built-up in the total landscape area.
3	**Largest Patch Index (Percentage of built up)**	$LPI = \frac{\max_{i=1}^{n}(a_i)}{A}(100)$ a $_i$ = area (m^2) of patch i A= total landscape area	0 ≤ LPI≤100	LPI = 0 when largest patch of the patch type becomes increasingly smaller. LPI = 100 when the entire landscape consists of a single patch of, when largest patch comprise 100% of the landscape.
4	**Mean patch size MPS**	$MPS = \frac{\sum_{i=1}^{n} a_i}{n_i}\left(\frac{1}{10,000}\right)$ i=ith patch a=area of patch i n=total number of patches	MPS>0,without limit	MPS is widely used to describe landscape structure. Mean patch size index on a raster map calculated, using a 4 neighbouring algorithm.
5	**Number of Urban Patches**	$NPU = n$ NP equals the number of patches in the landscape.	NPU>0, without limit.	It is a fragmentation Index. Higher the value more the fragmentation
6	**Patch density**	f(sample area) = (Patch Number/Area) * 1000000	PD>0,without limit	Calculates patch density index on a raster map, using a 4 neighbor algorithm.

7	**Patch area distribution coefficient of variation (PADCV)**	$$PAD_{CV} = \frac{SD}{MPS}(100)$$ with:SD: standard deviation of patch area size $$SD = \sqrt{\frac{\sum_{i=1}^{Npatch}(a_i - MPS)^2}{Npatch}}$$ • MPS: mean patch area size • ai: area of patch i • N_{patch}: number of patch	PADCV≥0	PADCV is zero when all patches in the landscape are the same size or there is only one patch (no variability in patch size). .
8	**Perimeter-Area Fractal Dimension PAFRAC**	$$\frac{\left[N\sum_{i=1}^{m}\sum_{j=1}^{n}(\ln P_{ij}.\ln a_{ij})\right] - \left[\left(\sum_{i=1}^{m}\sum_{j=1}^{n}\ln p_{ij}\right)\left(\sum_{i=1}^{m}\sum_{j=1}^{n}\ln a_{ij}\right)\right]}{\left(N\sum_{i=1}^{m}\sum_{j=1}^{n}\ln p_{ij}^2\right) - \left(\sum_{i=1}^{m}\sum_{j=1}^{n}\ln p_{ij}\right)}$$ a_{ij} = area (m^2) of patch ij. p_{ij} = perimeter (m) of patch ij. N = total number of patches in the landscape	1≤PAFRAC≤2	It approaches 1 for shapes with very simple perimeters such as squares, and approaches 2 for shapes with highly convoluted, perimeters. PAFRAC requires patches to vary in size.
		Category : Edge/border metrics		
9	**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 **eik** :total length of edge in landscape involving patch type k **Area**: total landscape area	ED ≥ 0, without limit. ED = 0 when there is no class edge.	ED measures total edge of urban boundary used to compare landscape of varying sizes.
10	**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	1≤AWMPFD≤ 2	AWMPFD approaches 1 for shapes with very simple perimeters, such as circles or squares, and approaches 2 for shapes with highly convoluted perimeter. AWMPFD describes the fragmentation of urban patches. If Sprawl is high then AWMPFD value is high.
11	**Perimeter Area Weighted Mean Ratio. PARA_AM**	PARA_AM= $\frac{Pij}{Aij}$ Pij = perimeter of patch ij Aij= area weighted mean of patch ij $$AM = \sum_{J=1}^{n}[Xij[\frac{aij}{\sum_{j=1}^{n} aij}]]$$	>0,without limit	PARA AM is a measure of fragmentation; it is a measure of the amount of 'edge' for a landscape or class. PARA AM value increased with increasing patch shape complexity.
12	***A. Mean Patch Fractal Dimension (MPFD)***	*B.* $$MPFD = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}\left(\frac{2\ln(0.25 pij)}{\ln aij}\right)}{N}$$ *C. pij = perimeter of patch ij* *D. aij= area weighted mean of patch ij* *E. N = total number of patches in the landscape*	1<=MPFD<2	MPFD is another measure of shape complexity, approaches one for shapes with simple perimeters and approaches two when shapes are more complex.

13	**Mean Patch Fractal Dimension (MPFD) coefficient of variation (COV)**	$$MPFD = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}\left(\frac{2\ln(0.25pij)}{\ln aij}\right)}{N}$$ $$CV = \frac{SD}{MN}(100)$$ 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.	It gives coefficient of variation of patches.
Category : Shape metrics				
14	**NLSI (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.	0≤NLSI<1	NLSI = 0 when the landscape consists of single square or maximally compact almost square, it increases when the patch types becomes increasingly disaggregated
15	**Mean Shape index MSI**	$$MSI = \frac{\sum_{j=i}^{n}\left(\frac{0.25p_{ij}}{\sqrt{a_{ij}}}\right)}{n_i}$$ p_{ij} is the perimeter of patch i of type j. a_{ij} is the area of patch i of type j. n_i is the total number of patches.	MSI ≥ 1, without limit	Explains Shape Complexity.MSI is equal to 1 when all patches are circular (for polygons) or square (for raster (grids)) and it increases with increasing patch shape irregularity
16	**Area Weighted Mean Shape Index (AWMSI)**	$$AWMSI = \frac{\sum_{i=1}^{i=N} p_i / 4\sqrt{s_i}}{N} \times \frac{s_i}{\sum_{i=1}^{i=N} s_i}$$ Where s_i and p_i are the area and perimeter of patch i, and N is the total number of patches	AWMSI ≥ 1, without limit	AWMSI = 0 when all patches in the landscape are circular or square. AWMSI increases without limit as the patch shape becomes irregular.
Category: Compactness/ contagion / dispersion metrics				
17	**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≤ CLUMPY ≤1 .	It equals 0 when the patches are distributed randomly, and approaches 1 when the patch type is maximally aggregated.

18	**Area weighted Euclidean mean nearest neighbor distance AW_MNND**	$ENN = h_{ij}$ h_{ij}isdistance(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.
19	**ENND coefficient of variation**	$ENN = h_{ij}$ $CV = \frac{SD}{MN}(100)$ 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.	In the analysis of urban processes, greater isolation indicates greater dispersion.
20	**Aggregation index**	$AI = \left[\sum_{i=1}^{m}\left(\frac{g_{ii}}{\max \to g_{ii}}\right)P_i\right](100)$ gii=number of like adjacencies (joins) between pixels of patch type (class) i based on thesingle count method.	1≤AI≤100	AI equals 1 when the patches are maximally disaggregated and equals 100 when the patches are maximally aggregated
21	**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	IJI is used to measure patch adjacency. IJI approach 0 when distribution of adjacencies among unique patch types becomes increasingly uneven; is equal to 100 when all patch types are equally adjacent to all other patch types.
Category : Open Space metrics				
22	**Ratio of open space (ROS)**	$ROS = \frac{s'}{s} \times 100\%$ Where s is the summarization area of all "holes" inside the extracted urban area, s is summarization area of all patches	It is represented as percentage.	The ratio, in a development, of open space to developed land.
23	**Patch dominance**	$Dominance = ln(m) + \sum_{i=1}^{m} pi\ ln(pi)$ **m**: number of different patch type **i**: patch type; **pi**: proportion of the landscape occupied by patch type i	----------	Computes dominance's diversity index on a raster map.

Appendix II:

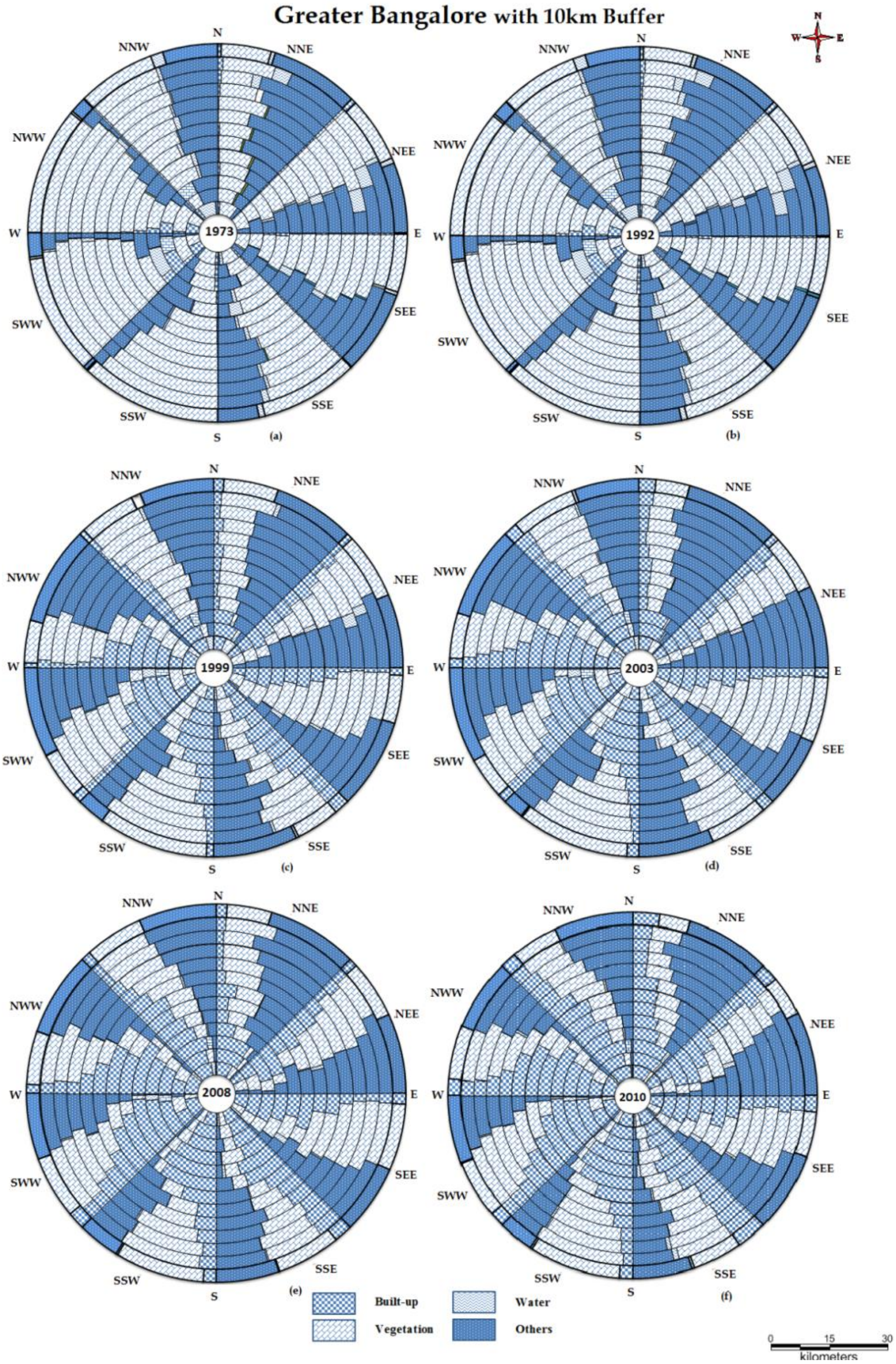

Fig. 6 Land use dynamics for Bangalore Zone-wise and circle-wise (1973 to 2010)

Appendix III:

Patch Area metrics

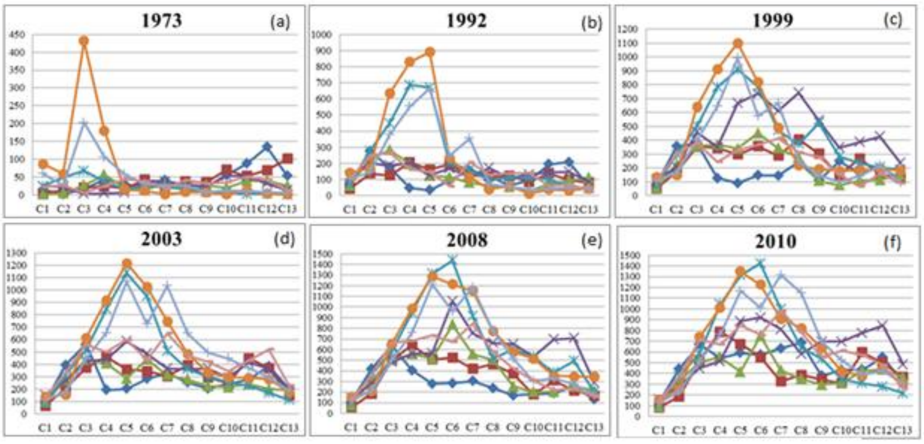

Fig. 7(a, b, c, d, e, f) Built-up area in Ha

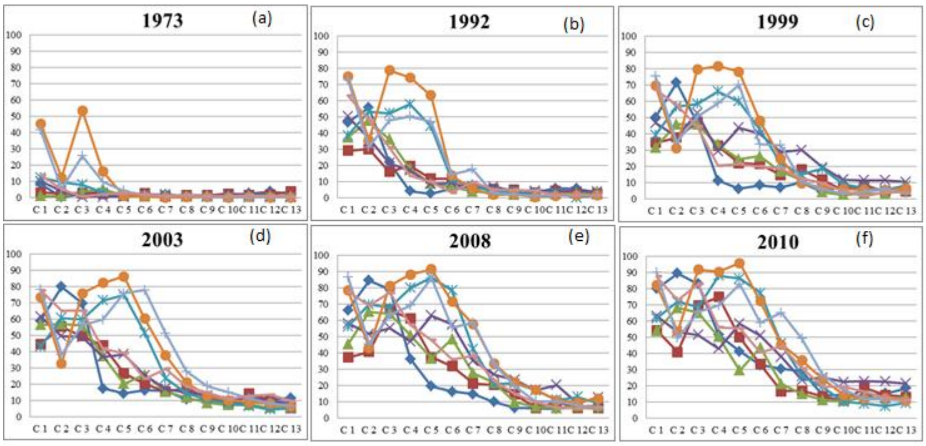

Fig. 8 (a, b, c, d, e, f) Built-up area in %

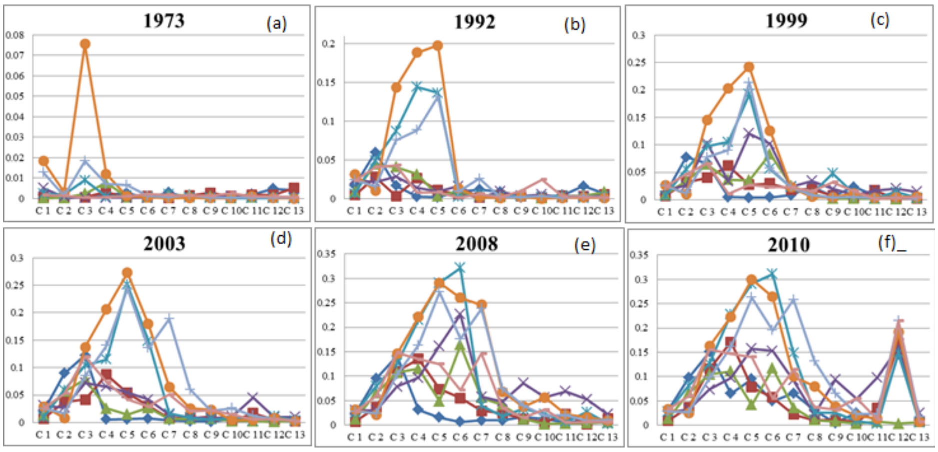

Fig. 9 (a, b, c, d, e, f) Largest Patch Index (Built-up area)

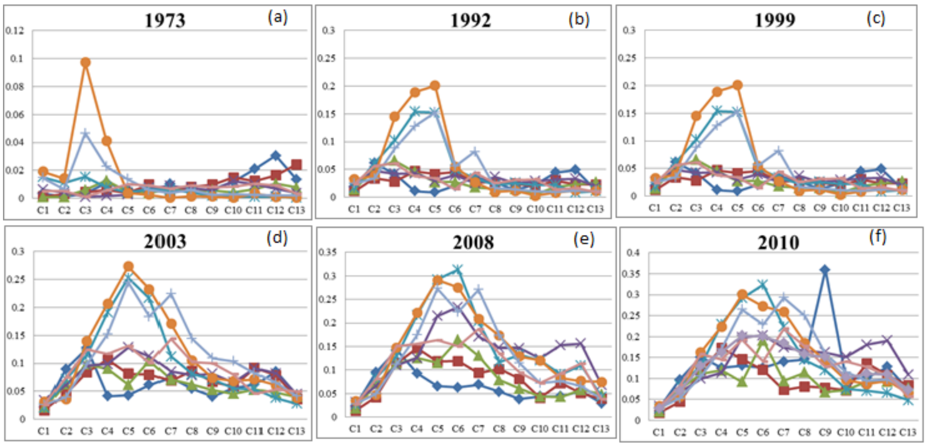

Fig. 10 (a, b, c, d, e, f) Largest Patch Index (landscape)

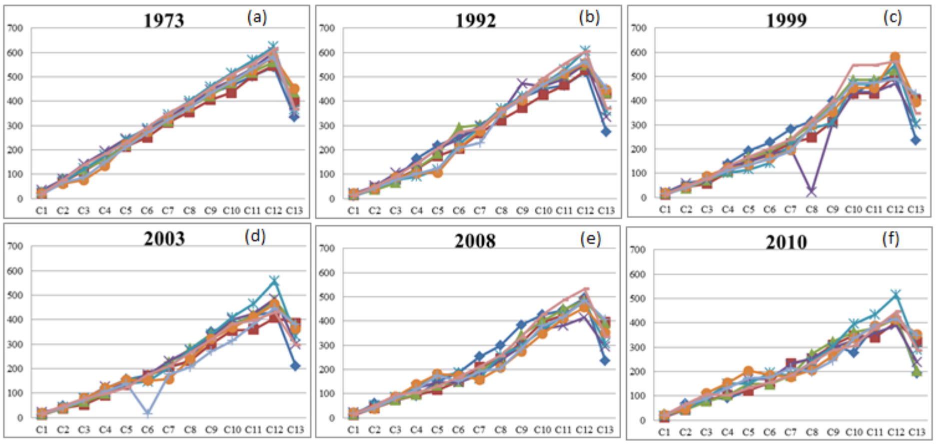

Fig. 11(a, b, c, d, e, f) Mean Patch Size

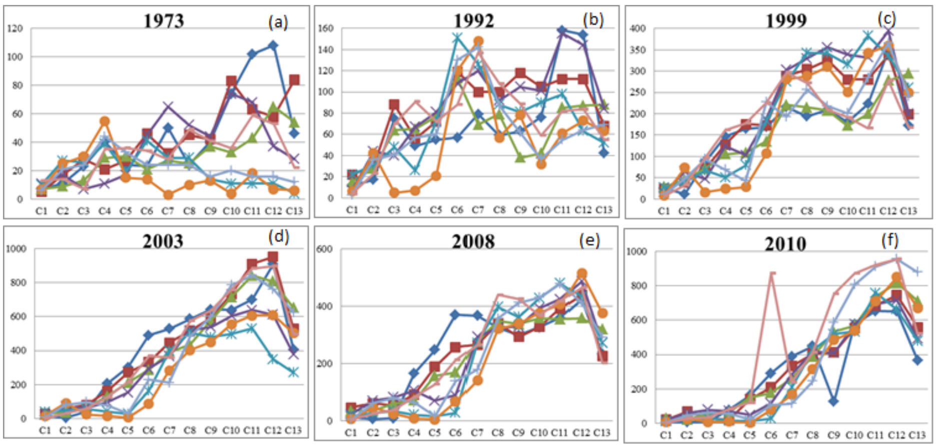

Fig. 12(a, b, c, d, e, f) Number of Patches (NP)

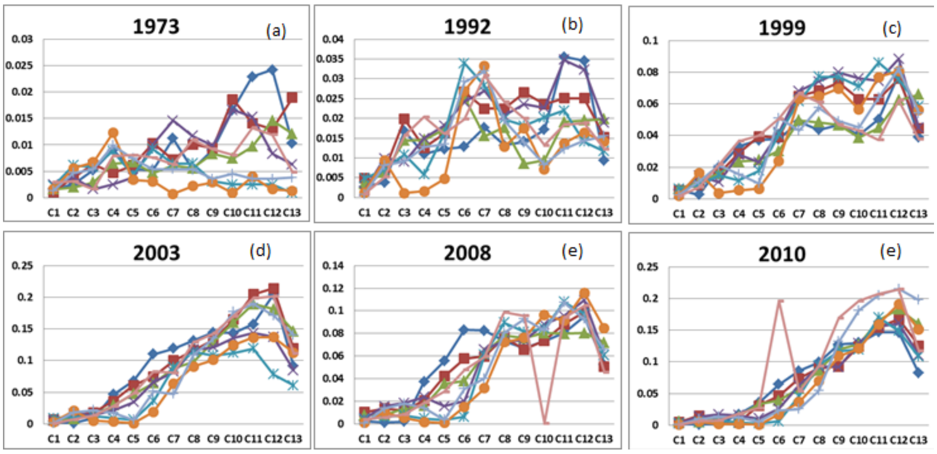

Fig. 13 (a, b, c, d, e, f) Patch Density (PD)

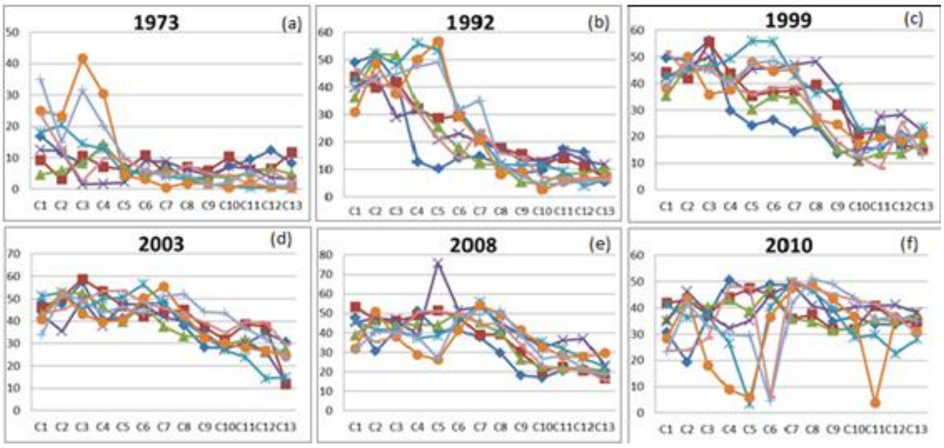

Fig. 14 (a, b, c, d, e, f) PADCV

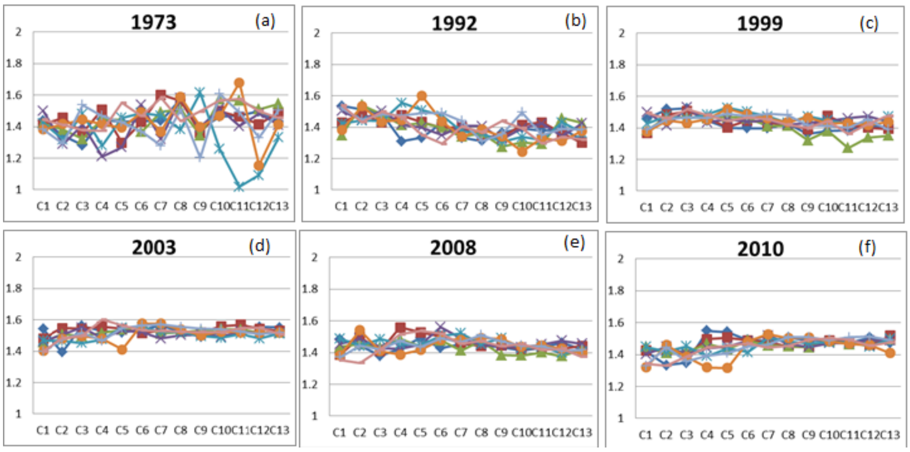

Fig. 15 (a, b, c, d, e, f) PAFRAC

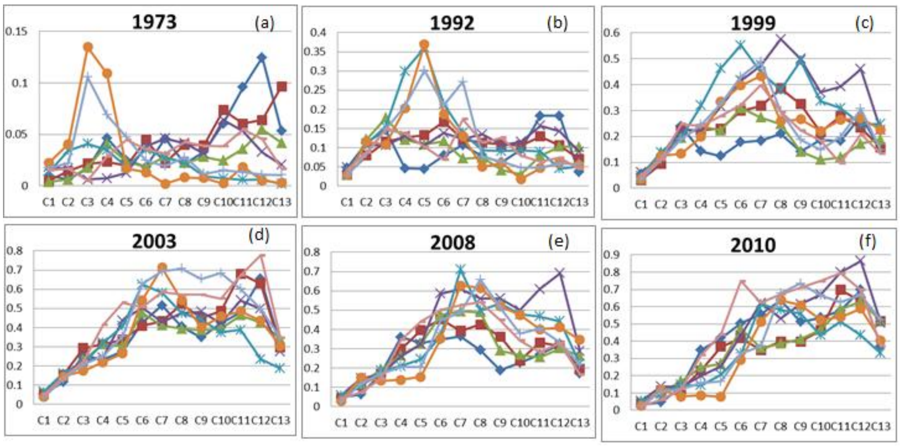

Fig. 16 (a, b, c, d, e, f) Edge Density(ED)

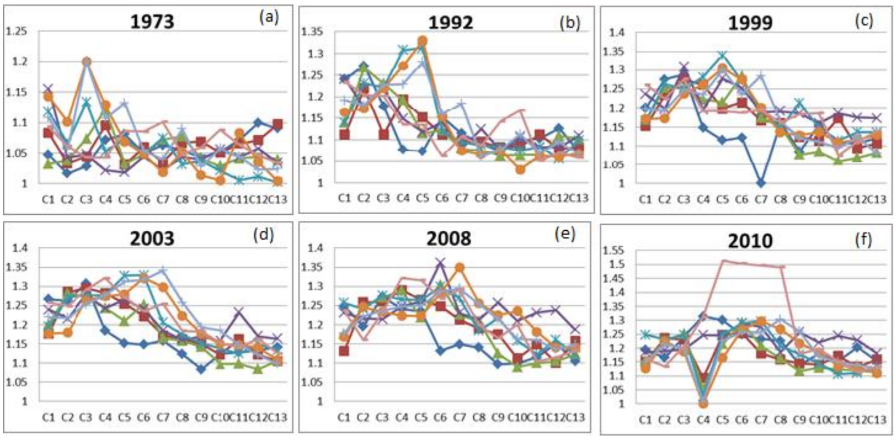

Fig. 17 (a, b, c, d, e, f) AWMPFD

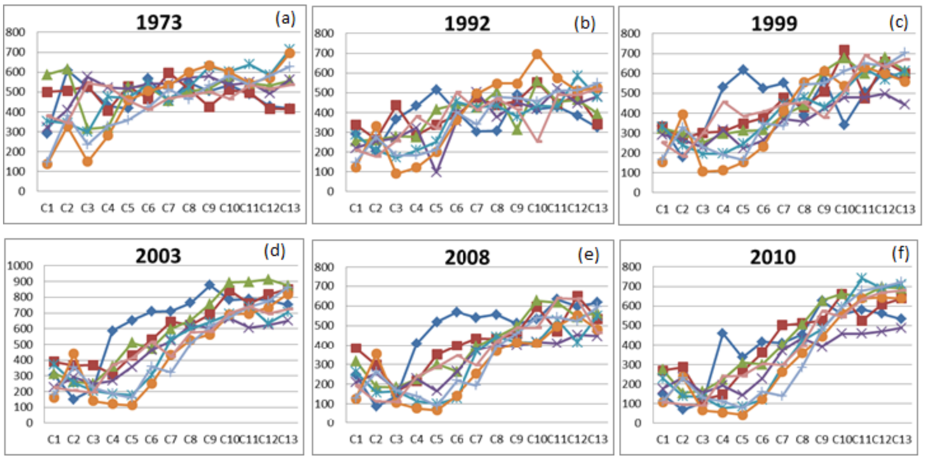

Fig. 18 (a, b, c, d, e, f) PARA_AM

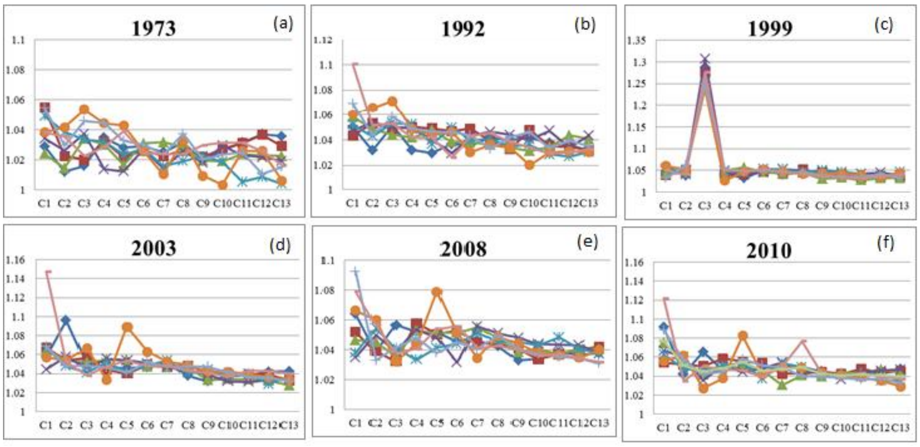

Fig. 19 (a, b, c, d, e, f)MPFD

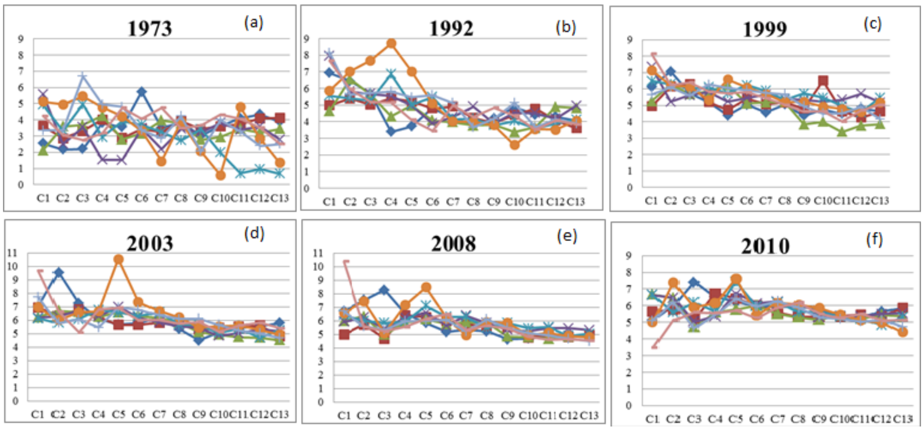

Fig. 20 (a, b, c, d, e, f) MPFD_CV

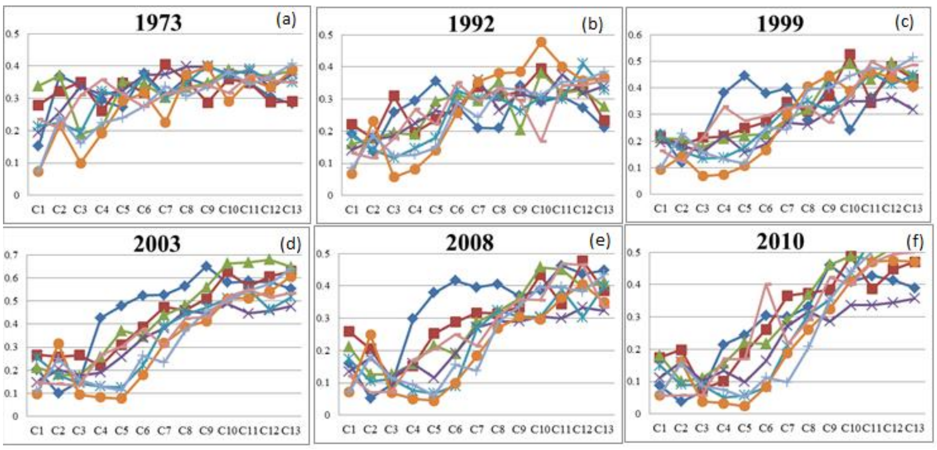

Fig. 21 (a, b, c, d, e, f) NLSI

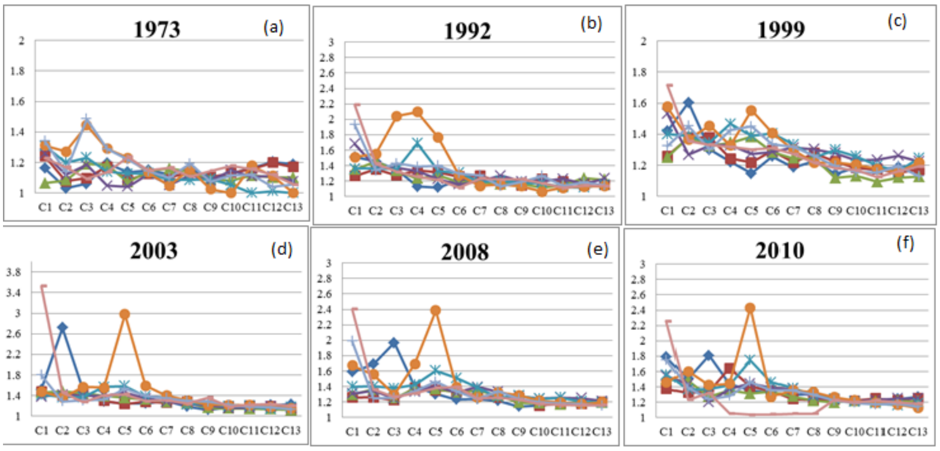

Fig. 22 (a, b, c, d, e, f) MSI

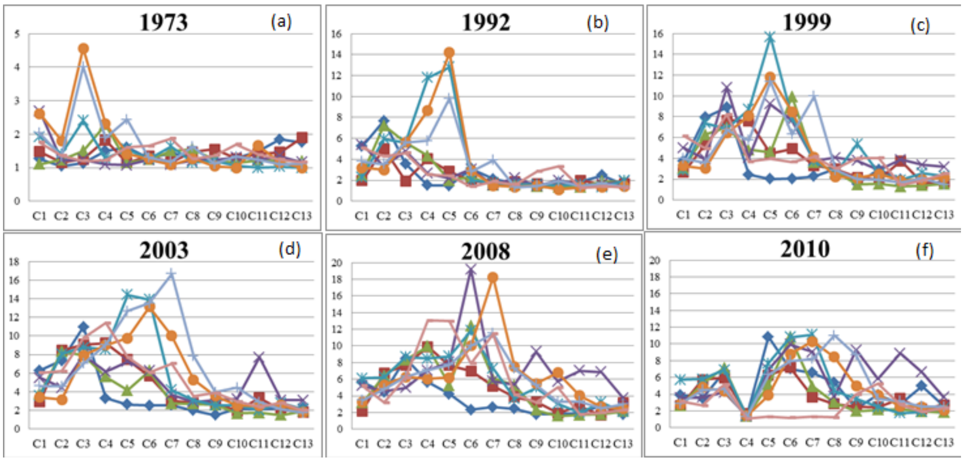

Fig. 23 (a, b, c, d, e, f) AWMSI

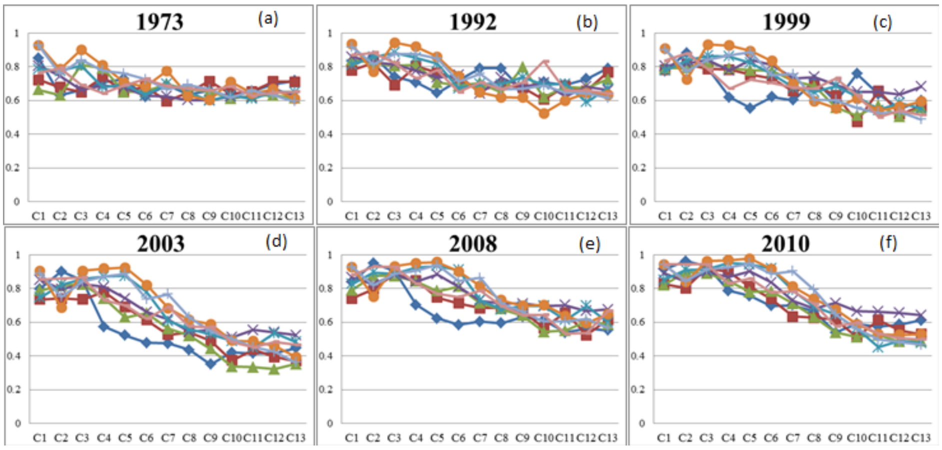

Fig. 24 (a, b, c, d, e, f) Clumpiness

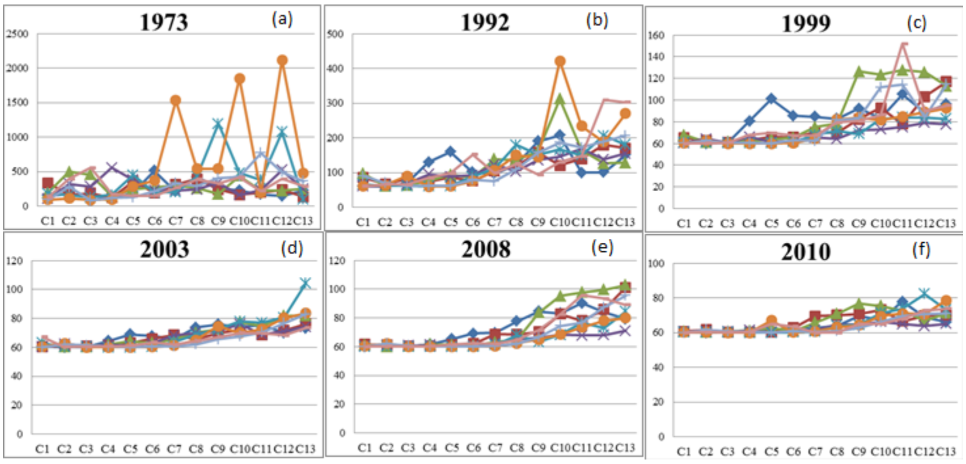

Fig. 25 (a, b, c, d, e, f) ENN_AM

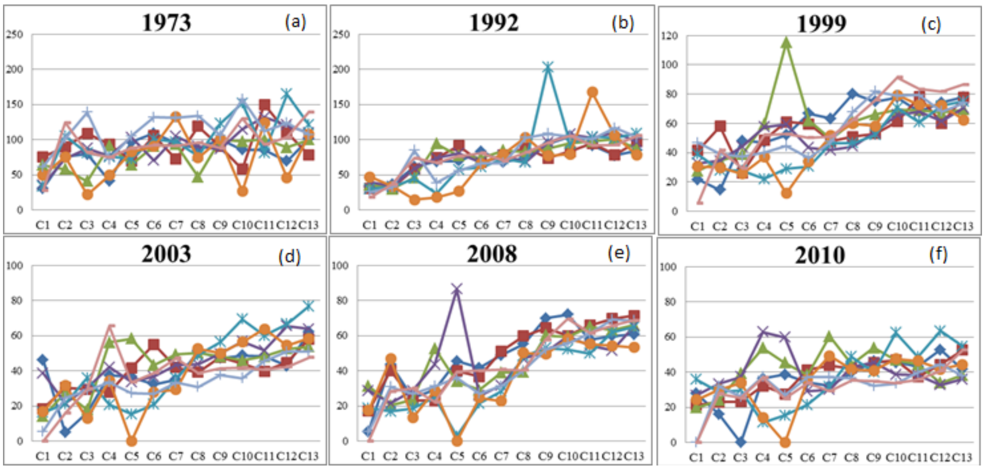

Fig. 26 (a, b, c, d, e, f) ENN_CV

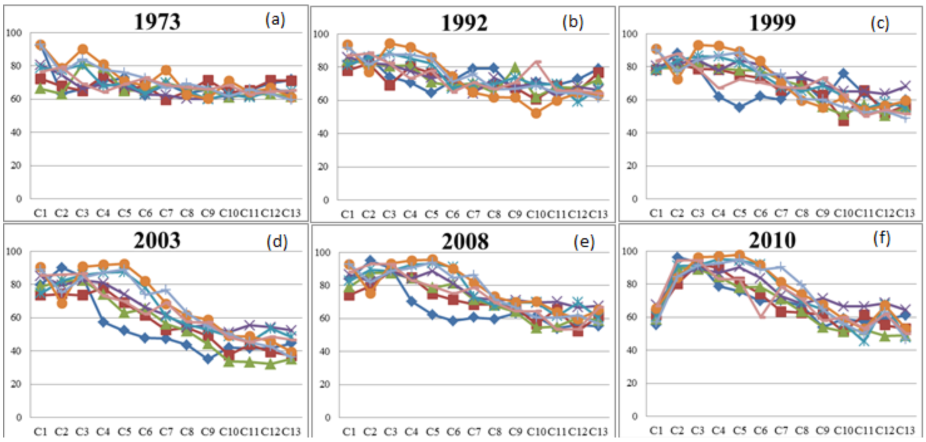

Fig. 27 (a, b, c, d, e, f) AI

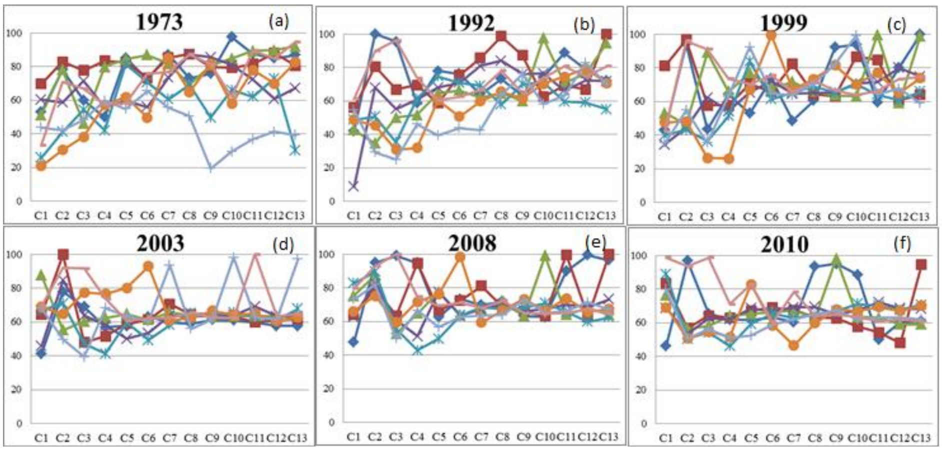

Fig. 28 (a, b, c, d, e, f) IJI

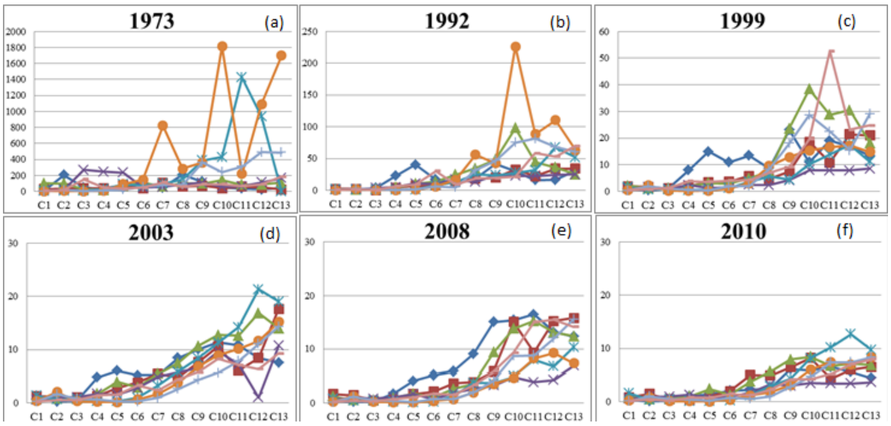

Fig. 29 (a, b, c, d, e, f) ROS

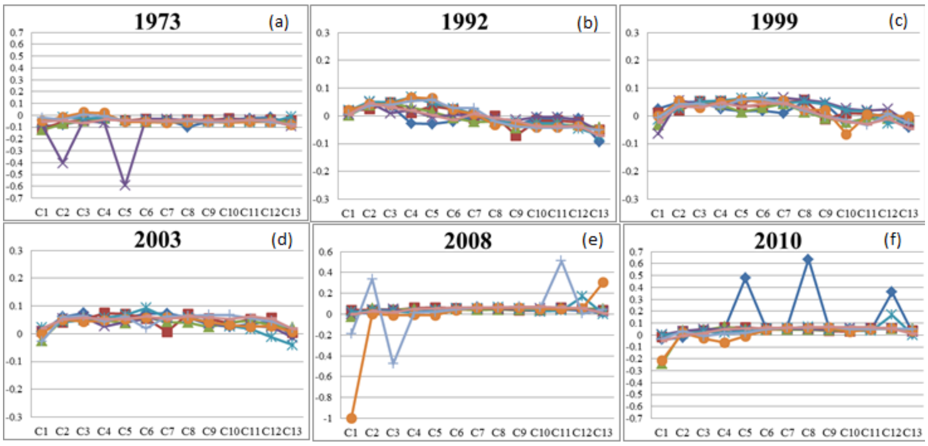

Fig. 30 (a, b, c, d, e, f) Dominance

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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

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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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

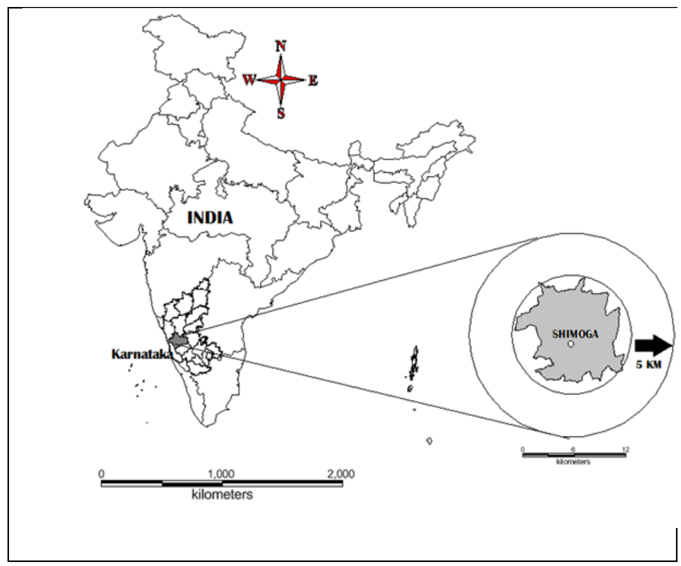

Figure 1: Study area considered for the analysis

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.

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.

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

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.	$-1 \leq CLUMPY \leq 1$

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6.	Aggregation index	$$AI = \left[\sum_{i=1}^{m}\left(\frac{g_{ii}}{\max \to g_{ii}}\right)P_i\right](100)$$	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)	$$PLAND = P_I = \left(\sum_{J=1}^{n} a_{ij} / A\right)$$ 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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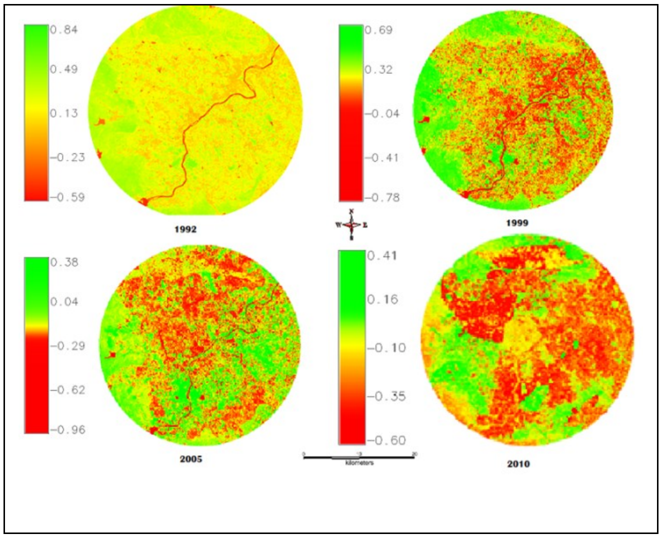

Figure 2: Temporal Land cover dynamics

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

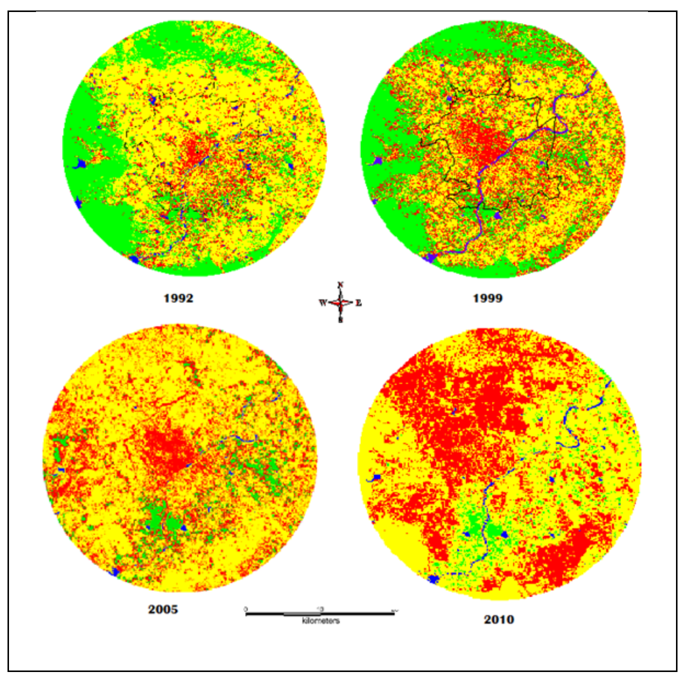

Figure 3: Results of Land use analysis

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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 .

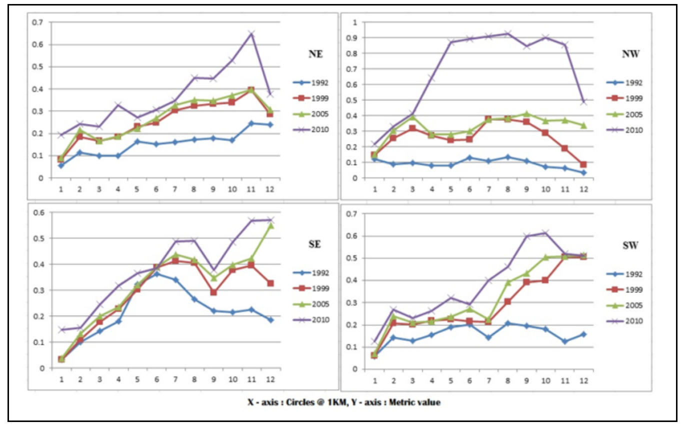

Figure 4a: Pland metric calculated for the study region

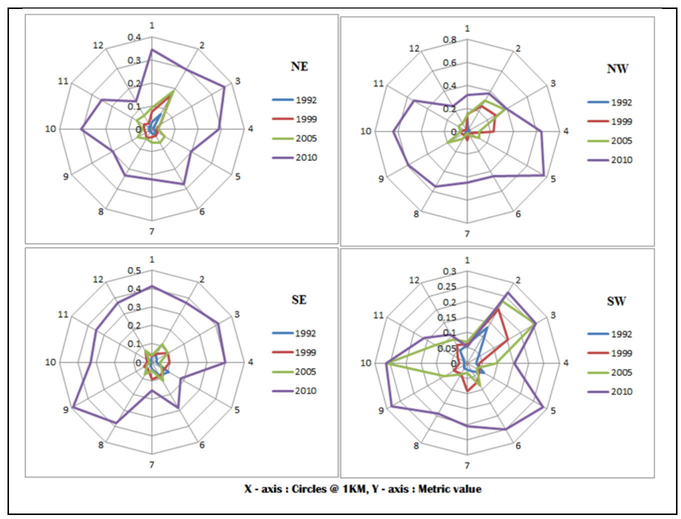

Figure 4b: Largest Patch Index

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.

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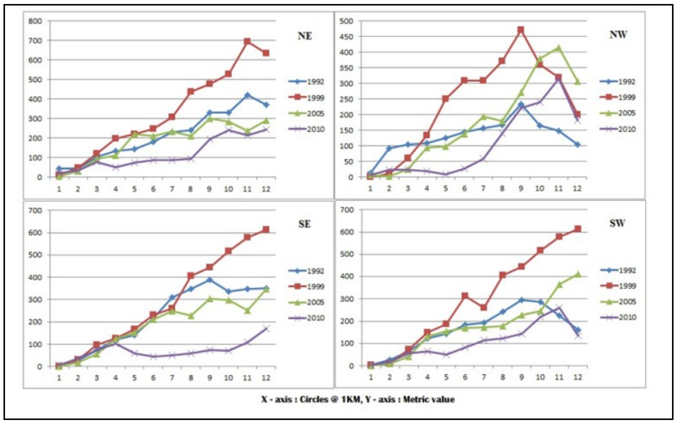

Figure 4c: Number of urban patches

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.

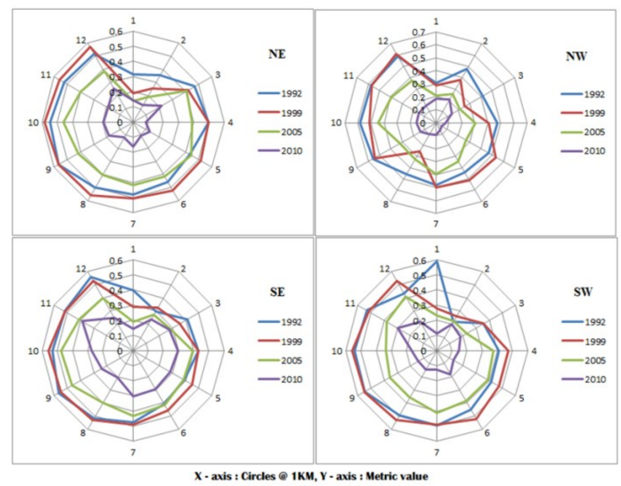

Figure 4d: NLSI index

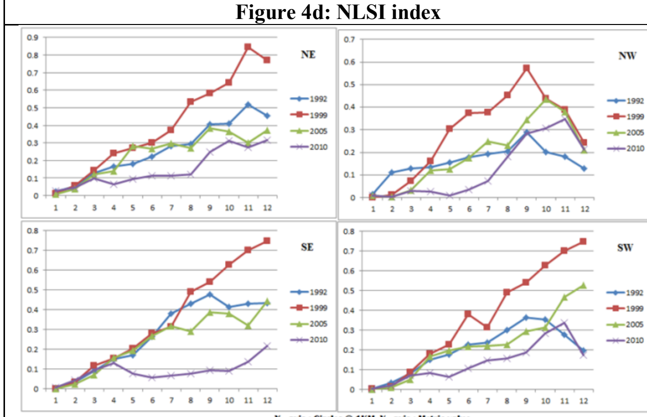

Figure 4e: Patch Density

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.

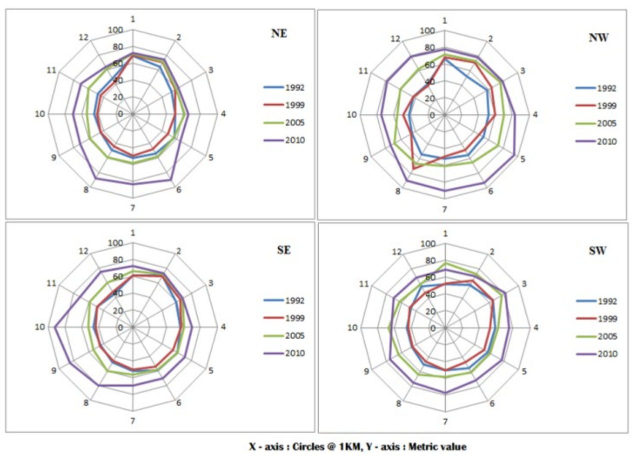

Figure 4f: Aggregation index

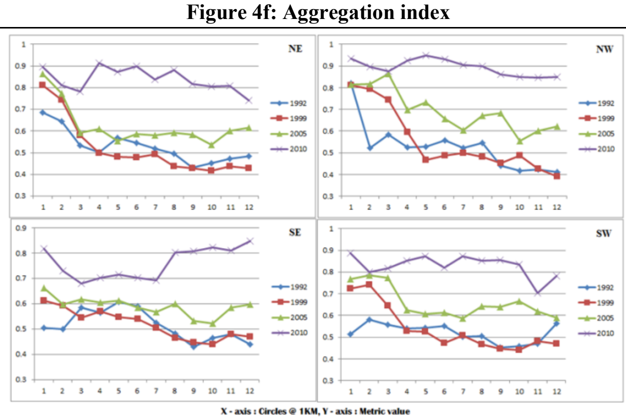

Figure 4g: Clumpiness index

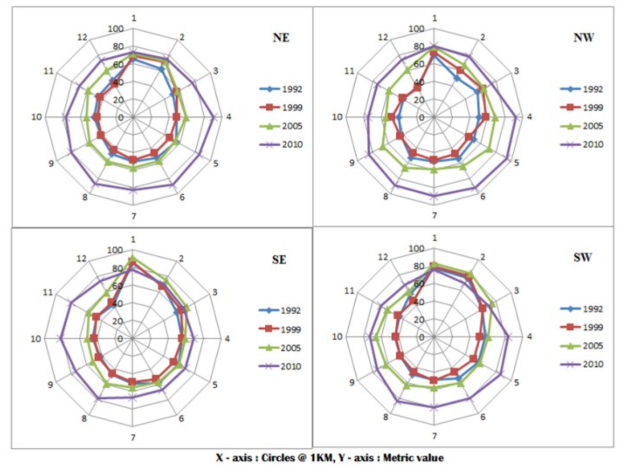

Figure 4h: Percentage of Land adjacency

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

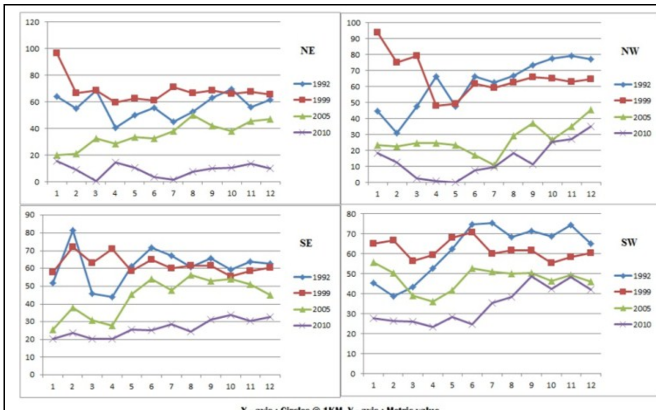

Figure 4i: IJI index

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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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REFERENCES

[1] Baldwin, D. J. B., Weaver, K., Schnekenburger, F., & Perera, A. H. 2004. Sensitivity of landscape pattern indices to input data characteristics on real landscapes: implications for their use in natural disturbance emulation. Landscape Ecology, 19, 255 - 271.

[2] Bailey, D., Herzog, F., Augenstein, I., Aviron, S., Billeter, R., Szerencsits, E., et al. 2007. Thematic resolution matters: indicators of landscape pattern for European agro-ecosystems. Ecological Indicators, 7, 692-709.

[3] Benedek , Z., Nagy, A., Rácz, I. A., Jordán, F., & Varga, Z. (2011). Landscape metrics as indicators: quantifying habitat network changes of a bush-cricket Pholidoptera transsylvanica in Hungary. Ecological Indicators, 11, 930 - 933.

[4] Berberoglu, S., Akin, A., 2009. Assessing different remote sensing techniques to detect land use/cover changes in the eastern Mediterranean. International Jour-nal of Applied Earth Observation and Geoinformation 11, 46–53.

[5] Bharath Setturu, Bharath H Aithal, , Sanna Durgappa D and Ramachandra T. V., 2012, Landscape Dynamics through Spatial Metrics, Proceedings of India GeoSpatial Conference, Epicentre, Gurgaon, India, 7-9 February, 2012.

[6] Bhatta, B. 2009. Analysis of urban growth pattern using remote sensing and GIS: A case study of Kolkata, India. International Journal of Remote Sensing, 30(18), 4733–4746.

[7] Bhatta, B., Saraswati, S., & Bandyopadhyay, D. 2010a. Quantifying the degree-of-freedom, degree-of-sprawl, and degree-of-goodness of urban growth from remote sensing data. Applied Geography, 30(1), 96–111.

[8] Bhatta, B., Saraswati, S., & Bandyopadhyay, D. 2010b. Urban sprawl measurement from remote sensing data. Applied Geography, 30(4), 731–740.

[9] Botequilha Leitão, A., & Ahern, J. 2002. Applying landscape ecological conceptsb and metrics in sustainable landscape planning. Landscape and Urban Planning, 59, 65 -93.

[10] Cowen, D.J., Jensen, J.R., 1998. Extraction and modeling of urban attributes using remote sensing technology. In: Diana, L. (Ed.), People and Pixels: Linking Remote Sensing and Social Science. National Academy Press, Washington, DC, 164–188.

[11] Cushman, S. A., McGarigal, K., & Neel, M. C., 2008. Parsimony in landscape metrics: strength, universality, and consistency. Ecological Indicators, 8, 691-703.

[12] Dietzel, C., Oguz, H., Hemphill, J. J., Clarke, K. C., & Gazulis, N. 2005. Diffusion and coalescence of the Houston Metropolitan Area: Evidence supporting a new urban theory. Environment and Planning B, 32(2), 231–246.

[13] Fernandez, M. R., Aguiar, F. C., & Ferreira, M. T. 2011. Assessing riparian vegetation structure and the in fluence of land use using landscape metrics and geo-statistical tools. Landscape and Urban Planning, 99, 166 -177

[14] Gao, J., & Li, S., 2011. Detecting spatially non-stationary and scale-dependent relationships between urban landscape fragmentation and related factors using geographically weighted regression. Applied Geography, 31(1), 292 - 302.

[15] Herold, M., Goldstein, N.C., Clarke, K.C., 2003. The spatiotemporal form of urban growth: measurement, analysis and modeling. Remote Sens. Environ. 86, 286–302.

[16] Herold,M., Couclelis, H., Clarke, K.C., 2005. The role of spatial metrics in the analysis and modeling of urban land use change. Comput. Environ. Urban 29, 369–399.

[17] Hung, W.-C., Chen, Y.-C., & Cheng, K.-S. (2010). Comparing land cover patterns in Tokyo, Kyoto, and Taipei using ALOS multispectral images. Landscape and Urban Planning, 97, 132–145.

[18] Iverson, L. R. (1988). Land-use changes in Illinois, USA: the influence of landscape attributes on current and historic land use. Landscape Ecology, 2, 45- 61.

[19] Kelly, M., Tuxen, K. A., & Stralberg, D., 2011. Mapping changes to vegetation pattern in a restoring wetland: fi nding pattern metrics that are consistent across spatial scale and time. Ecological Indicators, 11, 263- 273.

[20] Lata, K.M., Sankar Rao, C.H., Krishna Prasad, V., Badrinath, K.V.S., and Raghavaswamy, 2001. Measuring urban sprawl: a case study of Hyderabad", GIS Development, 5(12), 26-29

[21] Li, T., Shilling, F., Thorne, J., Li, F., Schott, H., Boynton, R., et al. 2010). Fragmentation of China's landscape by roads and urban areas. Landscape Ecology, 25, 839-853

[22] Li, X., Yeh, A.G.O., 2004. Analyzing spatial restructuring of land use patterns in a fast growing region using remote sensing and GIS. Landsc. Urban Plan. 69, 335–354.

[23] Luck, M., & Wu, J. G. 2002. A gradient analysis of urban landscape pattern: A case study from the Phoenix metropolitan region, Arizona, USA. Landscape Ecology, 17(4), 327–339.

[24] Luck, M., Wu, J., 2002. A gradient analysis of urban landscape pattern: a case study from the Phoenix metropolitan, Arizona, USA. Landsc. Ecol. 17, 327–339.

[25] McGarigal, K. 2002). Landscape pattern metrics. In El-Shaarawi, A. H., & Piegorsch, W. W. (Eds.). (2002). Encyclopedia of environmetrics, Vol. 2 (pp.11 35-1142). Sussex, England: John Wiley & Sons.

[26] McGarigal, K., & Marks, B. J., 1995. FRAGSTATS: Spatial pattern analysis program for quantifying landscape structure. U.S. Department of Agriculture, Forest Service, Pacific Northwest Researc Station.

[27] McGarigal, K., Cushman, S. A., Neel, M. C., & Ene, E., 2002. FRAGSTAT S: Spatial pattern analysis program for categorical maps. Computer software program produced by the authors at the University of Massachusetts, Amherst. Available from www.umass.edu/landeco/research/fragstats/fragstats.html

[28] Muller, K., Steinmeier, C., & Kuchler, M. 2010. Urban growth along motorways in Switzerland. Landscape and Urban Planning, 98(1), 3–12.

[29] Nelson, A. C. 2010. From sprawl to sustainability: smart growth, new urbanism, green development, and renewable energy, 2nd edition. Journal of the American Planning Association, 76(4), 516–517

[30] Peng, J., Wang, Y. L., Zhang, Y., Wu, J. S., Li, W. F., & Li, Y., 2010. Evaluating the effectiveness of landscape metrics in quantifying spatial patterns. Ecological Indicators, 10(2), 217–223.

[31] Petrov, L. O., Lavalle, C., & Kasanko, M. 2009. Urban land use scenarios for a tourist region in Europe: Applying the MOLAND model to Algarve, Portugal. Landscape and Urban Planning, 92(1), 10–23.

[32] Pôças, I., Cunha, M., & Pereira, L. S., 2011. Remote sensing based indicators of changes in a mountain rural landscape of Northeast Portugal. Applied Geography, 31, 871-880.

[33] Ramachandra T.V., Bharath A.H. and Durgappa D.S.. 2012. Insights to urban dynamics through landscape spatial pattern analysis, Int. J Applied Earth Observation and Geoinformation, 18, 329-343, http://dx.doi.org/10.1016/j.jag.2012.03.005.

[34] Ramachandra. T.V., Bharath.H.Aithal and Sreekantha S, 2012. Spatial Metrics based Landscape Structure and Dynamics Assessment for an emerging Indian Megalopolis, International Journal of Advanced Research in Artificial Intelligence, 1(1), 48-57.

[35] Schwarz, N. 2010. Urban form revisited–Selecting indicators for characterizing European cities. Landscape and Urban Planning, 96, 29–47

[36] Seto, K.C., Fragkias,M., 2005. Quantifying spatiotemporal patterns of urban land-use change in four cities of China with time series landscape metrics. Landsc. Ecol.2, 871–888.

[37] Sudhira H S, Ramachandra T V and Jagadish, K S, 2004. Urban sprawl: metrics, dynamics and modelling using GIS. Int. J. Appl. Earth Observ. Geoinform. 5. 29–39.

[38] Sudhira, H S, Ramachandra, T V & Jagadish, K S, 2003, Urban sprawl pattern recognition and modeling using GIS, Paper presented at Map India, January 28- 31, 2003, New Delhi.

[39] Turner, M. G., & Ruscher, C. L., 1988. Changes in landscape patterns in Georgia, USA. Landscape Ecology, 1,241-251.

[40] Turner, M. G., O 'Neill, R. V., Gardner, R. H., & Milne, B. T., 1989. Effects of changing spatial scale on the analysis of landscape pattern. Landscape Ecology, 3 ,153 -162

[41] Weng, Y.C., 2007. Spatiotemporal changes of landscape pattern in response to urbanization. Landsc. Urban Plan. 81, 341–353.

[42] Wu, J. 2004. Effects of changing scale on landscape pattern analysis: scaling relations. Landscape Ecology, 19, 125-138.

[43] Wu, J., Shen, W., Sun, W., & Tueller, P. T., 2002. Empirical patterns of the effects of changing scale on landscape metrics. Landscape Ecology, 17,761-782

[44] www.ces.iisc.ernet.in/grass

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[45] Xian, G., & Crane, M., 2005. Assessments of urban growth in the Tampa Bay watershed using remote sensing data. Remote Sensing of Environment, 97(2), 203–215.

[46] Xu, C., Liu, M. S., Zhang, C., An, S. Q., Yu, W., & Chen, J. M., 2007. The spatiotemporal dynamics of rapid urban growth in the Nanjing metropolitan region of China. Landscape Ecology, 22(6), 925–937.

[47] Yang, L.M., Xian,G., Klaver, J.M., Deal, B., 2003. Urban land-cover change detection through sub-pixel imperviousness mapping using remotely sensed data. Photogramm. Eng. Remote Sens. 69, 1003–1010.

[48] Yeh, A.G.O., and Liu, X., 2001. Measurement and Monitoring of urban sprawl in a Rapidly growing region using Entropy, Photogramm Engg & Remote Sensing, 67(I), 83-90.

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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

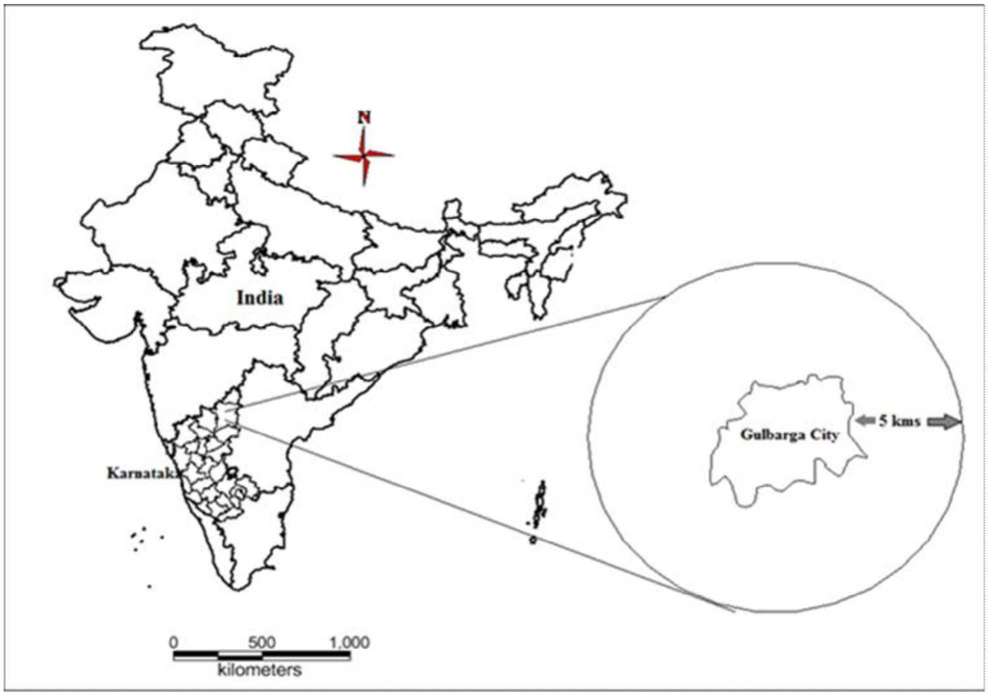

Figure 1: Study Area: Gulbarga

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:

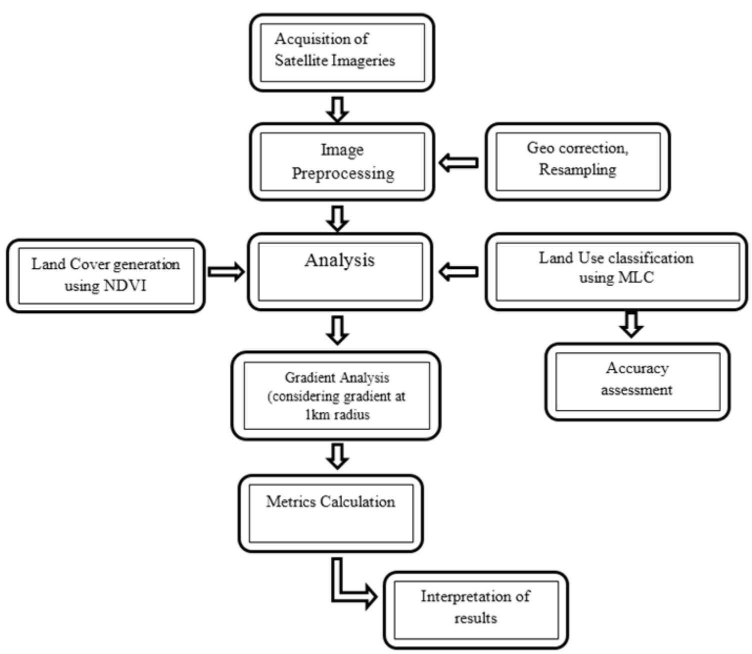

Figure 2: Procedure to understand the changes in spatial pattern and its dynamics

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.

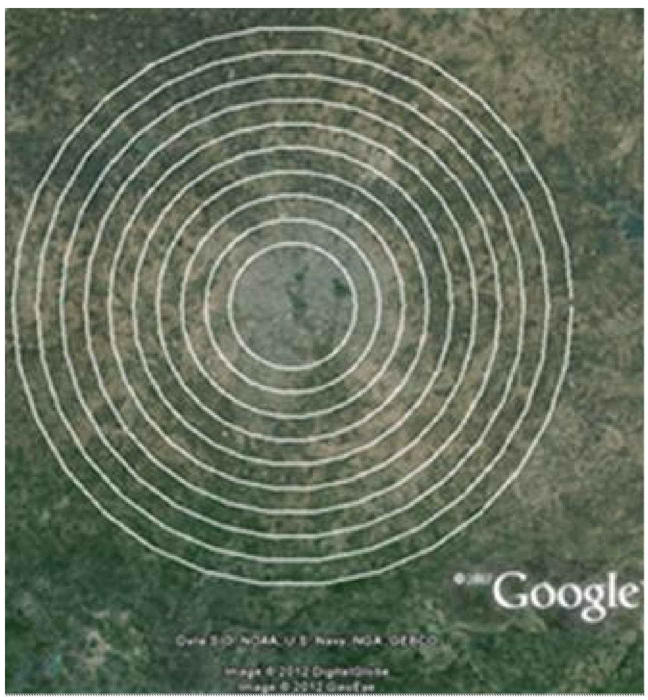

Figure 3: Google earth representation of the study region along with the gradients

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.

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

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.

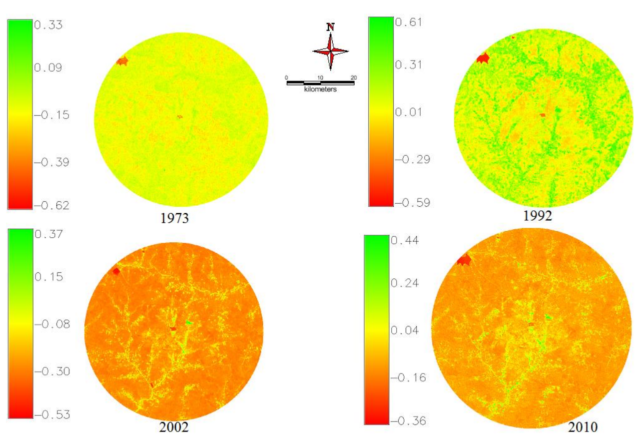

Figure 4: Temporal Land cover changes during 1973 – 2009;

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.

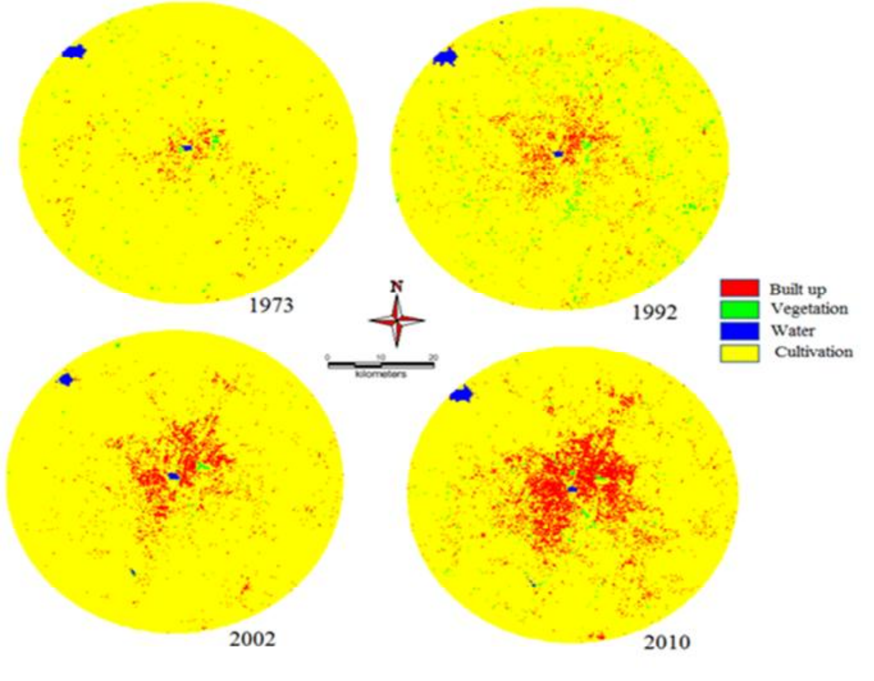

Figure 5: Classification output of Gulbarga

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

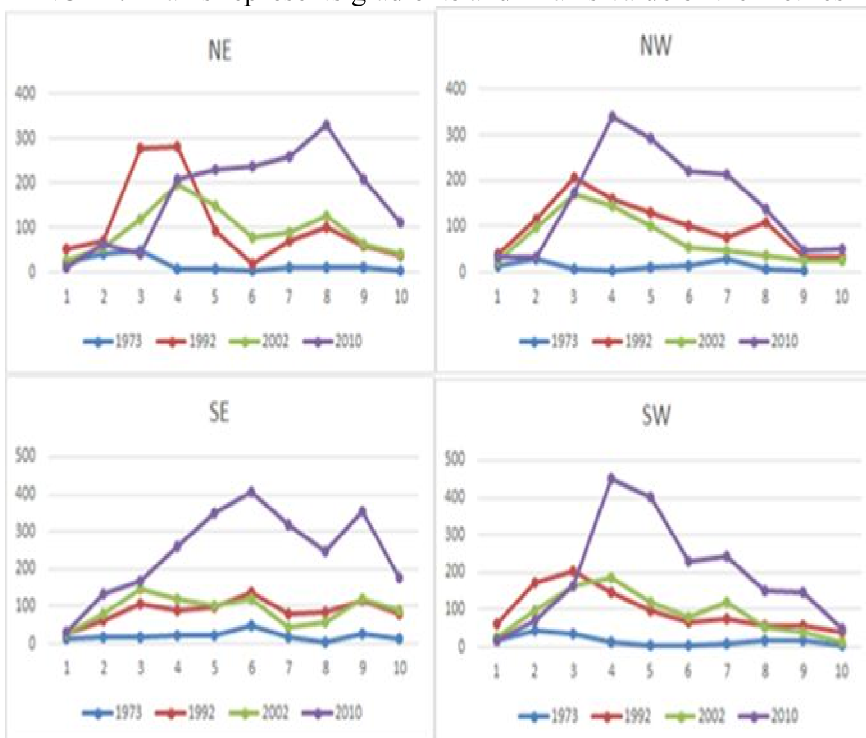

Figure 6a: Number of urban patches (zone, circlewise); Fig 6b: Patch density – zone, circle wise

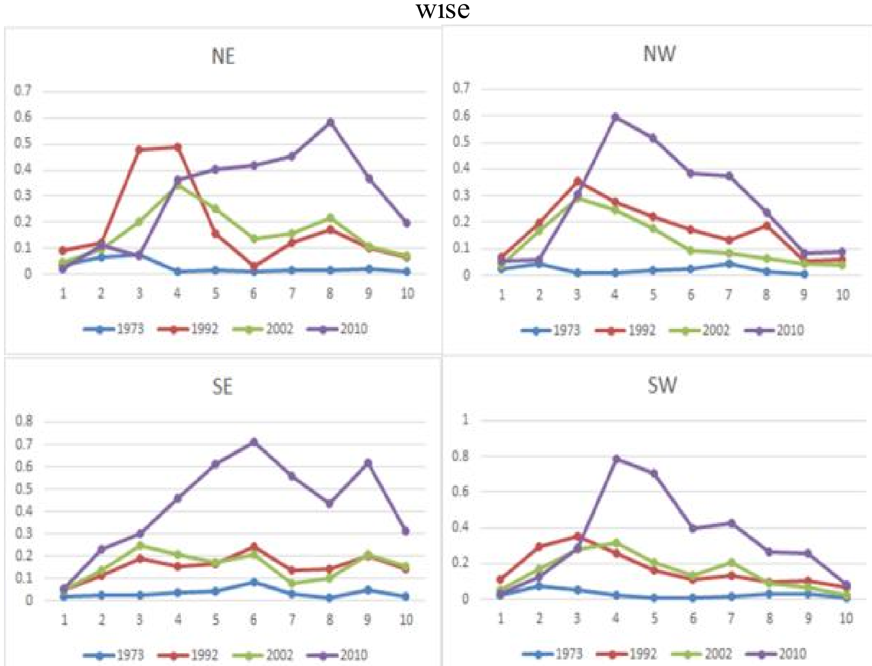

Figure 6b: Patch density – zone, circle wise

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.

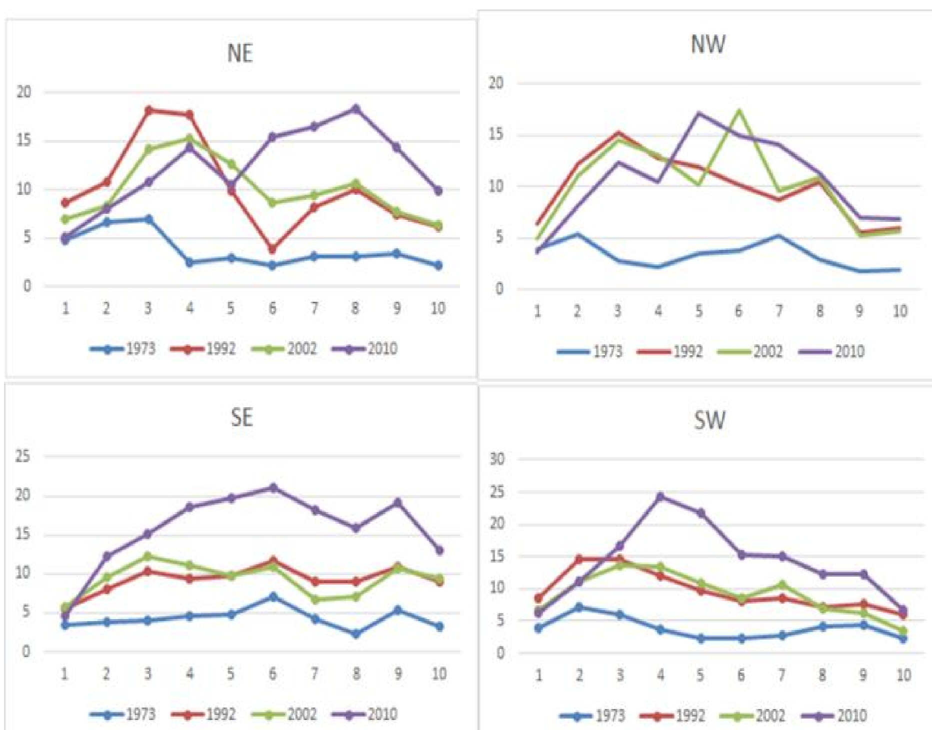

Figure 6c: Landscape Shape index – zone andcirclewise

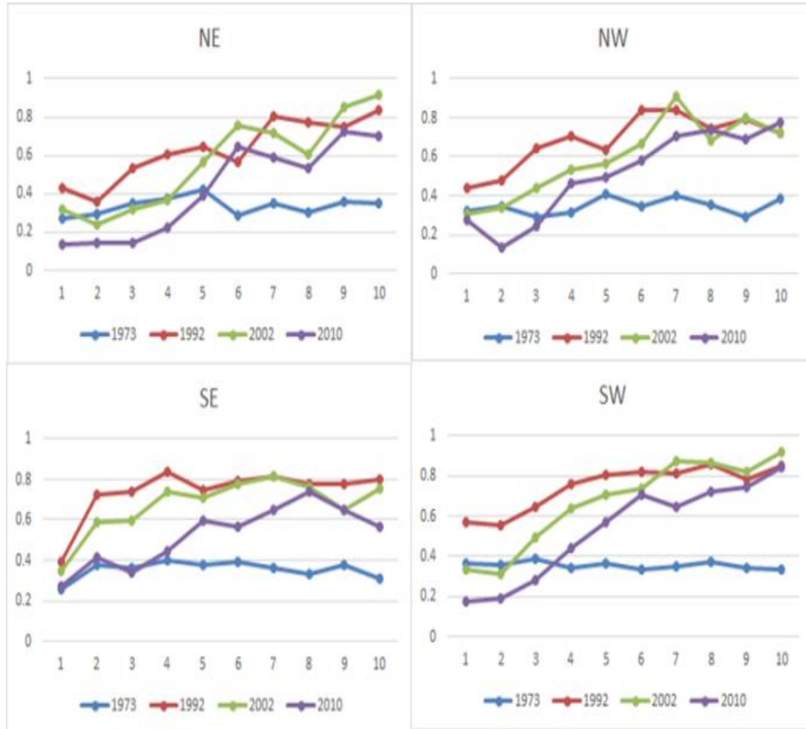

Figure 6d: Normalised Landscape Shape index – zone and circlewise

Figure 6e: Clumpiness – zonewise, circle wise;

Figure 6f: Aggregation-zone and circle wise

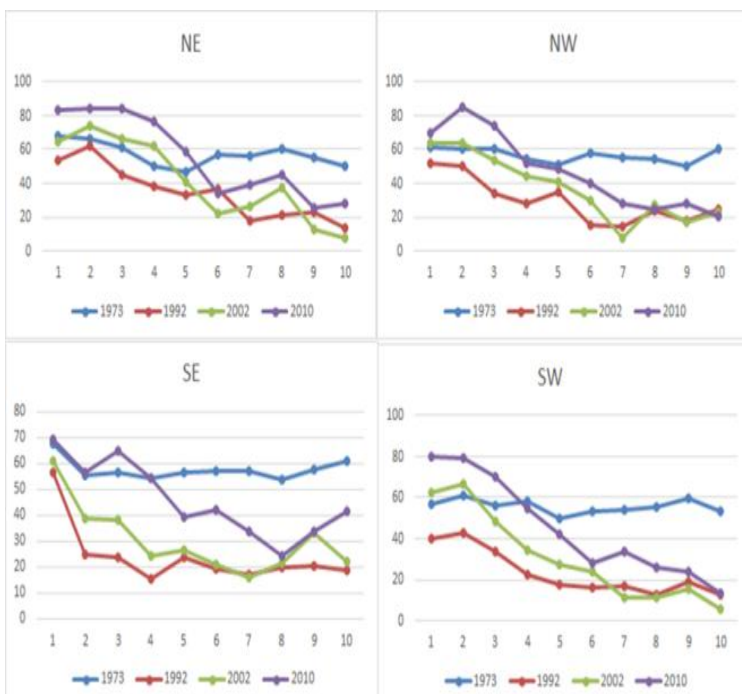

Figure 6g: Zone and circle wise – Pladj

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.

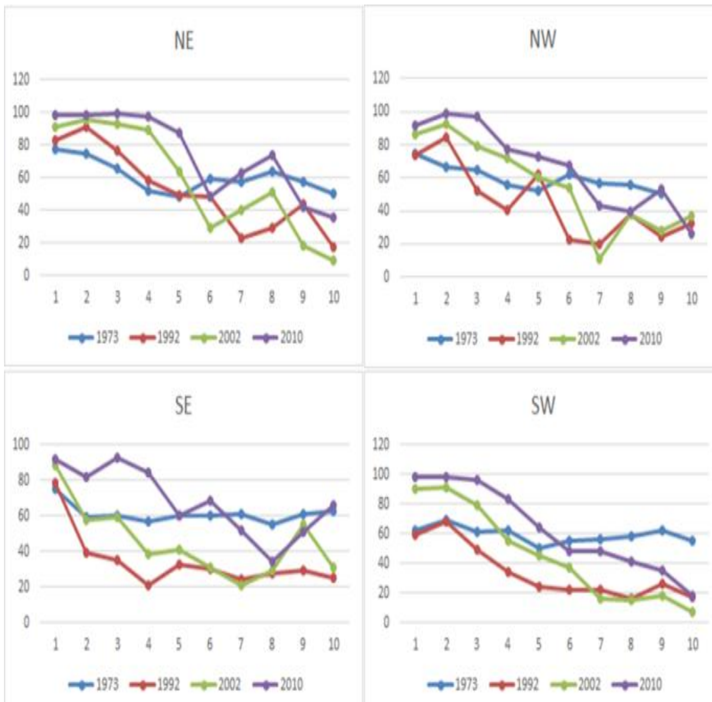

Figure 6h: Cohesion Index

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.

Acknowledgement

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6. References

1. Bender, D. J., Tischendorf L., Fahrig, L, 2003. Using patch isolation metrics to predict animal movement in binary landscapes. Landscape Ecology. 18, pp 17–39.
2. Bharath H. Aithal, Bharath Setturu, Sreekantha S, Sanna Durgappa D and Ramachandra, T. V, 2012. Spatial patterns of urbanization in Mysore: Emerging Tier II City in Karnataka, Proceedings of NRSC User Interaction Meet- 2012, 16th & 17th February 2012, Hyderabad.
3. Bhatta, B, 2010a. Analysis of urban growth and sprawl from remote sensing data. Heidelberg: Springer-Verlag.
4. Bhatta, B., Saraswati, S., Bandyopadhyay, D, 2010b. Quantifying the degree-of-freedom, degree-of-sprawl, and degree-of-goodness of urban growth from remote sensing data. Applied Geography, 30(1), pp 96–111
5. Congalton R. G, 1991). A review of assessing the accuracy of classifications of remotely sensed data. Remote Sensing of Environment, 37, pp. 35-46.
6. Congalton R. G., Oderwald R. G., Mead R. A, 1983. Assessing Landsat classification accuracy using discrete multivariate analysis statistical techniques. Photogrammetric Engineering and Remote Sensing, 49, pp. 1671-1678.
7. Crews-Meyer K. A, 2002. Characterizing landscape dynamism using paneled-pattern metrics. Photogrammetric Engineering and Remote Sensing 68, pp 1031– 1040.
8. Duda, R.O., Hart, P.E., Stork, D.G., 2000, Pattern Classification, a Wiley-Interscience Publication, Second Edition, ISBN 9814-12-602-0.
9. Gibert, K., Sanchez-Marre, M, 2011. Outcomes from the iEMSs data mining in the environmental sciences work shop series. Environmental Modelling & Software, 26 (7), pp. 983 -985.

10. Hall, F.G, Botkin, D.B., Strebel D.E., Woods K.D and Goetz. S.J, 1991. Large-scale patterns of forest succession as determined by remote sensing. Ecology. 72, pp 628–640.
11. Jenerette, G.D., Potere, D, 2010. Global analysis and simulation of land-use change associated with urbanization. Landscape Ecol. 25 (5), pp. 657–670.
12. Kim, K.H., Pauleit, S, 2007. Landscape character, biodiversity and land use planning: The case of Kwangju City Region, South Korea. Land Use Policy 24(1), pp 264–274.
13. Lata, K.M., Rao C.H.S., Prasad V.K., Badarianth K.V.S., Raghavasamy, V, 2001. Measuring Urban sprawl A case study of Hyderabad, gis@development, 5(12), pp. 26-29.
14. Lausch, A., Herzog F., 2002. Applicability of landscape metrics for the monitoring of landscape change: issues of scale, resolution and interpretability. Ecological Indicators 2(1-2), pp 3-15.
15. Lin, Y.P., N.M. Hong, Wu, P.J., Wu, C.F., Verburg, P.H, 2007. Impacts of land use change scenarios on hydrology and land use patterns in the Wu-Tu watershed in Northern Taiwan. Landscape and Urban Planning. 80(1-2), pp 111–126.
16. McGarigal, K., & Marks, B. J, 1995. FRAGSTATS: spatial pattern analysis program for quantifying landscape structure. USDA Forest Service General Technical Report PNW-351.
17. Müller, K., Steinmeier, C., Küchler, M, 2010. Urban growth along motorways in Switzerland.Landscape and Urban Planning, 98(1), pp 3–12
18. O'Neill, R. V., Krummel, J. R., Gardner, R. H., Sugihara, G., Jackson, B., DeAngelis, D. L., Milne, B. T., Turner, M. G., Zygmunt, B., Christensen, S., Dale, V. H., and Graham, R. L, 1988. Indices of landscape pattern. Landscape Ecology. 1, pp 153-162.
19. Ramachandra T. V., Kumar, U, 2008. Wetlands of Greater Bangalore, India: Automatic Delineation through Pattern Classifiers. Electronic Green Journal, Issue 26, Spring 2008 ISSN: 1076-7975.
20. Ramachandra T.V., Bharath A.H. And Durgappa D.S, 2012. Insights to urban dynamics through landscape spatial pattern analysis, Int. J Applied Earth Observation and Geoinformation, 18, pp 329-343, http://dx.doi.org/10.1016/j.jag.2012.03.005.
21. Rossi J.P., van Halder I, 2010. Towards indicators of butter?y biodiversity based on a multiscale landscape description. Ecological Indicators, 10, pp. 452–458
22. Sing, A. 1989. Digital change detection techniques using remotely-sensed data. International Journal of Remote Sensing 10(6), pp 989-1003.
23. Sudhira H.S., Ramachandra T.V., Jagadish K.S, 2004. Urban sprawl: metrics, dynamics and modelling using G1S. International journal of Applied Earth Observation and Geoinformation, 5, pp. 29-39.
24. Sudhira, H.S., Ramachandra, T.V., Raj, K.S., Jagadish, K.S, 2003. Urban Growth Analysis using Spatial and Temporal Data", Photonirvachak, Journal of Indian Society of Remote Sensing, 31(4), pp 299-311.
25. www.census.gov.in
26. Yu X. J., Ng C.N, 2007. Spatial and temporal dynamics of urban sprawl along two urban-rural transects: a case study of Guangzhou, China. Landscape and Urban Planning, 79, pp. 96–109.
27. Zhao, P., Lu, B., de Roo, G, 2011. The impact of urban growth on commuting patterns in a restructuring city: Evidence from Beijing. Papers in Regional Science, 90(4), pp 735–754.

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Comprehension of temporal land use dynamics in urbanising landscape

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ABSTRACT

Land use changes are irreversible changes and directly influence the regional and global environmental quality. Urbanisation is one of the major drivers of land use land cover (LULC) changes. Planned urbanisation would help in maintaining the environmental quality and sustenance of natural resources while meeting the demand of population in cities. However, unplanned urbanization in most of the rapidly urbanising cities has caused serious concerns in both environmental quality and on human's livelihood due to urban sprawl. Urban sprawl refers to the uncoordinated land use resulting from lack of integrated and holistic approach in regional planning. Information related to the rate of growth, pattern and extent of sprawl is required by urban planners to provide basic amenities. This paper discusses land cover and land use dynamics of Belgaum a tier II city in Karnataka. Temporal land use dynamics is assessed for urbanizing landscape - Belgaum city with a buffer of 5 km. Vegetation over changes have been analysed using slope based vegetation indices NDVI, which show 91.74% vegetation in 2012. Temporal land use analysis for the period 2006 to 2012 show that urban area has increased from 4.81% to 5.74%.

Keywords: Land use, Land cover, Urbanisation, Belgaum, IRS.

1. INTRODUCTION

Land use Land cover (LULC) dynamics is a major concern, as the abrupt changes in these dynamics has a negative impact on ecology, climate, regional hydrology, and also people's livelihood in the region. LULC dynamics are specific to a region and vary from region to region (Ramachandra et al., 2012). Land Cover refers to the observed physical cover on the earth's surface. Land cover essentially distinguishes the region under vegetation with that of non-vegetation (Lillesand and keifer, 2005). Land use refers to use of the land surface through modifications by humans and natural phenomena (Lillesand and keifer, 2005). Land use can be classified into various classes such as water bodies, built up, forests, agriculture, open lands, sand, soil, e*tc*. Land use modifications alter the structure of the landscape and hence the functional ability of the landscape (Ramachandra, et al., 2012). The modification includes conversion of forest lands, scrublands to agricultural fields, cultivation lands to built up, construction of storage structures for water bodies leading to submergence of land features that may vary from small scale to large scale.

Land use and land cover patterns and their changes over time for the region are quantified with the spatial data acquired through space borne sensors. Remote sensing data with synoptic repetitive coverage aids in understanding the landscape dynamics. The spatial data are analysed using Geographic Information System (GIS). Temporal remote Sensing data with GIS platforms have been used to acquire and comprehend the changes in land use, land cover and the urban sprawl dynamics of urbanizing landscape Belgaum city during 1989 and 2012. Satellite remote sensing technology has the ability to provide consistent measurements of landscape condition, allowing detection of abrupt or slow trend in changes over time. Long-term change detection results provide insight into the stressors and drivers of change, potentially allowing for management strategies targeted toward cause rather than simply the symptoms of the cause (Kennedy et al., 2009).

Analyzing the spatio-temporal characteristics of landscape dynamics are essential for understanding and assessing ecological consequence of urbanization. Urbanization is taking place all over the world, but most commonly now in cities/towns of developing nations. In countries like India, urbanization is due to the increase in population in a region due to industrialization. Large scale land use land cover changes with industrialization prominently took place in outskirts during post 2000. Spurt in IT and BT sectors lead to the large scale migration from different parts of the country and also from other parts of the globe for the employment opportunities in the industry. To meet the residential requirements, dispersed growth or sprawl has taken place in per-urban areas. Sprawl phenomenon drives drastic changes in land use patterns leading to haphazard growth affecting local ecology and the environment. Sprawl occurs either in radial direction around the city centre or in linear direction along the highways, ring roads, etc. The built-up is the parameter used for quantifying urban sprawl. The study on urban sprawl is attempted in the developed countries and recently in developing countries such as China (Yeh and Li, 2001) and India (Ramachandra et al., 2012, Sudhira et al., 2003, Sudhira et al., 2004). In India alone currently 25% of the population (Census of India, 2001) lives in the urban centers and it is projected that in the next fifteen years about 33% would be living in the urban centers (Sudhira et al 2004). In order to understand the dynamics, urbanization quantification and assessment of the extent of sprawl is necessary. Shannon's entropy helps to measure the degree of spatial concentration or dispersion among 'n' zones (Yeh and Li, 2001; Sudhira et al., 2003; Sudhira et al 2004; Ramachandra et al., 2012). Objective of the current study is to analyze the land use land cover dynamics of urbanizing landscape apart from assessing the underlying effects of urbanisation such as urban sprawl through Shannon's entropy.

2. STUDY AREA

Belgaum City (Figure1) geographically located in the north western part of Karnataka state. The city extends from $74^0$28'29.071" to $74^0$34'54.92" E and $15^0$49'23.189" to $15^0$54'0.142" N with an average elevation of 751m above mean sea level and spatial extent of 5798 hectares. For the study a 5 km buffer from the administrative boundary was considered as shown in Figure 2, with a gross area of 38013.27 hectares, to account for the growth in peri urban regions. The city has about 58 wards, with population of 488292 (2011 Census provisional) and population density of 84.21 persons per hectare, the population in the region has a decadal increase of 7.31%. Temperature varies from as low as 18 ^{0}C (winter) to 40 ^{0}C (summer) and annual average rainfall is about 1418 mm. Soils in the region consist of shallow to very deep black soils, red loamy soils, lateritic soils, etc. The city is surrounded by Kanburgi, Yamanspura, Kangrali.B, Kangrali.K villages to the north, Hindalga, Binakanahalli, Savagaon, Madoli to the West, Angol, Wadgaon, Madhavapura, Haldge to the South and Sindoli, Mutuge, Nilage Villages to the East.

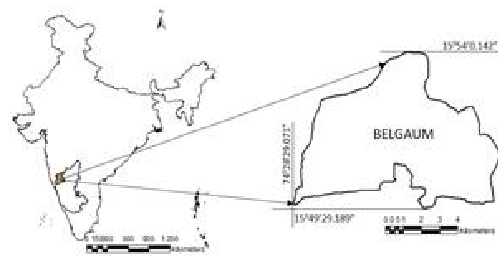

Figure 1: Study Area

Figure 2 demarcates the study area (Google earth) with 5 km buffer along the city administrative boundary

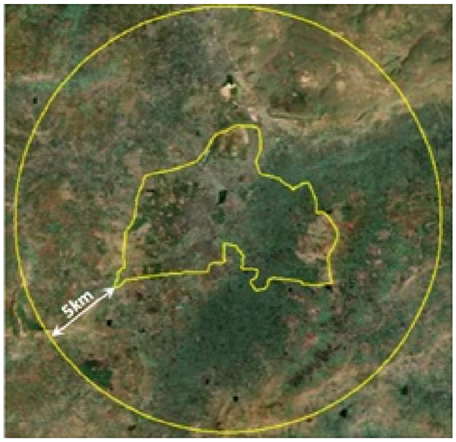

Figure 2: Study Area with 5 Km Buffer Overlaid on Spatial Data (Google Earth)

3. DATA COLLECTION

Multi resolution remote sensing data from of Landsat TM, IRS (Indian Remote Sensing) LISS 3 Sensors were used, specifically from IRS 1C and IRS R2. Training data were collected from field using pre-calibrated Global Positioning System (GPS) and online map Google earth. The details of the data used are given in table 1. The administrative boundary was digitized from topo-sheets (1:50000) of the Survey of India, online village map (http://bhuvan.nrsc.gov.in).

Table 1: Data Used

Data	Year	Purpose
IRS LISS III (24m)	2006 2012	Land cover and Land use analysis
Survey of India (SOI) toposheets of 1:50000 and 1:250000 scales		To Generate boundary and Base layer maps.
ISRO - Bhuvan and Google Earth		For verification and preparation of boundary
Field visit data – captured using GPS		For geo-correcting and generating validation dataset

4. METHODOLOGY

Temporal landscape dynamics are assessed through LULC changes. Figure 3 outlines the process followed for the study. Data acquisition includes obtaining data about the region such as the satellite images, Statistics, the ancillary data (Gazetteer, Census), the Maps such as Village maps, District maps. Preprocessing of the data is done to remove the haze and other factors through atmospheric correction, removal of noise and other radiometric errors through radiometric corrections. Image enhancement is done using standard image processing techniques. The data pertaining to the study region is extracted by cropping using the boundary. For visual interpretation and for creation of the training sets for classification of the images, a false color Composite (FCC) image of the study area is created. FCC is created by composition of band 2 (green), band 3 (red) and band 4 (IR).

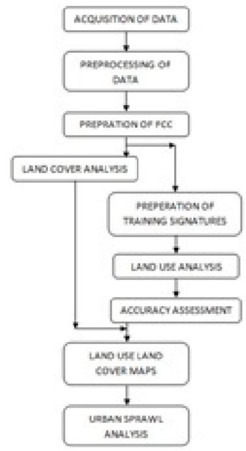

Figure 3: Procedure involved in data analysis

Assessment of landscape dynamics involves the analysis of temporal land use and land cover. Land cover analysis involves the computation of extent of vegetation through well-established vegetation indices. Vegetation indices help in mapping the regions under vegetation and non-vegetation. Vegetation Indices are the Optical measures of Vegetation Canopy. Vegetation indices are dimensionless radiometric measurements that indicate the relative abundance and activity of green vegetation; this includes the leaf area index (LAI), percentage green cover, chlorophyll content, and green biomass. The main requirement of vegetation indices measurement is to combine the chlorophyll absorbing (Red Band) spectral region with the non-absorbing (NIR band) spectral region to provide a consistent and robust measure of area under the canopy. Vegetation Indices algorithms are designed to extract the active greenness signal from the terrestrial land cover. The accuracy of the VI product varies with time, space, geology, seasonal variations, canopy background (soil, water). Among all techniques Normalized Difference Vegetation Index (NDVI) is most widely used for LC analysis. NDVI is expressed as the ratio of difference in NIR and Red bands to the sum of NIR and Red band. NDVI has the ability to minimize the topographic effect in the region. NDVI ranges between -1 to +1, ratio less than 0 i.e., the negative values represent non-vegetation and positive values represent vegetation.

$$\mathbf{NDVI} = \frac{\text{NIR}-\text{Red}}{\text{NIR}+\text{Red}}$$

Land use analysis involves categorizing each pixel in the spatial data into different land use themes such as water bodies, vegetation, built up, cultivable land, barren lands, *etc*. A multispectral data is useful to perform classification as it shows the numerous spectral patterns/signatures for different features. Spectral pattern recognition refers to the family of classification procedures that utilizes pixel by pixel spectral information as a basis for land use classification. Land use analysis involves collection of training data from field, attribute data for the chosen polygons in FCC, and goggle earth. These training sets were employed for classification of the data into various classes. 60% of training data is used from classifying the spatial data, while the balance has been used for verification. GRASS GIS, open source software was used for analysis of the data. Land use analysis was carried out using the Gaussian maximum likelihood classifier (GMLC) algorithm. Accuracy assessment is done through error matrix, comparing on a category by category basis, the relationship between reference data (ground truth) and the corresponding classified results.

Computation of Shannon's entropy: Shannon's entropy (Yeh and Li, 2001, Ramachandra et al., 2012) was computed to detect the urban sprawl phenomenon and is given by,

$$H_n = -\Sigma P_i \log (P_i)$$

Where; Pi is the Proportion of the urban density in the i^{th} zone and n the total number of zones. This value ranges from 0 to log n, indicating very compact distribution for values closer to 0. The values closer to log n indicates that the distribution is much dispersed. Larger value of entropy reveals the occurrence of urban sprawl.

5. RESULTS AND DISCUSSIONS

Land Cover Analysis: Slope and Distance based vegetation indices were computed, of which NDVI shows significant results and is given in Figure 5 and the details in Table 2. The vegetation cover has decreased from 96.35% (2006) to 91.74% (2012).

Table 2: Land Cover details

Year	Vegetation	Non Vegetation
2006	96.35 %	3.65 %
2012	91.74 %	8.26 %

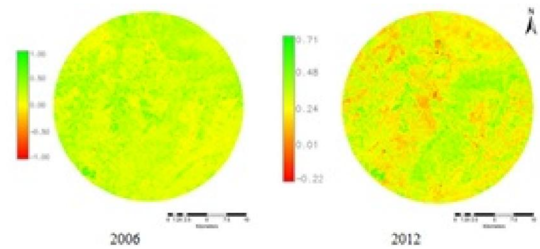

Figure 5: Land cover Classification

Land Use Analysis: Temporal land use changes during 2006 and 2012 are given in Figure 6 and in Table 3. Results show an increase built-up from 4.81 % (2006) to 5.74 % (in 2012), water bodies and vegetation fairly constant, while other category (including the cultivation lands, barren lands, open lands, *etc.*) have changed from 92.93% % (2006) to 91.58% in 2012. Overall classification accuracy achieved is about 93 % for the classified images, and table 4 gives the summary of overall accuracy and the agreement between the true value and the sensed value i.e., kappa statistics. Higher kappa indicates that the classified data (sensed data) is in agreement with the ground data (true data).

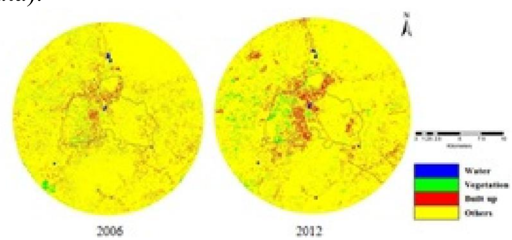

Figure 6: Land Use Classification

Table 3: Land use details

Particulars	Percentage	Area(Ha)
Year 2006		
Water	0.23 %	87.47
Vegetation	2.33 %	886.07
Built up	4.81 %	1829.17
Others & Cultivation	92.93 %	35339.95
Year 2012		
Water	0.24 %	92.03
Vegetation	2.44 %	928.73
Built up	5.74 %	2190.15
Others & Cultivation	91.58 %	34904.41

Table 4: Overall Accuracy and Kappa Statistics

Year	Overall Accuracy	Kappa Value
2006	93.64 %	0.92
2012	93.12 %	0.93

Urban sprawl assessment: Shannon's entropy was calculated in four directions and the results are given in figure 7 and table 5 respectively. The threshold limit of Shannon's Entropy is log 11 (1.0414), and the values closer to the threshold value indicates the growth is scattered indicating sprawl in the region. The Shannon's Entropy values close to zero indicates that the growth is clustered and confined. The results show increasing tendency of urban sprawl in 2006 and 2012, indicating that a tendency of dispersed growth in all directions and is evident in Figure 6.

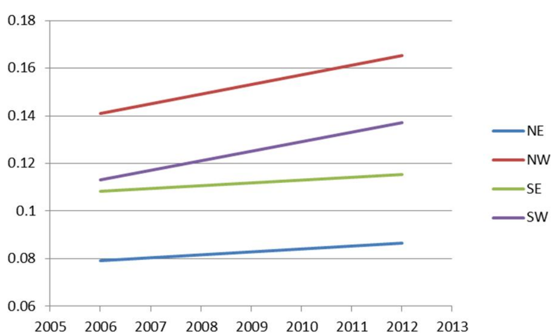

Figure 7: Shannon Entropy

Table5: Shannon's Entropy Analysis

	NE	NW	SE	SW
2006	0.079145	0.14097	0.108442	0.113038
2012	0.086431	0.165239	0.115427	0.137098

6. CONCLUSION

LULC change analysis depicts the landscape dynamics, which show conversion of agriculture lands into built up area. Also, open lands and scrub lands are converted to agricultural fields. Land cover analysis show an increase in vegetation cover in the region from 96.35% (2006) to 91.74% (2012). The temporal land use analysis through supervised Gaussian MLC show an increase in built up from 4.81% (2006) to 5.74% (2012). Shannon's entropy values indicate the increasing tendency of urban sprawl in the region.

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7. REFERENCES

1) District at a Glance - Belgaum District 1986, 2000, 2006, 2010
2) IDRISI Taiga Guide to GIS and Image Processing, Clark Labs, USA, Ver. 16.02, pp 213 – 222
3) Landsat 7 Science Data Users Handbook, NASA
4) Mysore District Gazetteer – Belgaum District 1970, Government Press Publication, 1-28
5) Firmino, A., 1999. Agriculture and landscape in Portugal. Landscape Urban Plann. 46, 83–91.
6) Gyanesh Chander , Brian L. Markham, Dennis L. Helder ,"Summary of current radiometric calibration coefficients for Landsat MSS, TM, ETM+, and EO-1 ALI sensors", 895- 896
7) http://censusindia.gov.in/
8) ICIMOD, 1999. Integration of GIS, remote sensing and ecological methods for biodiversity inventory and assessment. In Issues in Mountain Development.
9) Jin S. Deng, Ke Wang, Yang Hong, Jia G. Qi, 2009, Spatio-temporal dynamics and evolution of land use change and landscape pattern in response to rapid urbanization, Elsevier
10) Lillesand, T.M., Kiefer. R. W., 2002. Remote Sensing and Image Interpretation, Fourth Edition, John Wiley and Sons, ISBN 9971-51-427-3, 215-216
11) Maria Zomeni, Joseph Tzanopoulos, John D. Pantis, 2008, Historical analysis of landscape change using remote sensing techniques: An explanatory tool for agricultural transformation in Greek rural areas , Landscape and Urban Planning,
12) Ramachandra T V, 2007, "Comparative Assessment of Techniques for Bioresource Monitoring using GIS and Remote sensing", Vol1, No2.
13) Ramachandra T V, Uttam Kumar, 2009, Geoinformatics for Urbanization and Urban Sprawl pattern Analysis, NOVA Science

14) Ramachandra. T.V., Bharath H. Aithal and Durgappa D. Sanna, 2012. Insights to Urban Dynamics through Landscape Spatial Pattern Analysis. 2012. International Journal of Applied Earth Observation and Geoinformation, Vol. 18, 329-343.
15) Robert E. Kennedy, Philip A. Townsend, John E. Gross, et al., 2009, Remote sensing change detection tools for natural resource managers: Understanding concepts and tradeoffs in the design of landscape monitoring projects, Elsevier.
16) Sudhira H.S, Ramachandra T.V and Jagadish K.S, 2004, Urban sprawl: metrics, dynamics and modelling using GIS, International Journal of Applied Earth Observation and Geoinformation
17) Sudhira, H. S., Ramachandra, T. V., and Jagadish, K. S., 2003. Urban sprawl pattern recognition and modelling using GIS. Paper presented at Map India, New Delhi. January 28–31, 2003.
18) Thomas M Lillesand, Ralph W Kiefer, Jonathan W Chipman 2004, Remote Sensing and Image Interpretation", Edition 5, John Wiley and Sons
19) Wood, R., Handley, J., 2001. Landscape dynamics and the management of change. Landscape Res. 26 (1), 45–54.
20) Yeh, A.G.O., Li, X., 2001. Measurement and monitoring of urban sprawl in a rapidly growing region using entropy. Photogrammetr. Eng. Remote Sens. 67 (1), 83.

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Spatio temporal patterns of urban growth in Bellary, Tier II City of Karnataka State, India

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Abstract: Globalization and subsequent opening up of Indian markets has given impetus to the urbanization process in most urban pockets in India leading to large scale irreversible land cover changes. Tier II cities in Karnataka with spurt in urban activities are trying to be infrastructural competitive. However this approach has marginalized the planned interventions through the understanding and visualisation of the trends of future growth. In the absence of proper planning and visualization of growth trends, dispersed growth with lack of basic amenities is unabated in most of the metropolis of India. This communication analyses the growth patterns in one of the prominent tier II city in Karnataka –Bellary. The spatio–temporal analysis has been done for the past four decades considering buffer to account for the sprawl at outskirts. Land use and Land cover analysis with Shannon's entropy and Landscape metrics aided in visualizing the urban growth with the emerging spatial patterns. Land use analysis indicate the growth of urban areas in the city and Shannon's entropy indicates of sprawl and the need for appropriate strategies to manage natural resources while providing basic amenities . Landscape metrics highlight of aggregated growth at the centre with the tendency to form single clumped urban patch, whereas the city outskirts and the buffer region with fragmented landscapes reveal of dispersed growth. This analyses help city planners in understanding the urban growth and for institutionalizing the future developments

Keywords: Urbanisation, sprawl, Bellary city, landscape metrics, entropy.

I. Introduction

Unplanned urbanisation heralds the irreversible changes in the land cover threatening the sustence of natural resources and local; ecology. Indian cities underwent a rapid transition from the concentrated growth at city centre to very dispersed and fragmented model to accommodate the growth and demand of urban land that connects the major cities [42]. This has led to huge expansion around the urban area in an unplanned and uncontrolled manner [3]. Opening Indian markets during post 1990's due to globalization process has directly or indirectly led to the severe fragmentation of land in major urban Metropolis [40]. Major metropolitan cities experienced large scale land use changes with the compact or concentrated growth at city centre leading to a single land use urban class due to the availability of development conducive infrastructure and natural resources([1], [10], [42]). Most of the metropolitan urban fringe regions have experienced a rapid transition from rural cultivable land to urban area due to exurban development during post 2000 ([13], [7], [2], [11], [43]). Dispersed industrial and commercial units with human settlements in peri urban area of most metropolitan regions have linked the respective sprawl pockets with dense city road networks. These metropolitan regions have reached the growth threshold evident from the inability to meet the basic needs of the growing population in urban fringes [40]. Hence the focus is towards tier II cities to meet the requirements of further growth. The tier II cities have the adequate resources to meet the requirements of basic amenities of the dependent urban population. There has been an increased interest in recent times by the federal government agencies in giving further impetus as ubiquitous and self-sustained cities, since this has necessitated to understand and visualize the spatial patterns of the growth in these regions in order to plan and implement sustainable management of natural resources such as land, water, etc. Visualization and understanding of patterns of urbanisation is possible with the spatial data available at different time intervals. Remote-sensed data acquired through space borne sensors since 70's at regular intervals has aided mapping the compositions of cities and analyzing the changes over time ([18], [34], [33], [42]). The prominent characteristics of remotely sensed data, is availability in temporal mode and synoptic coverage of wide area, useful in analysing changes over the past four decades. This helps the planners and decision makers to visualise and understand the current patterns of urbanization processes ([5],[6]) apart from predicting the likely changes in future. The potential applications of remote sensing data in urban environmental research and policy has been well documented [35]. Further, the utility of multi resolution data for various environmental applications is reviewed by Sliuzas et al., 2010 [36]. Remote sensing data has been used to understand the spatio-temporal dynamics of urbanization, peri-urbanization, and urban morphology through land use land cover dynamics([32], [8], [41], [25], [9], [29], [12], [15], [16], [17], [14], [42], [40]). This forms the basis for current analysis of urban growth through remote sensing data through the temporal dynamics of land cover and land uses. Landscape metrics through Fragstat [26] are computed to detect and understand the patterns of variations in peri- urban or urban sprawl trends across the study region, along with multi-resolution remote sensing data. Landscape metrics aid in quantifying the spatial patterns of land use patches in a geographic area [26]. It provides both a quantitative and qualitative data and information on urban forms ([42], [4], [30]). Changes in landscape pattern have been detected and described through spatial metrics which aided in quantifying and categorizing complex landscapes ([28], [29], [31], [4], [19], [42]). Buffer region was considered in addition to the city's administrative boundary to account for the current and likely peri-urban development. Bellary a rapidly urbanising Tier II city of Karnataka, was considered for the current analysis and the objectives of the study are to (a) quantify urban growth dynamics considering the administrative boundary with 4 km buffer through Land cover and land use analyses, (b) to understand the pattern of urban growth through gradient approach, and (c) understand the dynamics of growth using spatial metrics. The qualitative and quantitative information support policy-making in urban planning and the sustainable management of natural resources.

II. Study Area

Bellary city is located at Latitude 15° 9' Longitude 76° 55' 60E in Karnataka State, India with a jurisdiction of about 82 Sq. Km (Figure 1). . Population is about 0.4 million as per recent 2011 population census (provisional). Gadag borders on the west, Andhra Pradesh on the East, Chitradurga and Davangere on the south and Raichur on the north. Temperature ranges from 25^0c to 45^0c and mean annual rainfall is about 700mm. The city is a hub industrial activities and is one of the major centers in the production of textiles in the country. Spatial extent of Bellary city is about 6km radius, and 4 km circular buffer is considered from the boundary for the analysis of spatio-temporal dynamics

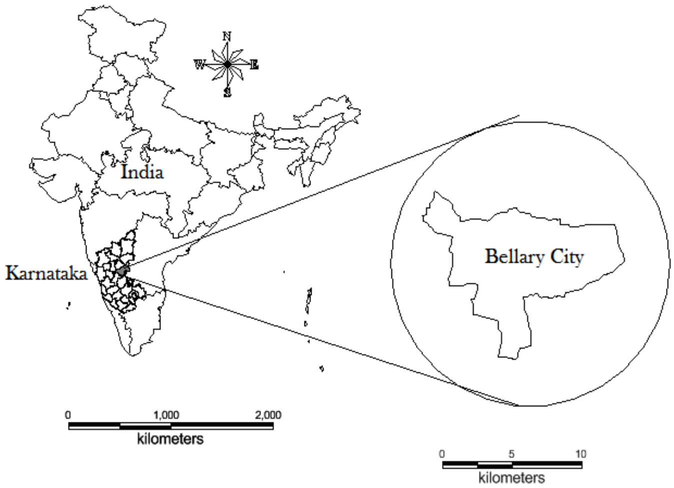

Figure 1: Study Area. Bellary City and 4 km buffer considered

Materials and methods

Urban dynamics has been assessed using remote sensing data of the period 1989 to 2010. Time series spatial data acquired from Landsat Series Thematic mapper (28.5m) sensors for the period 1989 and 2000were downloaded from public domain [23], IRS LISS III data (24 m) for 2005 and 2010 were procured from the National remote Sensing Centre [24], Hyderabad. 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 [21]. 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 toposheets (1:50000, 1:250000 scale), and virtual spatial maps - Google earth and Bhuvan ([22], [20]). See table1.

DATA	Year	Purpose
Landsat Series TM (28.5m) and ETM	1973	Land cover and Land use analysis
IRS LISS III (24m)	2001,2005, 2010	Land cover and Land use analysis
Survey of India (SOI) topo-sheet of 1:50000 and 1:250000 scales		To generate base layer maps (city boundary, etc.).
Field visit data –captured using GPS		For geo-correcting and generating validation dataset

Table 1. Materials used in Analysis

A three-step approach, illustrated in Figure 2 was adopted to understand the urban dynamics , which includes (i) a normative approach to understand the land use and land cover, (ii) a gradient approach of 1km radius to understand the pattern of growth during the past 4 decades, (iii) spatial metrics analysis for quantifying the growth. Various stages in the data analysis are:

i. 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.

ii. 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 temporal dynamics of the vegetation cover. NDVI values range from -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).

iii. Land use analysis: Further land use analysis was performed to investigate the changes in the landscape. Categories as listed in Table II, were classified with the training data (field data) using Gaussian maximum likelihood supervised classifier. 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 and 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 and Bhuvan v) 60% of the training data has been used for classification, while the balance is used for validation or accuracy assessment.

iv. Gaussian maximum likelihood classifier (GMLC) is applied to classify the remote sensing data of the study region using the training data. GMLC uses various classification decisions using probability and cost functions [39] 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). 60% of field data were used for classifying the data and the balance 40% were used in validation and accuracy assessment. Thematic layers were generated of classifies data corresponding to four land use categories (Table 2). 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 assess the effectiveness of the classifiers ([37], [38]).

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.

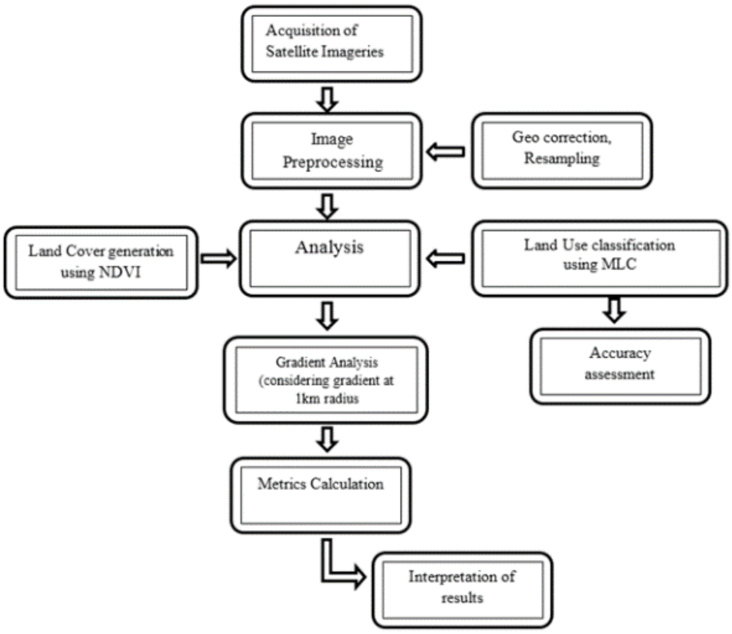

Figure 2: Procedure followed to understand the spatial pattern of landscape change

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, Cropland, nurseries.
Others	Rocks, quarry pits, open ground at building sites, kaccha roads.

Table 2. Land use categories

a) ***Urban sprawl analysis***: Direction-wise Shannon's entropy (H_n) is computed (equation 1) to understand the extent of growth: compact or divergent ([27], [42], [40]). This provides an insight into the development (clumped or disaggregated) with respect to the geographical parameters across 'n' concentric regions in the respective zones.

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

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).

b) ***Spatial pattern analysis***: Landscape metrics provide quantitative description of the composition and configuration of urban landscape. These metrics were computed for each circle, zone-wise using classified landuse data at the landscape level with the help of FRAGSTATS. 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.

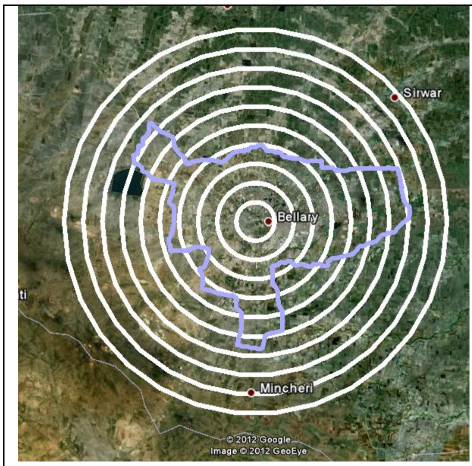

Figure 3. Google earth representation of Bellary

	Indicators	Formula
1	Number of Urban Patches (NPU)	$NPU = n$ NP equals the number of patches in the landscape.
2	Largest Patch Index (Percentage of built up)	$LPI = \frac{\max_{i=1}^{n}(a_i)}{A}(100)$ a_i = area (m^2) of patch i A= total landscape area
3	Normalized Landscape Shape Index (NLSI)	$NLSI = \frac{\sum_{i=1}^{i=N} \frac{p_i}{s_i}}{N}$ Where s_i and p_i are the area and perimeter of patch i, and N is the total number of patches.
4	Landscape Shape Index (LSI)	$LSI = e_i / \min e_i$ e_i =total length of edge (or perimeter) of class i in terms of number of cell surfaces; includes all landscape boundary and background edge segments involving class i. Min e_i=minimum total length of edge (or perimeter) of class i in terms of number of cell surfaces.

5	Clumpiness	$CLUMPY = \begin{bmatrix} \frac{G_i - P_i}{P_i} \; for G_i < P_i \,\&\, P_i < 5, else \\ \frac{G_i - P_i}{1 - P_i} \end{bmatrix}$ $G_{i=} \left(\frac{g_{ii}}{\left(\sum_{k=1}^{m} g_{ik}\right) - \min e_i} \right)$ gii $= number\ of\ like\ adjacencies\ between\ pixels\ of\ patch\ type\ gik$ $= number\ of\ adjacencies\ between\ pixels\ of\ patch\ types\ \ i\ and\ k.$ $Pi\ = proportion\ of\ the\ landscape\ occupied\ by\ patch\ type\ (class)\ i.$
6	Percentage of Like Adjacencies (PLADJ)	$PLADJ = \left(\frac{g_{ii}}{\sum_{k=1}^{m} g_{ik}} \right)(100)$ $gii\ = \quad number\ of\ like\ adjacencies\ (joins) between\ pixels\ of\ patch\ type$ $gik\ = \quad number\ of\ adjacencies\ between\ pixels\ of\ patch\ types\ i\ and\ k$
7	Cohesion	$Cohesion = \left[1 - \frac{\sum_{j=1}^{n} P_{ij}}{\sum_{j=1}^{n} P_{IJ} \sqrt[2]{a_{ij}}}\right] \left[1 - \frac{1}{\sqrt[2]{A}}\right]^{-1} * 100$

Table 3. Landscape metrics analysed

RESULTS AND DISCUSSION

Land use Land Cover analysis:

Land cover analysis: Vegetation cover of the study area assessed with the temporal remote sensing data through NDVI is given in Figure 4. NDVI values indicate the spatial extent of vegetation and non-vegetation in the region. This is based on the reflectances of earth features (such as trees, agriculture, and scrub vegetation) which have higher values in Near IR region. The area under vegetation in 1973 is 57.53% mainly composed of cultivated vegetative area and the balance are open soil. During 1973-2001 there was an increase in the area under cultivation and some increments in urban pockets evident from the land cover of 2001, 2005 and 2010. Land use investigation was carried out to understand the dynamics under respective land use categories. Temporal NDVI values are listed in Table 4.

Year	Vegetation %	Non-Vegetation %
1973	57.51	42.47
2001	94.87	5.13
2005	94.8	5.2
2010	93.7	6.27

Table 4: Temporal Land cover details.

Land use analysis*:* Land uses assessed for the period 1973 to 2010 using Gaussian maximum likelihood classifier are listed Table 5 and in figure 5. The overall accuracy of the classification ranges from 78% (1973), 86% (2001), 84% (2005) to 89% (2010) respectively. 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 table 5. There has been a decrease in tree vegetation cover in the region during the past four decades. Significant increase in other land use categories including urban class was observed.

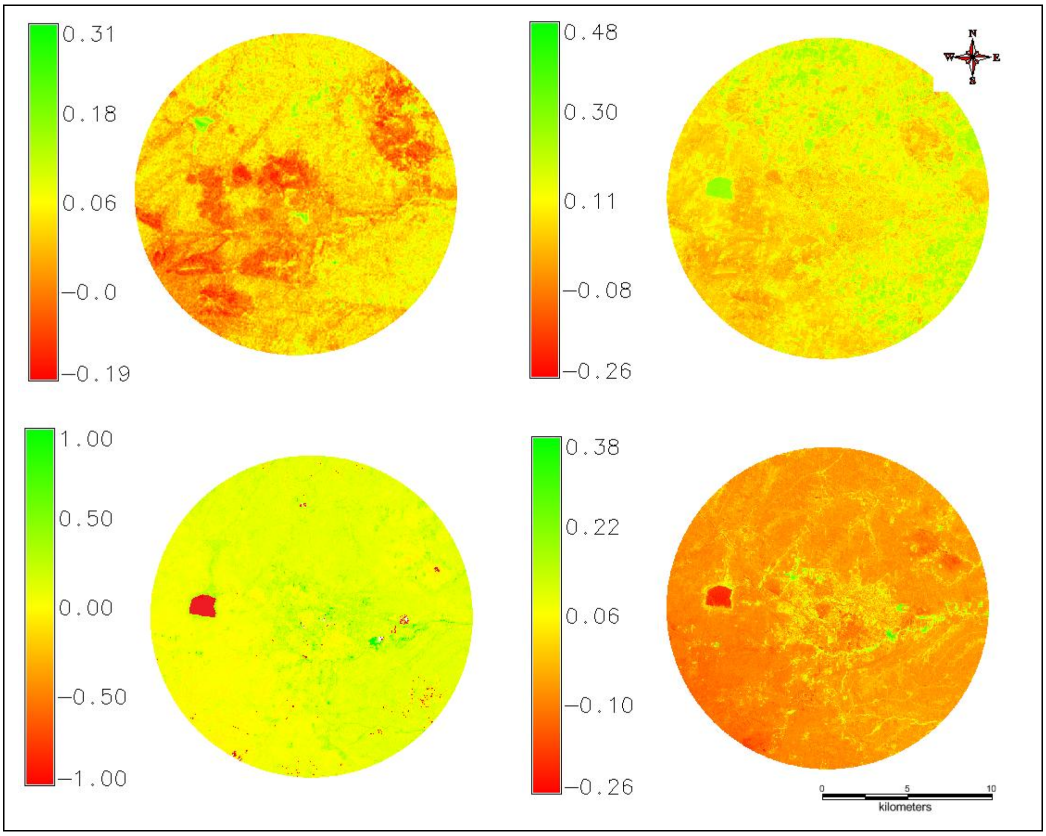

Figure 4: Temporal Land cover changes during Past three Decades

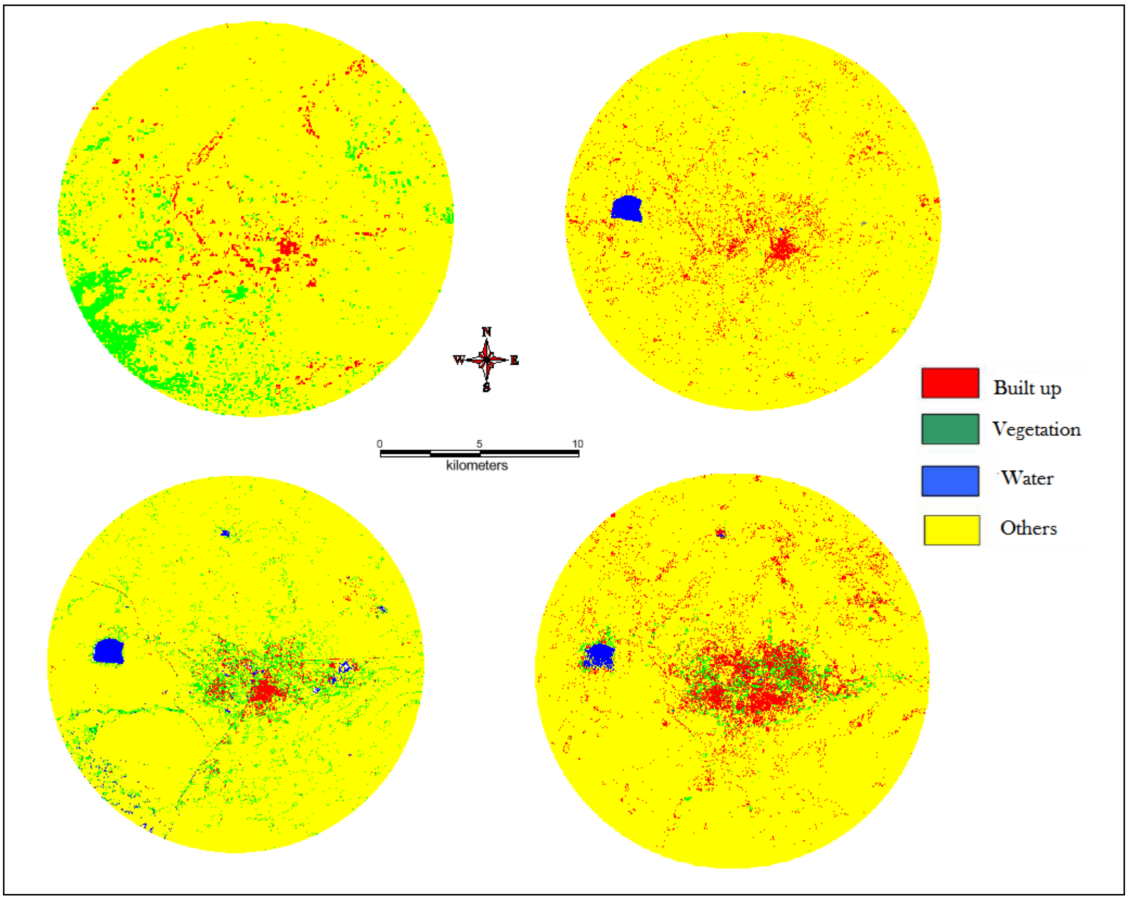

Figure 5:Classification output of Bellary

Land use / Year	**Urban**	**Vegetation**	**Water**	**Cultivation and others**
2010	7.42	0.48	2.04	90.07
2005	4.23	0.92	4.73	90.12
2001	2.64	0.41	2.01	94.94
1973	2.12	4.61	2.35	90.92

Table 5: Temporal land use details for Bellary

Year	**Kappa coefficient**	**Overall accuracy (%)**
1973	0.69	78.32
2001	0.84	86.94
2005	0.82	84.53
2010	0.86	89.69

Table 6: Kappa statistics and overall accuracy

Shannon's entropy: The entropy is calculated considering 10 gradients in 4 directions and are listed in table 7. The reference value is taken as Log (10) which is 1 and the computed Shannon's entropy values are inching closer to the threshold value, indicating tendency of sprawl. Consistently increasing entropy values from 1973 to 2010 shows the tendency of dispersed growth of built-up area in the city with respect to 4 directions as we move towards the outskirts and this phenomenon is most prominent in SE and NE directions**.**

	NE	**NW**	**SE**	**SW**
2010	0.37	0.32	0.389	0.33
2005	0.23	0.25	0.26	0.24
2001	0.1	0.09	0.12	0.14
1973	0.04	0.03	0.08	0.06

Table 7: Shannon Entropy Index

Spatial patterns of urbanisation: Spatial dynamic pattern of urban growth was analysed for 4 decades using eight landscape level metrics that were computed zone wise for each circle of 1 km radius. 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 the temporal dynamics of number of patches. Increase in number of patches indicates the land fragmentation, while decline in patches indicates the fragmented landscape forming a single land use patch. As observed from the figure, urban patches are least in the landscape in 1970's as the growth was concentrated on at the city center. In 2000's Bellary city saw a gradual increase in the number of patches, which can be understood as features of fragmented landscape, further in 2010, these patches are increasingly forming a single patch at the center during 2010 indicative that the urban area forming a single clump patch destroying all other land uses, but the case in the buffer regions has been indicative of higher fragmentation during the latter years. Clumped patches at center are more prominent in NE and SE directions and patches are agglomerating to a single urban patch.

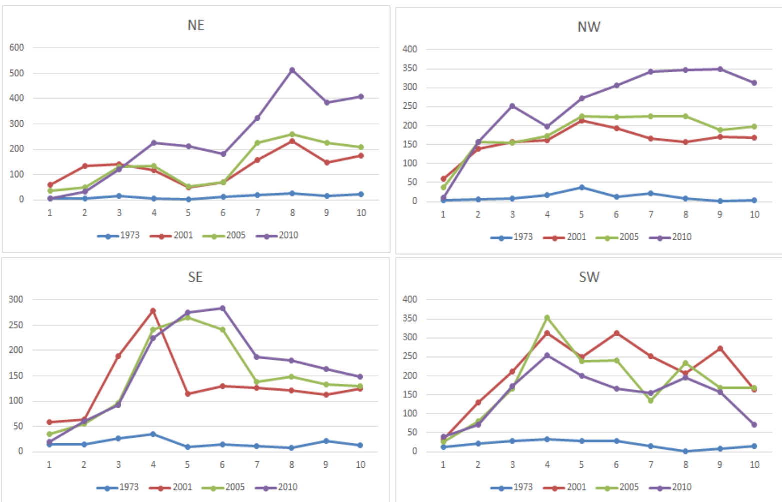

Figure 6a: Number of urban patches (zonewise, circlewise)

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. Results (Fig 6b) indicate that there were low LSI values in 1973 as there were minimal urban areas and were concentrated in the center. The city since 2001 has been experiencing dispersed growth in all direction and in every gradient, towards 2010 it shows aggregating urban land use at the center forming a simple shaped single patch as the value is close to 1, whereas, the values of LSI are very high in the outskirts indicating a complex shaped growth with also is indicative of fragmented landscape in the buffer zone.

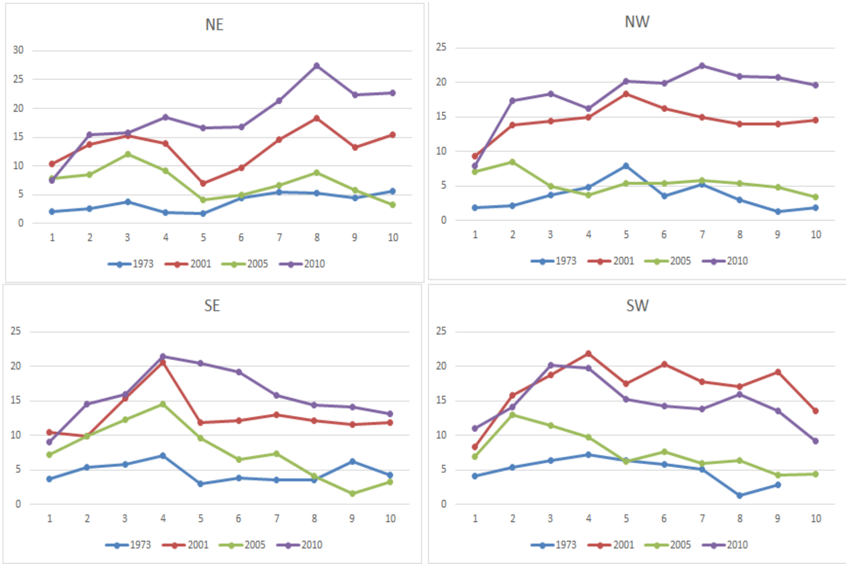

Fig 6b: Landscape Shape index – zonewise, circlewise

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 (Fig 6c) indicate that the landscape post 2000 is fragmented and in 2010, the landscape has 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 0 when patches are distributed randomly, and approaches 1 when the patch type is maximally aggregated. Clumpiness exhibit similar temporal trends and highlights that the center of the city is more compact in 2010 with more clumpiness and aggregation in NW and NE directions. In 1973 the results indicate that there were a small number of urban patches existing in all direction and in every circle. Post 2000's and in 2010 large number of urban patches are close to each other almost forming a single patch especially at the center and in NW and NE direction in different gradients (Fig 6d). Lower values of these metrics in the outer circles indicate that there is a tendency of sprawl in the outskirts since non clumped patches exist in this region.

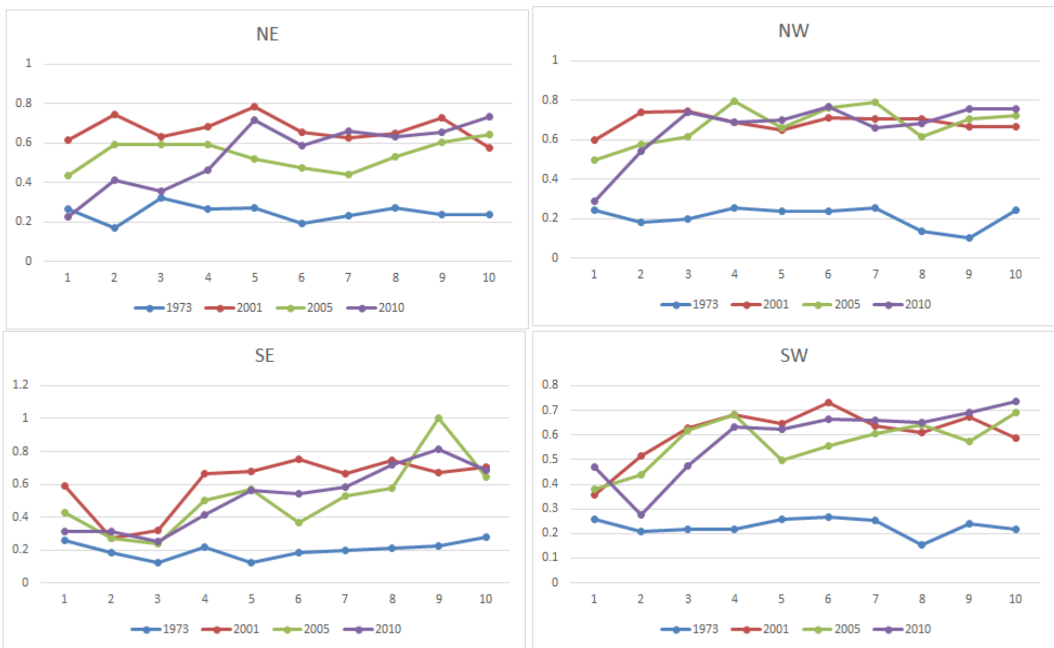

Fig 6c: Normalised Landscape Shape index – zonewise, circlewise

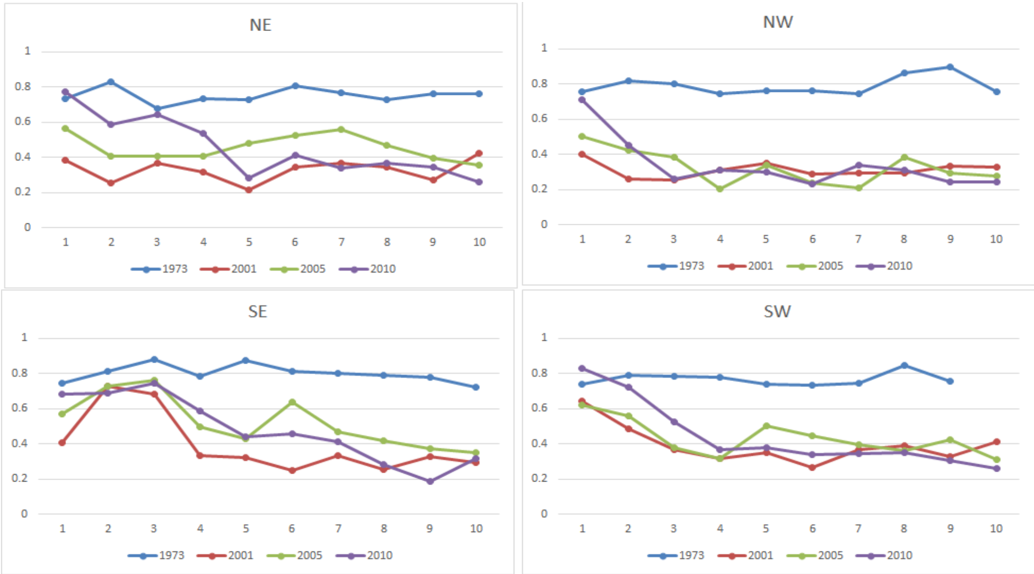

Figure 6d: Clumpiness – zonewise, circle wise

Percentage of like adjacencies (Pladj) is the percentage of cell adjacencies involving the corresponding similar patch type those are adjacent. The analysis of results of this metrics also indicates (Figure 6e) clumped urban single land use growth at the city center in 2010, adjacent patches of urban are much closer and are forming a single patch in 2010 and outskirts are relatively sharing different internal adjacencies with patches not immediately adjacent but have since these have a relatively small adjacency value it can be understood as a trend to become adjacent to each other, which is also indicative of sprawl.

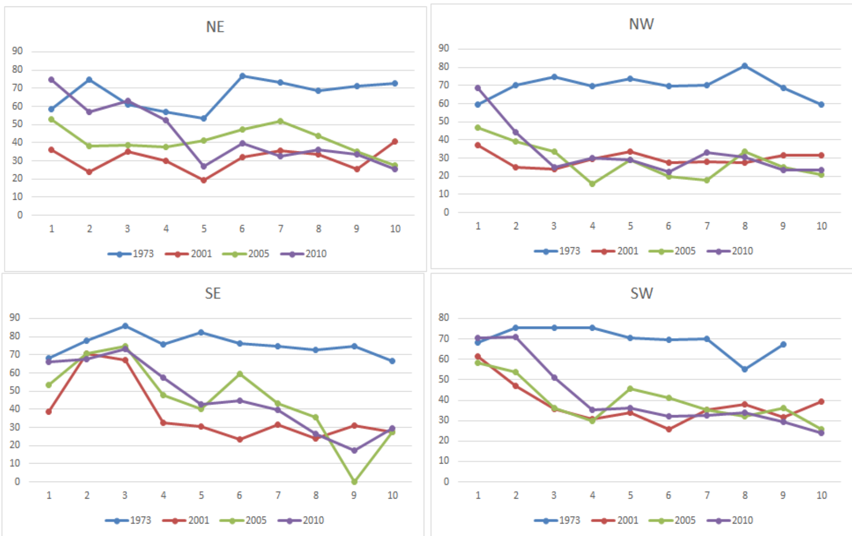

Figure 6e: Zone and circle wise: Pladj

Patch cohesion index measures the physical connectedness of the corresponding patch type. Figure 6f describes the results of the analysis of physical connectedness of the urban patch with the higher cohesion value (in 2010) indicating that the urban count is higher in the considered study region. Lower values in 1973 illustrate that the urban patches were rare in the landscape.

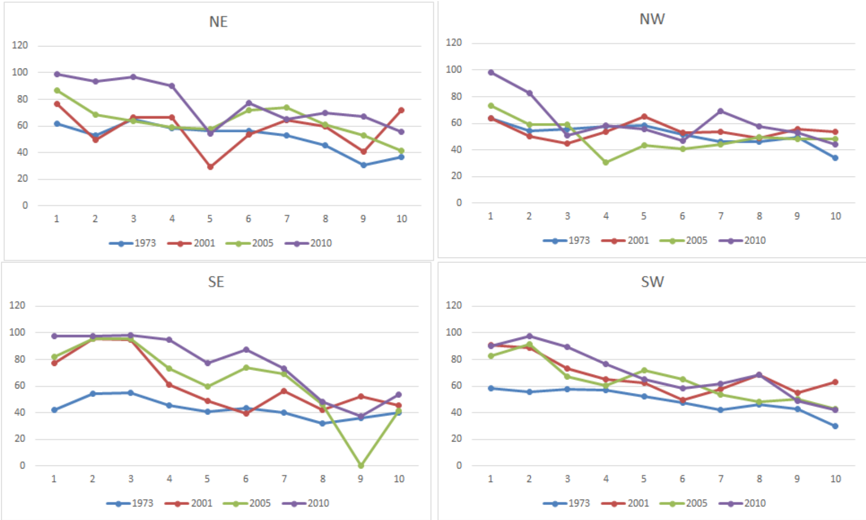

Figure 6f: Cohesion Index

Largest Patch Index (LPI): This metric reveals information about the largest patches in the Landscape and its native existence. Urban patch again counted as a largest patch in 2010 in the central area of Bellary, whereas the buffer zones had a mixture of other patches. Figure 6g is illustrative of results of this analysis.

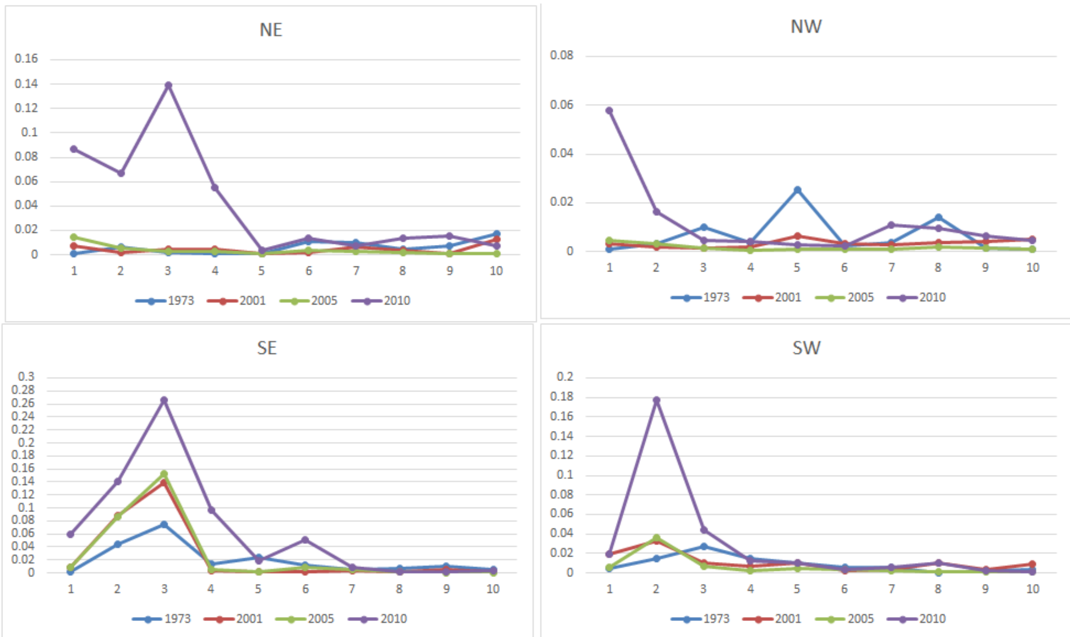

Figure 6g: Largest patch index

The trends of landscape metrics aided in quantifying the density and the shape of the urban growth, which is useful in the regional planning for provision of basic amenities and infrastructure in the region.

CONCLUSION

Multi resolution spatial data acquired through satellite borne sensors provided vital inputs of land use and land cover in Bellary, Tier II city in Karnataka, India. Analysis reveals that urbanization is in progress but neither uniform in space nor planned , Land use analysis show an increase of urban area from 2.12% (1973) to 7.42% (in 2010) in and around Bellary. The present land-use is predominantly cultivation or agriculture and open area. Shannon entropy illustrated the tendency of urban sprawl in and around the periphery and buffer zones. Further the zonal approach with gradients supplemented with landscape metrics brought out the fact that during the past four decades the center of the city is forming a clumped urban patch, while the periphery and the buffer regions are experiencing dispersed growth or sprawl. The judicious use of land by checking the haphazard growth of urbanization is imperative to maintain he environmental quality and health in the region. . Spatial models provide vital inputs for the decision makers and city planners to visualize and plan a sustainable management strategies.

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References

[1] A. Gospodini, “Portraying, classifying and understanding the emerging landscapes in the post-industrial city”, Cities, vol. 23, 2006, pp. 311–330.
[2] A. Gospodini, “Post-industrial trajectories of Mediterranean European cities: the case of post-Olympics Athens”, Urban Studies, vol. 46, 2009, pp. 1157–1186.
[3] A. Schneider, and C. E. Woodcock, “Compact, dispersed, fragmented, extensive? A comparison of urban growth in twenty-five global cities using remotely sensed data, pattern metrics and census information”. Urban Studies, vol. 45, 2008, pp. 659–692
[4] Anindita Dasgupta, Uttam Kumar, T.V. Ramachandra., “Urban Landscape analysis through spatial metrics, In the proceedings of the Conference on Infrastructure, Sustainable Transportation and Urban Planning, CISTUP@CISTUP2010, 18 - 20 October, JN Tata Auditorium, Indian Institute of Science, Bangalore. 2010.
[5] B. Bhatta, S. Saraswati, D. Bandyopadhyay, “Quantifying the degree-of-freedom, degree-of-sprawl, and degree-of-goodness of urban growth from remote sensing data”, Applied Geography, vol. 30(1), 2010a, pp. 96–111.
[6] B. Bhatta, S. Saraswati, D. Bandyopadhyay, “Urban sprawl measurement from remote sensing data”. Applied Geography, vol. 30(4), 2010b, pp.731–740.
[7] B. Catalan, D. Sauri, and P. Serra, “Urban sprawl in the Mediterranean? Patterns of growth and change in the Barcelona Metropolitan Region 1993– 2000.Landscape and Urban Planning, vol.85, 2008, pp. 174–184
[8] D. Lu and Q. Weng, “Spectral mixture analysis of the urban landscape in Indianapolis with Landsat ETM+ imagery”. Photogrammetric Engineering and Remote Sensing, vol.70 (9), 2004, 1053–1062.
[9] D. Yu, C. Wu, “Incorporating remote sensing information in modeling house values: A regression tree approach”, Photogrammetric Engineering and Remote Sensing, vol. 72(2), 2006, pp. 129–138.
[10] D.L. Johnson and L.A. Lewis, “Land degradation. Creation and destruction”. Lanham: Rowman & Littlefield Publishers, 2007
[11] F. Munoz, “Lock living: Urban sprawl in Mediterranean cities”. Cities, vol.20, 2003, pp. 381–385.
[12] F.A. Galeon, “Estimation of population in informal settlement communities using high resolution satellite image”, The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. 37(Part B4), 2008, pp.1377–1382.
[13] G. Cakir, C. Un, E. Z., Baskent, S. Kose, F. Sivrikaya, S. Keles, S., “Evaluating urbanization, fragmentation and land use/cover change pattern in Istanbul city, Turkey from 1971 to 2002”. Land Degradation and Development, vol. 19, 2008, pp. 663–675.
[14] G. Tian, J. Jiang, Z. Yang, and Y. Zhang, “The urban growth, size distribution and spatio-temporal dynamic pattern of the Yangtze River Delta megalopolitan region, China”, Ecological Modelling, vol.222(3), 2011, pp. 865–878.
[15] H. Taubenböck, M. Wegmann, A. Roth, H.Mehl, and S.Dech, “Urbanization in India: Spatiotemporal analysis using remote sensing data”. Computers, Environment and Urban Systems, vol.33 (3), 2009a, pp. 179–188.
[16] H. Taubenböck, M. Wurm, N. Setiadi, N. Gebert, A. Roth, G. Strunz, et al. Integrating remote sensing and social science – The correlation of urban morphology with socioeconomic parameters. In IEEE, editor, urban remote sensing joint event, London, 2009b.
[17] H. Taubenböck, T. Esch, A. Felbier, M. Wiesner, A. Roth, and S. Dech , “Monitoring urbanization in mega cities from space” ,Remote sensing of Environment, vol.117, 2012, pp. 162–176.
[18] H.S. Sudhira, T.V. Ramachandra, and K.S. Jagadish, “Urban sprawl: metrics, dynamics and modelling using GIS”. Int. J. Appl. Earth Observ. Geoinform. vol.5, 2004, pp. 29–39.
[19] H.S. Sudhira, T.V. Ramachandra, K.S. Raj, and K.S. Jagadish, “Urban Growth Analysis using Spatial and Temporal Data,” Photonirvachak”, Journal of Indian Society of Remote Sensing, vol. 31(4), 2003, pp. 299-311.
[20] http://bhuvan.nrsc.gov.in
[21] http://censuskarnataka.gov.in
[22] http://earth.google.com,
[23] http://glcf.umiacs.umd.edu/data
[24] http://nrsc.gov.in
[25] J. Mennis, and J. W. Liu, “Mining association rules in spatio-temporal data: An analysis of urban socioeconomic and land cover change”, Transactions in GIS, vol. 9(1), 2005, pp. 5–17.
[26] K. McGarigal, B.J. Marks, “FRAGSTATS: spatial pattern analysis program for quantifying landscape structure.” USDA Forest Service General Technical Report PNW-351, 1995
[27] K.M. Lata, C.H.S. Rao, V.K. Prasad, K.V.S. Badarianth, V. Raghavasamy, “Measuring Urban sprawl A case study of Hyderabad,” gis@development, vol. 5(12), 2001, pp. 26-29.
[28] M. Antrop, V. Van Eetvelde, “Holistic aspects of suburban landscapes: visual image interpretation and landscape metrics,” Landscape Urban Plan, Vol. 50 (1–3), 2000, pp. 43–58.
[29] M. Herold, H. Couclelis, and K.C. Clarke, “The role of spatial metrics in the analysis and modeling of urban land use change”. Comput. Environ. Urban, vol.29, 2005, pp. 369–399.
[30] M. Herold, J. Scepan, K.C. Clarke, “The use of remote sensing and landscape metrics to describe structures and changes in urban land uses,” Environ. and Plan. Vol. 34, 2002, pp. 1443–1458
[31] M.G. Turner, R.H. Gardner, R.V. O’Neill, “Landscape Ecology in Theory and Practice,” Springer-Verlag, New York. 2001.
[32] P. Griffiths, P. Hostert, O. Gruebner, and S.V. der Linden, “Mapping megacity growth with multi-sensor data”, Remote Sensing of Environment, vol. 114(2), 2010, pp. 426–439
[33] Q Weng, “Remote sensing of impervious surfaces in the urban areas: Requirements, methods, and trends”, Remote Sensing of Environment, vol.117, 2012. pp. 34–49.
[34] Q. Weng, D.A. Quattrochi, Urban remote sensing. Boca Raton: CRC Press –Taylor & Francis Group, 2006.
[35] R. B. Miller, and C. Small, “Cities from space: Potential applications of remote sensing in urban environmental research and policy”. Environmental Science & Policy, vol. 6(2), 2003, pp.129–137.
[36] R. Sliuzas, M. Kuffer, and I. Masser “The spatial and temporal nature of urban objects. In T. Rashed & C. Jürgens (Eds.), Remote sensing of urban and suburban areas Netherlands”, Dordrecht: Springer.2010, pp. 67–84.
[37] R.G. Congalton, “A review of assessing the accuracy of classifications of remotely sensed data,” Remote Sensing of Environment, vol. 37, 1991, pp. 35-46.

[38] R.G. Congalton, R.G. Oderwald, and R.A. Mead, "Assessing Landsat classification accuracy using discrete multivariate analysis statistical techniques," Photogrammetric Engineering and Remote Sensing, vol. 49, 1983, pp. 1671-1678.
[39] R.O. Duda, P.E. Hart, D.G. Stork, "Pattern Classification", a Wiley-Interscience Publication, Second Edition, ISBN 9814-12-602-0, 2005.
[40] S. Bharath, H. A. Bharath, D. Sanna Durgappa, T.V. Ramachandra, "Landscape Dynamics through Spatial Metrics", Proceedings of India GeoSpatial Conference, Epicentre, Gurgaon, India, 7-9 February, 2012.
[41] T. Rashed, "Sustainable hazards mitigation. In M. Campagna (Ed.),GIS for sustainable Development: Bringing geographic information science into practice towards sustainability". New York: Taylor & Francis (CRC Press), 2005, pp. 287–309
[42] T.V. Ramachandra, A.H. Bharath and D.S. Durgappa, "Insights to urban dynamics through landscape spatial pattern analysis", Int. J Applied Earth Observation and Geoinformation, vol. 18, 2012, pp. 329-343.
[43] T.V. Ramachandra, A.H. Bharath, S. Sreekantha, "Spatial Metrics based Landscape Structure and Dynamics Assessment for an emerging Indian Megalopolis", International Journal of Advanced Research in Artificial Intelligence, vol.1(1), 2012b, pp 48-57.

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Spatio-Temporal Dynamics of Urbanising Landscape in Twin Cities in Karnataka, India

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***Abstract*— Urbanisation is a form of metropolitan growth fuelled by sets of economic, social, and political forces apart from the physical geography of an area. As population and activities increases in a city, the boundary of the city expands to accommodate the growth on the urban fringes, which is referred as sprawl. Sprawl generally infers to the regions with highly fragmented urban morphology impacting ecologically sensitive habitats. Cities in India have become a centre of urban agglomerations and have already attracted considerable attention because of their growth, population size, environmental influence and associated infrastructure, mobility issues. This is evident from the increase of mega urban centers (with more than 1 million inhabitants), which were four in 1990's has increased to 48 cities (post 2010). There has been 2.1% increase in urban population during the last decade and the current share is about 27.8%. As per 2011 census there has been tremendous increase in the population and most of urban areas have reached the threshold. Tier II cities in India are also undergoing rapid changes in recent times which necessitates planned interventions to minimize the impacts of unplanned urbanization and consequent impacts on natural resources including basic amenities. This communication analyses the spatio-temporal patterns of urbanisation in the tier II twin cities of Karnataka state: Hubli and Dharwad. The urbanization dynamics of the region with 5 km buffer from the city boundary has been studied considering the temporal remote sensing data of five decades. Five km buffer has been chosen to account for possible urban sprawl regions. A gradient-oriented approach using multi-temporal remotely sensed data was adopted to systematically monitor the spatiotemporal dynamics of the twin cities. Land cover analysis shows that area under vegetation (cultivation and forests) has declined from 97% (1989) to 78% (2010) in Hubli and from 98% (1989) to 86% (2010) in Dharwad. Urban area has increased from 1.08 (1989) to 14.62 (2010)%. Shannon entropy shows that Hubli-Dharwad is experiencing the tendency of sprawl in all directions. Spatial metrics reveal that the urban core of Hubli - Dharwad changed moderately over time and exhibited a spread out pattern of urban development with a moderate to low concentration of urban area towards the periphery. The new urban areas of developed rapidly along major transportation route connecting Hubli - Dharwad, resulting in urban development assuming an unusual outgrowth pattern.**

***Keywords*– Land use, Land Cover, Remote Sensing, Image Classification, Spatial Metrics, Twin Cities, Tier II cities.**

I. Introduction

Urbanization is a dynamic process involving the spatial and demographic changes leading to the increase in urban area with the concentration of population mainly due to migration ([1], [2],[3],[4]) and anthropogenic activities. Problems of urbanisation, which include inadequate housing and infrastructure, lack of basic amenities (water and sanitation), enhanced levels of pollution (water, air and land) are the manifestations of unplanned urbanisation, regions with poor economic base, lopsided urbanisation. This involves radical changes in land uses resulting in the alterations in spatial structure and configurations of the landscape affecting its functional ([1],[5]). The spatio-temporal analysis of land use dynamics helps in understanding various processes and interactions of the study area. Evaluating these processes that change temporally helps in understanding the complex dynamics that aid in understanding and visualizing the future spatial and temporal changes and in identification of local forces ([6],[7], [8]).

Urban population in India is increasing at about 2.3% per annum and 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 [9]. India has been experiencing rapid urbanisation with globalization and consequent opening of markets. There are 48 urban agglomerations (Mega cities, Tier I) having a population of more than one million in India (in 2011). Tier 1 cities have reached the saturation level evident from lack of natural resources (water, electricity, infrastructure), higher levels of pollution (crossing the assimilative and supportive capacity of ecosystems), having higher traffic bottlenecks, higher crime rates due to burgeoning population. This has necessitated the focus shift from Tier 1 urban areas to Tier 2 cities that offer humongous potential with the scope for meeting the basic amenities with appropriate urban planning. This 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. This is conceivable with modeling and visualization of urban growth using the historical spatio-temporal data. Failing to visualise and plan such growth would again lead to urban outgrowth depriving the local population with the basic amenities.

In this backdrop, current study focuses on urban growth and its forms and transition of rural area to urban forms in terms of urban land-use classes. Urban sprawl, also known as Peri urban area is defined as a low-density development pattern of urban growth having various social, environmental disadvantages ([10],[11],[12],[13], [14]). It is important to characterize urban sprawl in order to develop a comprehensive understanding of the causes and effects of urbanization processes. Urban sprawl is often evaluated and

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characterized exclusively based on major socioeconomic indicators such as population growth, commuting costs, employment shifts, city revenue change, and number of commercial establishments [15]. However, this approach does not portray the spatial dynamic of urban sprawl. Land use spatial variability and urban sprawl have been monitored by transition patterns of spatial configurations reflecting dynamics of land uses using temporal remote sensing data ([16], [17], [1]). Subsequent contributions include gradient analyses, geospatial tool applications such as landscape metrics to understand the process urban growth pattern ([18], [19], [1]). Mapping urban areas remains a complex challenge, thus a multitude of indicators have been created in order to characterize landscape structure and landscape pattern. One such indicator is Landscape metrics. Landscape metrics quantify spatial patterning of land use patches of a geographic area [20]. It provides both a quantitative and qualitative data and information on urban forms ([1], [21]; [22]). Changes of landscape pattern have been detected and described by spatial metrics which aided in quantifying and categorizing complex landscapes ([23],[24], [25], [26],[21],[1]). Applications of landscape metrics include landscape ecology (number of patches, mean patch size, total edge and mean shape), geographical applications [27], etc.

Tier II twin cities Hubli Dharwad was considered for the current analysis and the objectives of the study are to (a) quantify urban growth dynamics considering the administrative boundary with 5 km buffer through Land cover and land use analyses, (b) to understand the pattern of urban growth through gradient approach, and (c) understand the dynamics of growth using spatial metrics. Such information can support policy-making in urban planning and natural resource conservation.

II. Study Area

Hubli - Dharwad are twin cities in Indian state of Karnataka. Hubli-Dharwad is the second-largest urbanized centers in Karnataka. The twin cities have common governance and are governed by Hubli - Dharwad Municipal Corporation (HDMC) with a corporation governing area of 202.3Sq km. The population of the Twin cities is about 1 million (Census 2011). Hubli is a commercial and industrial hub with various commercial establishments. Dharwad is an educational and administrative centre with numerous colleges, universities and government offices. Hubli-Dharwad District encompasses an area of 4263 sq. kms lying between the latitudinal parallels of 15002' and 15051' N and longitudes of 73043' and 75035' E (Figure 1) with an altitude of about 800 m above the sea level. The district is bounded on the North by Belgaum, on the East by Gadag, on the South Haveri and on the West by Uttara Kannada. The district enjoys a moderate and healthy climate. The district has an agro-based economy to a large extent, trade and commerce are completely dependent on agriculture. In order to understand the influence of urban system in the rural vicinity, 5 km buffer is considered from each city boundary. Hubli city boundary is 7km in radius and Dharwad has a boundary of 2.45km in radius.

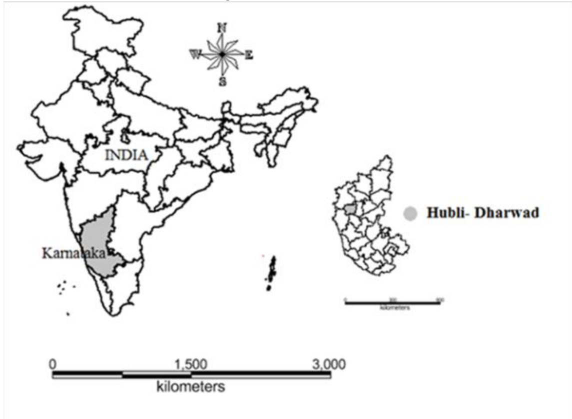

Figure 1: Showing the geographical location of Hubli Dharwad district

III. Materials and Methods

Urban dynamics was analysed using temporal remote sensing data of the period 1989 to 2010. The time series spatial data acquired from Landsat Series Thematic mapper (28.5m) sensors for the period 1989 and 2000were downloaded from public domain (http://glcf.umiacs.umd.edu/data). IRS LISS III data (24 m) for 2005 and 2010 were procured from the National remote Sensing Centre (http://nrsc.gov.in), Hyderabad. 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).

Table I: Materials used in Analysis

DATA	Year	Purpose
Landsat Series TM (28.5m) and ETM	1989, 2000	Landcover and Land use analysis
IRS LISS III (24m)	2005, 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

A three-step approach was adopted to understand the dynamics of the urbanizing city (Figure 2), which includes (i) a normative approach to understand the land use and land cover, (ii) a gradient approach of 1km radius to understand the pattern of growth during the past 4 decades, (iii) spatial metrics analysis for quantifying the growth. Various stages in the data analysis are:

A. Preprocessing: The remote sensing data of Landsat were downloaded from GLCF (Global Land Cover Facility; http://glcf.umiacs.umd.edu/data)) 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.

B. 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).

C. Land use analysis: Further to investigate the changes in the landscape land use analysis was performed. Categories included are as listed in Table II, were classified with the training data (field data) using Gaussian maximum likelihood supervised classifier. 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 (www.googleearth.com) and Bhuvan (bhuvan.nrsc.gov.in) v) 60% of the training data has been used for classification, while the balance is used for validation or accuracy assessment.

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 [28] 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). 60% of field data were used for classifying the data and the balance 40% 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 ([29][30]).

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.

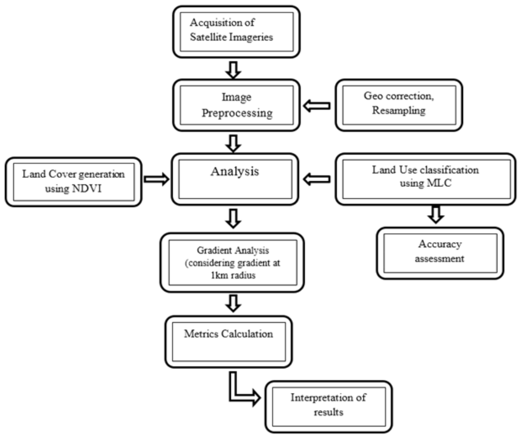

Fig.2. Procedure followed to understand the spatial pattern of landscape change

Table II: 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, Cropland, nurseries.
Others	Rocks, quarry pits, open ground at building sites, kaccha roads.

a) Urban sprawl analysis: Direction-wise Shannon's entropy (H_n) is computed (equation 1) to understand the extent of growth: compact or divergent ([31], [1]). This provides an insight into the development (clumped or disaggregated) with respect to the geographical parameters across 'n' concentric regions in the respective zones.

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

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).

b) 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 [12]. 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 III.

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Hubli city with 1km buffer, Dharwad city with 1km buffer
Fig.3. Google earth representation of the study region

Table III: Landscape metrics analysed

	Indicators	Formula
1	Number of Urban Patches (NPU)	$NPU = n$ NP equals the number of patches in the landscape.
2	Patch density (PD)	f(sample area) = (Patch Number/Area) * 1000000
3	Normalized Landscape Shape Index (NLSI)	$NLSI = \frac{\sum_{i=1}^{i=N} \frac{p_i}{s_i}}{N}$ Where $s_i$and p_i are the area and perimeter of patch i, and N is the total number of patches.
4	Landscape Shape Index (LSI)	$LSI = e_i / \min e_i$ e_i =total length of edge (or perimeter) of class i in terms of number of cell surfaces; includes all landscape boundary and background edge segments involving class i. $\min e_i$=minimum total length of edge (or perimeter) of class i in terms of number of cell surfaces.
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 between pixels of patch type g_{ik}=number of adjacencies between pixels of patch types i and k. P_i =proportion of the landscape occupied by patch type (class) i.
6	Percentage of Like Adjacencies (PLADJ)	$PLADj = \left(g_{ij} / \sum_{k=1}^{m} g_{ik} \right)(100)$ g_{ii} = number of like adjacencies (joins) between pixels of patch type g_{ik} = number of adjacencies between pixels of patch types i and k
7	Aggregation index(AI)	$AI = \left[\sum_{i=1}^{m} \left(\frac{g_{ii}}{\max \rightarrow g_{ii}} \right) P_i \right] (100)$ g_{ii} =number of like adjacencies between pixels of patch type P_i= proportion of landscape comprised of patch type.

IV. Results

I. Land use Land Cover analysis:

a) Vegetation cover analysis: Both Hubli and Dharwad being dominated by cultivable land area has a huge green area which includes both Green cover and cultivation. Temporal NDVI values are listed in Table IV. Vegetation cover of the study area assessed through NDVI (Figure 4), shows that area under vegetation has declined from 97% (1989) to 78% (2010) in Hubli and from 98% (1989) to 86% (2010) in Dharwad.

b) Land use analysis: Land use assessed for the period 1973 to 2009 using Gaussian maximum likelihood classifier is listed Table V and the same is depicted in figure 5. The overall accuracy of the classification ranges from 76% (1989), 83% (2000), 81% (2005) to 94% (2010) respectively. Kappa statistics and overall accuracy was calculated and is as listed in Table VI. There has been a significant increase in built-up area during the last decade evident from table IV. Other category covers major portion of the land use. Consequent to these, there has been a slight decrease of vegetation cover especially in the Dharwad region during the past three decades.

Table IV: Temporal Land cover details.

Year	Hubli - Vegetation %	Hubli - Non-Vegetation %	Dharwad-vegetation %	Dharwad Non - vegetation %
1989	97.0	3.0	98.12	1.88
2000	94.35	5.65	96.48	3.52
2005	89.73	10.27	92.21	7.79
2010	78.31	21.69	86.43	13.57

Table V (a): Temporal land use details for Hubli

Land use -Hubli	Urban	Vegetation	Water	Others
Year				
1989	1.08	0.22	0.64	98.06
2000	2.25	0.45	0.98	96.31
2005	9.85	0.71	0.74	88.70
2010	14.62	0.42	0.65	84.30

Table V (b): Temporal land use details for Dharwad

Land use - Dharwad	Urban	Vegetation	Water	Others
Year				
1989	0.62	1.43	0.51	97.45
2000	1.93	1.41	1.13	95.52
2005	3.75	1.29	0.25	94.71
2010	6.47	0.69	0.47	92.36

Table VI: Kappa statistics and overall accuracy

Year	Kappa coefficient	Overall accuracy (%)
1989	0.82	76.34
2000	0.89	83.54
2005	0.83	81.62
2010	0.91	94.86

c) Urban sprawl analysis: Shannon entropy computed using temporal data are listed in Table VII. Hubli-Dharwad is exhibiting the tendency of sprawl in all directions in recent times, as entropy values are inching closer to the threshold value (for Hubli: log (12) = 1.07. For Dharwad: log (7) = 0.845). Lower entropy values of 0.02 (NW), 0.011 (SW) during late 80's shows an aggregated growth as most of urbanization were concentrated at city center.

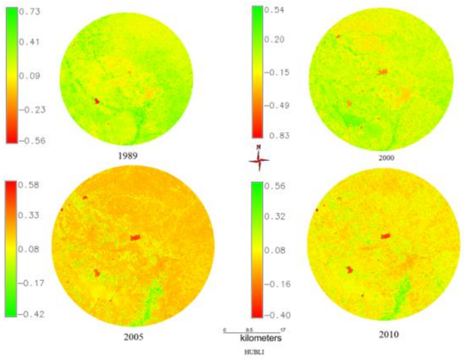

Fig.4.a. Temporal Land cover changes in Hubli during Past three Decades

However, the region experienced dispersed growth in 90's reaching higher values of 0.36 (NE), 0.49 (SE) in 2010 during post 2000's. The entropy computed for the city (without buffer regions) shows the sprawl phenomenon at outskirts. However, entropy values are comparatively lower when buffer region is considered. Shannon's entropy values of recent time confirms of minimal fragmented dispersed urban growth in the city. This also illustrates and establishes the influence of drivers of urbanization in various directions.

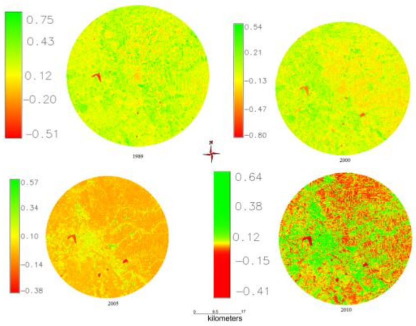

Fig.4.b. Temporal Land cover changes in Dharwad during Past three Decades

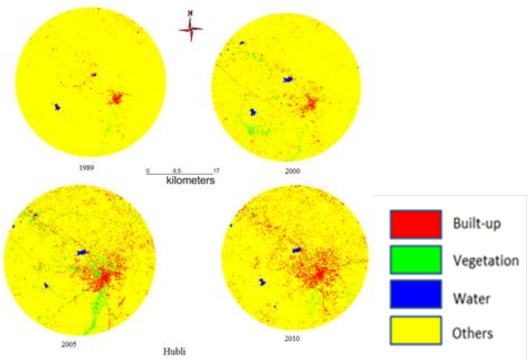

Fig.5.a. Classification output of Hubli

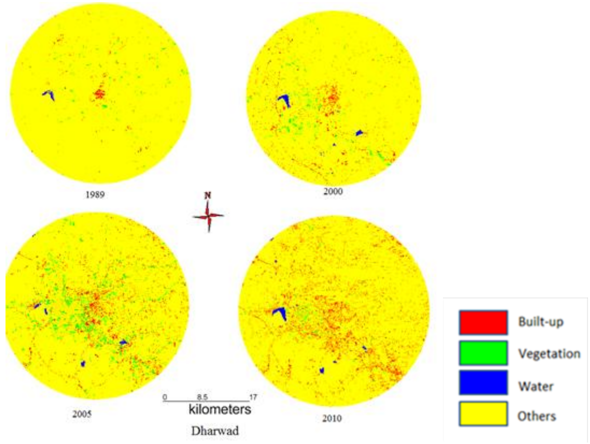

Fig.5.b. Classification output of Dharwad

Table VII: Shannon Entropy Index

Hubli	**NE**	**NW**	**SE**	**SW**
1989	0.027	0.02	0.055	0.011
2000	0.029	0.053	0.102	0.042
2005	0.146	0.09	0.21	0.059
2010	0.369	0.134	0.49	0.128
Dharwad	**NE**	**NW**	**SE**	**SW**
1989	0.011	0.013	0.008	0.006
2000	0.016	0.023	0.014	0.018
2005	0.08	0.086	0.09	0.0745
2010	0.168	0.164	0.213	0.216

d) Spatial patterns of urbanisation: In order to understand the spatial pattern of urbanization, ten landscape level metrics were computed zone wise 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 that the Hubli city is forming patched that are clumped at the center but is relatively disaggregated at the outskirts, but compared to the year 2005, 2010 results is indicative of clumped urban patch in the city and is directive of forming a single urban patch. Clumped patches are more prominent in NE and SW directions and patches is agglomerating to a single urban patch. The case with Dharwad is different as in case it has started to disaggregate in 2010, until 2010 there were less no of urban patches in the city, which have increased in 2010, which is indicative of sprawled growth in the city.

*The patch density (*Figure 6b) is calculated on a raster map, using a 4 neighbor algorithm. Patch density increases with a greater number of patches within a reference area.

Patch density in Hubli and Dharwad was higher in 2005 as the number of patches is higher in all directions and gradients due to increase in the urban built area, which remarkably increased post 1989 (SW, NE) and subsequently reduced in 2010, indicating the sprawl in the region in in early 90's and started to clump during 2010. The patch density is quite high in the outskirts also in both the cities.

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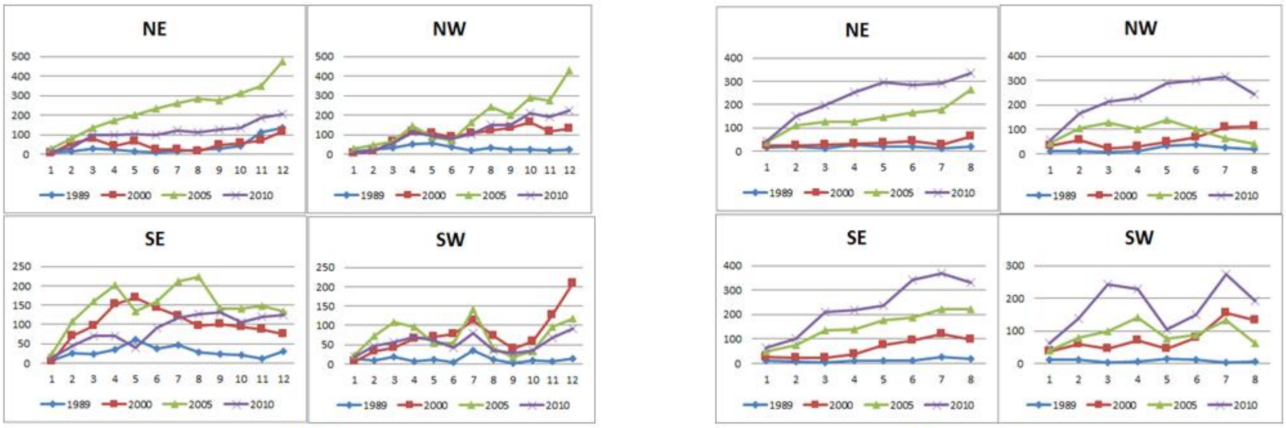
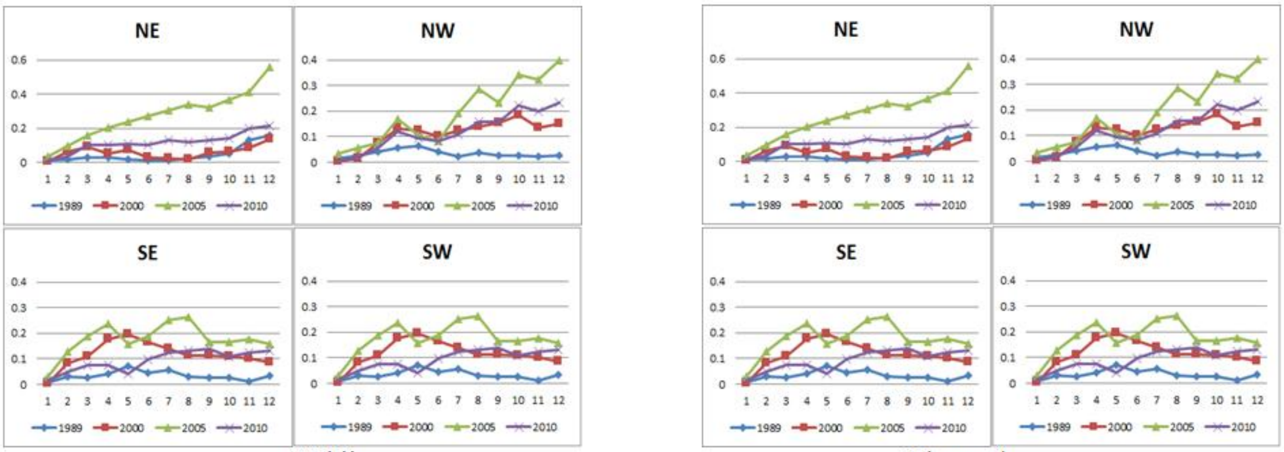
Landscape Shape Index (LSI): LSI equals to 1 when the landscape consists of a single square or maximally compact (i.e., almost square) patch of the corresponding type and LSI increases without limit as the patch type becomes more disaggregated. Figure 6c indicate that there were low LSI values in 1989 as there was minimal urban areas in both Hubli and Dharwad which were mainly aggregated at the center. Since late 1990's both the city has been experiencing dispersed growth in all direction and circles and Hubli reached the peak of dispersed growth during 2005, towards 2010 it shows a aggregating trend in Hubli, whereas In Dharwad it is showing an dispersed growth.



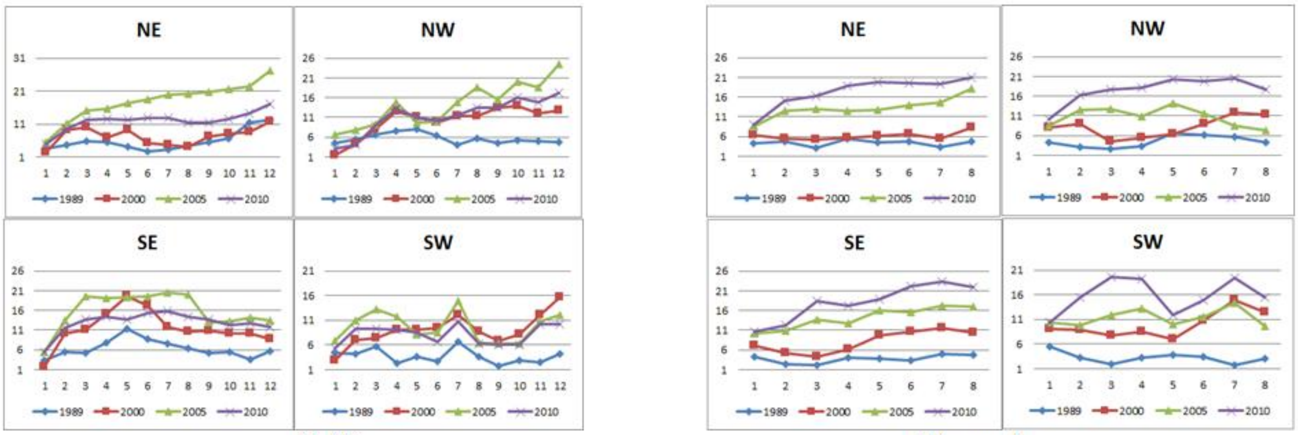
Hubli Dharwad

Fig.6.a. Number of urban patches (Directionwise, circlewise)



Hubli Dharwad

Fig.6.b. Patch Density (Directionwise, circlewise)



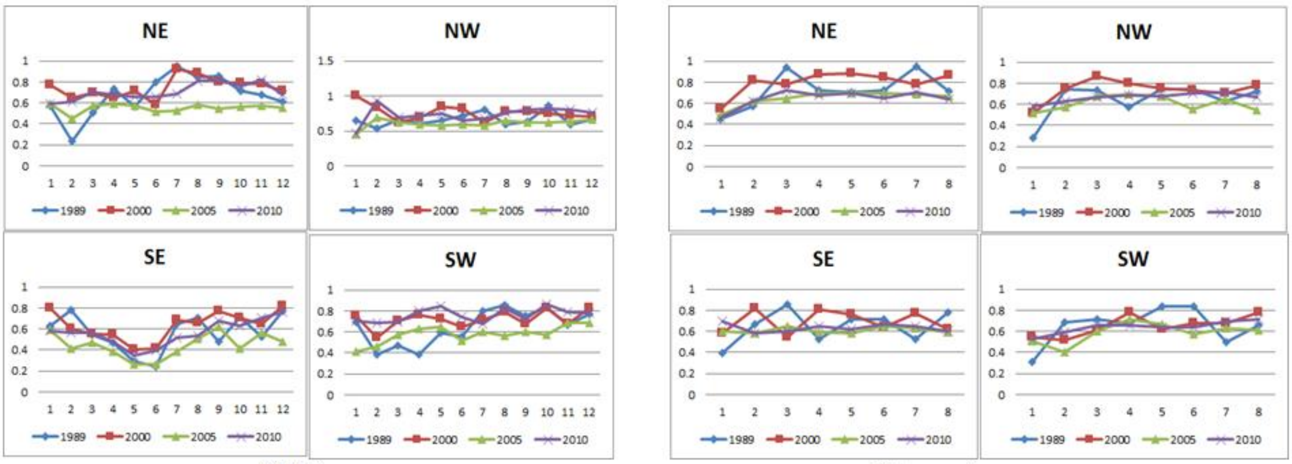
Hubli Dharwad

Fig.6.c. Landscape Shape Index (Directionwise, circlewise)

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 of NLSI (Figure 6d) indicates that the landscape had a highly fragmented urban class, which became further fragmented during 2000 and started clumping to form a single square in late 2010 especially in NE and SW direction in all circle and few inner circles in SE and SW directions, conforming with the other landscape metrics.

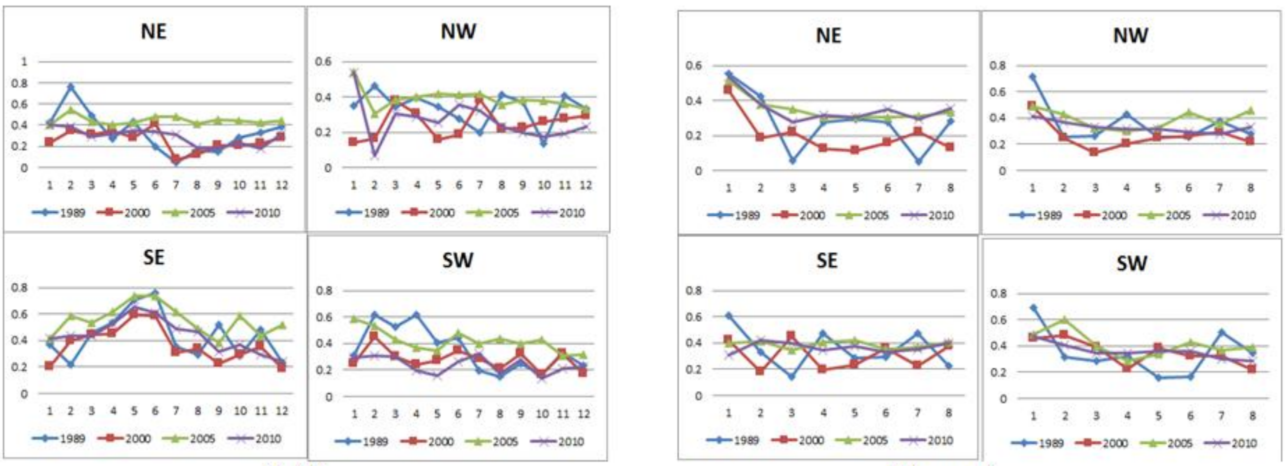
Clumpiness index equals 0 when the patches are distributed randomly, and approaches 1 when the patch type is maximally aggregated. Aggregation index equals 0 when the patches are maximally disaggregated and equals 100 when the patches are maximally aggregated into a single compact patch. Clumpiness index, Aggregation index highlights that the center of the both the cities is more compact in 2009 with more clumpiness and aggregation in SW and NE directions. In 1989 the results indicate that there were a small number of urban patches existing in all direction and in every circle and due to which disaggregation is more. Post 2000 and in 2010 we can observe large urban patches very close almost forming a single patch especially at the center and in SW direction in different gradients (Figure 6e and Figure 6f). Hubli in 2010 has become much aggregated while Dharwad is yet aggregating to form a single or maximally compact area.

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 explains the adjacencies of urban patches that the city center is getting more and more clumped with similar class (Urban) and outskirts are relatively sharing different internal adjacencies. Hubli city shows more adjacent clumped growth, whereas Dharwad shows more disaggregated growth (Figure 6g).



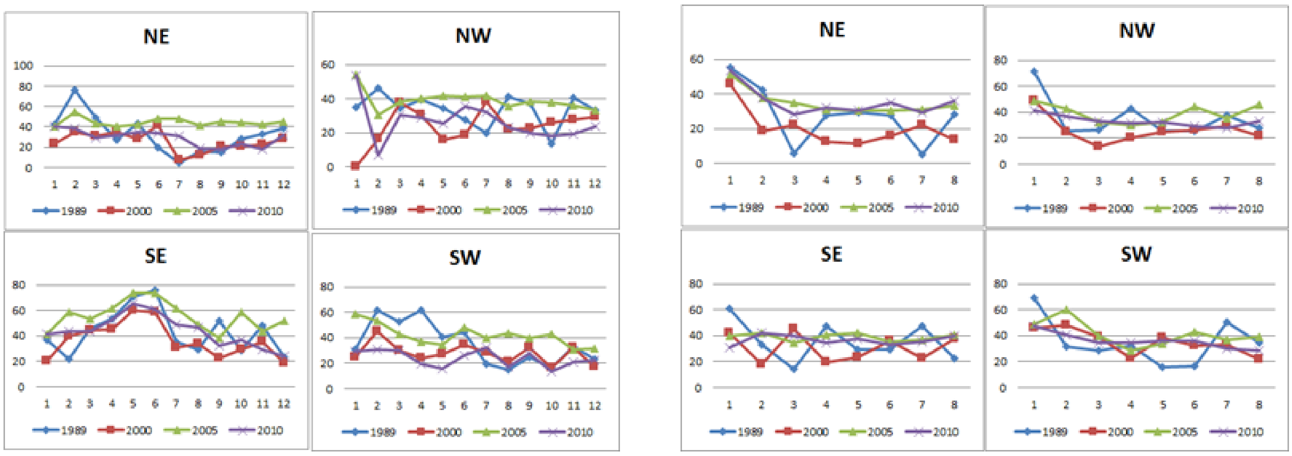
Hubli Dharwad

Fig.6.d. Normalized Landscape Shape Index (Direction wise, circle wise)



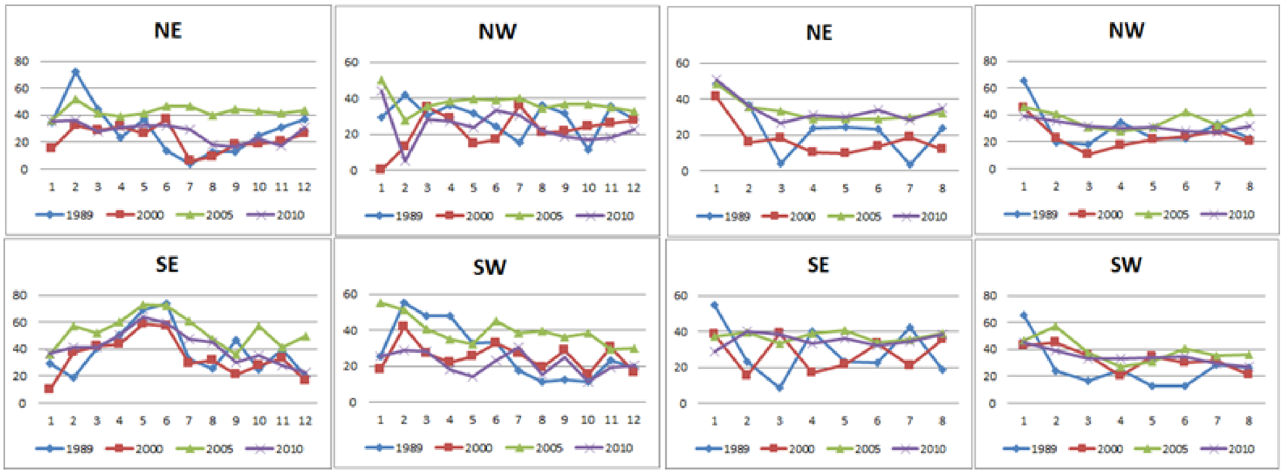
Hubli Dharwad

Fig.6.e. Clumpiness Index (Direction wise, circle wise)



Hubli Dharwad

Fig.6.f. Aggregation Index (Direction wise, circle wise).



Hubli Dharwad

Fig.6.g. Percentage of like Adjacencies (Direction wise, circle wise)

V. CONCLUSION

The analysis of land cover dynamics for the period of analysis 1989 - 2010 shows that area under vegetation (cultivation and forests) has declined from 97% (1989) to 78% (2010) in Hubli and from 98% (1989) to 86% (2010) in Dharwad. Urban area has increased from 1.08 (1989) to 14.62 (2010)%. Shannon entropy shows that Hubli-Dharwad is experiencing the tendency of sprawl in all directions. Spatial metrics reveal that the urban core of Hubli – Dharwad changed moderately over time and exhibited a spread out pattern of urban development with a moderate to low concentration of urban area towards the periphery.

Time series data analyses reveal the transformation for the urban sector along with different sectors, revealing the importance and use of detailed analysis of changes in land use. The evaluation also identified a continuous increase in the urban areas that is replacing the predominant agricultural areas in both the twin cities. The gradient pattern of analysis and the landscape metric analysis demonstrated distinct transformation phases and the complexity of changes in land use, indicating a transfer from agricultural dominated characteristics to an intensive process of peri-urbanisation or sprawl and finally, ending in urban consolidation.

Spatial metrics computed for gradients using temporal data aided in visualizing and modeling the patterns of urban growth which is required for planning framework associated with the future Master Plan for the evolution of systematic processes, and also to regulate abrupt transition processes, given their importance in urban growth. Results of the study produced very interesting results both qualitative and quantitative outputs, especially as inputs for the spatial decision-making support systems, to play a vital role in better decision-making.

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REFERENCES

[1] T.V. Ramachandra, A.H. Bharath, D.S. Durgappa, “Insights to urban dynamics through landscape spatial pattern analysis,” Int. J Applied Earth Observation and Geoinformation, vol. 18, 2012, pp. 329-343.

[2] B. Bhatta, S. Saraswati, D. Bandyopadhyay, “Quantifying the degree-of-freedom, degree-of-sprawl, and degree-of-goodness of urban growth from remote sensing data,” Applied Geography, vol. 30(1), 2010a, pp. 96–111.

[3] H.S. Sudhira, T.V. Ramachandra, K.S. Jagadish, “Urban sprawl: metrics, dynamics and modelling using G1S.” Int. J Applied Earth Observation and Geoinformation, vol. 5, 2004. pp. 29-39.

[4] M. Luck, J. Wu, “A gradient analysis of urban landscape pattern: a case study from the Phoenix metropolitan, Arizona, USA,” Landsc. Ecol. Vol. 17, 2002, pp. 327–339.

[5] K.C. Seto, M. Fragkias, “Quantifying spatiotemporal patterns of urban land-use change in four cities of China with time series landscape metrics,” Landsc. Ecol. Vol.20, 2005, pp. 871–888.

[6] E. F. Lambin, H. Geist, “Land-use and land-cover change: Local processes and global impacts” Berlin, Springer, 2006.

[7] M. Sherestha, A. York, C. Boone, S. Zhang, “Land fragmentation due to rapid urbanization in the Phoenix metropolitan area: analyzing the spatio-temporal patterns and drivers,” Applied Geography, vol. 31, 2011, pp. 522-531.

[8] M.G. Turner, R.H. Gardner, “Quantitative method in landscape ecology: an introduction,” Ecolog. Stud. Vol. 82, 1990, pp. 3–14.

[9] T. V. Ramachandra, U. Kumar, “Wetlands of Greater Bangalore, India: Automatic Delineation through Pattern Classifiers.” Electronic Green Journal, vol. 26, 2008, pp. 1076-7975.

[10] B. Bhatta, S. Saraswati, D. Bandyopadhyay, “Urban sprawl measurement from remote sensing data,” Applied Geography, vol. 30(4), 2010b, pp. 731–740.

[11] L. Petrov, C. Lavalle, M. Kasanko, ”Urban land use scenarios for a tourist region in Europe: applying the MOLAND model to Algarve, Portugal,” Landsc. Urban Plann. Vol. 92, 2009, pp. 10–23.

[12] A. Schneider, C.E. Woodcock, “Compact, dispersed, fragmented, extensive? A comparison of urban growth in twenty-five global cities using remotely sensed Data pattern metrics and census information,” Urban Studies, vol. 45(3), 2008, pp. 659–692.

[13] R. Peiser, “Decomposing urban sprawl,” Town Planning Review, vol. 72(3), 2001, pp. 275–298.

[14] M. P. Johnson, “Environmental Impacts of urban sprawl: a survey of the literature and proposed research agenda,” Environment and Planning, vol. 33(4), 2001, pp. 717–735.

[15] J. K. Brueckner, “Urban Sprawl: Diagnosis and remedies,” International Regional Science Review, vol. 23(2), 2000, pp. 160–171.

[16] J. Epstein, K. Payne, E. Kramer, “Techniques for mapping suburban sprawl,” Photogrammetric Engineering and Remote Sensing, vol. 63(9), 2002, pp. 913 – 918.

[17] X. Li, A.G.O. Yeh, “Zoning land for Agricultural protection by the integration of remote sensing, GIS, and Cellular Automata,” Photogramm. Engg. & Remote Sensing, vol. 67(4), 2001, pp. 471-477.

[18] C. Dietzel, M. Herold, J.J. Hemphell, K.C. Clarke, “Spatio-temporal dynamics in California's central valley: Empirical links to urban theory,” Int. J. Geographic Information Science, vol. 19(2), 2005, pp. 175-195

[19] J. Peng, Y.L. Wang, Y. Zhang, J.S. Wu, W.F. Li, Y. You Li, “Evaluating the effectiveness of landscape metrics in quantifying spatial patterns,” Ecological Indicators, vol. 10 (2), 2010, pp. 217–223.

[20] K. McGarigal, B. J. Marks, “FRAGSTATS: spatial pattern analysis program for quantifying landscape structure.” USDA Forest Service General Technical Report PNW-351, 1995.’

[21] AninditaDasgupta, Uttam Kumar, T.V. Ramachandra., “Urban Landscape analysis through spatial metrics, In the proceedings of the Conference on Infrastructure, Sustainable Transportation and Urban Planning, CISTUP@CISTUP2010, 18 - 20 October, JN Tata Auditorium, Indian Institute of Science, Bangalore. 2010.

[22] M. Herold, J. Scepan, K.C. Clarke, “The use of remote sensing and landscape metrics to describe structures and changes in urban land uses,” Environ. and Plan. Vol. 34, 2002, pp. 1443–1458.

[23] M. Antrop, V. Van Eetvelde, “Holistic aspects of suburban landscapes: visual image interpretation and landscape metrics,” Landscape Urban Plan, Vol. 50 (1–3), 2000, pp. 43–58.

[24] M.G. Turner, R.H. Gardner, R.V. O’Neill, “Landscape Ecology in Theory and Practice,” Springer-Verlag, New York. 2001

[25] M. Herold, H. Couclelis, K.C. Clarke, “The role of spatial metrics in the analysis and modelling of urban land use change,” Computers, Environment and Urban Systems, vol. 29, 2005, pp. 369-399.

[26] H.S. Sudhira, T.V. Ramachandra, K.S. Raj, K.S. Jagadish, K.S, “Urban Growth Analysis using Spatial and Temporal Data,” Photonirvachak, Journal of Indian Society of Remote Sensing, vol. 31(4), 2003, pp. 299-311.

[27] M. Pereira dos Santos Silva, G. Camara, M. Sobral I. Escada, R.C. Modesto de Souza, “Remote sensing image mining: detecting agents of land-use change in tropical forest areas.” International Journal of Remote Sensing, vol. 29(16), 2008, pp. 4803-4822.

[28] R.O. Duda, P.E. Hart, D.G. Stork, “Pattern Classification”, a Wiley-Interscience Publication, Second Edition, ISBN 9814-12-602-0, 2005.

[29] R. G. Congalton, “A review of assessing the accuracy of classifications of remotely sensed data,” Remote Sensing of Environment, vol. 37, 1991, pp. 35-46.

[30] R. G. Congalton, R. G. Oderwald, & R. A. Mead, “Assessing Landsat classification accuracy using discrete multivariate analysis statistical techniques,” Photogrammetric Engineering and Remote Sensing, vol. 49, 1983, pp. 1671-1678.

[31] K.M. Lata, C.H.S. Rao, V.K. Prasad, K.V.S. Badarianth, V. Raghavasamy, “Measuring Urban sprawl A case study of Hyderabad,” gis@development, vol. 5(12), 2001, pp. 26-29.

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Urbanisation and Sprawl in the Tier II City: Metrics, Dynamics and Modelling Using Spatio-Temporal Data

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Abstract

Urbanisation is a dynamic complex phenomenon involving large scale changes in the land uses at local levels. Human induced land use and land cover (LULC) changes have been the major drivers of the changes in local and global environments. Urbanisation pattern has a direct influence on urban growth process, which extends its influence on the neighborhood resulting in the sprawl or peri-urban growth. Unplanned urbanization and consequent impacts on natural resources has necessitated the investigation and understanding of mechanisms and dynamics of land use and land-use change on a range of spatial scales as well as evaluation on the environmental consequences of these changes at the landscape scale. Rapid urbanization subsequent to globalization in Karnataka state shows 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. Rapid burgeoning population pressure has resulted in unplanned growth in the urban areas to accommodate these migrant people leading to sprawl. It is a growing concern for city planners during the past decade in India. This paper has analysed urbanisation pattern of Raichur-a Tier II city of Karnataka considering a buffer region of 5 km from the current administrative boundary to account for the likely urbanizing regions. Temporal land cover and land use analysis provide the temporal dynamics. The built-up area of the city has increased from 1.41% in 1973 to 8.51% in 2010. Shannon's Entropy (an urban sprawl index) shows that there is a remarkable urban sprawl in and around the city. As a result, the urban ecosystem has changed in the last four decades. Landscape metrics indicate a convoluted and a single patch urban growth at the center and a fragmented outgrowth near the boundary of the city and Buffer regions. This paper provides a valuable basis to understand the urban growth dynamics of Raichur City in India as a consequence of land use changes and helps the urban planners to visualize the developments for a sustainable future.

Keywords

Spatio Temporal Dynamics; Remote Sensing; Shannon's Entropy; Raichur; Urban Sprawl; Spatial Metrics

Introduction

Urban growth is a spatial and demographic process, involving concentration of human population with higher level of economy [37]. 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 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 ([37] [7]). Structural composition and rate of growth of most Indian metropolitan cities or tier 1 cities have an aggregated core region and cities are expanding into the rural fringe areas. Due to burgeoning population and concentrated developmental activities, most of Tier 1 cities have exceeded their carrying capacities, which is evident from poor assimilative capacity (higher levels of pollutants in land, water and air), supportive capacity (lack of appropriate infrastructure, traffic bottlenecks) and lack of basic amenities (treated water supply, electricity and sanitation facilities. This necessitates policy measures to decongest tier I cities. This entails providing an alternative region for development and hence the current focus is on Tier II cities. Advance visualization of urbanisation process will aid in better regional planning to provide basic amenities and infrastructure. Urbanisation being the complex and dynamic process, planners and city developers need to monitor and visualize the growth pattern and land use dynamics in the urban and peri-urban areas of the Tier II cities. Otherwise, peri urban regions prone to the sprawl that would be devoid of basic amenities and inefficient and consumptive use of its associated resources.

Mapping and monitoring sprawl helps in identifying the environmental degradation process as well as to visualize the future sprawling growth patterns [3]. Several studies in this regard ([6] [36] [13] [5] [17] [15] [19] [11] [33] [25]), have quantified the sprawl through the diverse techniques. The most common approach is to consider the spatial and temporal dynamics of the regions with impervious surfaces [15].

Many studies have employed large number of indicators, including land-use conversion, population change and energy requirement [2]. Other researchers focused on measuring sprawl through the use of population data as an indicator [35] 37). These patterns of sprawl on landscapes can be detected, mapped and analyzed using remote sensing data along with certain image processing ([32] [14] [26] [12] 37). Thomas [29] considered Shannon's entropy model as a good measure of urban sprawl, i.e., the degree of spatial concentration and dispersion exhibited by a geographical variable. Various researchers have used shannon's entropy, ([1] [17] [10], [37], [7]) which reflects the concentration of dispersion of spatial variable in a specified area/zone, to measure and differentiate types of sprawl. This is why for this study Shannon's entropy has been used to assess the urban sprawl. Further, to understand the growth dynamics and the pattern Landscape, metrics as indicators have been used.

Landscape metrics or so called spatial metrics are numerical measurements that quantify spatial patterns in the form of compactness/edge/shape of land use patches of a geographic area [18]. There is a large number of studies that have used these spatial metrics in order to understand the pattern of urban landscape ([22] [23] [16] [8] [9] [37]). Landscape metrics currently used in satellite data analysis have a long history of usage in various fields such as ecological modeling ([20] [4]). Herold et al., [21] defined and described the function of spatial metrics as digital analysis measurements on the thematic-categorical maps that have a spatial heterogeneity at a particular resolution. Spatial metrics have found important applications in quantifying urban growth, sprawl, and fragmentation [34] [24]. Angel et al., [31] demonstrated five metrics for measurement of sprawl. Ramachandra et al., [37] have successfully applied the metrics and found very useful in understanding the urban growth process. Hence, spatial metrics have been used in the study to understand the process and pattern of growth.

In the present study, an attempt has been made to study the impact of growing urbanization on the land-use and land-cover pattern of Raichur city and its effects on the rural fringe considering a 5 km buffer region. To examine the urban growth distribution and variation outward from the city center and model the growth, gradient approach and landscape metrics are employed.

Study area

Raichur district (Fig. 1) is one of major district in northern Karnataka, India, with 5 taluks and 37 hobli's and 120 hamlets, an area of 8386 sq. km and a population density of 181 persons per sq. km (2001). Raichur is drought prone, and falls in the northeast dry agro climatic zone. The normal annual rainfall of the district is 621 mm and the average temperature is 35^0C. Raichur urban city falls in this boundary of Raichur district, which has been considered for the analysis. Raichur city, located at $16^0$10'2" and $16^0$14' N latitude and $77^0$19', is famous for its imposing Raichur Fort and has huge stone inscriptions in Persian and Arabic languages, referring to its construction in 1200's. Among the ruins of the immense fort, there are many tanks and old temples. Krishna and Tungabhadra are two water sources which cater to the needs of drinking water supply to Raichur city. Raichur is famous for its rice mills which exports high quality rice and has a production of pure cotton.

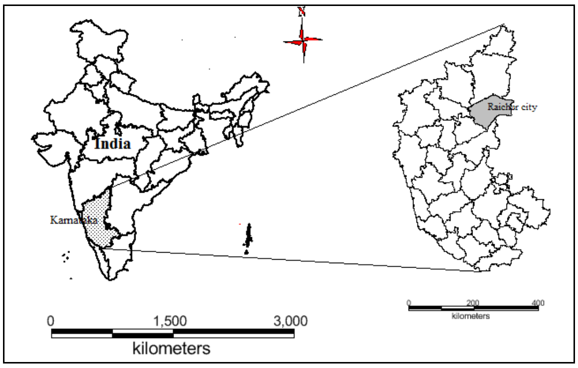

FIG. 1 STUDY AREA

Materials used

Urban dynamics was analysed using temporal remote sensing data during the period 1975 to 2010. The time series spatial data acquired from Landsat Series Thematic mapper (28.5m) and ETM sensors for the period 1975 to 1989 were downloaded from public domain (http://glcf.umiacs.umd.edu/data). Data pertaining IRS 1C of 2001 and 2010 (23.5m) were procured from the National remote Sensing Centre (http://www.nrsc.gov.in), Hyderabad. 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 was digitized based on the city administration map. Population data was collected from the Directorate of Census Operations, Bangalore region (http://censuskarnataka.gov.in). Table 1 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).

Method

A stepwise normative gradient approach was adopted to understand the dynamics of the city, including (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 as shown in Fig. 2.

TABLE 1 MATERIALS USED IN ANALYSIS

Data used	Year	Purpose
Landsat Series TM (28.5m) and ETM	1975, 1989	Land cover and Land use analysis
IRS LISS III (24m)	2001, 2010	Land cover 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

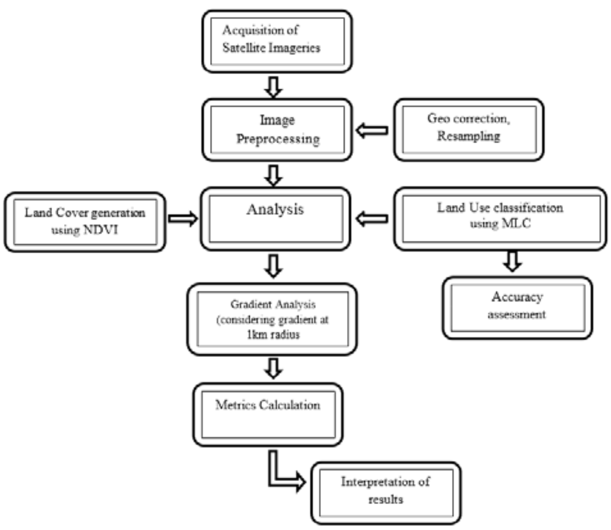

FIG. 2 PROCEDURE TO UNDERSTAND THE CHANGES IN SPATIAL PATTERN AND ITS DYNAMICS

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 satellite data were enhanced using histogram equalization for the better interpretation and to achieve better classification accuracy. Furthermore, the images including topographical sheet and ward map were rectified to a common Universal Traverse Mercator (UTM) projection/co-ordinate system. All data sets were resampled to 30m spatial resolution using the nearest neighborhood re-sampling technique.

2) Vegetation Cover Analysis: Vegetation cover analysis was performed using the index Normalized Difference Vegetation index (NDVI) that 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 -1 to +1, where -0.1 and below indicates 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) Land use analysis: Further to investigate the different changes in the landscape land use analysis was performed. Categories listed in Table II, were classified with the training data (field data) using Gaussian maximum likelihood supervised classifier. This analysis includes generation of False Color Composite (bands – green, red and NIR), which basically helps in visualization of the different heterogeneous patches. The further use of 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 based on Google earth (www.googleearth.com) and Bhuvan (bhuvan.nrsc.gov.in). These polygons were overlaid on FCC to supplement the training data to classify landsat data.

Gaussian maximum likelihood classifier (GMLC) is applied to classify the data using the training data, in which various classification decisions are involved by means of probability and cost functions [30] 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 to classify the data and the balance 30% were used in validation and accuracy assessment. Thematic layers were generated for the study region corresponding to four land use categories.

Evaluation on the performance of classifiers has been done through accuracy assessment techniques to test 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 [27][28].

4) Further each zone was divided into concentric circle of increment radius of 1 km (Fig. 2.) from the center of the city to visualize 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.

TABLE II 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.

5) Urban sprawl analysis: Shannon's entropy (H_n) is computed (equation 1) direction-wise to understand the extent of growth: compact or divergent. This provides an insight into the development (clumped or disaggregated) with respect to the geographical parameters across 'n' concentric regions in the respective zones.

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

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 particular direction. Shannon's Entropy values ranges from zero (maximally concentrated) to log n (dispersed growth).

6) Spatial pattern analysis: Landscape metrics provide quantitative description on the composition and configuration of the urban landscape. These spatial metrics have been computed for each circle, zone wise with the help of FRAGSTATS [18] using classified land use data at the landscape level. Urban dynamics is characterized with 7 prominent spatial metrics chosen based on complexity, and density criteria. The metrics including the patch area, shape, epoch/contagion/dispersion are listed in Table III.

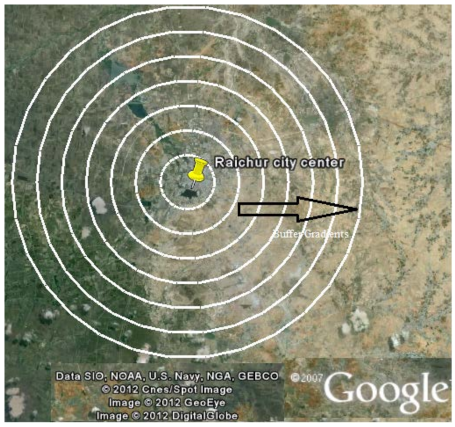

FIG. 2 GOOGLE EARTH REPRESENTATION OF THE STUDY REGION ALONG WITH THE GRADIENTS

Results and Discussion

Land use Land Cover analysis

Vegetation cover analysis: Vegetation cover of the study area assessed through NDVI (Fig. 3), shows that area under vegetation has declined by about 19%. Temporal NDVI values are listed in Table III, which shows that there has been a substantial increase in the Non Vegetative area. There has been an increase from 3 % to 17%, tells us that there has been staggering growth of impervious cover in the region resulting from decrease in vegetative cover.

Land use analysis: Land use assessed during the period from 1973 to 2010 by means of Gaussian maximum likelihood classifier is listed in Table IV and the same is depicted in Fig. 4. The overall accuracy of the classification ranges from 69.28% (1973) to 88.12% (2010). Kappa statistics and overall accuracy was calculated and listed in Table V. There has been a significant increase in built-up area during the last decade evident from 590% increase in urban area 1.44% in 1975 and has grown to 8.51% considering buffer area. Other category also had an enormous decrease in the land use. Consequently, cultivable area has come down drastically.

TABLE III TEMPORAL LAND COVER DETAILS.

Year	Vegetation	Non vegetation
	%	%
1975	96.32	3.68
1989	92.18	7.82
2001	89.36	10.64
2010	82.48	17.52

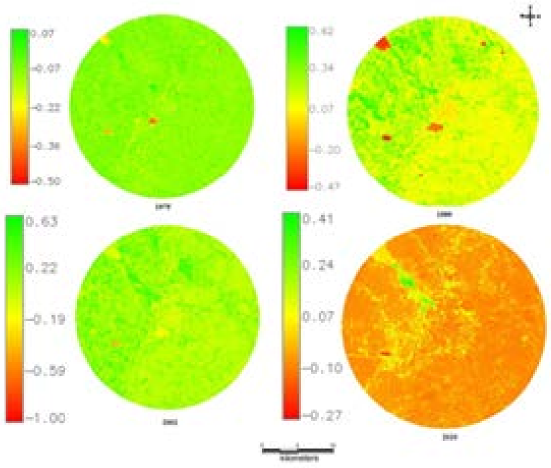

FIG. 3 TEMPORAL LAND COVER CHANGES DURING 1973 – 2010

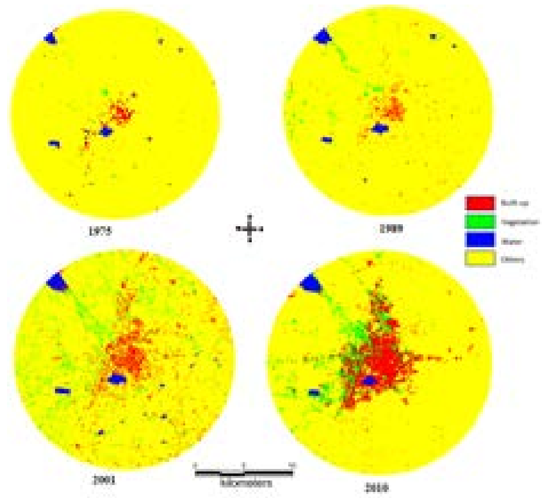

FIG. 4 CLASSIFICATION OUTPUT OF RAICHUR

TABLE III LANDSCAPE METRICS ANALYSED

	Indicators	Formula	Range
1	Number of Urban Patches (NPU)	$NPU = n$ NP equals the number of patches in the landscape.	NPU>0, without limit.
2	Patch density(PD)	f(sample area) = (Patch Number/Area) * 1000000	PD>0
3	Normalized Landscape Shape Index (NLSI)	$NLSI = \frac{\sum_{i=1}^{i=N} \frac{p_i}{s_i}}{N}$ Where s_i and p_i are the area and perimeter of patch i, and N is the total number of patches.	0≤NLSI<1
4	Landscape Shape Index (LSI)	$LSI = e_i / \min e_i$ e_i =total length of edge (or perimeter) of class i in terms of number of cell surfaces; includes all landscape boundary and background edge segments involving class i. Min e_i=minimum total length of edge (or perimeter) of class i in terms of number of cell surfaces.	LSI>1, Without Limit
5	Clumpiness	$CLUMPY = \left[\begin{matrix} \frac{G_i - P_i}{P_i} \; for G_i < P_i \,\&\, P_i < 5, else \\ \frac{G_i - P_i}{1 - P_i} \end{matrix} \right]$ $G_i = \left(\frac{g_{ii}}{\left(\sum_{k=1}^{m} g_{ik}\right) - \min e_i} \right)$ g_{ii} =number of like adjacencies between pixels of patch type g_{ik} =number of adjacencies between pixels of patch types i and k. P_i =proportion of the landscape occupied by patch type (class) i.	-1≤ CLUMPY ≤1.
6	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 g_{ik} = number of adjacencies between pixels of patch types i and k	0<=PLADJ<=100
7	Aggregation index(AI)	$AI = \left[\sum_{i=1}^{m} \left(\frac{g_{ii}}{\max \rightarrow g_{ii}} \right) P_i \right](100)$ g_{ii} =number of like adjacencies between pixels of patch type P_i= proportion of landscape comprised of patch type.	1≤AI≤100
8	Cohesion	$Cohesion = \left[1 - \frac{\sum_{j=1}^{n} p_{ij}}{\sum_{j=1}^{n} p_{ij} \sqrt[2]{a_{ij}}}\right]\left[1 - \frac{1}{\sqrt[2]{A}}\right]^{-1} * 100$	0≤cohesion<100

TABLE IV TEMPORAL LAND USE DETAILS FOR RAICHUR

Land use / Year	Urban	Vegetation	Water	Cultivation and others
2010	8.51	4.81	0.97	85.71
2002	5.21	3.58	1.36	89.85
1992	2.48	0.91	1.04	95.57
1973	1.44	1.62	0.88	96.16

TABLE V KAPPA STATISTICS AND OVERALL ACCURACY

Year	Kappa coefficient	Overall accuracy (%)
1973	0.69	69.28
1989	0.83	81.69
1999	0.83	84.53
2010	0.89	88.12

Shannon's entropy: The entropy is calculated considering 7 gradients in 4 directions and listed in table VI. The reference value is taken as Log (7) which is 0.77 and the computed Shannon's entropy values are closer to this, indicating sprawl. Increasing entropy values from 1973 to 2010 shows the tendency of dispersed growth of built-up area in the city with respect to 4 directions as we move towards the outskirts and this phenomenon is most prominent in SE and SW directions**.**

TABLE VI SHANNON ENTROPY INDEX

	NE	NW	SE	SW
2010	0.135	0.146	0.168	0.194
2002	0.078	0.083	0.084	0.097
1992	0.023	0.026	0.026	0.027
1973	0.01	0.006	0.007	0.005

Spatial patterns of urbanisation: Spatial dynamic pattern of urban growth has been analyzed for 4 decades using eight landscape level metrics computed zone wise for each circle of 1 km radius. These metrics are discussed below:

Number of Urban Patch (Np) , a landscape metric indicates the level of fragmentation and ranges from 0 (fragment) to 100 (clumpiness).

Fig. 8a illustrates the temporal dynamics of number of patches. Urban patches are less at the center in 1970's as the growth was concentrated in central pockets. There is a gradual increase in the number of patches in 80's and further in 2001, but these patches form a single patch during 2010, indicating that the urban area get clumped as a single patch at the center, but in the buffer regions there has been a tremendous increase in 2001. Clumped patches at center are more prominent in NE and SE directions and patches are agglomerating to a single urban patch.

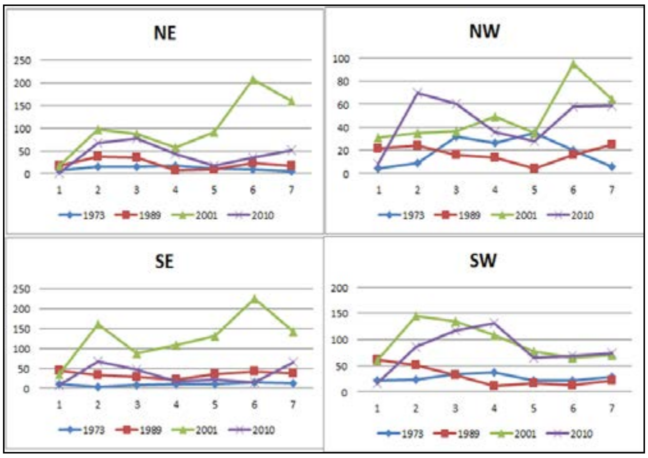

FIG. 8A NUMBER OF URBAN PATCHES (ZONEWISE, CIRCLEWISE)

The patch density (Fig. 8b) calculated on a raster map, using a 4 neighbor algorithm, increases with a greater number of patches within a reference area. Patch density was higher in 1989 and 2001 as the number of patches was higher all the directions. Density declined at the central gradients in 2010. In the outskirts the patch density has increased in early 2000's, which is indicative of sprawl in the region and PD is low at center indicating the clumped growth during late 2000's, which is in accordance with number of patches.

Landscape Shape Index (LSI): LSI is equal 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. Results (Fig. 8c) indicated that there were low LSI values in 1973 due to minimal and concentrated urban areas in the center. Since 1990's the city has experienced dispersed growth in all direction and circles, towards 2010 it showed a aggregating trend at the center as the value was close to 1, whereas it was 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, and increases as patch types becomes increasingly disaggregated while it is 1 when the patch type is maximally disaggregated. Results (Fig. 8d) indicate that the landscape in 2010 had a highly fragmented urban class in the buffer region and is aggregated class in the center, in accordance with the other landscape metrics.

Clumpiness index equals 0 when patches are distributed randomly, and approaches 1 when the patch type is maximally aggregated. Aggregation index equals 0 when patches are maximally disaggregated and equals 100 when the patches are maximally aggregated into a single compact patch.

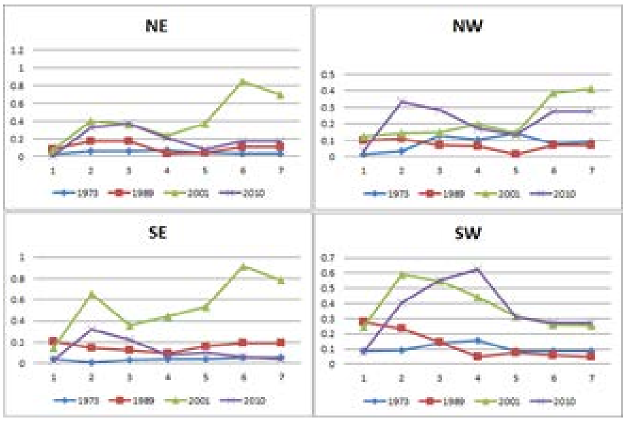

FIG. 8B PATCH DENSITY – ZONEWISE, CIRCLE WISE

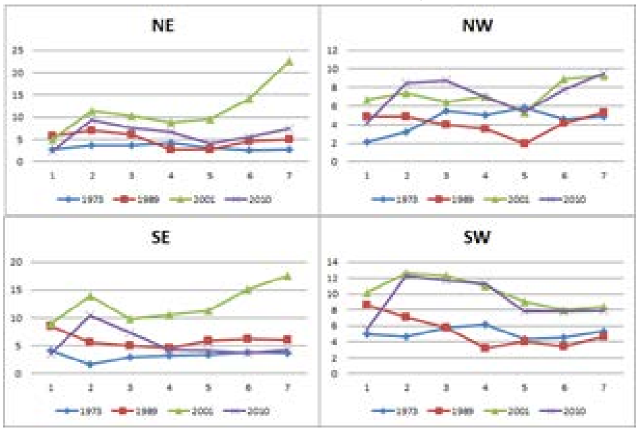

FIG. 8C LANDSCAPE SHAPE INDEX – ZONEWISE, CIRCLEWISE

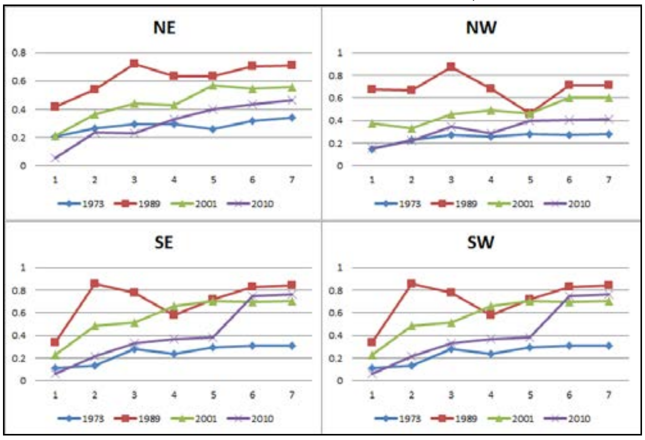

FIG. 8D NORMALISED LANDSCAPE SHAPE INDEX – ZONEWISE, CIRCLEWISE

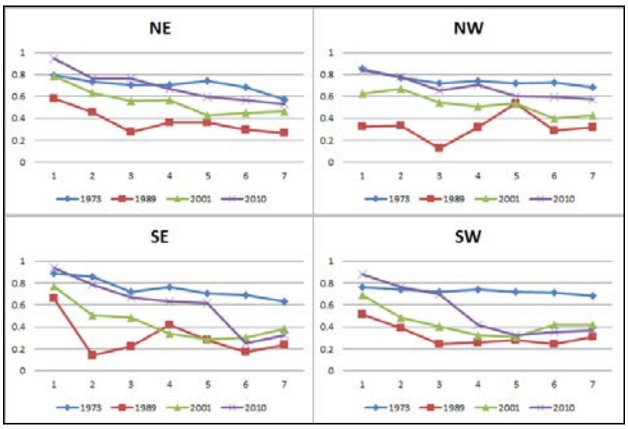

FIG. 8E CLUMPINESS – ZONEWISE, CIRCLE WISE

Clumpiness and aggregation indices exhibit similar temporal trends and highlights that the center of the city is more compact in 2010 with more clumpiness and aggregation in NW and NE directions. In 1973 the results indicated that there were a small number of urban patches existing in all direction and in every circle. Post 2000 and in 2010, a large number of urban patches close to each other almost form a single patch especially at the center and in NW and NE direction in different gradients (Fig. 8e, Fig. 8f). Lower values of these metrics in the outer circles indicate that there is a tendency of sprawl in the outskirts.

Percentage of Like Adjacencies (Pladj), the percentage of cell adjacencies involving the corresponding patch type are like adjacent. This metrics also indicates (Fig. 8g) that the city center gets more and more clumped and the adjacent patches of urban much closer have formed a single patch in 2010 and outskirts relatively sharing different internal adjacencies with patches not immediately adjacent but have a trend to become adjacent to each other, which is also indicative of sprawl.

Patch cohesion index measures the physical connectedness of the corresponding patch type. Fig. 8h indicates physical connectedness of the urban patch with higher cohesion value (in 2010). Lower values in 1973 illustrated that the patches were rare in the landscape.

Conclusions

Urbanisation with its Spatio-temporal form, pattern and structure has been quantified for Raichur, atier II city in Karnataka through the gradient approach using temporal remote sensing data, land use analysis, Shannon's entropy, and spatial metrics. Land use analysis shows an increase of urban area from 1.44% (1973) to 8.51% (in 2010) in and around Raichur. The present land-use is predominantly cultivation or agriculture.

Shannon's entropy, a measurement on the degree of sprawl in city, highlights the tendency of sprawl in recent times at outskirts. Spatial metrics in accordance with the Shannon's entropy indicates a clumped growth at city centre and dispersed growth at outskirts. This analysis visualizes the spatial patterns of urbanisation which helps in the regional planning to provide basic amenities and infrastructure. It is imperative to maintain the environmental quality through the judicious use of land by checking the haphazard growth of urbanization. Spatial models provide vital inputs for the decision makers and city planners to visualize and plan a sustainable growth process.

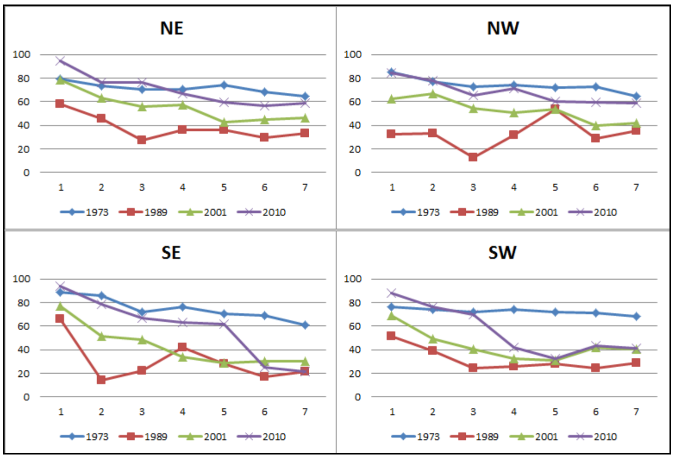

FIG. 8F AGGREGATION-ZONE AND CIRCLE WISE

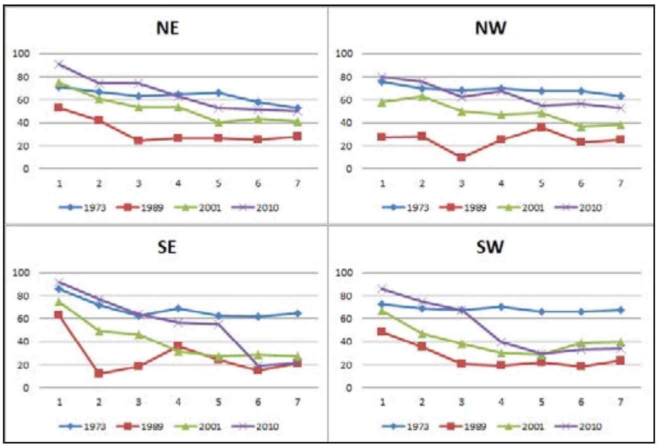

FIG. 8G ZONE AND CIRCLE WISE: PLADJ

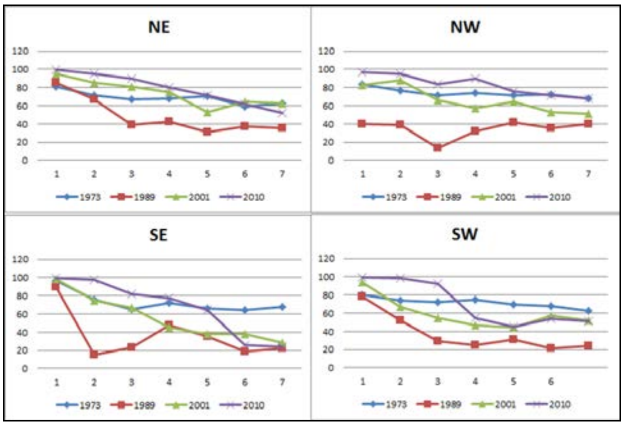

FIG. 8H COHESION INDEX

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REFERENCES

Angel, S., Parent J., and Civco, D., "Urban sprawl metrics: an analysis of global urban expansion using GIS," Proceedings of ASPRS 2007 Annual Conference, Tampa, Florida May 7–11, (2007).

Banzhaf, E., Grescho V., and Kindler, A. "Monitoring urban to peri-urban development with integrated remote sensing and GIS information: A Leipzig, Germany case study," Int. J. Remote Sens., 30(7) (2009):1675–1696.

Barnes, K. B., Morgan, J. M. III, Roberge, M. C., and Lowe, S. "Sprawl Development: Its Patterns, Consequences, and Measurement," Towson University, 2001. Available: http://chesapeake.towson.edu/landscape/urbansprawl/download/Sprawl_white_paper.pdf.

Batty, M. Xie, Y. and Sun, Z. "The Dynamics of Urban Sprawl," University College London, Centre for Advanced Spatial Analysis, 15(1999), Working Paper Series. Available:
http://www. casa.ac.uk/working_papers.

Bharath, H. A., Setturu Bharath, Sreekantha, S., Durgappa D.S., and Ramachandra, T. V. "Spatial patterns of urbanization in Mysore: Emerging Tier II City in Karnataka," Proceedings of NRSC User Interaction Meet-2012, 16th & 17th, Hyderabad, February 2012.

Congalton, R. G. "A review of assessing the accuracy of classifications of remotely sensed data" Remote Sensing of Environment, 37(1991):35-46.

Congalton, R. G., Oderwald R. G., and Mead, R. A., "Assessing Landsat classification accuracy using discrete multivariate analysis statistical techniques." Photogrammetric Engineering and Remote Sensing, 49(1983):1671-1678.

Cushman, S.A., Wallin, D.O. "Rates and patterns of landscape change in the Central Sikhote-alin Mountains, Russian Far East," Landsc. Ecol. 15(2000): 643–659.

Duda, R.O., Hart, P.E., Stork, D.G. Pattern Classification, a Wiley-Interscience Publication, 2nd Edition, 2000.

Epstein, J., Payne, K., and Kramer, E. "Techniques for mapping sub-urban sprawl," Photogramm. Eng. Remote Sens., 63(9) (2002):913–918,.

Eryilmaz, S.S., Cengiz, H., Eryilmaz, Y. "The Urban Sprawl Model For An Affected Metroplolis: Bursa – Istanbul Example," 44th ISoCaRP Congress, (2008).

Gadal, S. Fournier, S. Emeric, P. "3D Dynamic Representation for Urban Sprawl Modelling: Example of India's Delhi-Mumbai Corridor," S.A.P.I.E.N.S, Online: http://sapiens.revues.org/index932.html. (2009).

Hardin, P. J., Jackson M. W., and Otterstrom, S. M. "Mapping, measuring, and modeling urban growth," In Jensen, R. R., Gatrell, D. J. & McLean D. (Eds.) (2nd ed). Geo-Spatial Technologies in Urban Environments. Berlin: Springer (2007):141–176.

Herold, M., Couclelis, H., Clarke, K.C. "The role of spatial metrics in the analysis and modeling of urban land use change," Comput. Environ. Urban, 29(2005):369–399,.

Herold, M., Goldstein N. C., and Clarke, K. C. "The spatiotemporal form of urban growth: Measurement, analysis and modeling," Remote Sensing of Environment, 86(2003):286–302,.

Herold, M., Scepan J., and Clarke, K. C. "The use of remote sensing and landscape metrics to describe structures and changes in urban land uses". Environment and Planning A, 34(2002):1443–1458.

Hurd, J. D., Wilson, E.H., Lammey, S.G., Civeo, D.L., "Characterization of forest fragmentation and urban sprawl using time sequential Landsat Imagery". Proc. ASPRS Annual Convention, St. Louis, MO. April 23-27, 2001.

Jim C. Y., and Chen, W. Y. "Diversity and distribution of landscape trees in the compact Asian city of Taipei," Applied Geography, 29(4) (2009):577–587.

Jothimani, P. "Operational urban sprawl monitoring using satellite remote sensing: Excerpts from the studies of Ahmedabad, Vadodara and Surat, India," in 18th Asian Conf. Remote Sensing, Malaysia, (1997), Oct. 20–24.

Kumar, J. A. V., Pathan, S. K., and Bhanderi, R. J., "Spatio-temporal analysis for monitoring urban growth – A case study of Indore city," J. Indian Soc. Remote Sens., 35(1), (2007):11–20.

Kumar, J.M., Garg, P.K., Khare, D. "Monitoring and Modelling of Urban Sprawl Using Remote Sensing and GIS Techniques," Int. J. Appl. Earth Observ. Geoinformation, 10(1) (2008): 26-43. 2008.

Lata, K. M., Prasad, D. V. K., Badarinath, K. V. S., Raghavaswam, V., and Sankar, R. C. H. "Measuring urban sprawl: A case study of Hyderabad," GIS Development, Noida, 5(12) (2001).

McGarigal K., and Marks, B. J. "FRAGSTATS: spatial pattern analysis program for quantifying landscape structure," USDA Forest Service General Technical Report, (1995):351.

Nelson, A.C. "Comparing States with and without growth management: analysis based on indicators with policy implications." Land Use Policy 16(1999):121-127.

Ramachandra, T.V., Bharath, A.H., and Durgappa, D.S. "Insights to urban dynamics through landscape spatial pattern analysis," Int. J Applied Earth Observation and Geoinformation, 18(2012):329-343.

Seto, K. C., and Fragkias, M. "Quantifying spatiotemporal patterns of urban land-use change in four cities of China with a time series of landscape metrics" Landscape Ecology, 20(2005):871–888.

Shekhar, S. "Urban sprawl assessment entropy approach," GIS Development, Noida, (2004).

Simmons, C. "Ecological footprint analysis: A useful method for exploring the interaction between lifestyles and the built environment," in Sustainable Urban Development. London: Routledge, (2007):223–235.

Sudhira, H.S., Ramachandra, T.V., Karthik, R.S., Jagadish, K.S. "Urban Growth Analysis Using Spatial and Temporal Data," J. Indian Soc. Remote Sens., 31(4), (2003):29-39.

Sun, Forsythe, W., and Waters, N. "Modelling urban land use change and urban sprawl: Calgary, Alberta, Canada," Netw. Spat. Econ., 7(2007):353–376.

Taubenbock, H., Wegmann, M., Berger, C., Breunig, M., Roth A., and Mehl, H. "Spatiotemporal analysis of Indian megacities," In Proceedings of the international archives of the photogrammetry, remote sensing and spatial information sciences, XXXVII(2008a): 75–82, Beijing.

Taubenbock, H., Esch, T., Thiel, M., Wurm, M., Ullmann, T., Roth, A., et al. "Urban structure analysis of mega city Mexico City using multisensoral remote sensing data," In Proceedings of SPIE-Europe (international society for optical engineering) conference, Cardiff, Wales, (2008b).

Theobald, D. M. "Quantifying urban and rural sprawl using the sprawl index," in Annual Conf. Assoc. American Geographers, New York, Mar. 2nd, 2001.

Thomas, R. W., "Information Statistics in Geography, Geo-

Abstracts" Norwich, United Kingdom: University of East Anglia, (1981).

Turner, M. G., Gardner R. H., and O'Neill, R. V. "Landscape ecology in theory and practice: Pattern and process," New York, Springer. 2001.

Yeh, A.G.O., and Li, X. "Measurement and monitoring of urban sprawl in rapidly growing region using entropy." Photogramm. Eng. Remote Sens., 67(1) (2001):83–90,.

Zhu, Q., Hu, M.Y. "Semantics-based 3D Dynamic Hierarchial House Property Model" Int. J. Geogr. Info. Sci., 24(2)(2010):165-188.

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Land Use Land Cover Dynamics in a Rapidly Urbanising Landscape

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Abstract

Landscape transformations in the rapidly urbanizing landscape are the most dynamic process affecting the local ecology and environment. The urbanized landscape do provide to its inhabitants the complex social and economic environment leading to further increase in population. Consequences of the unplanned urbanisation are enhanced pollution levels, lack of adequate infrastructure and basic amenities. This necessitates understanding of spatial patterns of the growth for an effective urban planning. This communication analyses the landscape dynamics of Belgaum City with 5 km buffer using Shannon's entropy and explores landscape patterns through spatial metrics applied to the temporal land use data. Remote sensing data acquired at regular intervals through satellite borne sensors enables the synoptic monitoring of urban growth patterns and dynamics. Spatial metrics enables the quantification of urban footprint. Assessment of spatial and temporal dynamics of the landscape and quantification of patterns through metrics helps in the understanding of urbanisation process. . This communication focuses on the monitoring of land use and land cover dynamics of Belgaum City with a buffer of 5 km. Land cover analysis is done through the slope based vegetation indices show a decline of vegetation from 98.8% (1989) to 91.74% (in 2012). Temporal land use analysis reveal that the increase of urban pockets (built up and other paved surfaces) from 0.31% (in 1989) to 6.74% (2012), the tree cover has decreased from 4.62% (in 1989) to 2.44% (in 2006). Direction wise gradient analysis through spatial metrics and the Shannon entropy highlight an increase of fragmented growth during post 2000 in all directions.

Keywords: *Belgaum, Land Use, Land Cover, Urbanisation, Urban Sprawl, Landscape Metrics, Remote Sensing, Geoinformatics.*

1. Introduction

Large scale land-use land-cover (LULC) dynamics leading to deforestation is one of the drivers of global climate changes and alteration of biogeochemical cycles. This has given momentum to investigate the causes and consequences of LULC by mapping and modelling landscape patterns and dynamics and evaluating these in the context of human-environment interactions in the rapidly urbanizing landscapes. Human induced environmental changes and consequences are not uniformly distributed over the earth. However their impacts threaten the sustenance of human-environmental relationships. Land cover refers to physical cover and biophysical state of the earth's surface and immediate subsurface and is confined to describe vegetation and manmade features [1,2,3,4,5]. Thus land cover reflects the visible evidence of land cover of vegetation and non-vegetation. Land use refers to use of the land surface through modifications by humans and natural phenomena [1,2,3,5,6]. Land use is characterized by the arrangements, activities and inputs people undertake in a certain land cover type to produce, change or maintain it [5]. Alteration the structure of the landscape through large scale LULC has influenced the functioning of landscape, which include nutrient, regional water and bio-geo chemical cycles [3, 7].

Post-independence period, particularly during the globalization era in 1990's, the government facilitated the interactions of global industries with in-house industries. Large scale industrialization paved way for major land use land cover changes, caused by migration of people from different parts of the country, also from other parts of the globe and country for the employment opportunities. These led to intense urbanisation of major metropolitan cities with spurt in human population due to migration and also sprawl in peri-urban pockets [1,8,9,10,11,12]. Unplanned urbanisation are characterized by the loss of diversity, with changes in the coherence and identity of the existing landscapes. The drastic landscape changes are a threat or a negative evolution, as it affects the sustenance of natural resources. Urbanisation process leads to conversion of ecological land use (such as vegetation. Open area, cultivable lands, water) in to impervious layers on the earth surface. Increasing unplanned urbanisation is an important cause for depletion of resources species extension, hydro-geological alterations, loss of crop lands [3,13]. Unplanned urbanisation has various underlying effects such as dispersed growth or sprawl.

Urban Sprawl refers to an uncontrolled, scattered urban growth as a consequence of socio economic infrastructural development leading to increase in traffic, deficit of resources by depletion of the locally available resources while creating demand for more resources [3,10,14,15]. Often exceeding the carrying capacity of the land. The dispersed growth or sprawl occurs basically in the periphery and the outskirts and these regions are devoid of any basic amenities or infrastructure. Sprawl can be in the radial direction encircling the city center or in linear direction along the highways, ring roads, etc. The dispersed growth of urban pockets has been quantified through mapping of impervious surface in and around the city in the developed countries and in developing countries such as China [13,16] and India [1,14,17,18]. As per the population census, 25.73% [19] lives in the urban centers in India and it is projected that during the next decade about 33% would be living in the urban center [1,3] The extent or level of urbanisation and consequent sprawl has driven the changes in land use land cover patterns. LULC dynamics have altered the spatial landscape patterns [10] and these changes in the landscape (urban) pattern indicates the socio economic conditions and environmental impacts. The underlying phenomena of urban sprawl has been explained through the landscape index - Shannon entropy, a measure of urban growth [10,20]. It measures the degree of spatial concentration or dispersion of a geographical variable among n zones [3,14,16]. Larger value of entropy highlights the occurrence of dispersed growth or urban sprawl [1,3].

Multi resolution spatio-temporal data acquired since 1970's through space borne sensors helps in quantifying LULC dynamics through the temporal analysis of landscape patterns [1,18,21]. Evaluation of landscape dynamics qualitatively and quantitatively aids in understanding the changes and also help to determine the effect of anthropogenic activities [1,4,10,22]. The application of landscape metrics to spatio-temporal data helps in analysing the urban foot print. Landscape metrics aid in quantifying the spatial pattern of a particular landscape changes within the geographical area [1,3,14,22,23]. These metrics enables to quantify the landscape with respect to spatial dimension, alignment, pattern at a specific scale and resolution [6]. Metrics applied with the land use data help in evaluating the landscape heterogeneity and also in relating to urban growth pattern [1,23]. The spatial metrics have been used to quantify the urban form, describe the trend and growth of the land use patterns and to model the patterns of future urbanisation [3,22,23]. Gradient based spatial metrics analysis helps to visualize and understand the development in different directions and gradients with respect to the location as peaks and valleys along the direction [6,10,24].

The current focus of LULC analysis is to analyse the landscape dynamics of Belgaum City with 5 km buffer using Shannon's entropy and exploring insights to landscape patterns through spatial metrics applied to the temporal land use data.

The rest of this paper is organized as follows. Section 2 ....

2. Study Area

Belgaum City (see Fig.1) geographically located in the North Western Part of Karnataka State. The city with the spatial extent of about 58 sq.km. Extends from $74^0$28'29.071" E to $74^0$34'54.92" E and $15^0$49'23.189" N to $15^0$54'0.142" N with an average elevation of 751m above mean sea level. Five km buffer from the administrative boundary was considered as shown in Fig. 2 (with a gross area of 38 sq.km) to account for developments in the peri urban regions. The city has about 58 Wards, with population of 488292 (2011 Census Provisional)[19] and Population Density of 84.21 persons per hectare. Population has a decadal increase of 7.31%. BUDA (Belgaum Urban Development Authority) formed during 1988 is responsible for urban development including layout and town planning [25]. BUDA consists of local planning area of 182 sq.km, which includes the Belgaum city corporation, 26 surrounding villages and regions under conurbation limit. BUDA since 1988 has developed about 19 townships [26]. Temperature varies from 18 ^{0}C (winter) to 40 ^{0}C (summer) and city receives annual average rainfall of 1418 mm. Soils in the region consist of shallow to very deep black soils, red loamy soils, lateritic soils etc. The city is surrounded by Kanburgi, Yamanspura, Kangrali.B, Kangrali.K villages in the north, Hindalga, Binakanahalli, Savagaon, Madoli in the West, Angol, Wadgaon, Madhavapura, Haldge in the South and Sindoli, Mutuge, Nilage Villages in the East [27].

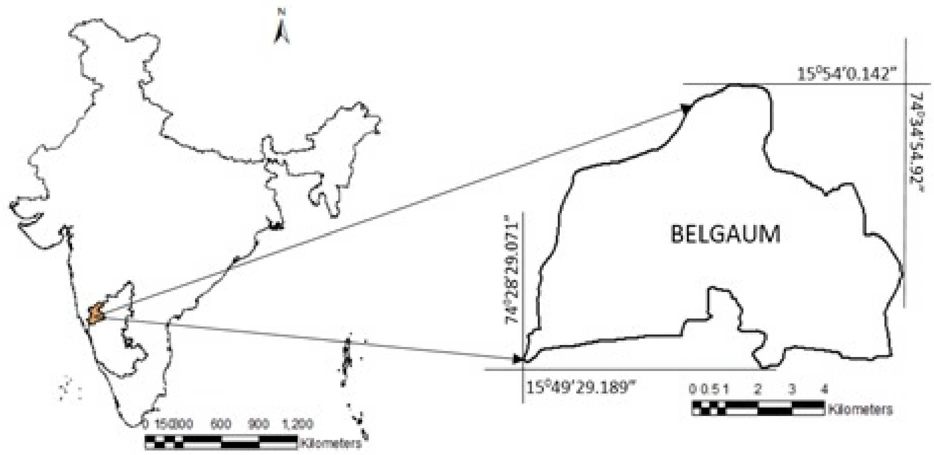


Figure 1. Belgaum City Administrative Boundary

3. Materials

Temporal remote sensing data of Landsat TM and Indian remote Sensing (IRS) were used to analyse LULC changes, urbanisation process, etc. The remote sensing data were supplemented with the Survey of India toposheets of 1:50000 and 1:250000 scale to generate base layers of the administrative boundary, drainage network, etc. Training data using pre calibrated Global Positioning System (GPS) and virtual online spatial maps such as Google Earth and Bhuvan were used for geometric correction, classification, verification and validation of the classified results (see Table I).

Table I: Materials used in Analysis *("Self Compiled")*

Data	Year	Purpose
Landsat Series TM (30m) and ETM	04/03/1989, 21/03/2000	Land cover and Land use analysis
IRS LISS III (24m)	01/04/2006	Land cover and Land use analysis
IRS R2 (5M)	16/03/2012	Land cover 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 –using GPS		For geo-correction, classification of remote sensing data and validation.

4. Method

A three-step approach as illustrated in Fig. 2 was adopted to understand the dynamics of the urbanizing city, which includes (i) a normative approach to understand the LULC dynamics (ii) a gradient approach of 1km radius to understand the pattern of growth during the past four decades.(iii) Quantifying the growth over time using spatial metrics.

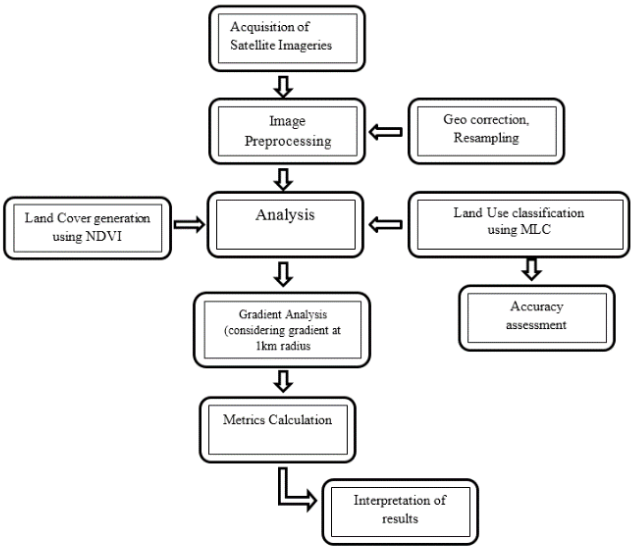


Figure 2. Procedure followed to understand the spatial pattern of landscape change
("Self Compiled")

Various stages in the data analysis are:

4.1. Preprocessing: The remote sensing data of Landsat were downloaded from GLCF (Global Land Cover Facility, http://glcf.umiacs.umd.edu/data) and IRS LISS III data were obtained from NRSC, Hyderabad (http://nrsc.gov.in). The data obtained were geo-referenced, rectified and cropped pertaining to the study area. Landsat data has a spatial resolution of 28.5 m x 28.5 m (nominal resolution) were resampled to uniform 30 m for inter temporal data comparisons.

4.2. 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).

4.3. Land Use Analysis: Further to account for changes in the landscape, land use analysis were performed and categories considered are listed in Table II.

Table II: Land use categories *("Self Compiled")*

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, Cropland, nurseries.
Others	Rocks, quarry pits, open ground at building sites, kaccha roads.

Data were classified with the training data (field data) using Gaussian maximum likelihood supervised classifier. Analysis involved 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 and 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 (http://www.googleearth.com) and Bhuvan (http://bhuvan.nrsc.gov.in) v) 60% of the training data has been used for classification, while the balance is used for validation or accuracy assessment.

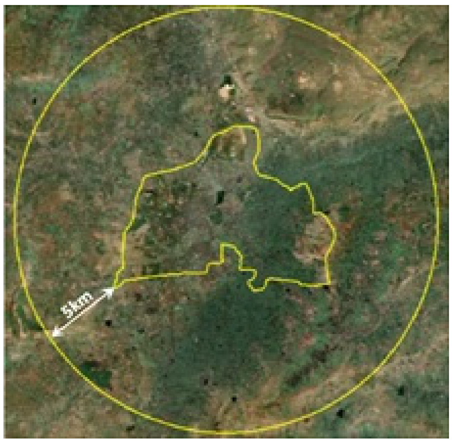


Figure 3: Study Area with 5 Km Buffer Overlaid on Spatial Data *(Source: Google Earth)*

Gaussian maximum likelihood classifier (GMLC) is used to classify the data using the training data.

GMLC uses various classification decisions using probability and cost functions [28] 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.

Table III. Landscape Metrics Analysed *("Self Compiled")*

	Indicators	Formula
1	Number of Urban Patches (NPU)	$NPU = n$ NP equals the number of patches in the landscape.
2	Patch density(PD)	f(sample area) = (Patch Number/Area) * 1000000
3	Normalized Landscape Shape Index (NLSI)	$NLSI = \frac{\sum_{i=1}^{i=N} \frac{p_i}{s_i}}{N}$ Where s_i and p_i are the area and perimeter of patch i, and N is the total number of patches.
4	Landscape Shape Index (LSI)	$LSI = e_i / \min e_i$ e_i =total length of edge (or perimeter) of class i in terms of number of cell surfaces; includes all landscape boundary and background edge segments involving class i. $\min e_i$=minimum total length of edge (or perimeter) of class i in terms of number of cell surfaces.
5	Total Edge (TE)	$TE = \sum_{k=1}^{m} e_{ik}$, where, e_{ik} = total length (m) of edge in landscape involving patch type (class) i; includes landscape boundary and background segments involving patch type i.
6	Percentage of Land (Pland)	$PLAND = P_i = \frac{\sum_{j=1}^{n} a_{ij}}{A}$, 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).
7	Aggregation index(AI)	$AI = \left[\sum_{i=1}^{m} \left(\frac{g_{ii}}{\max \rightarrow g_{ii}} \right) P_i \right] (100)$ g_{ii} =number of like adjacencies between pixels of patch type P_i= proportion of landscape comprised of patch type.
8	Cohesion	$Cohesion = \left[1 - \sum_{j=1}^{n} p_{ij} \Big/ \sum_{j=1}^{n} (p_{ij}) \sqrt{a_{ij}} \right] \left[1 - 1/\sqrt{A} \right]^{-1} *$ 100 p_{ij} = perimeter of patch ij in terms of number of cell surfaces. a_{ij} = area of patch ij in terms of number of cells. A = total number of cells in the landscape
9	Edge Density (ED)	$ED = 10000 * \sum_{k=1}^{m} e_{ik} / A$ e_{ik} = total length (m) of edge in landscape involving patch type (class) i; includes landscape boundary and background segments involving patch type i. A =total landscape area (m^2).
10	Contiguity Index	$CONTIG = \left[\left[\sum_{r=1}^{z} c_{ijr} / a_{ij} \right] - 1 \right] \Big/ v - 1$ c_{ijr} =contiguity value for pixel r in patch ij. v = sum of the values in a 3-by-3 cell template (13 in this case). a_{ij} = area of patch ij in terms of number of cells
11	Area weighted mean Fractal index	$AWMPFD = \frac{\sum_{i=1}^{i=N} 2 \ln 0.25 p_i / \ln S_i}{N} \times \frac{s_i}{\sum_{i=1}^{i=N} s_i}$

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 [3,18,29,30]. Further each zone was divided into concentric circle of incrementing radius of 1 km (see Fig. 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.

4.4. Urban Sprawl Analysis: Direction-wise Shannon's entropy (H_n) is computed (see eqn. 1) to understand the extent of growth: compact or divergent ([30], [10]). This provides an insight into the development (clumped or disaggregated) with respect to the geographical parameters across 'n' concentric regions in the respective zones.

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

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).

4.5. Spatial Pattern Analysis: Spatial metrics provide quantitative description of the composition and configuration of urban landscape. These metrics were computed for each circle, zonewise using classified land use data at the landscape level with the help of FRAGSTATS [32]. Urban dynamics is characterised by prominent spatial metrics chosen based on Shape, edge, complexity, and density criteria. The metrics include the patch area, shape, epoch/contagion/ dispersion and are listed in Table III.

5. Results

5.1. Land Cover Analysis: To understand the spatial extent of area under vegetation and non-vegetation, various land cover indices were analyzed. Among these NDVI index provide better insights to understand the extent of vegetation cover. Temporal NDVI were calculated and the results are given in Fig. 4 and in Table IV. The results indicate that the vegetation in the study region decreased for 98.8% (in 1989) to 91.74% (in 2012). Further temporal land use analyses are done to understand the changes in land uses.

Table IV. Land Cover Analysis *("Self Compiled")*

Year	Vegetation	Non Vegetation
1989	98.8%	1.2%
2000	98.41%	1.59%
2006	96.35%	3.65%
2012	91.74 %	8.26 %

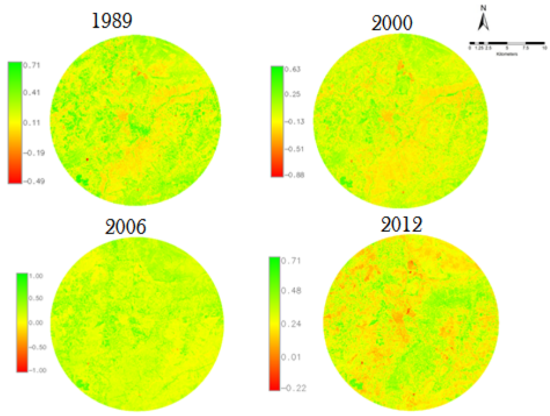


Figure 4: Land Cover Classification *("Self Compiled")*

5.2. Land Use Analysis: Temporal land use changes during 1989 to 2012 were analysed. Spatial data were analysed using maximum likelihood Classifier and the results are shown in Fig. 5 and Table V. The results of the analysis indicate that the urban impervious land use has increased from 0.31 % (in 1989) to 6.74% (in 2012); vegetation decreased from 4.62% (in 1989) to 2.44% (in 2012), while water category remained fairly constant.

Table V: Land Use Analysis *("Self Compiled")*

Year	1989		2000	
Land use	**%**	**Area(Ha)**	**%**	**Area(Ha)**
Water	0.14	53.24	0.33	125.49
Vegetation	4.62	1756.92	2.58	981.14
Built up	0.31	117.89	1.17	444.93
Others	94.9	36089.11	95.92	36477.00
Year	**2006**		**2012**	
Land use	**%**	**Area(Ha)**	**%**	**Area(Ha)**
Water	0.23	87.47	0.24	92.03
Vegetation	2.33	886.07	2.44	928.73
Built up	4.81	1829.17	6.74	2190.15
Others	92.93	35339.95	91.58	34904.41

Accuracy Assessment and Kappa Statistics: Kappa Statistics serves as an indicator of the extent pixels are correctly classified into the respective categories. The accuracy assessment was carried out for the classified data and the results are given in Table VI. The results indicated that the accuracy was above 90% and kappa values had strong agreement with the accuracy values with an average of 0.9.

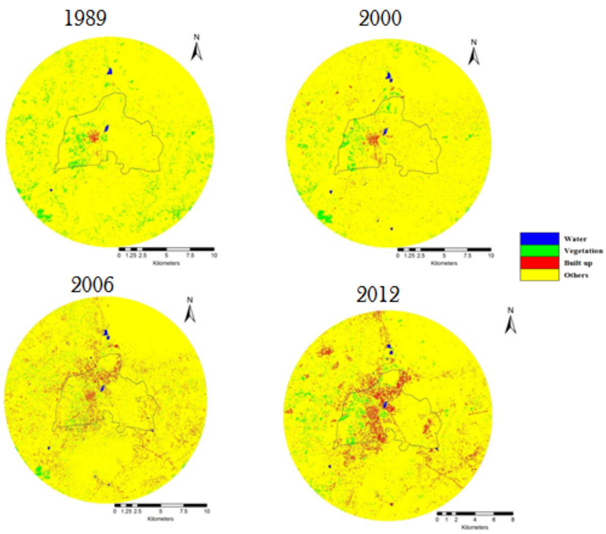


Figure 5: Land Use Classification *("Self Compiled")*

Table VI. Accuracy Assessment *("Self Compiled")*

Year	Overall Accuracy	Kappa Value
1989	94.85	0.87
2000	92.73	0.83
2006	93.64	0.92
2012	93.12	0.93

5.3. Urbanisation Analysis using Shannon's Entropy: Shannon entropy, as an indicator of urban sprawl was calculated and the results are shown in Fig. 6 and Table VII. The threshold limit of Shannon's Entropy is log11 or 1.041. The results indicated that though Belgaum and the buffer region is not experiencing urban sprawl. However increasing entropy values show the tendency of sprawl in the region.

Table VII: Built Up and Shannon's Entropy Analysis *("Self Compiled")*

Year	NE	NW	SE	SW
1989	0.0059	0.0191	0.0034	0.0088
2000	0.0283	0.0546	0.017	0.0334
2006	0.0791	0.140	0.108	0.113
2012	0.0864	0.1652	0.1154	0.137

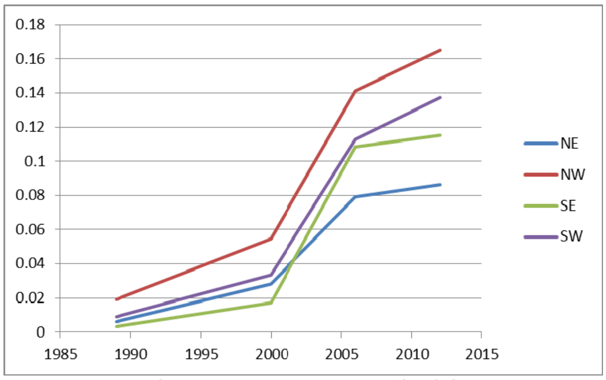
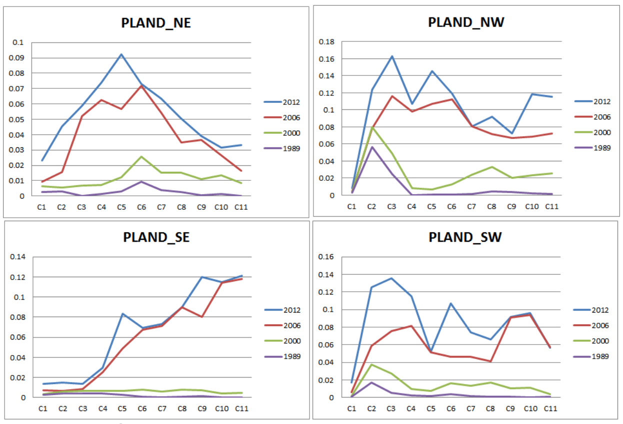


Figure 6: Shannon's Entropy *("Self Compiled")*

***5.4. Spatial Patterns Analysis*:** Spatial patterns of the landscape was analysed considering metrics based on the urban land use changes. Various landscape metrics were calculated as discussed.

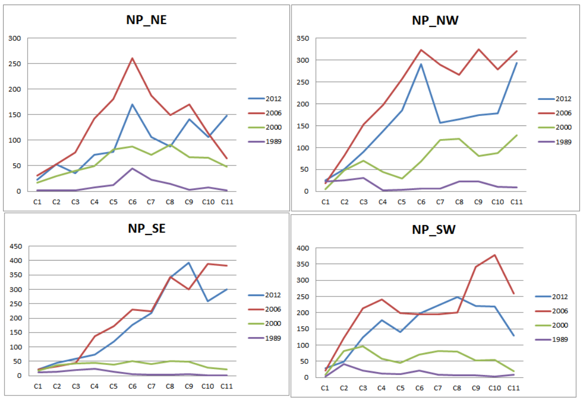
Proportion of Landscape (PLAND): PLAND indicates the percentage of urban land present in particular gradient and zone and ranges from 0 to 1, the value 1 indicates the landscape comprises of a single urban class and zero represents absence of urban class. The results of the analysis are represented in Fig. 7a, which indicates spurt in urban land use during post 2000 and especially in 2012 in almost all directions and all gradients.



X axis : Circles at every 1 km **Y axis**: Indices value

Figure. 7a: Proportion of Landscape Metric *("Self Compiled")*

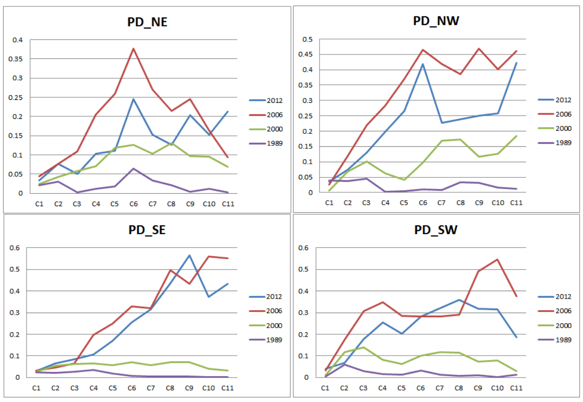
Number of Patches (NP): NP is a type of metric describes the growth of particular patches whether in an aggregated or fragmented growth in the region and also explains the underlying urbanization process. Number of Patch is always equal to or greater 1, NP = 1 indicates that there is only 1 patch of a particular class, showing aggregated growth, larger values of NP indicate fragmented growth. The results indicate that there growth of urban patches in all directions post 2000, which have increased specially in the buffer zones, due to fragments as in Fig. 7b.



X axis : Circles at every 1 km **Y axis**: Indices value

Figure 7b. Number of patches metric analysed *("Self Compiled")*.

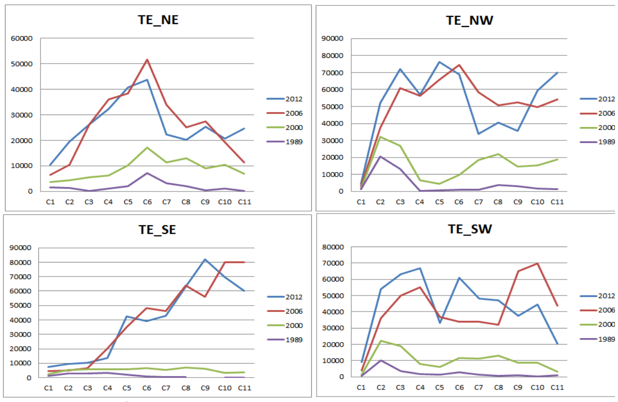
Patch Density (PD): PD is a landscape metric which is quite similar to number of patches but gives density about the landscape in analysis, The values vary from 0 to 1, 0 indicating a single homogenous patch, whereas values towards 1 indicates fragmented growth as the patches increase the patch density increases. The results as in Fig. 7c indicates an increase of NP in the outskirts, but at the core of the city, clumped patches are prominent in all directions specially post 2000. In 2012, this substantially decreased in almost all directions mainly due to patches getting clumped and forming a single patch.



X axis : Circles at every 1 km **Y axis**: Indices value

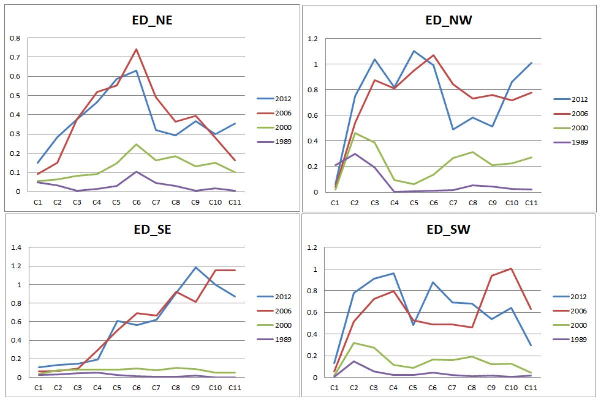
Figure 7c: Patch Density Metric *("Self Compiled")*

Total Edge (TE) and Edge density (ED): TE is the absolute measure of total length (perimeter) of each class of a particular patch in landscape in meters. TE considers true edges into consideration. Value of TE is greater than or equal to zero. Larger the edge values indicate larger continuous patches. ED is the ratio of total edge distance to the total Area. If ED is zero, it represents there is no class of the landscape. Fig. 7d explains the results of the analysis, which indicate that during 1980's the edges were smaller, which explains that the urban patch was rare in landscape and was concentrated, but post 2000 and in 2012 there are larger edges, which indicate that the urban area is continuous. This phenomenon is true in the city boundary, but the buffer region patches are yet fragmented and non-continuous. Fig. 7e explains the edge density which has the agreement with the metrics explained earlier, indicative of the fragmented patches becoming a single patch in 2012.



X axis : Circles at every 1 km **Y axis**: Indices value

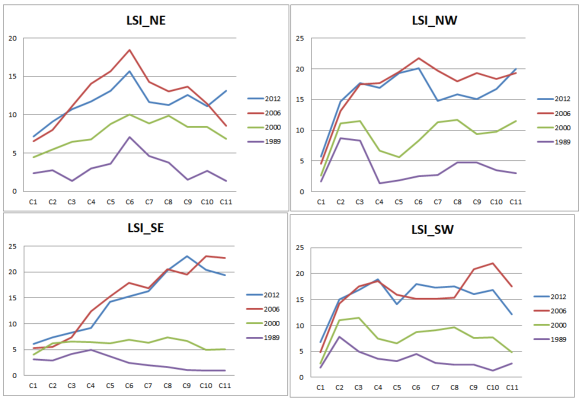
Figure 7d: Total Edge Metric *("Self Compiled")*



X axis : Circles at every 1 km **Y axis**: Indices value

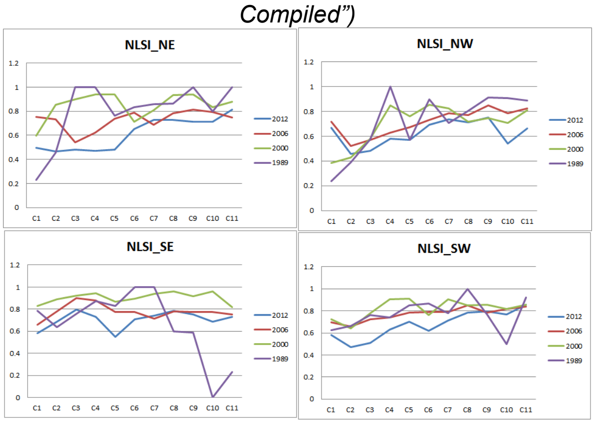
Figure 7e: Edge Density Metric *("Self Compiled")*

Landscape Shape Index (LSI) and *Normalized Landscape Shape Index(NLSI)*: LSI provides a measure of class aggregation or clumpiness depending on the shape of the class in analysis, when the value of LSI is 1, this indicates clumped growth, the increasing values of LSI indicates aggregation. NLSI is the normalized value of LSI, when zero or closer to zero indicates a clumped growth whereas NLSI towards 1 indicates aggregated growth of the landscape. Fig. 7f and 7g represents the results of LSI and NLSI. The results of both metrics puts out a fact that in 2012 landscape class shapes are becoming more complex indicative of fragmented growth, with comparison of simple shape in 1980's a clumped growth.



X axis : Circles at every 1 km **Y axis**: Indices value

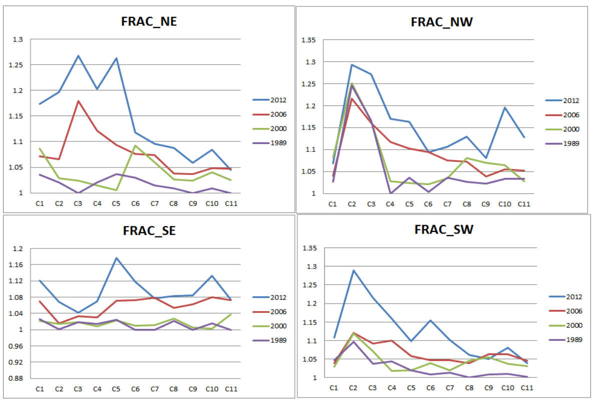
Figure 7f: Landscape Shape Index metric*(“Self Compiled”)*



X axis : Circles at every 1 km **Y axis**: Indices value

Figure 7g: Normalised Landscape Shape Index metric*(“Self Compiled”)*

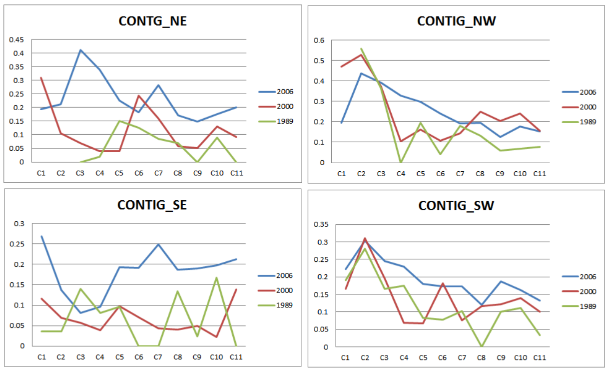
Fractal Dimension Index represents the complexity of the shape of the landscape. The values vary from 1 to 2; index values closer to 1 indicates simpler shapes of the land scape values closer to 2 indicate varying shape of the landscape. Fig. 7h explains that the complexity of shape increases in 2012 when compared to 1989 accompanied with simple shapes and perimeters.



X axis : Circles at every 1 km **Y axis**: Indices value

Figure 7h: Fractal Dimension Metrics in four directions*(“Self Compiled”)*

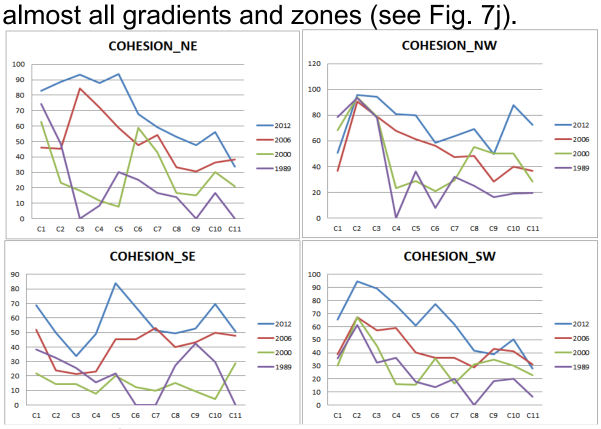
Contiguity indicates the continuity of the landscape, Contiguity index varies from 0 to 1, values closer to zero indicates single pixel, values closer to one indicates patch with large number of pixels of the particular class. Fig. 7i explains the output of the contiguity metric, explaining the dominance of the urban pixels in all directions post 2000, which was less in 1980’s.



X axis : Circles at every 1 km **Y axis**: Indices value

Figure 7i: Contiguity metric*(“Self Compiled”)*

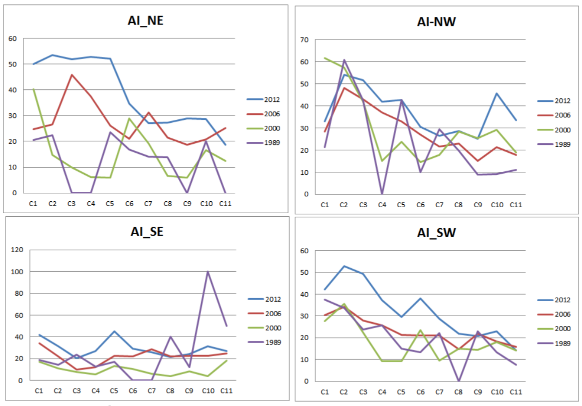
Cohesion measures the physical connectivity between adjacent patches; the cohesion value 0 indicates disaggregation and no inter connectivity between patches and higher value indicates clumped and connectivity between patches. Higher values during post 2000 illustrate of fragmented landscape forming clumped patches in almost all gradients and zones (see Fig. 7j).



X axis : Circles at every 1 km **Y axis**: Indices value

Figure 7j: Cohesion Metric *(“Self Compiled”)*

Aggregation index is a measure of disaggregation or aggregation of a landscape, the metric varies from zero to 100 percent, values closer to zero indicate disaggregation and values closer to 100 indicate aggregated growth of the landscape. Fig. 7k corroborates with the earlier metrics that post 1980’s the landscape had been fragmented which has started aggregating during post 2000.



X axis : Circles at every 1 km **Y axis**: Indices value

Figure 7k: Aggregation Index*("Self Compiled")*

6. Conclusion

Karnataka State Industrial & Infrastructure Development Corporation Limited has been greatly instrumental in the industrialisation of the State, especially in the large and medium sector and important arm of the state in bringing industrial boom in various sectors. The intense urbanisation process in Tier I cities with the associated environmental problems and poor infrastructure, basic amenities has necessitated planning of Tier II cities to minimize the consequences of urbanisation.

State government has plans to divert the new industrial establishments and activities to tier II cities. Also globalization process and subsequent opening of Indian markets has led to rapid urbanisation leading to unorganized and fragmented urban sprawl affecting the basic amenities. Belgaum city, with 5 km buffer has been analysed to understand LULC dynamics. LU was analysed through supervised Gaussian MLC algorithm. The Land cover results show decrease in vegetation cover in the region from 98.8% (1989) to 96.35% (2006). The temporal analysis of the LU shows an increase of built up area from 0.31% (1989) to 6.74% (2012), decline of tree cover from 4.62 % (1989) to 2.33% (2006).

LULC change analysis indicates an increase of urban area by 14 times during 1989 and 2012 while the vegetation has reduced by 2.45%. Shannon Entropy indicates the tendency of urban sprawl during post 2000 in all direction and predominantly in North West direction. Spatial metrics reveal concentrated urbanisation at the core of the city and is increasingly fragmented growth towards the outskirts of the city.

This type of analysis helps the town planning department and other departments, to understand and visualize the changes, extent and pattern spatially and temporally. This helps to plan the basic amenities and evolve appropriate land use polices.

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References

[1] H.S. Sudhira, T.V. Ramachandra and K.S. Jagadish, "Urban sprawl: metrics, dynamics and modelling using GIS" *International Journal of Applied Earth Observation and Geoinformation*, Vol. 5, pp.29-30, 2004.

[2] M. Thomas Lillesand, W. Ralph Kiefer, W. Jonathan Chipman, Remote Sensing and Image Interpretation, 5th ed. John Wiley and Sons. 2004

[3] T.V. Ramachandra, A.H. Bharath,and D.S. Durgappa, "Insights to urban dynamics through landscape spatial pattern analysis," *International Journal of Applied Earth Observation and Geoinformation*, Vol. 18, pp.329-343. 2012d.

[4] T.V. Ramachandra, "Comparative Assessment of Techniques for Bioresource Monitoring using GIS and Remote sensing," Vol.1(2). Available at http://wgbis.ces.iisc.ernet.in/energy/paper/ICFAI/TVR24_P3_ICFAI_Kolar.pdf

[5] E. John Wasige, A.ThomasGroen,Eric Smaling, Victor Jetten, "Monitoring basin-scale land cover changes in Kagera Basin of Lake Victoria using ancillary data and remote sensing," *International Journal of Applied Earth Observation and Geoinformation*, Vol. 21, pp. 32–42, 2013.

[6] H. Taubenbock, M.Wegmann, A. Roth, H. Mehl, S. Dech. "Urbanization in India: Spatiotemporal analysis using remote sensing data," *Computers, Environment and Urban Systems*, Vol. 33(3), pp. 179–188, 2009.

[7] Sushant Paudel, Fei Yuan, "Assessing landscape changes and dynamics using patch analysis and GIS modeling," *International Journal of Applied Earth Observation and Geoinformation*, Vol. 16, pp. 66–76, 2012.

[8] D. Anindita, U. Kumar, T.V. Ramachandra. "Urban Landscape analysis through spatial metrics," In the proceedings of the Conference on Infrastructure, Sustainable Transportation and Urban Planning, CISTUP@CISTUP2010, 18 - 20 October, JN

Tata Auditorium, Indian Institute of Science, Bangalore.2010.
[9] T.V. Ramachandra, A.H. Bharath, S. Sreekantha. "Spatial Metrics based Landscape Structure and Dynamics Assessment for an emerging Indian Megalopolis," *International Journal of Advanced Research in Artificial Intelligence*,Vol.1(1), pp.48 – 57, 2012a.
[10] A.H. Bharath, S. Sreekantha, D.S.Durgappa, T.V. Ramachandra, "Spatial patterns of urbanization in an emerging Tier II City, Mysore," *Proceedings of Samanway 2012*, Indian Institute of Science, Bangalore, India, 03-04 March, 2012.
[11] S. Jin Deng,Ke. Wang, Yang Hong, G. Jia Qi "Spatio-temporal dynamics and evolution of land use change and landscape pattern in response to rapid urbanization,"*Landscape and Urban Planning*,Vol.92(3-4), pp.187-198, 2009.
[12] T.V. Ramachandra, A.H. Bharath, "Spatio-Temporal Pattern of Landscape Dynamics in Shimoga, Tier II City, Karnataka State, India,"*International Journal of Emerging Technology and Advanced Engineering*, Vol. 2(9), pp.563 – 576, 2012b.
[13] Xi Jun Yu, Ng. Cho Nam, "Spatial and temporal dynamics of urban sprawl along two urban–rural transects: A case study of Guangzhou China," *Landscape and Urban Planning*,Vol.79, pp. 96–109, 2007.
[14] H.S. Sudhira, T.V. Ramachandra and K.S. Jagadish, "Urban sprawl pattern recognition and modelling using GIS," Paper presented at Map India, New Delhi. January 28–31, 2003
[15] T.V. Ramachandra and U. Kumar, "Geoinformatics for Urbanisation and Urban Sprawl pattern analysis*," Chapter 19, In: Geoinformatics for Natural Resource Management* (Eds. Joshi et al.). Nova Science Publishers, NY, pp. 235-272.
[16] A.G.O. Yeh,X. Li, "Measurement and monitoring of urban sprawl in a rapidly growing region using entropy," *Photogrammetry. Eng. Remote Sensing*,Vol. 67 (1), pp. 83-87, 2001.
[17] M.K. Jat, P.K.Garg, K. Deepak, "Monitoring and modelling of urban sprawl using remote sensing and GIS techniques," *International Journal of Applied Earth Observation and Geoinformation*, Vol. 10, pp.26–43, 2008.
[18] T.V. Ramachandra, A.H. Bharath, "Land Use Dynamics at Padubidri, Udupi District with the Implementation of Large Scale Thermal Power Project,"*International journal of Earth Sciences and Engineering*, Vol.5, pp. 409-417, 2012c.
[19] Census India 2001, 2011 (Provisional), http://censusindia.gov.in/
[20] S.K. Pathan, J.G Patel,et al., "Urban planning with specific reference to master plan of Indore city using RS and GIS techniques" Proc. of *GSDI-7 International Conference on Spatial Data Infrastructure for Sustainable Development*, held at Bangalore from Feb, 2-6, 2004.
[21] S. Bharath,A.H. Bharath, D.S. Durgappa, T.V. Ramachandra, "Landscape Dynamics through Spatial Metrics," Proceedings of *India GeoSpatial Conference*, Epicentre, Gurgaon, India, 7-9 February, 2012.
[22] M. Herold, H.Couclelis, K.C. Clarke,"The role of spatial metrics in the analysis and modeling of urban land use change,"*Computers, Environment and Urban Systems*, Vol.29, pp.369–399, 2005.
[23] JI. Wei, Jia Mia, R. W. Twibell, K. Underhill, "Characterizing Urban Sprawl using Multi Stage Remote Sensing Images and Landscape Metrics," *Computers, Environment and Urban Systems*, Vol.30, pp861 – 879, 2004
[24] P. Torrens, M. Alberti, "Measuring sprawl. CASA working paper series" 27, UCL.2000. http://www.casa.ucl.ac.uk/publications/workingpapers
[25] http://www.belgaum.nic.in/
[26] District at a glance, Belgaum District
[27] R.O. Duda, P.E. Hart, D.G. Stork, Pattern Classification, (2nd ed., Wiley-Interscience Publication, 2005. ISBN 9814-12-602-0.
[28] R.G. Congalton, "A review of assessing the accuracy of classifications of remotely sensed data," *Remote Sensing of Environment*,Vol. 37, pp. 35-46, 1991.
[29] R.G. Congalton, R.G. Oderwald, R.A. Mead, "Assessing Landsat classification accuracy using discrete multivariate analysis statistical techniques," *Photogrammetric Engineering and Remote Sensing*,Vol. 49, pp.1671-1678, 1983
[30] K.M. Lata, C.H.SRao, et al., "Measuring Urban sprawl A case study of Hyderabad" *gis@development*, Vol.5(12), pp.26-29, 2001.
[31] K. McGarigal, B. J. Marks,"FRAGSTATS: spatial pattern analysis program for quantifying landscape structure," USDA Forest Service General Technical Report PNW-351, 1995.

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Measuring urban sprawl in Tier II cities of Karnataka, India

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Abstract— **Rapid irreversible urbanisation has haphazard and unplanned growth of towns and cities. Urbanisation process is driven by burgeoning population has resulted in the mismanagement of natural resources. Human-induced land use changes are the prime drivers of the global environmental changes. Urbanisation and associated sub growth patterns are characteristic of spatial temporal changes that take place at regional levels. Rapid urbanization subsequent to opening up of Indian markets in early ninety's show dominant changes in land use during the last two decades. Urban regions in India are experiencing the faster rates of urban dominance, while peri-urban areas are experiencing sprawl. Tier II cities in India are undergoing rapid changes in recent times and need to be planned to minimize the impacts of unplanned urbanisation. This communication focuses on seven tier II cities, chosen based on population. Mysore, Shimoga, Hubli, Dharwad, Raichur, Belgaum, Gulbarga and Bellary are the rapidly urbanizing regions of Karnataka, India. In this study, an integrated approach of remote sensing and spatial metrics with gradient analysis was used to identify the trends of urban land changes with a minimum buffer of 3 km buffer from the city boundary has been studied (based on availability of data), which help in the implementation of location specific mitigation measures. Results indicated a significant increase of urban built-up area during the last four decades. Landscape metrics indicates the coalescence of urban areas has occurred in almost all these regions. Urban growth has been clumped at the center with simple shapes and dispersed growth in the boundary region and the peri-urban regions with convoluted shapes.**

Keywords - Landscape Metrics, Urbanisation, Urban Sprawl, Remote sensing, Tier II, Karnataka, India

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 [1]. Urban growth is a spatial and demographic process, involving concentrated human activities in the region, which has high economic potential ([2], [3], [4]). Urban growth pattern, have a direct influence on the region's development process and often it extends its influence on the neighborhood [1], leading to dispersed growth, which is often referred as urban sprawl or peri-urban growth. Urban sprawl refers to a small clusters of medium to low-density urban growth in the outskirts without proper basic amenities ([1], [5]). This form of peri urban low density growth apart from lacking basic amenities also have a number of social, economic and environmental disadvantages [4]. Mapping the urban sprawl dynamics helps not only to identify the environmental degradation but also to visualize the future patterns of sprawling growth. Techniques have evolved for identifying and quantifying the urban sprawl ([6], [7], [4]). Apt way to capture this process is to consider the spatial and temporal changes taking place in the regions covered with impervious surfaces [8].

A quantitative and qualitative analysis of the landscape structure is essential to analyse of the patterns of landuse changes. Thematic land-use and land-cover maps generated allow us to quantify characteristics of landscape heterogeneity [9] and landscape fragmentation [10]. Spatio-temporal data (Remote Sensing (RS) data acquired through space borne sensors) 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 [11]. Temporal RS data has been used to analyze and understand the changes and impacts of human activities on the natural ecosystem [12]. Urban growth is captured based on spatial configuration and its dynamics [13]. Spatial metrics are useful for describing the landscape structure ([14], [1]) and for a wide range of applications, including the assessments of land-use change required for landscape planning and management [15], detection of changes in vegetation patterns [16], changes in landscape structure [17], for assessing the impacts of urbanization on the landscape ([1] [2] [4] [18]). Common spatial metrics have been computed for describing the structural characteristics and growth patterns of the built-up area. This review illustrates that significant research contributions ranging from gradient analyses to geospatial tool applications have been made to understand the urban growth pattern, quantification of complex patterns or processes of urban growth [19]. The present scenario in India with attribute to structure composition and rate of growth of most Indian metropolitan cities or tier 1 cities have an aggregated urban cores, huge population and have been expanding into the rural fringe areas, and planners have failed in providing the basic necessities and infrastructure [4]. Thus there has been a need of providing an alternative region for development which has been in the form of Tier II cities, which have huge space for infrastructural development capabilities with good facilities for providing basic amenities. In order to be able to provide basic amenities and infrastructure for the complex and dynamic urban environment there is an obvious need for planners and city developers to monitor and visualize the growth pattern and changing land use along the urban area and the peri urban area of the tier two cities This communication analyses the growth pattern of developing cities in Karnataka State, India. These regions have 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, (c) 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.

II. Study Area

Karnataka is one of the largest states of South India. The state covers an area of 191,976 sq. kms or 5.83% of the total geographical area of India. It is the eighth largest Indian state by area, the ninth largest by population and comprises 30 districts. According to Population census of 2001, the Population of Karnataka was 5.273 crores (52.73 million). The Population of Karnataka has increased by 17.20% compared to the population census of 1991. Karnataka lies between the Latitudes 14 º 49' 37.15"N to 13 º18' 39.29"N, Longitude 76º56' 37.1"E to 77º28' 15.66"E. The study focuses on tier-II cities of Karnataka which have a population of 2 - 8 lakhs, namely Mysore, Shimoga, Hubli- Dharwad, Belgaum, Bellary, Raichur and Gulbarga (Fig. 1).

Mysore is the second largest city in the state of Karnataka, ndia. The vibrant royal city of South, with numerous heritage sites, is facing the rapid urbanization. This irreversible process of urbanisation has been altering the landscape. With the government planning to develop this area under various Projects which has invited the surge of investors to invest heavily in this heritage city, especially the IT Companies. Shimoga is located in central part of the state of Karnataka, India. It lies on the banks of the Tunga River. Shimoga encompasses an area of 8477 sq. km. Shimoga district has a population of 16.43 lakh (as per 2001 Census), with population density of 194 per sq. km. Hubli – Dharwad are twin cities in Indian state of Karnataka. Hubli-Dharwad is the second-largest urbanized centers in Karnataka. The twin cities have a common governance and are governed by Hubli - Dharwad Municipal

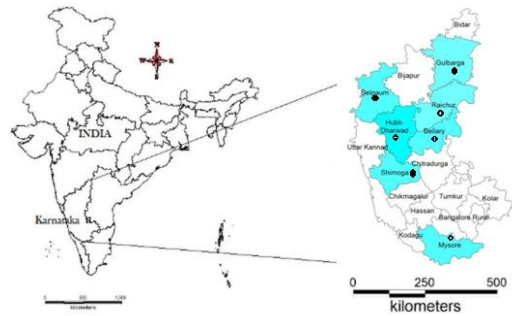

Figure 1. Study Area: Tier II Cities in Karnataka

Corporation (HDMC) with a corporation governing area of 202.3Sq km. The population of the Twin cities is about 1 million (Census 2011). Gulbarga is a biggest district in Karnataka State covering 8.49% of the area and 5.9% of State's population. Gulbarga is basically an agriculture dominated district. Raichur is one of major district in northern Karnataka, India, having 5 taluks and 37 hobli's and 120 hamlets, with an area of 8386 sq. km. and a population density of 181 persons per sq. km (2001). Bellary city is situated in the Karnataka State and has a jurisdiction over an area of 82 Sq. Kms. Population of about 0.4 million as per 2011 census (provisional). Belgaum City geographically located in the North Western Part of Karnataka State, with a gross area of 38013.27 hectares.

The city has about 58 wards, with population of 0.5 million (2011 Census Provisional) and Population Density of 84.21 persons per hectare, the population in the region has a decadal increase of 7.31%.

III. Materials and Methods

Data analysis: Preprocessing: The remote sensing data corresponding to the study region were downloaded, geo-referenced, rectified and cropped pertaining to the administrative boundary with 3km-5km buffer depending on data availability was considered. Landsat ETM+ bands of 2010 were corrected for the SLC-off by using image enhancement techniques, followed by nearest-neighbor interpolation. Data used for the analysis are listed in Table 1.

Land Cover Analysis: Among different land cover indices, NDVI - Normalised Difference Vegetation Index was found appropriate and NDVI was computed to understand the changes of land cover. NDVI is the most common measurement used for measuring vegetation cover. It ranges from values -1 to +1 depending on the earth features.

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 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, iv) Supplementing this information with Google Earth. Land use classification was done using supervised pattern classifier - Gaussian maximum likelihood algorithm based on various classification decisions using probability and cost functions [20]. Land use was computed using the temporal data through open source GIS: GRASS- Geographic Resource Analysis Support System (http://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. Statistical assessment of classifier performance based on the performance of spectral classification considering reference pixels is done which include computation of kappa (κ) statistics.

TABLE 1: DATA USED AND THE PURPOSE

Data	Purpose
Landsat Series MSS(57.5m)	Land cover and Land use analysis
Landsat Series TM (28.5m) and ETM	
IRS LISS III (24m)	
IRS R2 (5.6M) – LISS-IV(5.6m)	
IRS p6: LISS-IV MX data (5.6m)	
Survey of India (SOI) toposheets of 1:50000 and 1:250000 scales	Generate boundary and base layers.
Field visit data –captured using GPS	For geo-correcting and generating validation dataset

Density gradient and zonal analysis and computation of Shannon's entropy: Further the classified spatial data is 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. 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 [21]. To determine whether the growth of urban areas was compact or divergent the Shannon's entropy ([21] [1]) 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.

$$H_n = -\sum_{i=1}^{n} P_i \log P_i \; \ldots\ldots\ldots\ldots\ldots\; (1)$$

Where Pi is the proportion of the built-up in the i^{th} 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.

IV. RESULTS

Vegetation cover analysis: Vegetation cover was assessed through NDVI, Mysore shows that area under vegetation has declined to 9.24% (2009) from 57.58% (1973). Shimoga analysis reveals that there was reduction in the vegetation cover from 89% to 66% during the past two decades in the region. In Hubli vegetation has declined from 97% (1989) to 78% (2010) in Hubli and from 98% (1989) to 86% (2010) in Dharwad. Gulbarga and Raichur analysis showed area under vegetation has declined by about 19%. Belgaum analysis indicate that the vegetation in the study region decreased for 98.8% in 1989 to 91.74% in 2012. Temporal NDVI values are listed in Table 2 and outputs are presented in Appendix 1.

TABLE 2: LAND COVER ANALYSIS (V: ARE UNDER VEGETATION IN %; NV: AREA UNDER NON-VEGETATION IN %)

In %	Mysore	Shimoga	Hubli	Dharwad
1980's	V=57.58 Nv=42.42	V=89.35 Nv=10.65	V=97.0 Nv=3.0	V=98.12 Nv=1.88
2000's	V=09.24 Nv=90.76	V=66.72 Nv=33.28	V=78.31 Nv=21.69	V=86.43 Nv=13.57
In %	Gulbarga	Raichur	Belgaum	Bellary
1980's	V=94.72 Nv=5.28	V=92.18 Nv=7.82	V=98.41 Nv=1.59	V=94.87 Nv=5.13
2000's	V=79.41 Nv=20.57	V=82.48 Nv=17.52	V=91.74 Nv=8.26	V=93.7 Nv=6.27

Land use analysis: Land use assessed using Gaussian maximum likelihood classifier. In Mysore there has been a significant increase in built-up area during the last decade evident from 514 times increase in urban area from 1973 to 2009. Shimoga also witnessed increase in the urban category from 13% (1992) to 33% (2010), which is about 253 times during the last four decades. Hubli-Dharwad also saw a significant increase in built-up area during the last decade, Hubli saw an increase of about thousand times, whereas Dharwad was about 600 times growth in urban area, Gulbarga has seen a significant increase in built-up area during the last decade evident from 21% increase in urban area. Raichur and Bellary also witnessed increase in built-up area during the last decade about 590 and 700 times during the last 4 decades. Belgaum analysis indicate that the urban impervious land use has increased from 0.31 % in 1989 to 6.74% in 2012 Consequent to these, vegetation cover and water has declined drastically during the past four decades in all cities. Temporal Land use values are listed in Table 3 and outputs are presented in Appendix 2.

Shannon's entropy computed using temporal data as listed in table 4. Mysore is experiencing the sprawl in all directions as entropy values are closer to the threshold value (log (8) = 0.9). Lower entropy values during 70's shows an aggregated growth as most of urbanization were concentrated at city centre.

TABLE 3: LAND USE ANALYSIS

Class	Mysore	Shimoga	Hubli	Dharwad
Urban	1980's=1.1 2000's=18.68	1980's=13.58 2000's=33.56	1980's=1.08 2000's=14.62	1980's=0.62 2000's=6.47
Veg	1980's=65.85 2000's=5.7	1980's=30.94 2000's=5.52	1980's=0.22 2000's=0.42	1980's=1.43 2000's=0.69
Water	1980's=0.39 2000's=0.7	1980's=1.52 2000's=1.2	1980's=0.64 2000's=0.65	1980's=0.51 2000's=0.47
others	1980's=32.6 2000's=74.84	1980's=53.95 2000's=59.72	1980's=98.06 2000's=84.30	1980's=97.45 2000's=92.36
	Gulbarga	Raichur	Belgaum	Bellary
Urban	1980's=2.62 2000's=22.52	1980's=1.44 2000's=8.51	1980's=0.31 2000's=6.74	1980's=2.12 2000's=7.42
Veg	1980's=1.54 2000's=0.49	1980's=1.62 2000's=4.81	1980's=4.62 2000's=2.44	1980's=4.61 2000's=0.48
Water	1980's=0.40 2000's=0.39	1980's=0.88 2000's=0.97	1980's=0.14 2000's=0.24	1980's=2.35 2000's=2.04
others	1980's=95.44 2000's=76.60	1980's=96.16 2000's=85.71	1980's=94.9 2000's=91.58	1980's=90.92 2000's=90.07

However, the region experienced dispersed growth in 90's reaching higher values of 0.452 (NE), 0.441 (NW) in 2009. Sprawl analysis for Shimoga reveals 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. Hubli - Dharwad is experiencing the sprawl in all directions as entropy values are gradually increasing (for Hubli: log (12) = 1.07 For Dharwad: log (7) = 0.845). Lower entropy values of 0.02 (NW), 0.011 (SW) during late 80's shows an aggregated growth as most of urbanization were concentrated at city center. However, the region experienced dispersed growth in 80's reaching higher values in NE, and SE in 2010. Gulbarga is experiencing the sprawl in all directions as entropy values are closer to the threshold value (log (10) = 1). Lower entropy values during 0'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 (and threshold is 0.77). Increasing entropy values from 1982 to 2010 shows the tendency of dispersed growth of built-up area in the city with respect to 4 directions as we move towards the outskirts and this phenomenon is most prominent in SE and SW directions. Increasing entropy values from 1973 to 2010 shows the tendency of dispersed growth of built-up area in the city with respect to 4 directions as we move towards the outskirts and this phenomenon is most prominent in SE and NE directions. The threshold limit of Shannon's Entropy is log11 (1.041). The results indicated that though Belgaum considering the buffer region has effect of urban sprawl considering the values of 1980 and 2012, and the effect is gaining strength temporally considering the threshold value of 1.041.

TABLE 4: SHANNON ENTROPY INDEX

	NE	NW	SE	SW	
Mysore	0.067	0.007	0.0265	0.008	1980's
	0.452	0.441	0.346	0.305	2000's
Shimoga	0.23	0.24	0.18	0.25	1980's
	0.43	0.7	0.42	0.47	2000's
Hubli	0.027	0.02	0.055	0.011	1980's
	0.369	0.134	0.49	0.128	2000's
Dharwad	0.011	0.013	0.008	0.006	1980's
	0.168	0.164	0.213	0.216	2000's
Gulbarga	0.086	0.065	0.046	0.055	1980's
	0.268	0.212	0.193	0.141	2000's
Raichur	0.023	0.026	0.026	0.027	1980's
	0.135	0.146	0.168	0.194	2000's
Bellary	0.04	0.03	0.08	0.06	1980's
	0.37	0.32	0.389	0.33	2000's
Belgaum	0.005	0.0191	0.0034	0.008	1980's
	0.086	0.1652	0.1154	0.137	2000's

Spatial patterns of urbanisation: In order to understand the spatial pattern of urbanization, seven landscape level metrics were computed zone wise for each circle. Prominent two metrics ([1]) are discussed below: Number of Urban Patch (Np) reflects the extent of fragmentation 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 and ranges from 0 (fragment) to 100 (clumpiness). The analysis (Fig. 2) showed that all the cities except Hubli Dharwad and Belgaum are becoming clumped patch at the center, which indicates that the urban dominance and eradication of other classes present in past decades, while outskirts are relatively fragmented in all direction, but show a tendency of forming a single clumped class in the whole landscape considered. Hubli-Dharwad and Raichur have shown fragmentation over years both at the centre and outskirts indicative of newer urban patches in the landscape in recent decade. Further understanding this planners have to visualise the future to balance all land use to avoid unsustainable growth or complete urban dominance.

Normalised 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. Basically this metrics quantitatively captures the growth or phenomena through shape of a landscape. The analysis revealed and supported the previous metrics that the central gradients are in the process of converting to simple shapes and values are decreasing over decades, which again points to the fact of urban dominance over other land use classes in this region. However the Hubli, Dharwad and Belgaum analysis is an indicative of the yet more convoluted shapes the value being close to one than in 1980, and supports the argument that they have fragmented growth at the centre and outskirts extending to the buffer zones (Fig. 3).

V. CONCLUSION

The statistics and analysis both quantitatively and qualitatively presented here illustrate the spatial distribution of recent patterns of urbanisation in the tier II cities, Karnataka, India. Land cover analysis reveals that there was reduction in the vegetation cover during the past two decades in the study regions. Land use analysis reveals of increase in urban category increased in last two decades. Spatial analysis revealed that land use in the outskirts is fragmented. 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. 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 all these cities take a note of the situation and plan for further developmental urban activities in a sound and sustainable way.

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REFERENCES

[1] T.V. Ramachandra, A. H. Bharath, D.S. Durgappa, “Insights to urban dynamics through landscape spatial pattern analysis,” in Int. J Applied Earth Observation and Geoinformation, Vol. 18, pp. 329-343, 2012a.

[2] B. Bhatta, S. Saraswati and D. Bandyopadhyay, “Quantifying the degree-of-freedom, degree-of-sprawl, and degree-of-goodness of urban growth from remote sensing data,” in Applied Geography, vol. 30(1), pp. 96–111. 2010.

[3] M. Luck and J. G. Wu, “A gradient analysis of urban landscape pattern: A case study from the Phoenix metropolitan region, Arizona, USA” in Landscape Ecology, Vol. 17(4), pp. 327–339, 2002.

[4] T.V. Ramachandra, A. H. Bharath and S. Sreekantha, “Spatial Metrics based Landscape Structure and Dynamics Assessment for an emerging Indian Megalopolis,” in International Journal of Advanced Research in Artificial Intelligence, Vol. 1(1), pp. 48-57, 2012b.

[5] L. O. Petrov, C. Lavalle and M. Kasanko, “Urban land use scenarios for a tourist region in Europe: Applying the MOLAND model to Algarve, Portugal” in Landscape and Urban Planning, Vol. 92(1), pp. 10–23, 2009.

[6] J. Epstein, K. Payne, E. Kramer, “Techniques for mapping sub-urban sprawl,” Photogramm. Eng. Remote Sens., vol. 63(9), pp. 913–918, 2002.

[7] J.M. Kumar, P.K. Garg, D. Khare, “Monitoring and Modelling of Urban Sprawl Using Remote Sensing and GIS Techniques,” in Int. J Applied Earth Observation and Geoinformation, Vol. 10(1), pp. 26-43. 2008.

[8] K.B. Barnes, J.M. Morgan III, M.C. Roberge, S. Lowe, “Sprawl development: Its patterns, consequences, and measurement,” Towson University. 2001.

[9] D. J. B. Baldwin, K. Weaver, F. Schnekenburger, A. H. Perera, “Sensitivity of landscape pattern indices to input data characteristics on real landscapes: implications for their use in natural disturbance emulation,” in Landscape Ecology, Vol. 19, pp. 255 – 271, 2004.

[10] J. Gao and S. Li, “Detecting spatially non-stationary and scale-dependent relationships between urban landscape fragmentation and related factors using geographically weighted regression” in Applied Geography, Vol. 31(1), pp. 292 - 302. 2011.

[11] H.S. Sudhira, T.V. Ramachandra and K.S Jagadish, “Urban sprawl pattern recognition and modeling using GIS,” Paper presented at Map India, January 28- 31, New Delhi, 2003.

[12] S. Berberoglu, A. Akin, “Assessing different remote sensing techniques to detect land use/cover changes in the eastern Mediterranean,” in International Journal of Applied Earth Observation and Geoinformation, vol. 11, pp. 46–53. 2009.

[13] K. Muller, C. Steinmeier and M. Kuchler, “Urban growth along motorways in Switzerland” in Landscape and Urban Planning, Vol. 98(1), pp. 3–12, 2010.

[14] K. McGarigal, “Landscape pattern metrics,” In El-Shaarawi, A. H., & Piegorsch, W. W. (Eds.). (2002). Encyclopedia of environmetrics, Vol. 2 (pp.11 35-1142). Sussex, England: John Wiley & Sons. 2002.

[15] A. Botequilha Leitao and J. Ahern, Applying landscape ecological concepts and metrics in sustainable landscape planning. Landscape and Urban Planning, Vol. 59, pp. 65 -93. 2002.

[16] M. Kelly, K. A.Tuxen and D. Stralberg, “Mapping changes to vegetation pattern in a restoring wetland: finding pattern metrics

that are consistent across spatial scale and time," in Ecological Indicators, Vol. 11, pp. 263- 273. 2011.

[17] S, Bharath, H. A. Bharath, D.S. Durgappa and T. V. Ramachandra, "Landscape Dynamics through Spatial Metrics," in Proceedings of India GeoSpatial Conference, Epicentre, Gurgaon, India, 7-9 February. 2012.

[18] H.S. Sudhira, T.V. Ramachandra and K.S. Jagadish, "Urban sprawl: metrics, dynamics and modelling using GIS," in Int. J. Appl. Earth Observ. Geoinform. Vol. 5. pp. 29–39, 2004.

[19] J. Peng, Y. L. Wang, Y. Zhang, J. S. Wu, et al., "Evaluating the effectiveness of landscape metrics in quantifying spatial patterns" in Ecological Indicators, Vol. 10(2), pp. 217–223, 2010.

[20] R.O. Duda, P.E. Hart, D.G. Stork, "Pattern Classification," a Wiley-Interscience Publication, Second Edition, ISBN 9814-12-602-0. 2000.

[21] K. McGarigal and B. J. Marks, "FRAGSTATS: Spatial pattern analysis program for quantifying landscape structure. U.S. Department of Agriculture, Forest Service," Pacific Northwest Research Station. 1995.

[22] K.M. Lata, C.H. Sankar Rao, V. Krishna Prasad, K.V.S. Badrinath and Raghavaswamy, "Measuring urban sprawl: a case study of Hyderabad", in GIS Development, Vol. 5(12), pp. 26-29, 2001.

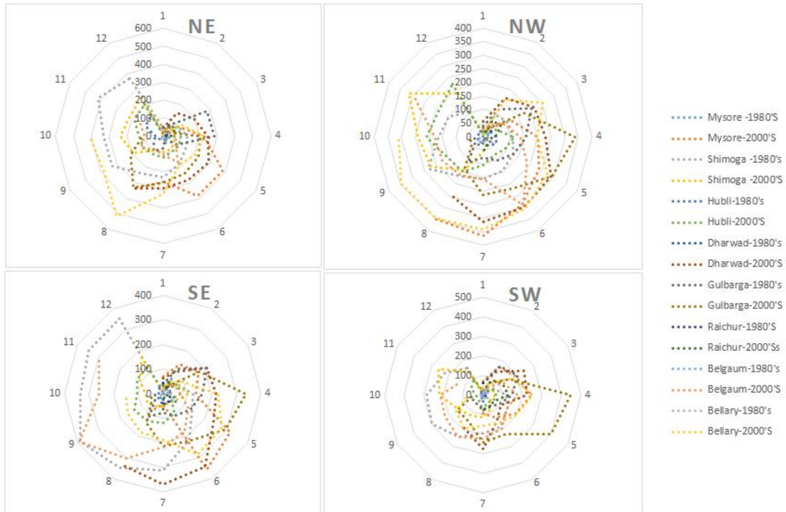


Figure 2: Number of urban patches in different zones and gradients

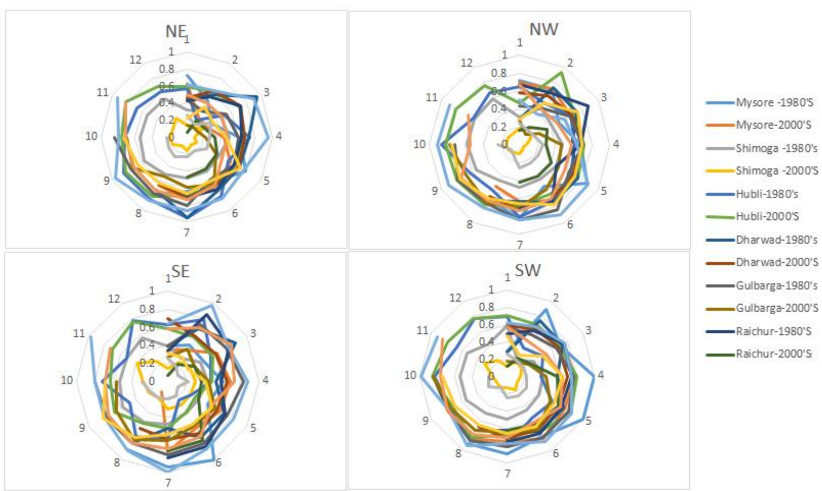
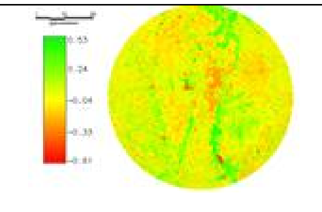
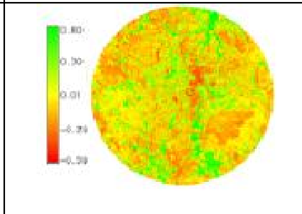
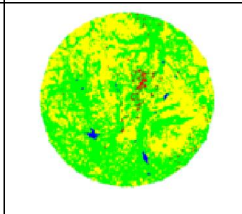
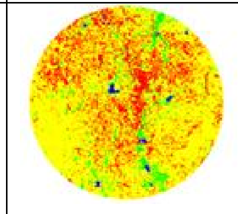
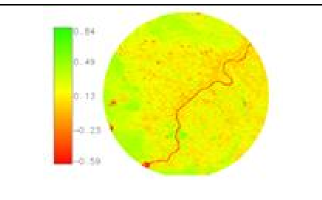
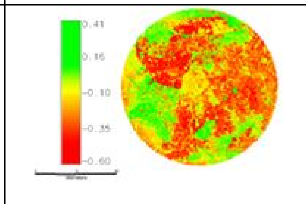
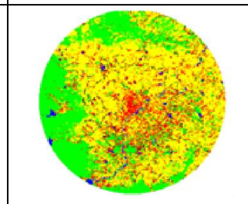
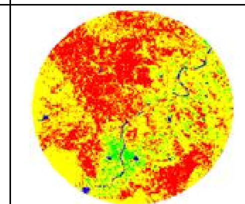
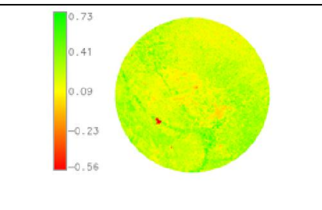
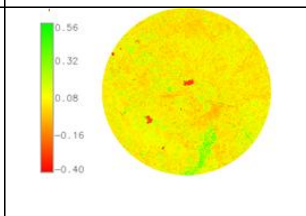
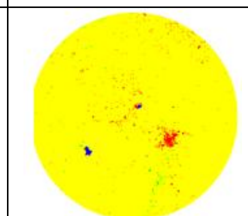
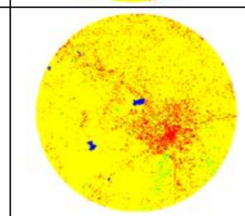
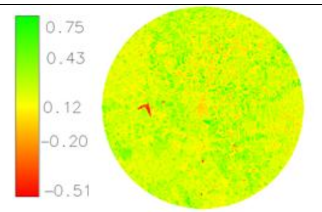
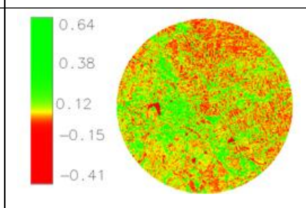
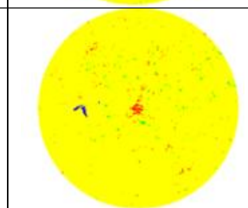
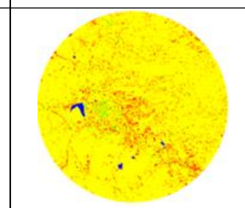
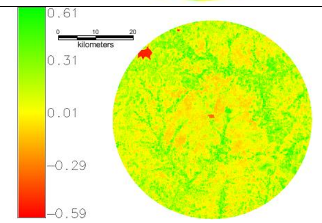
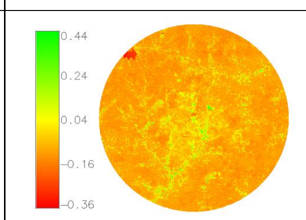
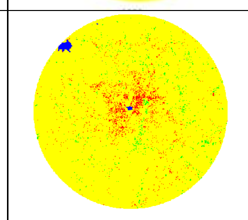
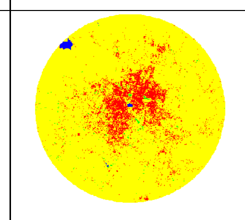
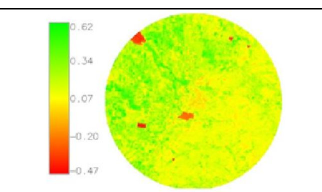
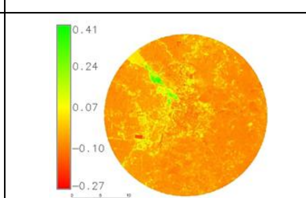
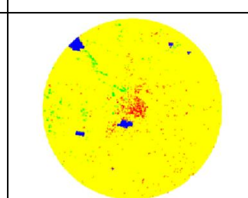
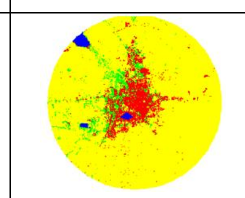
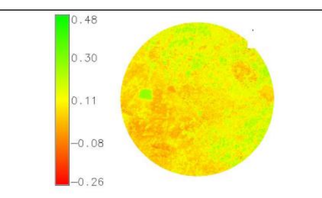
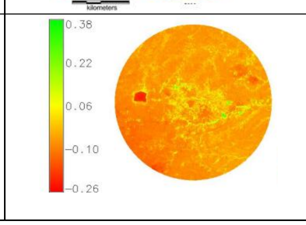
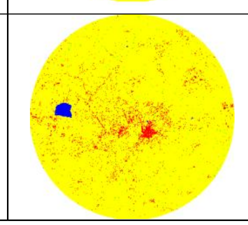
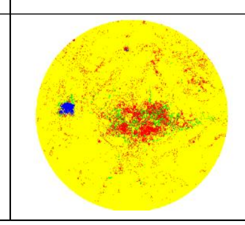
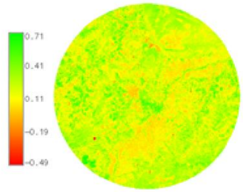
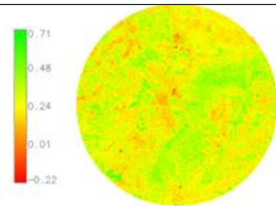
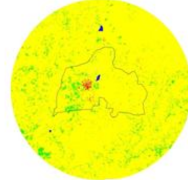
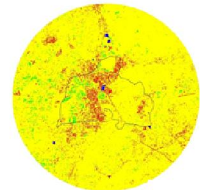


Figure 3: Normalised Landscape Shape Index in different zones and gradients

	Appendix I: Land cover		**Appendix II**: Land use	
	1980's	2000's	1980's	2000's
Mysore				
Shimoga				
Hubli				
Dharwad				
Gulbarga				
Raichur				
Bellary				

Belgaum				

Modeling and Simulation of Urbanisation in Greater Bangalore, India

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***Abstract*—the potential of Markov chain and cellular automata model for predicting the spatial and temporal urban growth dynamics has been evaluated for rapidly urbanizing Bangalore, India. The growth of Bangalore is visualized for the year 2020 using business as usual scenario. Multi temporal land use information, derived from remote sensing data of 2008, 2010 and 2012 have been used for simulation and validation. Urban growth patterns and processes were quantitatively assessed with the use of landscape metrics. The results indicate that the future expansion of greater Bangalore will be in the peri- urban landscapes, due to the current clumped urbanisation at the city core with little scope for further urban densification. Urban simulation modeling in conjunction with spatial metrics is effective in capturing and visualizing the spatio–temporal patterns of urbanisation with insights to the trajectory of urban growth for effective planning of the city.**

Keywords: Urban sprawl, Remote Sensing, Cellular Automata, Markov Chain, Modeling

I. INTRODUCTION

Urbanisation is a dynamic process involving the horizontal and vertical expansion of urban pockets in response to the population growth, industrialization, political, cultural and other socio-economic factors[1][2][3]. Unplanned urbanisation leads to the large scale land cover changes [4] affecting the ecological diversity with degradation of the environment, enormous consumption of resources, creation of urban heat islands, changes in local climate [5][6], soil erosion, changes in hydrological cycle impairing surface water and ground water regime [7]. This process often leads to unstable development with increasing economic, social and environmental problems [8] such as radical changes of vegetation, water bodies, etc., with the irretrievable loss of ground prospects due to drastic change in the landscape [9]. These are often driven by the uncontrolled and dispersed growth along the periphery, which is referred as urban sprawl. The process of urban sprawl is common in rapidly urbanizing metropolitan cities. Rapid rise in urban population has caused serious environmental damages with problems such as increasing slums, decrease in standard of living, etc. [10]. The urban sprawl process has been studied in many developing regions [11][12][13][14][15][16] as it leads to drastic change in the landscape. Therefore spatio-temporal changes in urbanisation pattern would help in assessing land use changes, which would provide insights to the extent and rate of urban sprawl. Land use refers to use of the land surface through modifications due to anthropogenic activities or natural phenomena [1][12][17]. Quantification of impervious manmade surfaces in and around the city through mapping would help in estimating the dispersed growth of urban pockets. . The traditional surveying and mapping techniques to monitor landscape changes over different time frames entails high expenses due to time as well as requirement of resources for mapping and inventorying exercises. Recent advancements in mapping and modeling [18] through spatial data acquired remotely through space-borne sensors (remote sensing data) and the analysis of spatial data through Geographic Information System [GIS] have enhanced the abilities of spatial data analysis. Remote sensing technique [1][12][15][16][17][18] has advantages such as wider synoptic coverage of the earth surface with varied temporal, spatial and spectral resolutions. Classifications of these data through already proven classification algorithms [1][17][18] provide land use information. These temporal information helps to measure, monitor and visualise changes, which are necessary to model and simulate the likely changes in spatial patterns. Modelling enables the prediction of likely future land cover changes, required for evolving strategies for appropriate decisions and policies, interventions [19] to mitigate the drastic land cover changes. Prediction of changes based on the current trend will help in understanding the role of influencing factors and constraints. Research in this direction have focused on modelling and predicting changes in forest and hydrology, effect of urbanisation on runoff, soil erosion, urban sprawl, etc. [19][20][21][22][23][24]. Models such as Cellular Automata (CA), CA-Markov, Geomod, Land Change Modeler (LCM), Sleuth, Agent Based Modeling (ABM), Multi Criteria Evaluation (MCE), Regression, Neural Networks, etc., have been used for simulating urban sprawl [20][25][26][27][28][29] [30]. Studies have demonstrated the use of Markov chains

combined with cellular automata as one of the effective technique in modeling urban sprawl pattern [20][26][28][29].
Markov chain and cellular automata:Cellular Automata (CA) are algorithms which define the state of the cell based on the previous state of the cells within a neighborhood, using a set of transition rules. CA have a potential for modelling complex spatio-temporal processes such as urban process. CA is made up of elements represented by an array of cells, each residing in a state at any one time, discrete number of class (states), the neighborhood effect and the transition functions, which define what the state of any given cell is going to be in the future time period. The cell space digitally in the CA consists of a rectangular grid of square cells each representing an area 30mx30m and matches the size as the minimum area mapped in urban areas in the land use datasets. Basic assumption that was used is cells are not homogeneous and are characterized by a vector of suitabilities, deciding the future land use. The suitabilities are defined as a weighted linear sum of a series various affecting factors characterizing each cell. They are normalized to values in the range of 0–1, and represent the inherent capacity of a cell to support a particular activity or land use which can be generated by Markovian random process, which is a stochastic process. In this urban cellular automaton, the neighborhood space is defined as a square region around the central cell with a radius of five cells. The neighborhood thus contains 24. The neighborhood influence area and the interactive area for urban land uses and its neighbors. The model uses 4 cell states. The active functions is urban land uses which are forced by demands for land generated exogenously to the cellular automaton in response to the growth of the urban area. Passive is represented by other land use classes. The effect on the neighborhood is thus calculated as summed effect of each transitional potential and its interaction with its neighbors and the transition rules: were determined by various demands of the land use classes, population growth etc.

Finally, spatial metrics have been useful to quantify the land use based on patch, shape, edge etc. This quantification provide insights to the historical and current spatial patterns, which is useful in evaluating the landscape heterogeneity in relation with urban growth [30][31][32]. The objective of the current research is to simulate urbanisation process of Bangalore city for 2020 through CA and CA-Markov model considering transition probabilities (based on Markov chain analysis). Spatial patterns of urbanisation is quantified using landscape metrics.

II. Study area

Bangalore the IT hub of India is located in the southern part of the country of Karnataka state. The region was known as “Bendakaaluru” (land of boiled beans), “land of lakes” where a large number of lakes were constructed to store water, during the regime of erstwhile princely state. Numerous parks, gardens such as Lalbhag, Cubbon Park etc. exist in the region, which aptly gave the name “Garden City”. However, during the post-independence due to industrialization, unplanned urbanisation the city has witnessed the decline in parks as well as water bodies / lakes. With the spurt in IT industries in the region during late 1990’s, the city was termed “Silicon Valley”. This policy interventions created job opportunities to different category of people. The city has grown spatially during the last year by 10 times and the current spatial extent is about 741 km^2.

Geographically Bangalore is located in the Deccan plateau, toward the south east of Karnataka state extending from 12^{o}49’5”N to 13^{o}8’32” N and 77^{o}27’29” E to 77^{o}47’2”E. To account for developments in the peri urban regions, the study area includes ten km buffer (from the administrative boundary) with a gross area of over 2250 km^2 as shown in Fig. 1. Bangalore has spatially increased from 69 sq.km (1901) to 741 sq.km (2006) [1].The decadal (2001 to 2011) increase in population for urban areas of India is 31.8% and in Karnataka is 31.5%, but Bangalore has a decadal increase of 44% very large compared to that of the state and country. The population has increased from 5.8 Million in 2001 (BMP – Bangalore Mahanagara Palike limits) to 8.4 Million in 2011 (current spatial extent of 741 sq.km, under jurisdiction of BBMP-Bruhat Bangalore Mahanagara Palike) [34][35]. The population density has increased from 7880 persons per square kilometer to over 11330 persons per square kilometer during the last ten years [34][36]. Bangalore receives an annual average rainfall of 896 mm [35][37]. The undulating terrain varying from about 700 m to about 962m AMSL in the region has resulted in the formation of large number of drainage network with inter connected lakes. Vegetation and water bodies are responsible for moderating the local climate and cooler days during summer.

Geologically [38][39], the prevailing rocks are light to dark grey Biotitic Granitic Gneiss and varies from place to place in texture, structure and appearance based on the fineness or coarseness of the grains, mode of disposition of dark minerals.

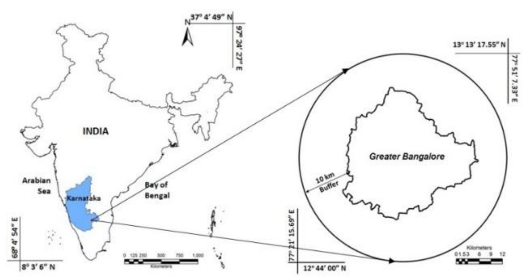

Fig.1. Study Area- greater Bangalore with 10 km buffer

The drainage network in Bangalore flows to Cauvery through its tributaries Arkavathi (East flowing), Pinakini/Pennar (East Flowing) and Shimsha (West Flowing). The central, northern and eastern portion is undulating with the upland tracts occupied by scrubs, while the low lands occupied by series of tanks formed by embanking the streams along the valley for irrigation purposes. These valleys vary in size with small ponds to large lakes. The southern portion of the land consists of hills that are close together and are surrounded by thick jungles.

III. DATA USED

Temporal remote sensing data of *Landsat 7 ETM+* sensors for the year 2008, 2010 and 2012 with resolution of 30 m were were downloaded from public domain (http://glcf.umiacs.umd.edu/data). 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 topo-sheet (1:50000 and 1:250000), Google earth (http://earth.google.com) and Bhuvan (http://bhuvan.nrsc.gov.in).

IV. METHOD

The process of urbanisation and sprawl in Bangalore (study area) have been assessed as outlined in Fig. 2, which includes (i) Land use analysis, (ii) Modeling and prediction, (iii) Urban Sprawl Analysis

A. Land use analysis:

The land use analysis was carried out for the 3 temporal data using the Gaussian maximum likelihood classifier. The data were classified under 4 different classes as shown in Table I. Satellite data classification involved (i) Preprocessing (ii) Classification (iii) Accuracy assessment.
Preprocessing: The raw satellite images geo-corrected, followed by radiometric correction and resampled to 30 m resolution to maintain uniformity for multi temporal data comparisons and for modeling.

Table I. Land use categories

Land use class	Land use included in class
Urban	Residential Area, Industrial Area, Paved surfaces, mixed pixels with built-up area
Water	Tanks, Lakes, Reservoirs, Drainages
Vegetation	Forest, Plantations
Others	Rocks, quarry pits, open ground at building sites, unpaved roads, Croplands, Nurseries, bare land

Land use classification and accuracy assessment: The method involves i) generation of False Color 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 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, iv) Supplementing this information with Google Earth/Bhuvan. Land use classification was done using supervised pattern classifier - Gaussian maximum likelihood algorithm based on various classification decisions using probability and cost functions [40].

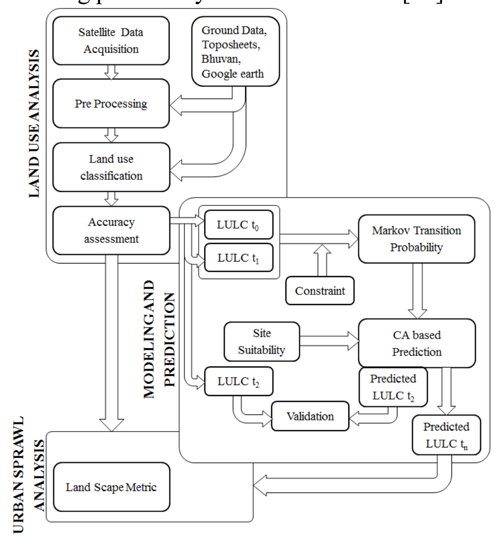

Fig .2. Procedure followed to model, understand the landscape changes

Land uses during the different period were computed using the temporal remote sensing data through open source GIS: GRASS- Geographic Resource Analysis Support System (http://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. Statistical assessment of classifier performance based on the performance of spectral classification considering reference pixels is done which include computation of kappa (κ) statistics.

Modeling and Prediction: The land use pattern is evolving dynamically and follows the Markovain random process properties with various constrains that include average transfer state of land use structure stable and different land use classes may transform to other land use class given certain condition (Such as non-transition of urban class to water or vice versa). Thus Markov was used for deriving the land use change probability map for the study region and was applied using Markov module. The probability distribution map was developed through Markov process. A first-order Markov model based on probability distribution over next state of the current cell that is assumed to only depend on current state [41]. CA was used to obtain a spatial context and distribution map. CA's transition rules use its current neighborhood of pixels to judge land use type in the future. State of each cell is affected by the states of its neighboring cells in the filter considered. Besides using CA transition rule and land use transition is governed by maximum probability transition and will follow the constraint of cell transition that happens only once to a particular land use, which will never be changed further during simulation. CA coupled with Markov chain was then used to predict urban land use state in 2020

Urban sprawl analysis: Post prediction and valdation with spatial metrics were employed to quantify the urban growth pattern. Spatial metrics aid in quantifying the land use pattern at a particular time [1][42]. Spatial metrics such as Number of urban patches (NP), Normalised landscape shape index (NLSI), edge density (ED), Clumpy, Pladj were used in the analysis.These selected metrics signify patch, contagion, edge, shape and adjacency.

V. Results and Discussions

A. Land use: Land use analysis was carried out for the year 2008, 2010, and 2012 using the Gaussian maximum likelihood classifier . Fig. 3 depicts land use and categorywise changes are listed in Table II. This illustrate an increase in urban area by about 2 folds i.e., from 24.86 % (in 2008) to 48.39% (2012) with the decline of vegetation from 38.34% to 26.40% and other category from 36.26% to 26.85% respectively, indicating a rapid urbanisation process.

*B. Accuracy Assessment:*Accuracy assessment of the classified information of land use was performed by generating the reference image through the traing data (30% of the ground truth data). Overall accuracy and Kappa was calculated using the module r.kappa in GRASS. The results of accuracy assessment are as shown in Table III.

C. Modeling and Prediction

Land use [LU] transitions were calculated to predict land use for the year 2012, using markov chain based on 2008 and 2010 LU and CA loop time of 2 years. With the knowledge of 2008 and 2012, LU for 2020 is predicted. CA filter (Fig.4) was used to generate spatially explicit contiguity weightage factor to change the state of the cell based on neighborhoods. This prediction has been done considering water bodies as constraint and assumed to remain constant over all time frames.

The Multi criterion analysis was used to generate transition probability areas based on transition rules and constraints for 2010 and 2012 LU data. The transition probabilities from Markov and the transition areas from CA were used to predict land use for the year 2012 (Fig. 3). The model was scrutinized for allowable error by validating the predicted versus the actual 2012 land use (Fig. 3). The validation results (Table V) showed a very good agreement between the actual and predicted 2012 LU with kappa of 0.73. On similar lines, LU is simulated for 2020 (Fig.5). The simulated land use (Table V, Fig.5) shows an increase in built up from 48.66 % (2012) to 70.64% (2020). The process of urbanization is observed to be high in the North East direction, near arterial roads and the national/state highways.

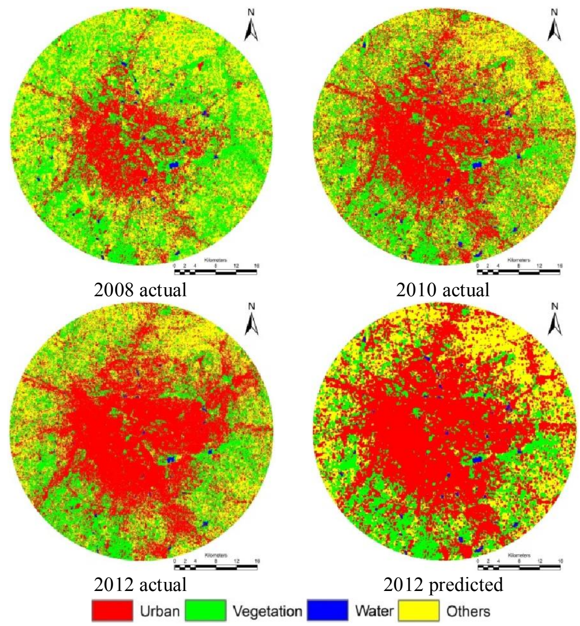

Fig.3. Time series land use maps between 2008 and 2012

TABLE I. Land use statistics

Year	2008	
Land use	Area in hectares	Percent
Urban	49,958.91	24.86
Vegetation	77,042.07	38.34
Water	1069.20	0.53
Others	72,852.48	36.26
Year	**2010**	
Land use	Area in hectares	Percent
Urban	85,012.20	42.30
Vegetation	57,148.47	28.44
Water	1271.43	0.63
Others	57,524.58	28.63
Year	**2012**	
Land use	Area in hectares	Percent
Urban	97,531.11	48.66
Vegetation	49,175.64	24.40
Water	723.60	0.63
Others	54,115.02	26.85
Year	**2012 - Predicted**	
Land use	Area in hectares	Percent
Urban	107,754.48	51.62
Vegetation	44,287.92	23.04
Water	1491.21	0.74
Others	47,423.07	21.60

TABLE II. Accuracy Assessment

Year	Overall accuracy %	Kappa
2008	86.35	0.78
2010	91.62	0.86
2012	90.43	0.85

0	0	1	0	0
0	1	1	1	0
1	1	1	1	1
0	1	1	1	0
0	0	1	0	0

Fig.4. Filter designed for analysis

TABLE III. MARKOV TRANSITION PROBABILITIES

	Urban	Vegetation	Water	Other
Urban	0.8	0.0667	0.0667	0.0667
Vegetation	0.2443	0.4697	0.0047	0.2813
Water	0.3372	0	0.6628	0
Other	0.3476	0.2046	0.0018	0.446

TABLE IV. VALIDATION BETWEEN PREDICTED AND ACTUAL 2012

Kno	0.8443
Klocation	0.8678
Kstandard	0.8557

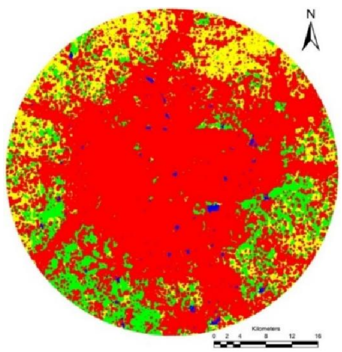

Fig.5. Predicted land use map for 2020

TABLE V. LAND USE 2020

Year	2020 - Predicted	
Land use	Area in hectares	Percent
Urban	142,381.08	70.64
Vegetation	27,316.44	13.55
Water	1491.21	0.74
Others	30,356.64	15.07

D. Urbanisation pattern analysis through spatial metrics:

Number of urban patches that gives us degree of fragmentation was calculated for the urban class. The results of the analysis showed the landscape was highly fragmented with 16000 patches in 2012 and by 2020 gets clumped to form an aggregated core connected (along highways) and some clumped developments at outskirts. This signifies the formation of an urban core (Fig. 6) with loss of all other land use (except water) and fragmented urban patches.

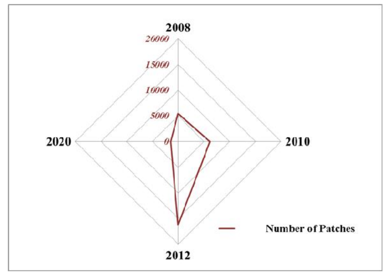

Fig. 6. Number of urban patches

Edge density and Percentage land adjacencies (Pladj) (Fig. 7) were also calculated. Edge is formed when the urban landscape in covered by other land uses. Edge density are significantly higher in 2012 due to fragmented urban landscape and in 2020, the edge density declines to 15 signifying the formation of homogenous urban landscape. Pladj metric accounts to percentage of adjacent landforms of same land use. This also implies that in 2020 the urban class becomes most adjacent dominating class with the loss of other classes.

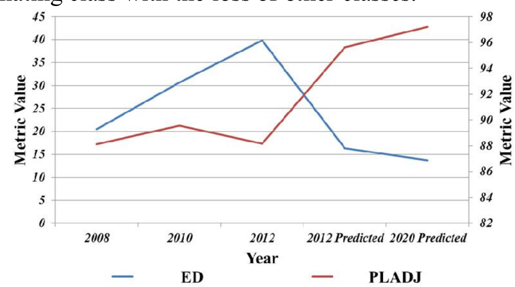

Fig. 7. Edge density and percentage of land adjacencies

Finally NLSI (Normalised landscape shape index) and clumpiness indices were calculated to understand the shape of the landscape and its form. NLSI shows increased value indicating a simple shape or clumped growth. While, in 2008 the lower value indicating convoluted shape, indicating heterogeneous or fragmented landscape with the presence of all land uses next to urban.

Clumpiness index show of clumped growth with the domination of urban land use in 2020, whereas in 2012 the region is with significantly higher proportion of other contributing land uses. Spatial metrics conform of clumped urban growth in Bangalore by 2020 with the loss of all other LU's indicating an urban paved jungle. This necessitates integrated approaches in land use planning to minimize the damage on local ecology and hydrology due to decline of LU other than urban category. The visualized outcome for 2020 indicates the certain doomsday for the Bangalore city with the current lopsided approaches in urban planning. This will lead to further changes in the regional climate; enhance pollutants in air and water, increase of temperature, consequent thriving of disease vectors and loss of vital natural resources.

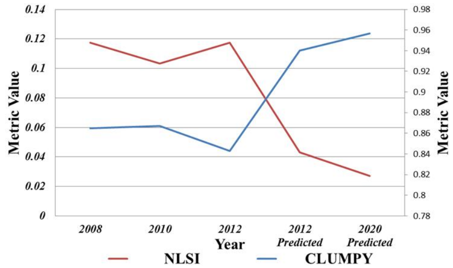

Fig. 8. Normalised Landscape Shape index and Clumpiness index

VI. CONCLUSION

Bangalore is in the forefront among rapidly urbanizing cities in India. The uncontrolled growth has led to the decline of landscape heterogeneity affecting the natural resources as well as local ecology. Visualization of the patterns of urbanisation provides insights required for an effective regional planning to ensure sustainability. The current work in this regard, through Markov based CA modeling predicts the urbanisation patterns in 2012 and compares with the actual growth. As there was a good agreement between the actual and predicted 2012, exercise was extended to predict LU in 2020.

This research demonstrate the applicability of urban growth modeling using Markov chain and CA. Visualization of likely changes (based on the current pattern of urbanisation) will provide crucial insights necessary to develop and plan for sustainable Bangalore. In this context, the prediction of homogenous landscape with clumped urban growth by 2020, and the disappearance of ecologically important landscape elements – vegetation, open spaces and water bodies. This necessitates integrated approaches in land use planning to minimize the damage on local ecology and hydrology due to decline of LU other than urban category. The visualized outcome for 2020 highlights the implications of the current lopsided approaches in urban planning. This will lead to further changes in the regional climate; enhance pollutants in air and water, increase of temperature, consequent thriving of disease vectors and loss of vital natural resources. However, the city development plans and policy documents still emphasize the continuation of the current approaches of urban expansion during the next decade. This would only lead to the concrete jungle with polluted environment and scarcity of lifeline (water and clean air) of the city.

Predicted scenario of 2020 reveals that apart from distinct developments driving urbanization in main urban road corridors, there will be spurt in the built-up area in northeast and northwest of Bangalore. This can be attributed to small towns gaining importance industrially and residentially due to Kempegowda international airport in the region. This research shows that new urban nuclei will emerge in the next two decades and will be significantly clustered in space, while the outer buffer region will be more fragmented. This endeavor provide invaluable inputs for sustainable city planning. Nevertheless the exercise is fruitful only when bureaucracy - policy makers, urban planners and city managers take note of the implications of poor planning. Further research in progress in this domain focusses on integration of various agents and evaluation of proposed development plans and likely scenario of integrating land use with mobility.

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REFERENCES

[1] T.V. Ramachandra, Bharath H. Aithal and D.S. Durgappa, “Insights to urban dynamics through landscape spatial pattern analysis”, International Journal of Applied Earth Observation and Geoinformation, vol.18, p. 329-343, 2012.

[2] H. Wang, S. He, X. Liu, L. Dai, P. Pan, S. Hong, W. Zhang, “Simulating urban expansion using a cloud-basied cellular model: A case study of Jiangxia, China”, Landscape and Urban Planning, vol.110, p. 99-112, 2013.

[3] H. Wang, S. He, X. Liu, L. Dai, P. Pan, and W. Zhang, “Simulating urban expansion using a cloud-based cellular automoat model: A case study of Juangxia,Wuhu,China”, Landscape and Urban Planning , vol.110, p. 99 – 112, 2013

[4] J. Mahesh Kumar , P.K. Garg, and K. Deepak, “Monitoring and modelling of urban sprawl using remote sensing and GIS techniques” International Journal of Applied Earth Observation and Geoinformation, vol.10, p. 26-43, 2008

[5] J.A. Foley, R. DeFries, G.P. Asner, C. Barford, G. Bonan, S.R. Carpenter, F.S. Chapin III, M.T. Coe, G.C. Daily, H.K. Gibbs, J.H. Helkowski, T. Holloway, E.A. Howard, C.J. Kucharik, C. Monfreda, J.A. Patz, C. PrenticenI, N. Ramankutty and P.K. Snyder, “Global consequences of land use”, Science, vol.309, p. 570–574, 2005.

[6] N.B. Grimm, S.H. Faeth, N.E.Golubiewski, C.L.Redman, J.G. Wu, X.M. Bai and J.M. Briggs, “Global change and the ecology of cities”, Science, vol.319, pp 756–760, 2008.

[7] Qihao Weng., 2001. “Modeling urban growth effects on surface runoff with the integration of remote sensing and GIS”. Environment. Management, vol.28 (6), p. 737–748

[8] P.A. Jean, “Urban sprawl modeling: A methodological approach”, 12th European Colloquium on Quantitative and Theoretical Geography. St-Valery-en-Caux, France, September 7-11, 2001.

[9] S.K. Pathan, J.G. Patel, R.J. Bhanderi Ajai, Kulshrestha, V.P. Goyal, D.L. Banarjee, S. Marthe, V.K. Nagar, and V. Katare, “Urban planning with specific reference to

master plan of lndore city using RS and GIS techniques". Proc. of GSDI-7 International Conference on Spatial Data Infrastructure for Sustainable Development, held at Bangalore from Feb, 2-6, 2004.

[10] V. Nath; and S.K. Aggarwa, "Urbanisation, Urban Development, and Metropolitan Cities in India". Concept Publishing Company. pp. 3, 2007

[11] K.M. Lata, C.H.S. Rao, V.K. Prasad, K.V.S. Badarianth, and V. Raghavasamy, "Measuring Urban sprawl: A case study of Hyderabad". gis@development, vol. 5(12), p. 26-29, 2001

[12] H.S. Sudhira, T.V. Ramachandra and K.S Jagadish, 2004, "Urban sprawl: metrics, dynamics and modelling using GIS". International Journal of Applied Earth Observation and Geoinformation, vol. 5, p. 29-30.

[13] A. Yeh, X. Li, "Measurement and monitoring of urban sprawl in a rapidly growing region using entropy. Photogrammetric engineering & remote sensing", vol. 67 (1), p. 83-87, 2001

[14] F. Fan, Y. Wang and Z. Wang, "Temporal and spatial change detecting (1998–2003) and predicting of land use and land cover in Core corridor of Pearl River Delta (China) by using TM and ETM+ images", Environ Monit Assess, vol. 137, p.127–147, 2008.

[15] T.V. Ramachandra, and H.A. Bharath, "Spatio-Temporal Pattern of Landscape Dynamics in Shimoga, Tier II City, Karnataka State, India" International Journal of Emerging Technology and Advanced Engineering, vol.2(9) ,p. 563-576, 2012.

[16] T.V. Ramachandra, H.A. Bharath and S. Sreekantha, "Spatial Metrics based Landscape Structure and Dynamics Assessment for an emerging Indian Megalopolis", International Journal of Advanced Research in Artificial Intelligence,vol.1(1), p. 48 – 57, 2012

[17] M.T. Lillesand, W.R. Kiefer, and W.J. Chipman, "Remote Sensing and Image Interpretation", 5th ed. John Wiley and Sons. 2004

[18] E. Jeanne, P. Karen, and K. Elizabeth, "Techniques for mapping suburban sprawl". Photogrammetric engineering & remote sensing, vol. 63 (9), p.913–918, 2002

[19] M. Pinki Mondal and S. Jane, "Evaluation of conservation interventions using a cellular automata-Markov model" Forest Ecology and Management, vol.260, p. 1716–1725, 2010

[20] C. Xu, Y.S. Xiao and Z.A. Ping, "Evaluation of Spatiotemporal Dynamics of Simulated Land Use/Cover in China Using a Probabilistic Cellular Automata-Markov Model", Pedosphere, vol.23(2), p. 243–255, 2013.

[21] P. Sushant, Y. Fei , " Assessing landscape changes and dynamics using patch analysis and GIS Modelling" ,International Journal of Applied Earth Observation and Geoinformation, vol.16, p. 66-76, 2012.

[22] R.G. Pontius Jr., D.C. Joseph, A.S. Charles Hall, "Modeling the spatial pattern of land-use change with GEOMOD2: application and validation for Costa Rica" Agriculture, Ecosystems and Environment, vol. 85, p. 191–203, 2001.

[23] F. Oñate-Valdivieso, Joaquín Bosque Sendra, "Application of GIS and remote sensing techniques in generation of land use scenarios for hydrological modeling", Journal of Hydrology, vol.395, p. 256–263, 2010

[24] D. Stevens, S. Dragicevic, and K. Rothley, 2007, "iCity: A GIS-CA modelling tool for urban planning and decision making", Environmental Modeling and Software, vol.22, p. 761-773, 2007

[25] C.King, N.Baghdadi, and V. Lecomte, O. Cerdan, 2005, "The application of Remote Sensing data to monitoring and modelling soil erosion", CATENA, vol.62, p. 79-93, 2005.

[26] H. Wang, S. He, X. Liu, L. Dai, P. Pan, S. Hong, W. Zhang, "Simulating urban expansion using a cloud-basied cellular model: A case study of Jiangxia, China", Landscape and Urban Planning, vol.110, p. 99-112, 2013.

[27] L. Apostolos, "Urban sprawl simulation linking macro-scale process to micro-dynamics through cellular automata, an application in Thessaloniki, Greece", Applied Geography, vol.34, p. 146-160, 2012

[28] D. Guan, H. Li, T.Inohae, W. Su, T. Nagaie, and Kazunori, "Modeling urban land use change by the integration of cellular automaton and Markov chain", ecological Modelling, vol.222, p. 3761 – 3722, 2011.

[29] J.A. Jokar, M. Helbich, W. Kainz, and B.A. Darvishi, " Integration of Logistic Regression and Markov Chain Models to Simulate Urban Expansion", International Journal of Applied Earth Observation and Geoinformation, vol.21, p. 265-275,2013

[30] M. Herold, H. Couclelis, K.C. Clarke, "The role of spatial metrics in the analysis and modeling of urban land use change," Computers, Environment and Urban Systems, Vol. 29, pp.369–399, 2005.

[31] JI. Wei, Jia Mia, R. W. Twibell, K. Underhill, "Characterizing Urban Sprawl using Multi Stage Remote Sensing Images and Landscape Metrics," Computers, Environment and Urban Systems, Vol.30, pp 861 – 879, 2004.

[32] McGarigal K, Marks BJ (1995) "FRAGSTATS: spatial pattern analysis program for quantifying landscape structure". USDA Forest Service General Technical Report PNW-351 http://www.fs.fed.us/pnw/pubs/gtr_351.pdf

[33] Ye.B and Bai.Z, "Simulating Land Use/Cover Changes of Nenjiang County Based on CA-Markov Model",

Computer and Computing Technologies In Agriculture, vol. 1, p. 321 – 329, 2008

[34] Census India, http://censusindia.gov.in/, accessed on 1 August 2013

[35] Bangalore urban district at a glance, Jilla Statistics Department Bangalore Urban, 2011-2012

[36] http://www.bbmp.gov.in/.

[37] http://www.imd.gov.in

[38] Bangalore District Gazetteer, 2012

Proc. of Int. Conf. on Advances in Computer Science, AETACS
NCR Delhi, December 13-14th .2013.

ELSEVIER

Prediction of Land use Dynamics in the Rapidly Urbanising Landscape using Land Change Modeller

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***Abstract*—Landscape transformations in the rapidly urbanizing landscape are the most dynamic process altering the local ecology, hydrology and environment. This necessitates understanding of spatial patterns of the growth for an effective urban planning. Remote sensing data acquired at regular intervals through satellite borne sensors enables the synoptic monitoring and visualization of urban growth patterns and dynamics. Focus of this communication is to model the land use dynamics in a rapidly urbanizing landscape with 10 km buffer considering all agents. Due to the unplanned urbanization, Bangalore a Silicon Valley of India has been facing numerous challenges of loss of green space, mobility constraints, higher pollution levels, flooding, indiscriminate disposal of solid and liquid waste, etc. Land Change Modeller (LCM) with Markov Cellular Automata was used to predict likely land use in 2020 with the knowledge of land use changes during 2006-2012 with the constraint of no-change in land use of water category. The results suggest an urban expansion of 108% (from 59103.9 in 2012 to 123061.6 hectares in 2020), with the decline of green space to 7% from 33.68% (2012). The visualised urban growth provide vital insights for better planning of urban space to ensure Bangalore regain the status of liveable and sustainable city.**

***Index Terms*— Urban growth, Modelling, Land change modeller, Cellular automata, Bangalore.**

I. INTRODUCTION

Large scale land-use land-cover (LULC) dynamics leading to the decline of vegetation cover is one of the drivers of global climate changes and alteration of biogeochemical cycles. Global warming and consequent changes in the climate has given momentum to investigate the causes of LULC by mapping and modelling landscape patterns and dynamics and evaluate these in the context of human-environment interactions in the rapidly urbanizing landscapes. Human induced environmental changes and consequences are not uniformly distributed over the earth. However their impacts threaten the sustenance of human-environmental relationships. Post-independence period in India, particularly during the globalization era in 1990's, the government facilitated the interactions of global industries with in-house industries. Large scale industrialization paved way for major LULC changes, caused by migration of people from different parts of the country, also from other parts of the globe and country for the employment opportunities. These led to intense urbanisation of major metropolitan cities with spurt in human population due to migration and also sprawl in peri-urban pockets. Unplanned urbanisation are characterized by the loss of diversity, with changes in the coherence and identity of the existing landscapes. The drastic landscape changes are a threat or a negative evolution, as it affects the sustenance of natural resources. Urbanisation process leads to conversion of ecological land use (such as vegetation. Open area, cultivable lands, water) into impervious layers on the earth surface. Increasing unplanned urbanisation is an important cause for depletion of resources species extension, hydro-geological alterations, loss of crop lands [1, 2]. Unplanned urbanisation has various underlying effects such as dispersed growth or sprawl.

Urban Sprawl refers to an uncontrolled, unplanned, scattered urban growth as a consequence of socio economic infrastructural development leading to increase in traffic, deficit of resources by depletion of the locally available resources while creating demand for more resources [3], often exceeding the carrying capacity of the land. Sprawl causes a major imbalance between urban spatial expansion and the underlying population growth [4].The dispersed growth or sprawl occurs basically in the periphery and the outskirts and these regions are devoid of any basic amenities or infrastructure. Sprawl can be in the radial direction encircling the city center or in linear direction along the highways, ring roads, etc. This necessitates visualization of urban trajectory for an effective urban planning.

Urban area currently with about 4 billion population, is projected to reach 8 billion by 2050 [4], which would be about 72% of the global population. Megacities, large agglomerations, are main consumers of natural resources (energy, food, etc.) with the generation of waste [5] beyond assimilative capacity of the region, continue to evolve and grow [6] with further loss of biodiversity, environmental degradation, affecting human health [1]. This phenomenon is most prevalent in developing countries [1, 6] especially the rapidly developing regions in India and other Asian countries [3]. This development may be due to various factors such as political, geographical, shortage of viable land for development etc., based on region and national scale [1, 2]. Urban sprawl with lack of appropriate infrastructure and basic amenities, affects urban space with due to the loss of agricultural and rural land, degradation of natural ecosystems, etc. The major causes of sprawl are attributed to huge growth of population, migration from rural to urban areas and unplanned developments. The urbanisation of core region also fuels the growth at outskirts as the population tends to move outskirts due to their lack of affordability. Demographic change not only imply the shift from high to low rates of fertility and mortality and is also associated with the development of households and features of their life cycle. The family or life-cycle features relate mainly to labour availability at the level of households, which is linked to migration, urbanization, and the breakdown of extended families into several nuclear families. At longer timescales, the increase of population also has a large impact on land use in a region. Hence there is a need for better planning and administration. For better land use planning changes in current land use patterns temporally is essential. This necessitates the analysis of land use changes and the prediction of likely changes in the future.

Availability of spatio-temporal data with the advancement of remote sensing technologies [7] has enabled unbiased land use analysis. Analysis of land use dynamics has attained research attention both at global and Indian contexts focusing on dynamically evolving cities [8]. Temporal land use changes at regional levels have s been attempted by various researchers [9, 10]. Several studies have assessed urban growth in various megacities around the world [1, 11, 12]. These studies though mapped and focused on temporally evolved current land use across various cities, have not addressed the likely growth required for the regional planning. Prediction of future growth are essential to control the uncontrolled development and plan for sustainable cities. Predictive models become very significant as they foresee spatial changes based on the historical land uses, which helps the decision makers in planning the growth including sprawl across the city periphery.

Urban growth models can be broadly grouped as (a) statistical models, based on regression and Markov chain [13] (b) dynamic evolving models, such as Cellular Automata (CA) [14]. Dynamic models are better suited to predict land use changes. Dynamical models coupled with agents of changes based on elements of different modelling techniques will help in better understanding of past land use changes for modelling land use dynamics.

A Multi-layer perceptron (MLP) based CA-Markov model with a capability to incorporate the agents of spatial changes is a powerful tool [15] to predict the growth. MLP helps in calibrating the agents and its relationship with land use changes. Markov chain helps in generating transition probability matrices based on the understanding of land use changes [16]. CA with markov considering spatial context based on neighbourhood configuration generates transition potential maps [17]. CA-Markov model is effective to model urbanisation [15]. However, for models to be effective there is a need for incorporating the agents such as social factors, economic factors, geography of an area which have decisive role in the urban process of a region. This has been demonstrated through incorporation of socioeconomic data into CA-Markov to predict land use changes [15]. this highlights the need for considering agents of changes, which still remains a research challenge.

The objective of this study is to simulate future land use changes in Bangalore, India based on the MLP-CA-Markov model considering the agents of current changes. MLP was used to calibrate the agents considering the transition of land use changes. Transition matrix is computed using the transition potential sub models based on the land use maps (2008, 2010, 2012) using the Markov chain module in Land use change modeller. Finally, spatial distribution of land uses from 2012 to 2020 are simulated through CA model with transition matrix and transition potential map.

II. Study Area And Data

Greater Bangalore capital of Karnataka, India with a spatial extent of 741 km^2 is geographically located at 12°49’5”N to 13°8’32”N and 77°27’29” E to 77°47’2”E in the south eastern part of Karnataka state (Fig. 1). Bangalore urban area has spatially increased from 69 sq.km (1901) to 741 sq.km (2006) [1]. The study has been carried out for Bangalore with ten km buffer (with a gross area of 2290 sq.km) to account for likely sprawl in peri-urban regions.

The undulating terrain with elevation ranging from 700 m to about 962m AMSL of the region has aided in the formation of cascaded lakes with interconnecting drains. Large number of water bodies with green cover has aided in moderating the city climate and maintaining salubrious climate. Temperature varies from 22°C to 38 ˚C during summer and 14 ˚C to 27 ˚C in winter. Bangalore receives an annual average rainfall of 824 mm. geologically the area consists of Granitic and Gneisses rocks in large scale [16].

The population [1] of Bangalore (BBMP) has increased to a large extent in a decade at a rate 44% i.e., from 5,840,165 (2001) to 8,395,947 (2011) at a rate of 4.4% annually, higher than the national average of 2.5%. The population density in the region has increased from 8179 (2001) to 11756 persons/km^2 (2011). Bangalore has a decadal increase of 44%, which is very high compared to that of Karnataka state (31.5%) and India (31.8%).

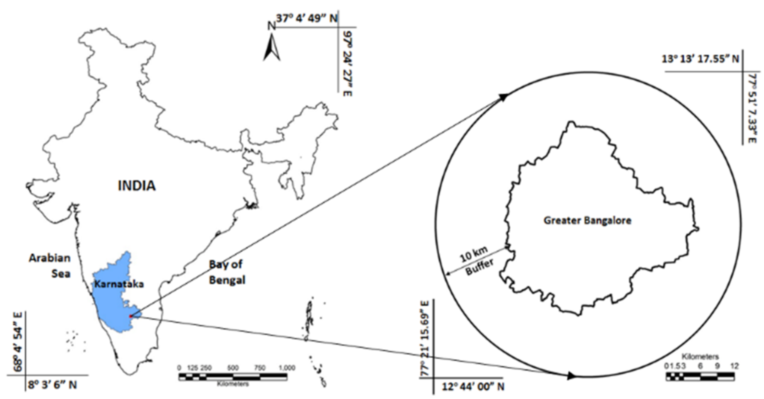

Fig.1. Study Area

Table 1 lists the data used for land use analysis. Temporal remote sensing data of Landsat TM and ETM+ were used to analyse and model LULC changes. Remote sensing data were supplemented with the Survey of India toposheets of 1:50000 and 1:250000 scale, and Bhuvan data, which were used to generate base layers of the administrative boundary, drainage network, Road network etc. Ground control points (GCPs) and training data were collected using pre calibrated Global Positioning System (GPS) and virtual online spatial maps such as Google Earth and Bhuvan GCPs were useful in geometric correction of remote sensing data.

Training data were used for classification, verification and validation of the classified results. Google earth data was also used to extract the point data such as location of industries, bus stops, railway stations, metro stations, social, religious structure’s, cemeteries, educational and others (police stations, hospitals, theatres) and line features such as road network. These features were verified in the field using handheld calibrated GPS.

TABLE1: MATERIALS USED IN ANALYSIS

Data	Year	Description
Landsat TM (28.5m)	2008, 2010, 2012	Land Use Land Cover Analysis
ASTER DEM (30 m)	2012	Generation of Slope map
SOI toposheets		1:250000 and 1: 50000 toposheets for delineating administrative boundaries, and geometric correction, Delineation of road network
Bhuvan		Support data for Site data, Delineation of road network, Delineation of village and city boundaries
GPS		classification and data validation
Google Earth		Support data for site data, Delineation of road network, preparation of point database files as input for modelling
Census	1991, 2001, Provisional 2011	Population census for growth monitoring

III. METHOD

Modelling of urbanization and sprawl as outlined in Fig. 2, involved

i) Remote Sensing data acquisition, geometric correction, field data collection,
ii) Classification of remote sensing data and accuracy assessment using GRASS,
iii) Identification of agents and development of attribute information using MapInfo,
iv) Designing three scenarios of urban growth and calibrating the model to find out the best weights based on the influence on the neighborhood pixels,
v) accuracy assessment and validation of the model,
vi) Prediction of future growth based on validated data
vii) Computation of spatial metrics and analysis.

Image pre-processing: The remote sensing data of Landsat TM with spatial resolution of 30 m were acquired from USGS. These data were geometrical corrected using polynomial transformations and pre-processed for noise removal.

Land use analysis: Analysis was carried out using supervised pattern classifier - Gaussian maximum likelihood algorithm. This method has already been proved as a superior method as it uses various classification decisions using probability and cost functions [17]. Mean and covariance matrix are computed using estimate of maximum likelihood estimator. Four major types of land use classes were considered: built-up area, vegetation, open area, and water body as described in table 2. The method involves a) generation of false colour composite (FCC) of remote sensing data (bands – green, red and NIR). This helped in locating heterogeneous patches in the landscape b) 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, c) loading these training polygons co-ordinates into pre-calibrated GPS, d) 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, e) supplementing this information with Google Earth f) 60% of the training data has been used for classification of the data, while the balance is used for validation or accuracy assessment.

Training data was collected in order to classify and also to validate the results of the classification. Land use analysis was carried out with supervised classification scheme using training data. The supervised classification approach is adopted as it preserves the basic land cover characteristics through statistical classification techniques using a number of well-distributed training pixels. Maximum likelihood algorithm is a common, appropriate and efficient method in supervised classification techniques by using availability of multi-temporal "ground truth" information to obtain a suitable training set for classifier learning. Supervised training areas are located in regions of homogeneous cover type. All spectral classes in the scene are represented in the various subareas and then clustered independently to determine their identity. ***GRASS GIS (Geographical Analysis Support System)*** an open source software has been used for the analysis, which has the robust support for processing both vector and raster files accessible at [18]

Accuracy assessment: Accuracy assessments decide the quality of the information derived from remotely sensed data. The accuracy assessment is the process of measuring the spectral classification inaccuracies by a set of reference pixels. These test samples are then used to create error matrix (also referred as confusion matrix), kappa (κ) statistics and producer's and user's accuracies to assess the classification accuracies. Kappa is an accuracy statistic that permits us to compare two or more matrices and weighs cells in error matrix according to the magnitude of misclassification [1, 2].

TABLE II: LAND USE CATEGORIES

Land use Class	Land use included in class
Urban	Residential Area, Industrial Area, Paved surfaces, mixed pixels with built-up area
Water	Tanks, Lakes, Reservoirs, Drainages
Vegetation	Forest, Plantations
Others	Rocks, quarry pits, open ground at building sites, unpaved roads, Croplands, Nurseries, bare land

Modelling Land use scenario: Land use Change Modeller (LCM), an ecological modeller was used for modelling the land use scenario based on the data of 2008, 2010 and 2012. LCM module provides quantitative assessment of category-wise land use changes in terms of gains and losses with respect to each land use class. This can also be observed and analysed by net change module in LCM. The Change analysis was performed between the images of 2008 and 2010, 2010 and 2012, to understand the transitions of land use classes during the years. Threshold of greater than 0.1 ha were considered for transitions. CROSSTAB was used between two images to generate a cross tabulation table in order to see the consistency of images and distribution of image cells between the land use categories. Multi-Layer perceptron neural network was used to calibrate the module and relate the effects of agents considered and obtain transition potential sub models. Further markov module was used to generate transition probabilities, which were used as input in cellular automata for prediction of future transitions. This has been analysed LCM or using the CA_Markov.

Validation: Land use of 2012 was predicted using land use transition during 2008 to 2010 considering 2008 as base year. The predicted 2012 land use was compared with classified land use of 2012 (based on remote sensing data of 2012). This was repeated with 2010 data as base year considering the transition during 2010 to 2012. Validation was performed using validate, calculating Kappa, K_{loc}, $K_{no,}$ $K_{standard}$ for simulated images and classified image of 2012. Similarly, prediction for 2020 was done considering 2010 and 2012 as base images.

Spatial pattern analysis: Spatial metrics provide quantitative description of the composition and configuration of urban landscape. These metrics were computed for classified land use data at the landscape level using FRAGSTATS. Urban dynamics is characterized by select spatial metrics [1, 3, 11, 13] listed in Table 3, chosen based on shape, edge, complexity, and density criteria. The metrics include the patch area, shape, epoch/contagion/ dispersion.

IV. RESULTS AND DISCUSSION

Land use analysis: Land use analysis was done using Maximum Likelihood classifier (MLC) considering training data collected from field. Land use analysis show an increase in urban area from 49915.42 (2008) to 59103 hectares (2012) which constitute about 30%. Fig. 3 illustrates the increase in urban area and the same is listed in table 4. Land use changes are due to various agents that have played role in urban growth. These agents include large IT sectors (in south east), Bangalore international airport (north east), several industrial areas (west and south west), etc. Gradual increase urban aggregations at periphery is noticed due to large availability of land at affordable price.

Accuracy assessment: Accuracy assessment of land use analysis was performed by generating the reference image through the 30% of training data. Overall accuracy and Kappa was calculated using the module r.kappa in *GRASS*. The results of accuracy assessment are as shown in table 5.

Visualising the urban growth by 2020: Urban data (2008, 2010) were used as input to the land change modeller. MLP, was used to obtain transition considering various agents. The markov module provided the

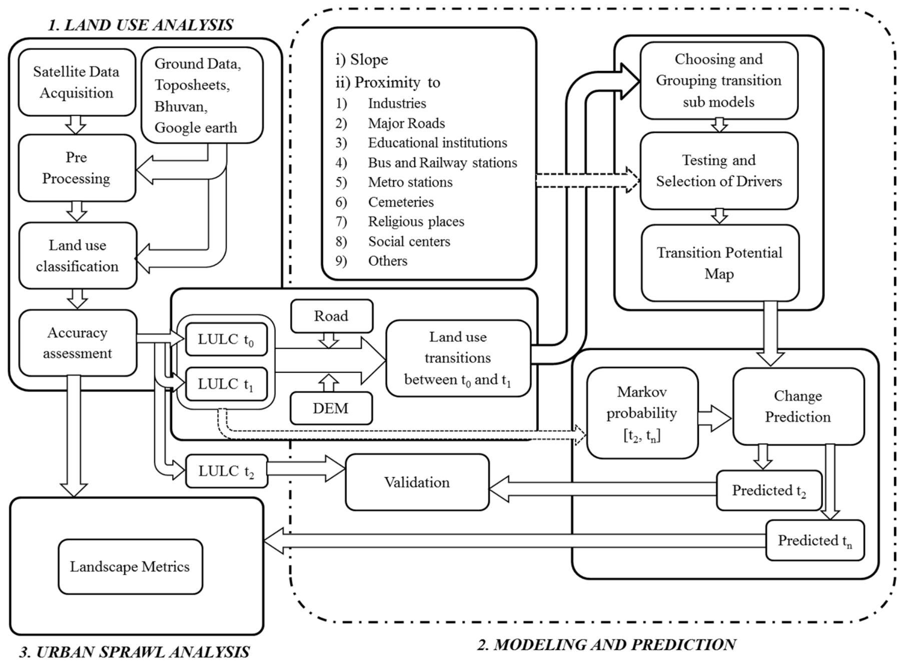

Fig. 2. Spatio-temporal analysis procedure

TABLE III: LANDSCAPE METRICS ANALYSED

	Indicators	Formula
1	Number of Urban Patches (NPU)	$NPU = n$ NP equals the number of patches in the landscape.
2	Normalized Landscape Shape Index (NLSI)	$NLSI = \frac{\sum_{i=1}^{i=N} \frac{p_i}{s_i}}{N}$ Where s_i and p_i are the area and perimeter of patch i, and N is the total number of patches.
3	Total Edge (TE)	$TE = \sum_{k=1}^{m} e_{ik}$ where, e_{ik} = total length (m) of edge in landscape involving patch type (class) i; includes landscape boundary and background segments involving patch type i.
4	Clumpiness index(Clumpy)	$G_i = \left[\frac{g_{ii}}{(\sum_{k=1}^{m} g_{ik}) - \min e_i}\right]$ $CLUMPY = \left(\begin{array}{c} \left[\frac{G_i - P_i}{P_i}\right] \text{ for } G_i < P_i \; and \; P_i < 5; else \\ \frac{G_i - P_i}{1 - P_i} \end{array}\right)$ Range: Clumpiness ranges from -1 to 1
5	Percentage of Land adjacency (Pladj)	$PLADJ = 100 * \left(g_{ij} / \sum_{k=1}^{m} g_{ik}\right)$ g_{ii} = number of like adjacencies (joins) between pixels of patch type g_{ik} = number of adjacencies between pixels of patch types i and k Range: 0<=PLADJ<=100

6

transition probability matric and finally growth for 2012 is predicted through CA_Markov (Fig. 4). The module was trained until the optimum accuracy was reached with good kappa value (Table 6). This module was optimized and calibrated to the evolving agents with urban change patterns. Considering the agents and the training data, prediction for the year 2020 was performed and given in Fig. 5 and table 7.

The predicted land use reveals of similar patterns of urbanisation of last decade. The main concentration will be mainly in the vicinity of arterial roads and proposed outer ring roads. Predicted land use also indicate of densification of urban utilities near the Bangalore international airport limited (BIAL) and surroundings. Further an exuberant increase in the urban paved surface growth due to IT Hubs in south east and north east. The results also indicated the growth of suburban towns such as Yelahanka, Hesaragatta, Hoskote and Attibele with urban intensification at the core area. The predicted urban area is about 123,061.59 hectares (62%), a considerable increase of 208 times by 2020 (compared to 2012). This highlights the need for appropriate infrastructure to cope up with the visualized growth to minimize drudgery to the common public.

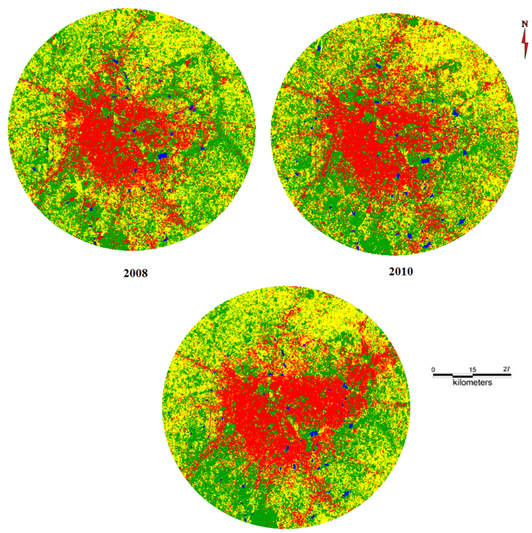

Fig. 3. Land use transitions during 2008 to 2012

TABLE IV: LAND USE DURING 2008, 2010 AND 2012

Class Year	Built-up Area		Water	
	Ha	%	Ha	%
2008	49915.42	24.85	1068.94	0.53
2010	57208.40	28.48	1571.41	0.78
2012	59103.90	29.33	1169.82	0.58

Class Year	Vegetation		Others	
	Ha	%	Ha	%
2008	77036.96	38.35	72851.95	36.27
2010	73460.57	36.57	68,656.40	34.17
2012	67883.85	33.68	73385.73	36.41

TABLE V: ACCURACY ASSESSMENT

Year	Overall accuracy %	Kappa
2008	86.35	0.78
2010	91.62	0.86
2012	90.43	0.85

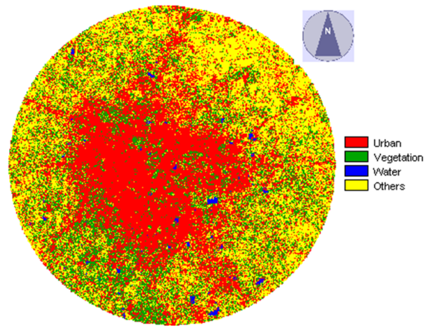

Fig. 4. Growth in 2012 (predicted) Bangalore

TABLE VI: COMPARISON OF PREDICTED LAND USE WITH ACTUAL LAND USE OF 2012 -ACCURACY AND KAPPA STATISTICS

Class Year	Built-up Area	Water	Vegetation	Others
	%	%	%	%
2012 classified	29.33	0.58	33.68	36.41
2012 predicted	31.13	0.6	29.42	38.85
Overall accuracy:93.64, Kappa:0.91, K_{loc}: 0.9265, K_{no}: 0.8938, $K_{standard}$: 0.8874				

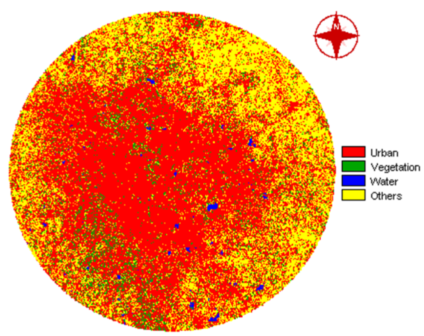

Fig. 5: Predicted growth of Bangalore by 2020 using LCM

TABLE VII: LAND USE STATISTICS OF BANGALORE FOR 2020

Class Year	Built-up Area	Water	Vegetation	Others
	%	%	%	%
2020 Predicted	61.27	0.55	7.00	31.18

Landscape metrics and urban analysis: Landscape metrics were calculated using Fragstat software to understand the extent of urban growth, its characteristics such as shape and contagion, etc.

Number of urban patches (NP): NP signifies the urban class growth in the landscape. It explains the kind of growth (patched/fragmented or unpatched/clumped) in the considered region. The results of this metric explains that there was increase in number of patches from 2008 to 2012, this signifies that there was a patched/fragmented growth. Post 2012 (Fig. 6) the NP decreases which indicates that there will be coalescence of grown urban patches to a single patch. Thus by 2020 urban densification is evident with the loss of other land uses.

Normalized landscape shape index (NLSI): This measures the shape of the class in the landscape and NLSI = 0 when the landscape consists of a single square or maximally compact and reaches 1 if the class becomes increasingly disaggregated or fragmented or shows convoluted shapes. This highlights of clumped growth by 2020 in conformity to the reduction of NP. Fig. 7 highlights the consolidation of urban patched to a clump.
Clumpiness index: Clumpiness index is a measure of adjacency indicating the extent of clumped or fragmentations in the urban growth. This values ranges from -1 (complete disaggregation) to 1 (maximal aggregation) and values near to 0 indicates of random distribution of patches. This index also indicates of highly concentrated aggregated clumped growth by 2020(Fig. 7).
Edge density: Edge density is also a fragmentation index, which counts the edges formed by forming new classes in the landscape, the edge density increases between 2008 to 2010 indicative of fragmented growth and during 2010 to 2020 declines, indicative of clumped growth (Fig. 8).
Percentage of land adjacencies (PLADJ): This index shows how adjacent are the same features, based on neighborhood adjacencies. Values close to 100 shows the adjacent growth (with disappearance of other land uses), values close to 0 indicates of the presence of heterogeneous landscape with all land use categories. Values close to 100 in 2020 is indicative of adjacent clumped growth in the region (Fig. 8).
These spatial metrics highlight of aggregated growth by 2020 and the formation of concrete jungle with the disappearance of all other land uses. This haphazard growth would fuel unsustainability with the decline of vegetation, etc.

V. Conclusion

The prediction of urban growth considering various agents of development with the knowledge of historical land uses through Land use change modeller with the help of Markov- CA. Integration of temporal remote sensing data with Geoinformatics are helpful to visualise the urban growth. Incorporation of agents in the modelling exercise provided a realistic picture of the growth. LCM model output validated with the actual data (2012) showed reliability and good accuracy.

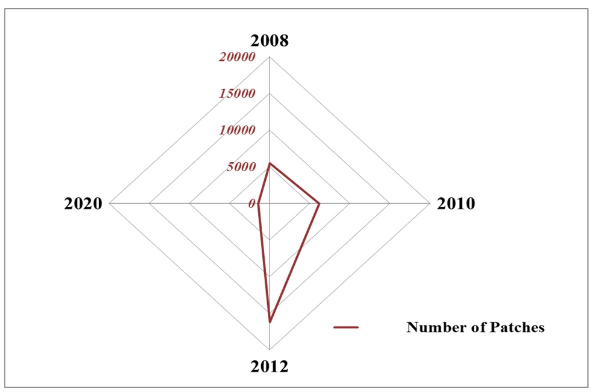

Fig. 6. Number of urban patches

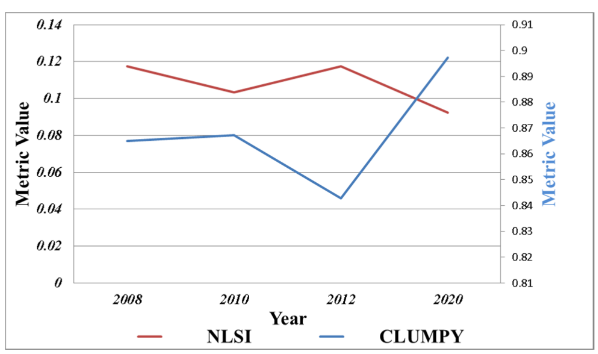

Fig. 7. Normalized landscape shape index and Clumpiness index

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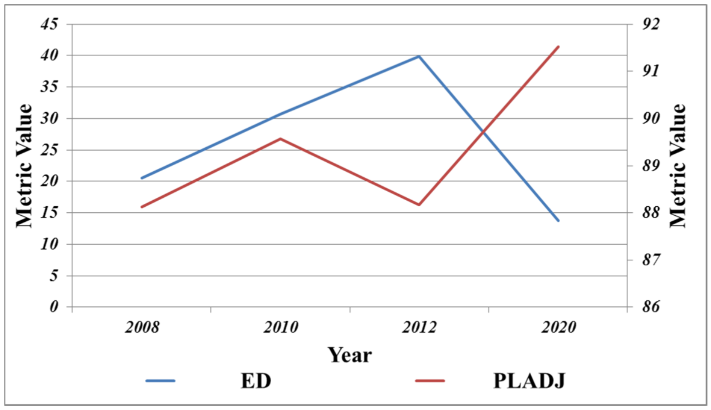

Fig. 8. Edge density and Percentage of land adjacencies

Validation of LCM with agents is further used to simulate the land uses by 2020. The land use scenario show a drastic increase from 24.85 % (2008) to 61.27% (by 2020) with the decline of vegetation and other category. Due to imposing constraint of no-change ion water category, remained constant. The spatial pattern analysis reveal of concentrated intensified growth at city centre with the increase in urban pockets at suburban, peripheral towns around Bangalore. The city would reach a threshold of urban development by 2020, with the continuation of current approach of urbanisation. This growth would ultimately threaten sustainability of natural resources affecting the livelihood of residents. The trajectory growth is a pointer to the city planners to provision basic amenities apart from conservation of vital natural resources. Land use modelling with the integration of agents (of changes) into Markov–CA and with GIS technology has aided in successful simulation of spatial changes and with the reliable forecast. This helps the decision makers in planning sustainable city with the provision of basic infrastructure and amenities. This exercise helps the local land use planners and city administrators with insights to the dynamically evolving complex land use system for conserving the ecological entities and other forms of land uses.

VI. ACKNOWLEDGEMENT

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REFERENCES

[1] T.V. Ramachandra, H.A Bharath and D.S. Durgappa, Insights to urban dynamics through landscape spatial pattern analysis, International Journal of Applied Earth Observation and Geoinformation, 18, (2012a) 329-343.

[2] H. A. Bharath, S. Bharath, D. S. Durgappa, T.V. Ramachandra, Effectiveness of landscape Spatial Metrics with reference to the Spatial Resolutions of Remote Sensing Data, Proceedings of India Conference on Geo-spatial Technologies and Applications 2012, IIT Bombay, Mumbai, India, 12-14 April, 2012.

[3] H. A. Bharath, T. V. Ramachandra, Measuring urban sprawl in Tier II cities of Karnataka, India, In Proceedings of IEEE GHTC SAS 2013 conference 23-24 August 2013, Technopark, Trivandrum, India. (2013).

[4] World Urbanization Prospects revised, 2011. United nation department of socioeconomic affairs. Available at http://esa.un.org/unup. Last accessed on 04th Aug 2013.

[5] B. N. Grimm, F. David, Peter Groffman, et al., The changing landscape: ecosystem responses to urbanization and pollution across climatic and societal gradients. Front Ecol Environ 6 (2008) 264–272

[6] H. Van Ginkel, Urban future. The cities of the developing world are spectacularly ill-prepared for the explosion in urban living. Nature, 456 (2008) 32-33

[7] J. E. Patino, J. C. Duque, A review of regional science applications of satellite remote sensing in urban settings. Computers, Environment and Urban Systems, 37 (2013) 1-17

[8] Q. Wu, H.Q. Li, R.S. Wang, et al., Monitoring and predicting land use change in Beijing using remote sensing and GIS. Landscape Urban Plann 78 (2006) 322–333

[9] H.S. Sudhira, T.V. Ramachandra and K.S. Jagadish, Urban sprawl: metrics, dynamics and modeling using gis. Int J Appl Earth Observ Geoinformation 5, (2004) 29–39

[10] S, Bharath, H. A. Bharath, D.S. Durgappa and T. V. Ramachandra, Landscape Dynamics through Spatial Metrics, in Proceedings of India GeoSpatial Conference, Epicentre, Gurgaon, India, 7-9 February. (2012).

[11] T.V. Ramachandra, A.H. Bharath and S. Sreekantha, Spatial Metrics based Landscape Structure and Dynamics Assessment for an emerging Indian Megalopolis, International Journal of Advanced Research in Artificial Intelligence, 1(1) (2012b) 48-57.
[12] S, Vinay, H.A. Bharath, T.V. Ramachandra, Spatio Temporal dynamics of Raichur City, In proceedings Lake 2012: Wetlands, Biodiversity and Climate change, 06-09, Nov 2012, Satish Dhawan Auditorium, Indian Institute of Science, Bangalore (2012)
[13] Z. Hu, C. Lo, Modeling urban growth in Atlanta using logistic regression. Computers, Environment and Urban Systems, 31 (2007) 667-688
[14] E. Vaz, P. Nijkamp, M. Painho, M. Caetano, A multi-scenario forecast of urban change: a study on urban growth in the Algarve. Landscape and Urban Planning, 104 (2012) 201-211
[15] K. Courage, A. Masamu, A. Bongo, M. Munyaradzi, Rural sustainability under threat in Zimbabwe—simulation of future land use/cover changes in the Bindura district based on the Markov–cellular automata model. Appl. Geogr. 29 (2009) 435–447.
[16] M. Sekhar, and M. S. Mohan Kumar, Geo-hydrological studies along the metro rail alignment in Bangalore, available at http://bmrc.co.in/pdf/news/iisc-report.pdf. (2009).
[17] R.O. Duda, P.E. Hart, D.G. Stork, Pattern Classification, a Wiley-Interscience Publication, Second Edition, ISBN 9814-12-602-0. (2000).
[18] http://wgbis.ces.iisc.ernet.in/grass/index.php.

Modelling Urban Revolution in Greater Bangalore, India

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***Abstract-* Land-use change is a main driving force for the development of the human and his surrounding environment and effects largely on local ecology, hydrology and environment and also globally. This has necessitated understanding changing land use spatial pattern for an effective planning. Remote sensing data enables the synoptic monitoring and visualization of urban growth patterns and dynamics. This study addresses the issue of urban sprawl through the perspective of simulation modeling over an urbanising landscape with a buffer of 10km. Bangalore, Silicon Valley of India is facing numerous challenges and problems of loss of green space, mobility constraints, etc. This study essentially brings out comparison of effective modelling algorithm considering three prime methods.**

Land Change Modeler (LCM), Markov Cellular Automata and Geomod were used to predict likely land use in 2020 with the knowledge of land use changes during 2006-2012 with the constraint of no-change in land use of water category. The results showed a drastic change in the land use, which were converted to urban. Thus necessitating the land use managers and city planners to understand future growth and plan the further developments.

I. INTRODUCTION

Large scale land-use land-cover (LULC) dynamics is leading to the drastic change in global climate changes and alteration of biogeochemical cycles. Human induced environmental changes and consequences are not uniformly distributed over the earth. Large scale industrialization during 90's era paved way for major LULC changes, caused by migration of people from different parts of the country, also from other parts of the globe and country for the employment opportunities. These led to intense urbanisation of major cities that in turn led to unplanned urbanisation. Unplanned urbanisation is charecterised by drastic landscape and local ecology changes that leads to conversion of ecological land use (such as vegetation. Open area, cultivable lands, water) into impervious layers on the earth surface. Increasing unplanned urbanisation is an important cause for depletion of natural resources [1, 2]. The unplanned urbanisation has various underlying effects such as sprawl that effect largely the natural resource and leading to depletion.

Urban Sprawl refers to an unplanned and scattered growth of paved land [2, 3], the sprawl occurs basically in the periphery and the outskirts and regions devoid of basic amenities.

Megacities or the metropolitan continue to evolve and grow [4] with leads to further environmental degradation [5]. This phenomenon is most prevalent in developing countries [3] such as India [6, 7]. Demographic and the degradation of the surrounding natural ecology at longer timescales has a large impact on land use in a region. Hence there is a need for better planning and administration. For better land use planning changes in current land use patterns temporally is essential [8].This necessitates the analysis of land use changes and the prediction of likely changes in the future.

Availability of spatio-temporal data and the advancement of remote sensing [9] has enabled unbiased land use analysis. Analysis of land use dynamics has attained research attention both at global and Indian contexts focusing on dynamically evolving cities [10]. Several studies have assessed urban growth in various megacities around the world [1, 8, 11, 12, 13]. These studies though mapped and focused on temporally evolved current land use across various cities, have not addressed the likely growth required for the regional planning. Prediction of future growth are essential to control the uncontrolled development and plan for sustainable cities. Predictive models become very significant as they foresee spatial changes based on the historical land uses, which helps the decision makers in planning the growth including sprawl across the city periphery.

CA with markov considering spatial context based on neighbourhood configuration generates transition potential maps [14, 15]. However, for models to be effective there is a need for incorporating the agents such as social factors, economic factors, geography of an area which have decisive role in the urban process of a region. This has been demonstrated through incorporation of socioeconomic data into CA-Markov to predict land use changes [16]. Geomod which is also determined using structure of CA markov is also proved as one of the main methods in modeling urban pattern this highlights the need for research, which still remains a research challenge. This communication analyses three different algorithms such as Geomod, CA Markov and land use change modeler, for modelling rapidly urbanising landscape, which will help the decision makers and city planners in planning further developments.

II. STUDY AREA:

Bangalore the IT hub of India is located in the southern part of the country of Karnataka state. With the spurt in IT industries in the region during late 1990's, the city was termed "Silicon Valley". This policy interventions created job opportunities to different category of people. The city has grown spatially during the last year by 10 times and the current spatial extent is about 741 km^2. Geographically Bangalore is located in the Deccan plateau, toward the south east of Karnataka state extending from 12^{o}49'5"N to 13^{o}8'32" N and 77^{o}27'29" E to 77^{o}47'2"E. To account for developments in the peri urban regions, the study area includes ten km buffer (from the administrative boundary) with a gross area of over 2250 km^2 as shown in Fig. 1. Bangalore has spatially increased from 69 sq.km (1901) to 741 sq.km (2006).The decadal (2001 to 2011) increase in population for urban areas of India is 31.8% and in Karnataka is 31.5%, but Bangalore has a decadal increase of 44% very large compared to that of the state and country.

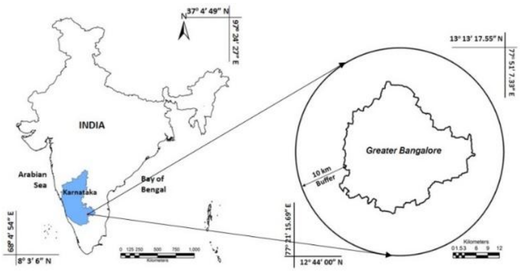

Fig.1. Study Area- greater Bangalore with 10 km buffer

III. DATA USED

Temporal remote sensing data of Landsat 7 TM AND ETM+ sensors for the year 2008, 2010 and 2012 with resolution of 30 m were downloaded from public domain (http://glcf.umiacs.umd.edu/data). 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 topo-sheet (1:50000 and 1:250000), Google earth (http://earth.google.com) and Bhuvan (http://bhuvan.nrsc.gov.in).

IV. METHOD

The process of urbanisation and sprawl in Bangalore (study area) have been assessed which includes (i) Land use analysis, (ii) Modeling and prediction. Land use data was used from the previous analysis (Bharath S et al., 2012). This data was reclassified into Urban and non-urban for Geomod analysis. But other modelling techniques such as CA Markov and LCM same data with 4 classes as described in table 1 was considered.

Modeling and Prediction: CA MARKOV: The land use pattern is evolving dynamically and follows the Markovain random process properties with various constrains that include average transfer state of land use structure stable and different land use classes may transform to other land use class given certain condition (Such as non-transition of urban class to water or vice versa). Thus Markov was used for deriving the land use change probability map for the study region and was applied using Markov module of IDRISI. The probability distribution map was developed through Markov process. A first-order Markov model based on probability distribution over next state of the current cell that is assumed to only depend on current state . CA was used to obtain a spatial context and distribution map. CA's transition rules use its current neighborhood of pixels to judge land use type in the future. State of each cell is affected by the states of its neighboring cells in the filter considered. Besides using CA transition rule and land use transition is governed by maximum probability transition and will follow the constraint of cell transition that happens only once to a particular land use, which will never be changed further during simulation. CA coupled with Markov chain was then used to predict urban land use state in 2020

Land use class	Land use included in class
Urban	Residential Area, Industrial Area, Paved surfaces, mixed pixels with built-up area
Water	Tanks, Lakes, Reservoirs, Drainages
Vegetation	Forest, Plantations
Others	Rocks, quarry pits, open ground at building sites, unpaved roads, Croplands, Nurseries, bare land

Table 1. Land use categories

Land use Change Modeller (LCM): an ecological modeller module in IDRISI Taiga was used for modelling the land use scenario based on the data of 2008, 2010 and 2012. LCM module provides quantitative assessment of category-wise land use changes in terms of gains and losses with respect to each land use class. This can also be observed and analysed by net change module in LCM (IDRISI manual). The Change analysis was performed between the images of 2008 and 2010, 2010 and 2012, to understand the transitions of land use classes during the years. Threshold of greater than 0.1 ha. Were considered for transitions. CROSSTAB module of IDRISI was used between two images to generate a cross tabulation table in order to see the consistency of images and distribution of image cells between the land use categories. Multi-Layer perceptron neural network was used to calibrate the module and relate the effects of agents considered and obtain transition potential sub models. Further markov module was used to generate transition probabilities, which were used as input in cellular automata for prediction of future transitions. This has been analysed with an inbuilt module of LCM or using the CA_Markov in IDRISI.

GEOMOD: GEOMOD was used for modeling the spatial patterns of urbanisation and predict likely land use changes. GEOMOD simulates the spatial pattern of land use changes [56], or change between two land categories (Binary images of urban and non-urban). GEOMOD selects the location of the grid cells based on the following decision rules:

[1] Persistence: simulates one way change.
[2] Regional stratification: simulate land use changes within a series of regions called strata.
[3] Neighborhood constraint: It is based on a nearest neighbor principle, whereby restricting land change within any one time step to cells that are on the edge between landscape A and landscape B
[4] Suitability map considering drivers.

If there is a net increase in the Class A category as the simulation proceeds from a beginning time to the ending time, then GEOMOD will search among the Class B grid cells in order to select the cells that are most likely to be converted to become Class A during the time interval and vice versa [56][57][58].

Suitability map is created using GEOMOD Module in IDRISI TAIGA (http://clarklabs.org) considering drivers. Each driver is considered as real number (%), obtained by comparing the driver map to the beginning time land-cover map. Site suitability of each cell is calculated using the equation (1) below, based on each reclassified attribute,

$$\boldsymbol{R(i)} = \sum_{a=1}^{A}\{\boldsymbol{Wa} * \boldsymbol{P_a(i)}\} \,/\, \sum_{a=1}^{A}\boldsymbol{Wa} \quad ..(1)$$

Where: R(i) = suitability value in cell(i), a = particular driver map, A = the number of driver maps,
Wa= the weight of driver map $\boldsymbol{a}$, and P_a (i) = percent-developed in category a_k of attribute map a, where cell (i) is a member of category a_k. Predictions were done considering three population growth rates of 5% (current average population growth of Karnataka)

V. RESULTS

Land use analysis: Land use analysis was done using Maximum Likelihood classifier (MLC) considering training data collected from field. Land use analysis show an increase in urban area from 49915.42 (2008) to 59103 hectares (2012) which constitute about 30%. Fig. 2 illustrates the increase in urban area and the same is listed in table 2. Overall accuracy and Kappa was calculated using the module r.kappa in GRASS and results shows an accuracy of 85% and 0.9 kappa was obtained on average.

Validation: Predicted land uses of 2010 and 2012 were compared with actual land uses of 2010 and 2012 classified based on remote sensing data with field data. The weights for each scenario was then obtained based on validation per pixel basis so that the developed semantics match the original land use. Validation of predicated land use was done using the actual land uses as reference and accuracy assessment was done with Kappa values which are given in table 5. Results reveal that predicted and actual land uses are in conformity to an extent of 87 to 91%. The prediction exercise is repeated for 2020 keeping 2012 as base year.

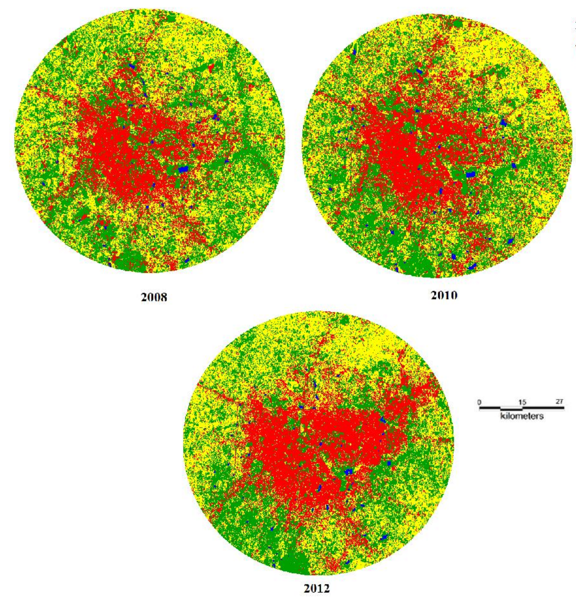

Fig. 2. Land use transitions during 2008 to 2012

Class Year	Built-up Area		Water	
	Ha	%	Ha	%
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2012	59103.90	29.33	1169.82	0.58
Class Year	**Vegetation**		**Others**	
	Ha	%	Ha	%
2008	77036.96	38.35	72851.95	36.27
2010	73460.57	36.57	68,656.40	34.17
2012	67883.85	33.68	73385.73	36.41

Table 2: Land use during 2008, 2010 and 2012

Modelling: Using *cellatom* module of IDRISI the results of CA_MARKOV were obtained as illustrated in Figure 5. The likely land use is indicated in Table 3. The land use change modeler of IDRISI was used to obtain the prediction, results of which are as shown in Figure 6 and tabulated in table 4. Geomod analysis required the land use derived data to reclassified into two classes: Urban and non-urban. Results of this analysis is as shown in Figure 7 and tabulated in table 5.

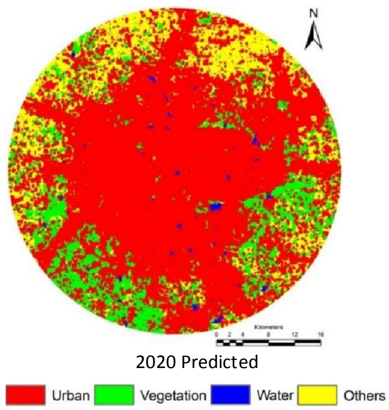

Fig.5. Predicted land use map for 2020

Year	2020 - Predicted
Land use	%
Urban	70.64
Vegetation	13.55
Water	0.74
Others	15.07

Table 3: Land use 2020

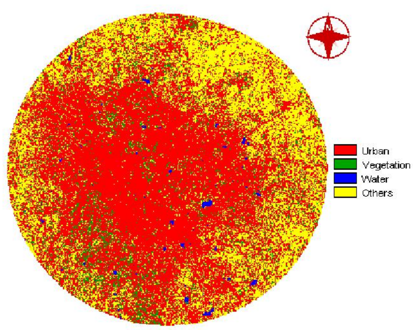

Fig. 6: Predicted growth of Bangalore by 2020 using LCM

Year	2020 - Predicted
Land use	%
Urban	61.27
Vegetation	7.00
Water	0.55
Others	31.18

Table 4. Land use statistics of Bangalore for 2020.

VI. Discussion

Three modelling techniques considered show relatively good accuracy with validation dataset. But Geomod gives a conclusive output considering the better validation results and proposed city development plan. But Geomod has a capability of using only two land use classes. Comparatively using 4 land use classes LCM provides better visual interpretation since it uses agents to derive the growth. CA-Markov is dependent on neighborhood and rules and shows an exaggerated output of further aggregation of already urbanised city.

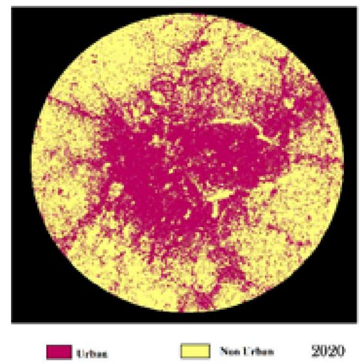

Fig. 7: Predicted growth of Bangalore by 2020 using Geomod

Year	Non-Urban	Urban
2020	49.62%	50.38%

Table 5: Land use 2020 using Geomod

The predicted land use reveals of similar patterns of urbanisation of last decade. The main concentration will be mainly in the vicinity of arterial roads and proposed outer ring roads. Predicted land use also indicate of densification of urban utilities near the Bangalore international airport limited (BIAL) and surroundings. Further an exuberant increase in the urban paved surface growth due to IT Hubs in south east and north east. The results also indicated the growth of suburban towns such as Yelahanka, Hesaragatta, Hoskote and Attibele with urban intensification at the core area in almost all modelling techniques used. The results indicate that the urban area would cover close to 50 to 60 % of the total land use in and surrounding Bangalore. Thus providing insights to relevant information. Further modelling can be improved using nature and bio inspired techniques.

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VIII. References

[1] Ramachandra, T.V., Bharath, H.A. and Durgappa, D.S. Insights to urban dynamics through landscape spatial pattern

analysis, International Journal of Applied Earth Observation and Geoinformation, 18, 2012a, 329-343.

[2] Bharath, H. A., Bharath, S., Durgappa, D.S. and Ramachandra, T.V. Effectiveness of landscape Spatial Metrics with reference to the Spatial Resolutions of Remote Sensing Data, Proceedings of India Conference on Geo-spatial Technologies and Applications 2012, IIT Bombay, Mumbai, India, 12-14 April, 2012.

[3] Ramachandra, T.V., Bharath, H.A. and Sreekantha, S. Spatial Metrics based Landscape Structure and Dynamics Assessment for an emerging Indian Megalopolis, International Journal of Advanced Research in Artificial Intelligence, 1(1), 2012b, 48-57.

[4] Van Ginkel, H., Urban future. The cities of the developing world are spectacularly ill-prepared for the explosion in urban living. Nature, 456, 2008, 32-33

[5] Czamanski, D., Benenson, I., Malkinson, D., et al., Urban sprawl and ecosystems can nature survive? International Review of Environmental and Resource Economics, 2, 2008, 321-366.

[6] Bhagat, R.B. Emerging pattern of Urbanization in India. Economic and Political Weekly, 46, 2011, 10-13

[7] Bharath, H.A. and Ramachandra, T.V., Measuring urban sprawl in Tier II cities of Karnataka, India, In Proceedings of IEEE GHTC SAS 2013 conference 23-24 August 2013, Technopark, Trivandrum, India. 2013.

[8] Bagan, H., Yamagata, Y. Landsat analysis of urban growth: how Tokyo became the world's largest megacity during the last 40 years. Remote Sensing of Environment, 127, 2012, 210-222

[9] Patino, J. E., Duque, J. C. A review of regional science applications of satellite remote sensing in urban settings. Computers, Environment and Urban Systems, 37, 2013, 1-17

[10] Wu, Q., Li, H.Q., Wang, R.S., et al., Monitoring and predicting land use change in Beijing using remote sensing and GIS. Landscape Urban Plann 78, 2006, 322–333

[11] Schneider, A., Woodcock, C. Compact, dispersed, fragmented, extensive? A comparison of urban growth in twenty-five global cities using remotely sensed data, pattern metrics and census information. Urban Studies, 45, 2008, 659-692

[12] Taubenbock, H., Wegmann, M., Roth, A., Mehl, H., Dech, S., Urbanization in India: Spatiotemporal analysis using remote sensing data. Computers, Environment and Urban Systems, 33, 2009, 179–188.

[13] Vinay, S., Bharath, H.A. and Ramachandra, T.V. Spatio Temporal dynamics of Raichur City, In proceedings Lake 2012: Wetlands, Biodiversity and Climate change, 06-09, Nov 2012, Satish Dhawan Auditorium, Indian Institute of Science, Bangalore, 2012.

[14] Batty, Xie, Y., Sun, Z.L. Modeling urban dynamics through GIS based cellular automata. Comput Environ. Urban. Syst. 23, 1999, 205–233.

[15] Clarke, K.C., Brass, J.A., Riggan, P.J. A cellular-automaton model of wildfire propagation and extinction. Photogramm. Eng. Remote Sens. 60, 1994, 1355–1367.

[16] Courage, K., Masamu, A., Bongo, A., Munyaradzi, M. Rural sustainability under threat in Zimbabwe—simulation of future land use/cover changes in the Bindura district based on the Markov–cellular automata model. Appl. Geogr. 29, 2009, 435–447.

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