14th Annual International Conference and Exhibition on Geospatial InformationTechnology and Applications

INDIA GEOSPATIAL FORUM

7-9 February, 2012

THEME: Geo-Budget: Enabling Sustainable Growth

Landscape Dynamics through Spatial Metrics

Bharath Settur[1], Bharath H. Aithal[1,2], SannaDurgappa D[2] and Ramachandra T V[1,2,3]

[1]Energy & Wetlands Research Group, Centre for Ecological Sciences,
[2]Centre for Sustainable Technologies (astra)
[3] Centre for *infrastructure*, Sustainable Transportation and Urban Planning [CiSTUP]
Indian Institute of Science, Bangalore, Karnataka, 560 012, India
*Corresponding Author: cestvr@ces.iisc.ernet.in

Abstract:

Understanding landscape dynamics aids in the planning and management of natural resources in order to improve economic, social & ecological health of the region. This involves persistent knowledge of landscape at temporal scale. Urbanisation involves large scale changes in the land cover in response to the economic & social goals. This influences the policy towards environmental conditions & ecological conservation goals of the region. Unplanned urbanisation witnessed in most growing cities in India has led to unsustainable development evident from lack of appropriate infrastructure & basic amenities. In this backdrop, spatial metrics aid in accurate understanding of economic-environmental effects from urbanization. Land use land cover (LULC) analysis with spatial metrics help in exploring the landscape dynamics towards better planning of the region.

Land use of the cities involves complex patterns of spatial heterogeneity. Expansions in response to urbanizing cities results in new low density suburbs with isolated or semi-detached housing. The present work addresses the spatio-temporal characteristics of the urban expansion in Bangalore metropolitan area from 1973 to 2010 captured through the multi-resolution temporal remote sensing data with landscape metrics. In order to account isolated or semidetached housing region 10 km buffer is considered from the city administrative boundary. The region has been divided into 13 circular gradients of 8 zones (as the dynamics of change in each direction are different (in response to the agents)). Land use analysis with computation of spatial metrics has been carried out for each region. Temporal LU analysis for the period 1973 to 2010 shows the decline in the vegetation cover, water bodies with the rapid increase in the urban area. The landscape metrics depicts the city is more Clumped at center and fragmented towards the periphery. The analysis at local scales would stimulate the regional decision making which help in monitoring of the urban landscapes to support sustainable development.

Key words: Landscape, Metrics, Urbanisation, GRASS, Remote sensing, Sprawl.

1. Introduction

Sustainable cities have become key issue to attain more equitable standards of living both within and among global populations. The development can be achieved without undermining the requirement of future generations of attaining similar standards of living or improved standards. Development is a process of transformation of combining socio-economic growth (Tanguay et al., 2010) and sustainability. This brings to the focus that environmental considerations have to be embedded in all sectors and policy areas. Sustainable urban development entails achieving a balance between the development of the urban areas and protection of the environment with equity in employment, basic amenities, and social infrastructure.Urbanisation isa dynamic process involving the growth of urban population resulting in landuse changes,which is being experienced by most of the developing nations (UNPD, 2005; Barney, 2006; Ramachandra and Kumar, 2010).Urbanisationhas been attributed to the changes in land use/land cover (Raffaella et al., 2011) coupled with thesocioeconomic aspects such as population or density. The rapid and uncontrolled growth of the urbanising cities brings numerous changes in the structure and hence the functioning of landscape (Solon, 2009).

Multi Resolution remote sensingdata acquired through the sensors of Earth Observation Satellites (EOS) provides a synoptic view of the landscape. This temporal data on spatial scale 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 (Lillesand et al, 1987).The increased availability and improved quality of spatial and temporal remote sensing data with the innovative analytical techniques, helps to monitor and analyze urban expansion of large areas in a digital format and land use change and landscape metrics in a timely and cost-effective way (Haack et al., 1997; Yang et al., 2003,Li and Yeh, 2000).

Landscape metrics also known as spatial metrics are invaluable for understanding and characterizing the urban processes and their consequences. These metrics, 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 (Li and Wu 2004). Recently there has been an increased interest in the application of spatial metrics techniques to analysethe landscape dynamics of change ecology and growth process (McGarigal et al., 1995, Zhou, 2000; Luck and Wu, 2002; Li and Yeh, 2000; Dietzel et al., 2005; Porter Bolland et al., 2007; Roy and Tomar, 2001).A variety of landscape metrics have been proposed to characterize the spatial configuration for the individual landscape class or the whole landscape base (Patton, 1975; Forman and Gordron, 1986; Imbernon and Branthomme, 2001; McGarigal et al., 2002; Herold et al., 2003; Li and Wu, 2004; Uuemaa et al., 2009). In this context, spatial metrics are a very valuable tool for planners who need to better understand and more accurately characterize urban processes and their consequences (Herold et al., 2005; DiBari, 2007; Kim and

Ellis, 2009). Scaling functions of the multi-resolution data describes the variations of different landscape pattern metrics with spatial resolution (Small, 2001, Saura et al 2007; Yu, 2006; Wu, 2002). Spatial metrics thus helps to categorize landscape diversity and differences of landscape diversity within urban regions.

2. Objective of the study:

The objectives of this study is to understand the Landscape dynamics which involves (i) temporal analysis of land use Land cover (LULC) pattern, (ii) understanding the spatial patterns of urbanization through metrics.

3. Study area:

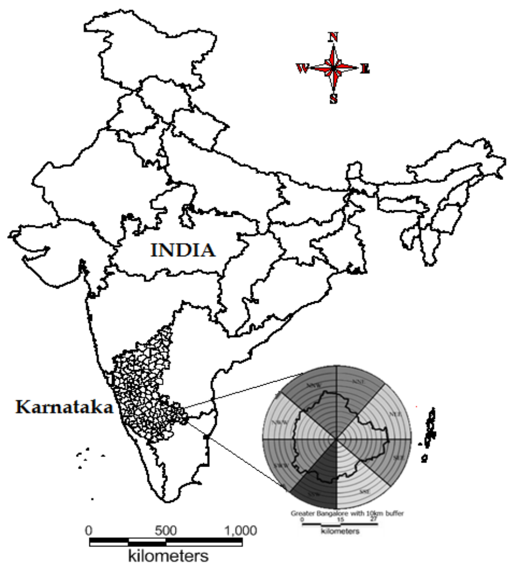


Figure 1: Study area, Greater Bangalore.

Bangalore is the administrative capital of Karnataka State, also known as the Garden City of India, is located in the Deccan Plateau to the south-eastern part of Karnataka, with an area of 741 sq. km and 949 m above sea levelhaving more than 9 million people. It lies between the latitudes 12°39’00’’ to 13°13’00’’N and longitude 77°22’00’’ to 77°52’00’’E. The present study includes a 10km circular buffer from the Bangalore administrative boundary by considering the centroid as City Business District (CBD). Bangalore has grown spatially more than ten times (741 sq. km) since 1949 (69 sq. km.) (Ramachandra and Kumar, 2008).

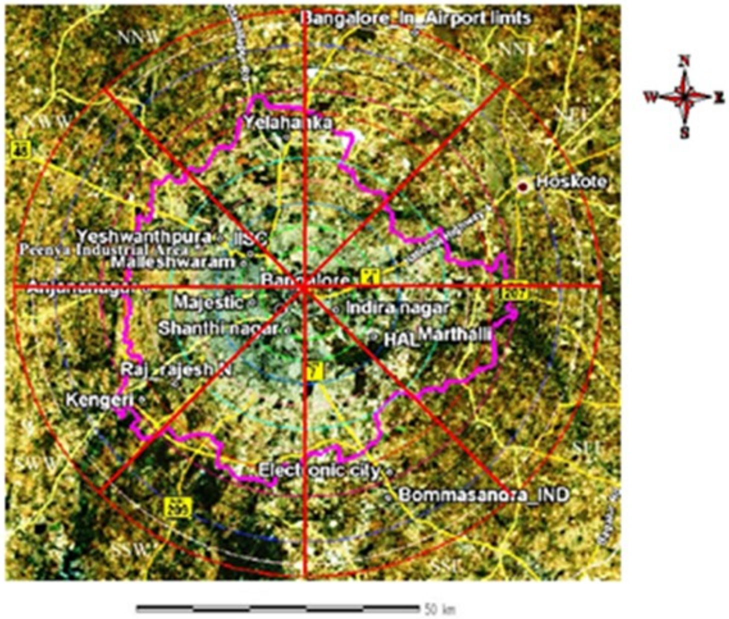


Figure 2: Study area with important landmarks (source: Google Earth)

4. Materials and method

DATA	Year	Purpose
Landsat Series Multispectral sensor(57.5m)	1973	Landcover and Land use analysis
Landsat Series Thematic mapper (28.5m) and Enhanced Thematic Mapper sensors	1992,1999, 2003, 2008, 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.

Table1. Materials used for the analysis

a. Analysis flow

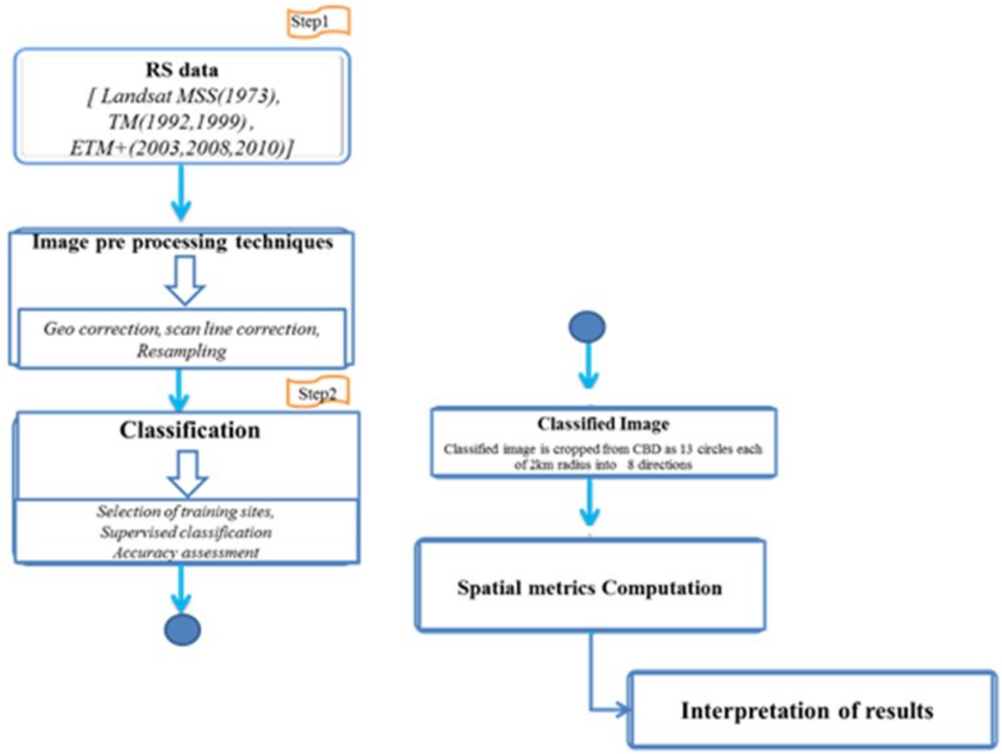


Figure 3: Method used to understand the process of landscape dynamics

Figure 3 illustrates the techniques followed in the analysis. Digital Remote sensing data were subjected to preprocessing to remove spectral and spatial biases. The data was geocorrected using GCPs (ground control points) and scan line correction especially for ETM+ data (SLC-off).The data is resampled to 30 m using nearest neighborhood algorithm, 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 with the help of training data using supervised classifier – Gaussian maximum likelihood. This preserves the basic land cover characteristics through statistical classification techniques using a number of well-distributed training pixels. GRASS (Geographical Analysis Support System)afree and open source software having robust support of processing both vector and raster files has been used for this analysis.Spectral classification inaccuracies are measured by a set of reference pixels. Based on the reference pixels, confusion matrix, kappa (κ) statistics and producer's and user's accuracies were computed. Accuracy assessment and kappa statistics are included in table 3. These accuracies relate solely to the performance of spectral classification.

In step2, to assess the spatio-temporal pattern of urban growth from the central business district(CBD) the classified image is divided into 13 circles in 8 directions (figure 1)with their origin from the 'city center(CBD)'. The Shannon entropy &spatial metrics are calculated &analysed using fragstat for all images in 8 directions & 13 circles.

b. Analysis of urban sprawl (Shannon's Entropy):

Shannon's entropy (Yeh& Li, 2001; Sudhira et al, 2004) is used to measure the extent of urban sprawl with remote sensing data. Shannon's entropy was calculated across all the directions considering each direction as an individual spatial unitis computed to detect the urban sprawl phenomenon given by the equation

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

Where, P_i is the Proportion of the variable in the i^{th} zone &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 (close to log n) indicates fragmented growth indicative of sprawl.

c. **Computation of Landscape metrics:**

The gradient based approach is adopted to explain the spatial variation of urbanization (from the core region to the periphery).Landscape metrics were computed for each circle (region) in each direction to understand the spatio-temporal pattern of the landscape dynamics at local levels due to the urbanization process.

Table 2 lists the spatial metrics that have been computed to reflect the landscape's spatial and temporal changes(Lausch& Herzog 2002). Thesemetrics are grouped into the five categoriesPatch area metrics, Edge/border metrics, Shape metrics, Compactness/ contagion / dispersion metrics,

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)	$BP = \frac{A_{builtup}}{A}(100)$ $A_{\text{built-up}}$ = 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	$LPI = \frac{\max_{i=1 \text{ to } n}(ai)}{A}$ ai = area (m^2) of patch i A= total landscape area	0 = LPI=1	LPI = 0 when largest patch of the patch type becomes increasingly smaller. LPI = 1 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=i^{th} patch a=area of patch i n=total number of patches	MPS>0,without limit	MPS is widely used to describe landscape structure. MPS is a measure of subdivision of the class or landscape. 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. Patch density increases with a greater number of patches within a reference area.
		Category : Shape metrics		
7	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 and is 1 when the patch type is maximally disaggregated
8	Mean Shape index MSI	$$MSI = \frac{\sum_{j=i}^{n} \left(\frac{0.25 p_{ij}}{\sqrt{a_{ij}}} \right)}{n_i}$$ 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
		Category: Compactness/ contagion / dispersion metrics		
9	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 (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.

10	Aggregation index	$$AI = \left[\sum_{i=1}^{m}\left(\frac{g_{ii}}{\max \to g_{ii}}\right)P_i\right](100)$$ 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. Aggregation corresponds to the clustering of patches to form patches of a larger size.
Category : Open Space metrics				
11	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.

Table 2: Landscape metrics with significance

5. Results and Discussion:

a. Land use Classification

Temporal land use changes listed in Table 3 and Figure 4respectively illustrates the temporal dynamics during 1973 to 2010. This highlights that the percentage of urban land is increasing in all directions due to the policy decisions of (i) industrialization (ii) boost to information technology and biotechnology sector in late 90's and consequent housing developments in the periphery. The urban growth is concentrated or clumpedat the center, while the sprawl or dispersed growth is observed in the periphery. Table 4 illustrates the accuracy assessment for the supervised classified images.

As shown in the table 3 the percentage of urban has increased from 1.87(year 1973) to 28.47% (year 2010) where as the vegetation has decreased from 62.38to 36.48%.

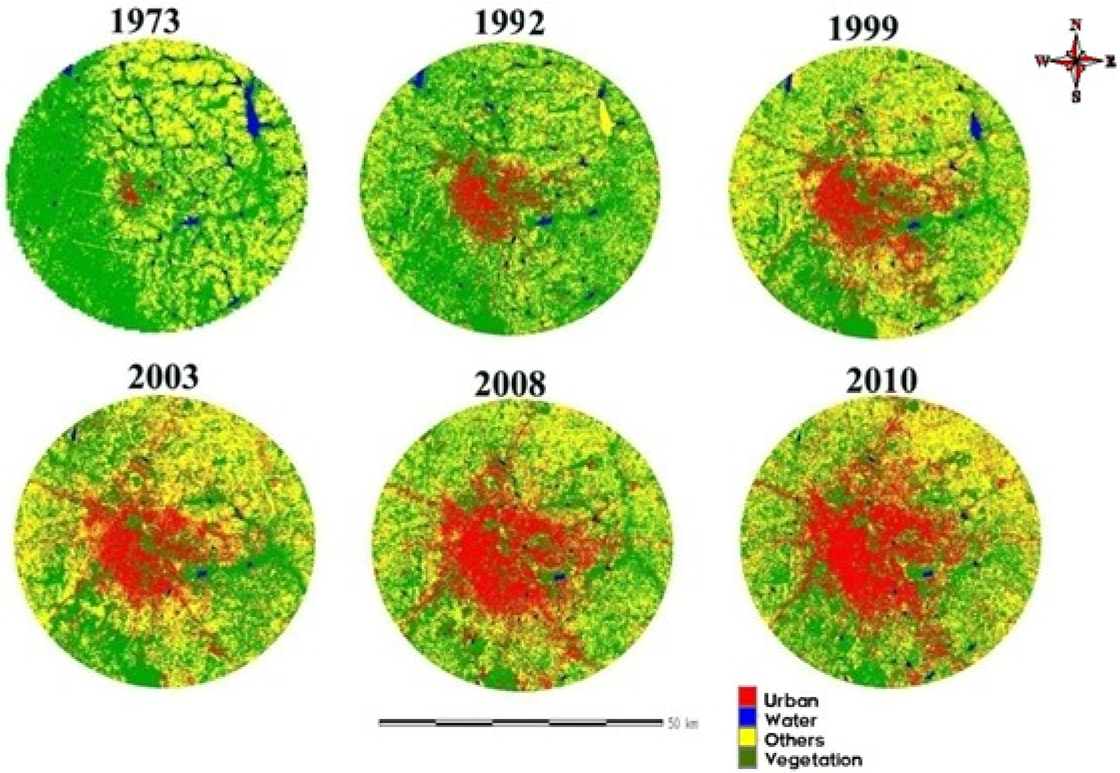


Figure 4: Bangalore from 1973, 1992, 1999, 2003, 2008 and 2010.

Land use Type	Urban		Vegetation		Water		Others	
Year	Ha	%	Ha	%	Ha	%	Ha	%
1973	3744.72	1.87	125116.74	62.38	6630.12	3.31	65091.6	32.45
1992	17314.11	8.22	123852.87	58.80	3063.69	1.45	66406.5	31.53
1999	32270.67	16.06	83321.65	41.47	2238.21	1.11	83083.05	41.35
2003	39576.06	19.7	77985.63	38.81	748.26	0.37	82611.18	41.12
2008	50115.96	24.94	76901.94	38.27	1065.42	0.53	72837.81	36.25
2010	57208.14	28.97	73286.46	36.48	1577.61	0.79	68848.92	34.27

Table 3: Temporal land use of Bangalore

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

Table 4: Accuracy assessment

b. **Shannon's entropy**

The entropy is calculated with respect to 13 circles in 4 directions. The reference value is taken as Log (n) where n=13, which is 1.114.Larger value of entropy (near to upper limit) reveals the occurrence and spatial distribution of the urban sprawl.The entropy values (table 5) show the increasing trend during 1973 to 2010 indicating the sprawl or higher degree of dispersion of built-up area in the city with respect to 4 directions and aremost prominent in SWW & NWW directions.

Direction / Year	**NNE**	**NEE**	**SEE**	**SSE**	**SSW**	**SWW**	**NWW**	**NNW**
1973	0.061	0.0425	0.0418	0.0357	0.0274	0.0591	0.0563	0.0486
1992	0.159	0.122	0.142	0.1652	0.186	0.200	0.219	0.146
1999	0.212	0.208	0.230	0.387	0.349	0.336	0.333	0.237
2003	0.298	0.250	0.274	0.331	0.357	0.395	0.453	0.366
2008	0.299	0.273	0.344	0.463	0.447	0.478	0.480	0.374
2010	0.462	0.321	0.375	0.499	0.496	0.502	0.543	0.441
Reference value	**1.114**							

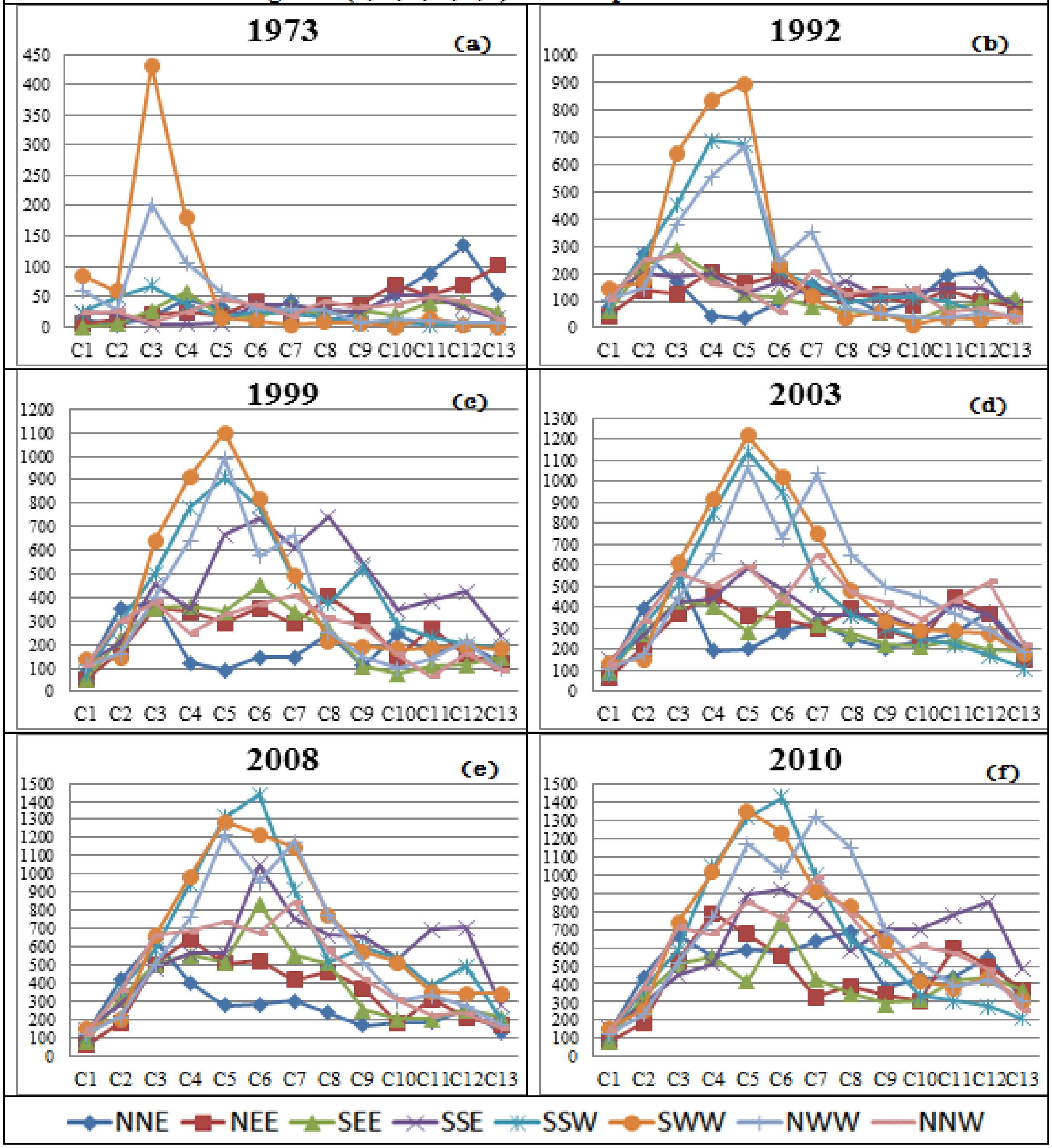
Table 5: Shannon entropy

c. **Landscape metrics Analysis**

The entropy values show the urbanization is reaching critical value in all the directions. To understand the driving forces of urban growth, landscape metrics are computed circlewise for each direction.Table 2 describes the spatial metrics computed at the landscape level explain relatively general information of entire landscape (unit) under investigation. Metrics computed at the class level are helpful for understanding of landscape development per particular class. The analysis of landscape metrics provided an overall summary of landscape composition and configuration.

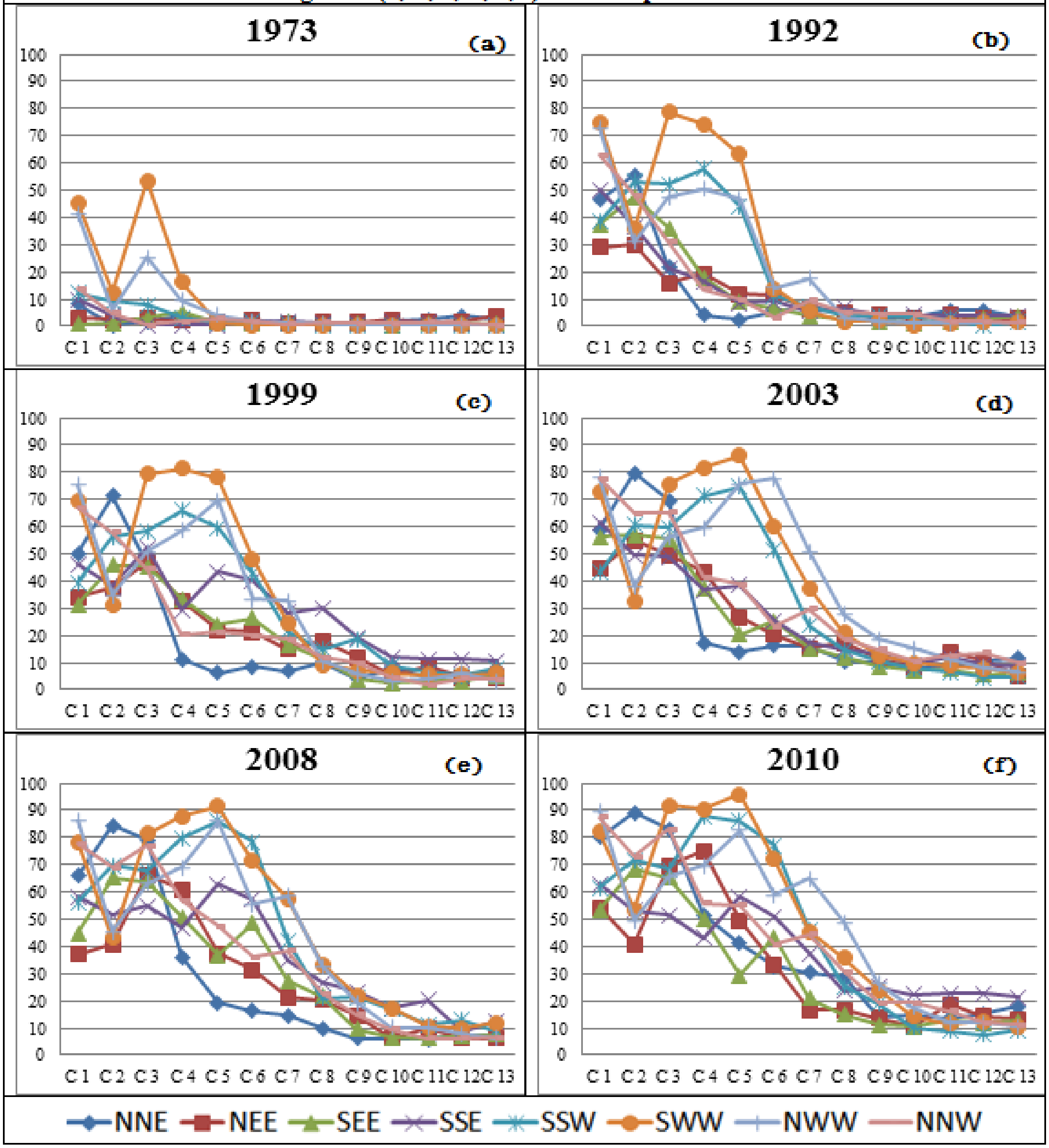
Figure 5and Figure 6 shows the built-up area and built-up percentage, for the year 1973 both the indices had higher values in the inner circles (1,2,3,and 4) which indicates of concentrated growth in the centre with higher values for SWW and NWW Regions. Towards 2010 there was intense growth in all zones of the city in all circles inside the boundary and less intense near the boundary and in 10km buffer. To understand the process of urbanisation it is necessary to know the kind of growth the particular direction is having and its intensity. Hence the patch index such as largest patch which tells us if there is aggregation or fragmented growth was computed.

Figure 5 (a, b, c, d, e, f): Built-up area in hectares



X axes: Circles of 2km radius; Y axes: Built up in Ha.

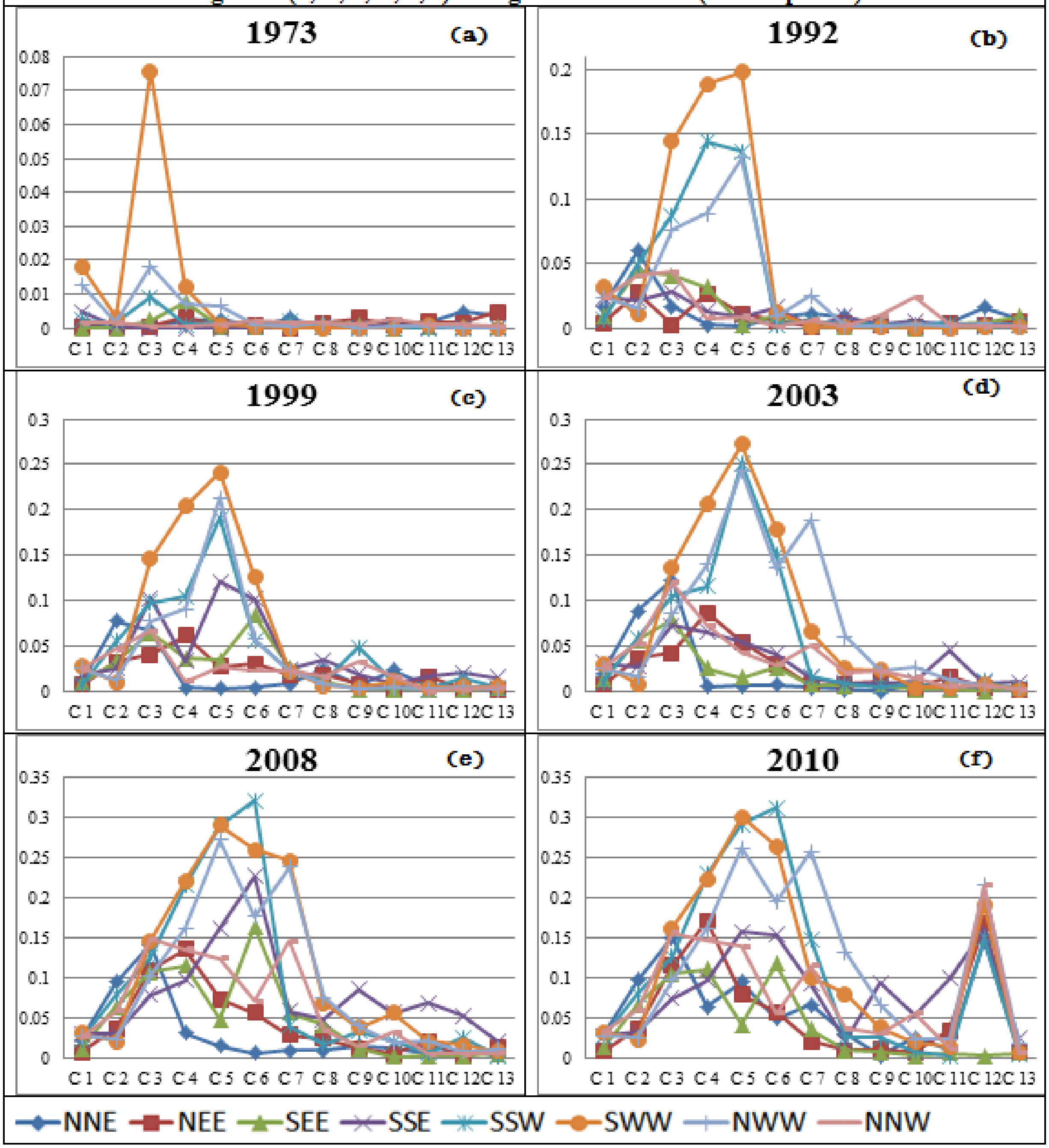
Figure 6 (a, b, c, d, e, f): Built-up area in %



X axes: Circles of 2km radius; Y axes: Built up in %.

Figure 7shows largest patch index with respect to built-up (i.e. class). In 1973 largest built-up patch existed in circle-3of SWW direction (a single patch), whereas as the transition from 1973 to 2010, show the increase in patches and the large patches were found in circle 4 to circle 10 and few large patches near the 10km buffer.

Figure 7 (a, b, c, d, e, f): Largest Patch Index (Built-up area)

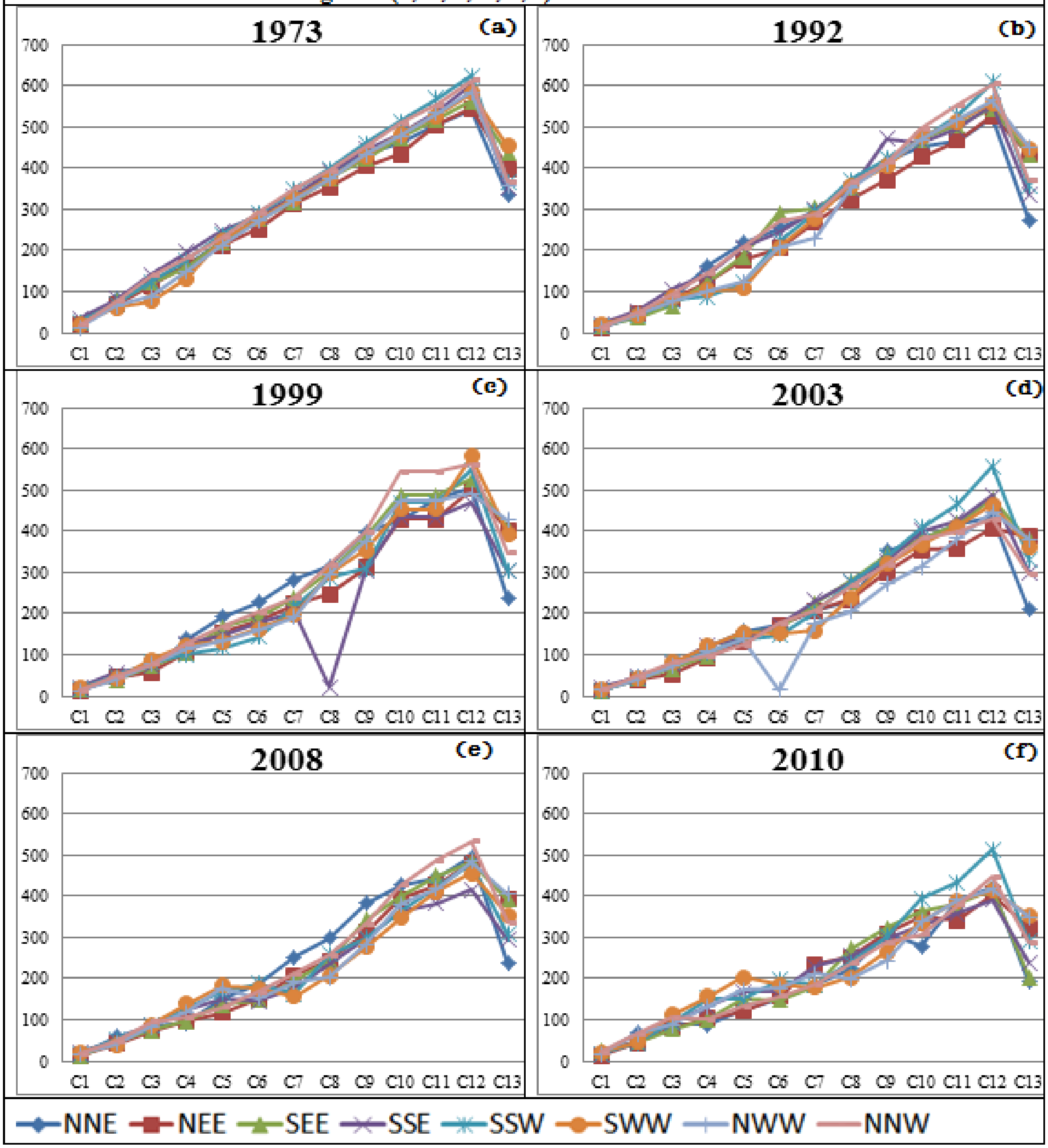


X axes: Circles of 2km radius; Y axes: Largest Patch Index.

Patches were retrieved, but to analyse the patch its size needs to be known with respect to other patches. To analyse this dimension mean patch size was computed. Figure 8shows MPS (mean patch size) with respect to built-up a measure of patch characteristics. MPS was higher near the periphery in 1973 as these were one single homogeneous patch as indicated above. Whereas the in 2010 the MPS showed higher value near the center where urban patches were prominent and were less near periphery which indicated of

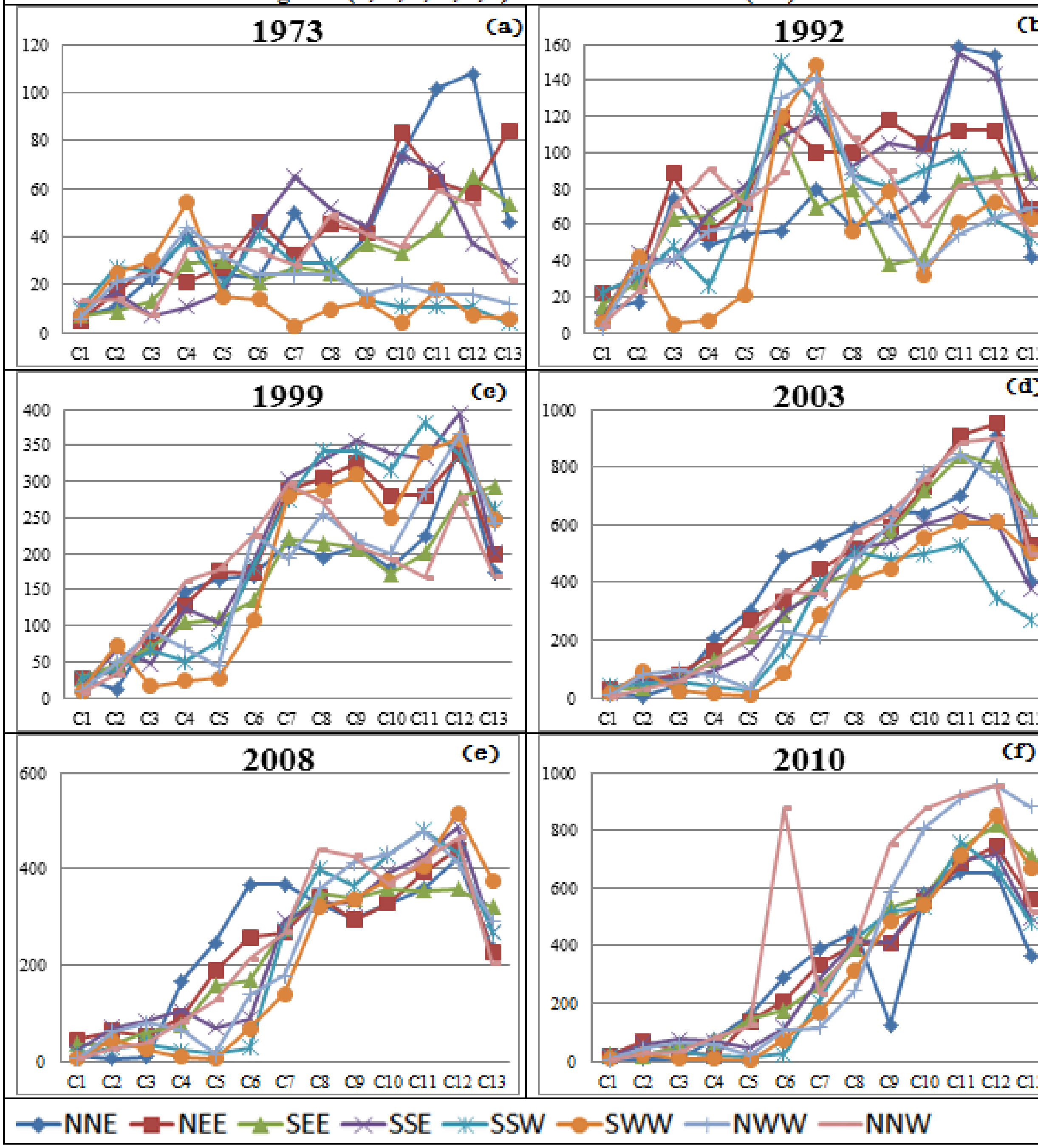
Fragmented growth. Figure 9shows number of patches (NP) index with respect to built-up from1973 to 2010, in the year 1973 NP are very less and in the year 2010 NP showing higher value means the city is more fragmented towards periphery and patches in the outer circles increases which means there is a fragmented growth which can be attributed to sprawl.

Figure 8(a, b, c, d, e, f): Mean Patch Size



X axes: Circles of 2km radius; Y axes: Mean Patch Size.

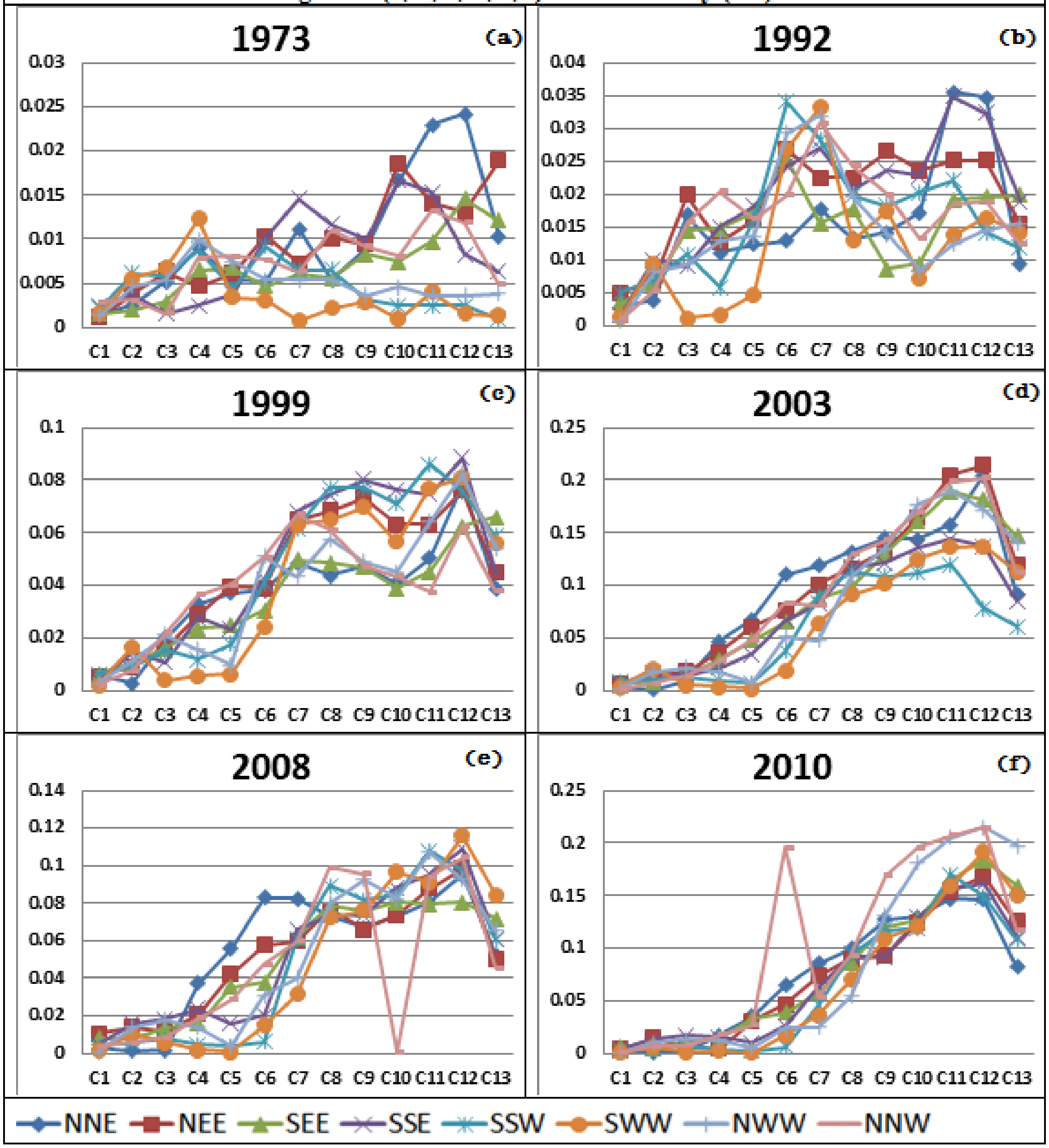
Figure 9(a, b, c, d, e, f): Number of Patches (NP)



X axes: Circles of 2km radius; Y axes: Number of Patches.

Figure 10shows patch density (PD) index with respect to built-up. In the year 1973 PD is less because NP are very less and in the year 2010 PD is high with higher value of NP, which indicates of fragmented landscapes towards periphery.

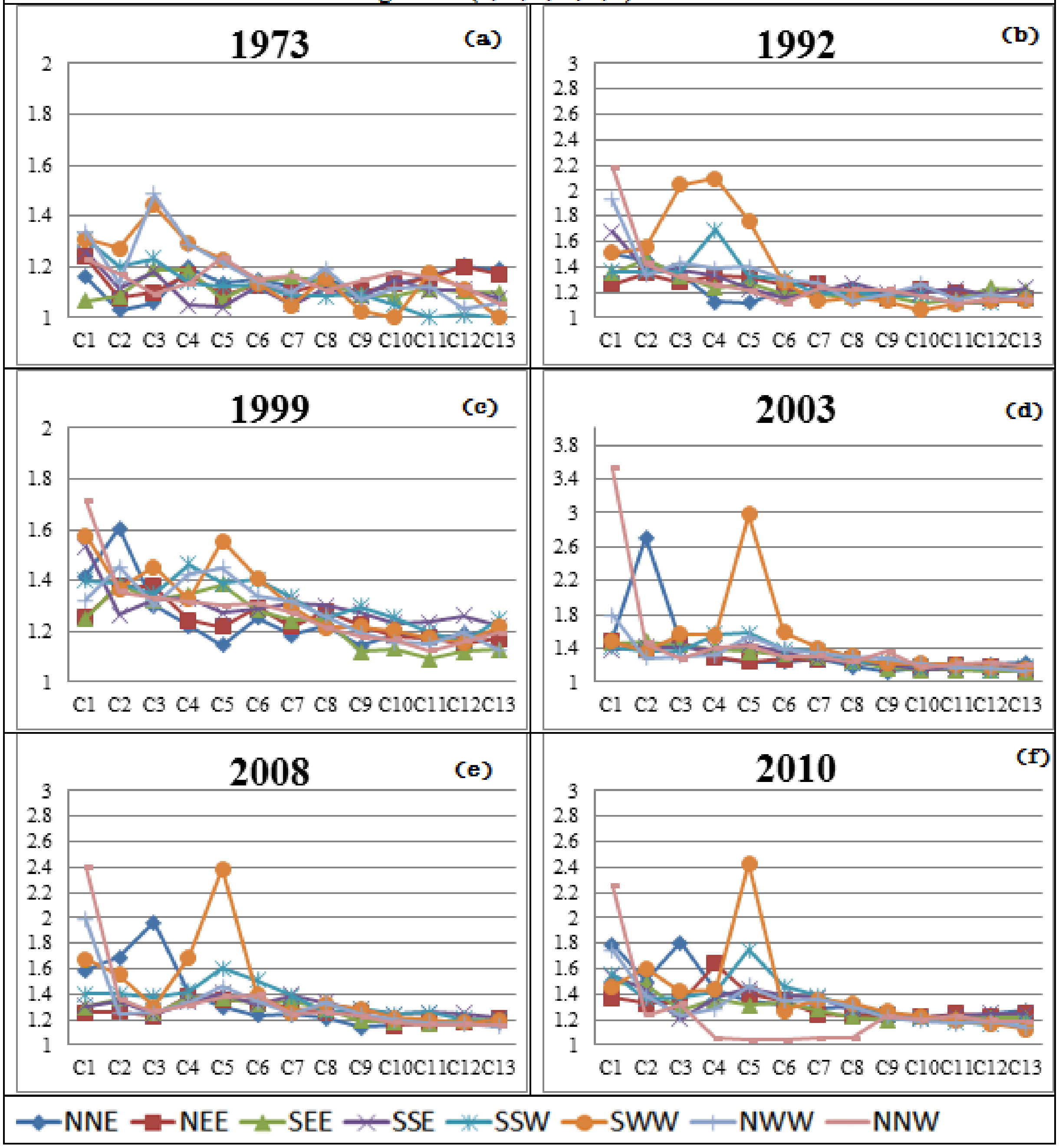
Figure 10(a, b, c, d, e, f): Patch Density (PD)



X axes: Circles of 2km radius; Y axes: Patch Density.

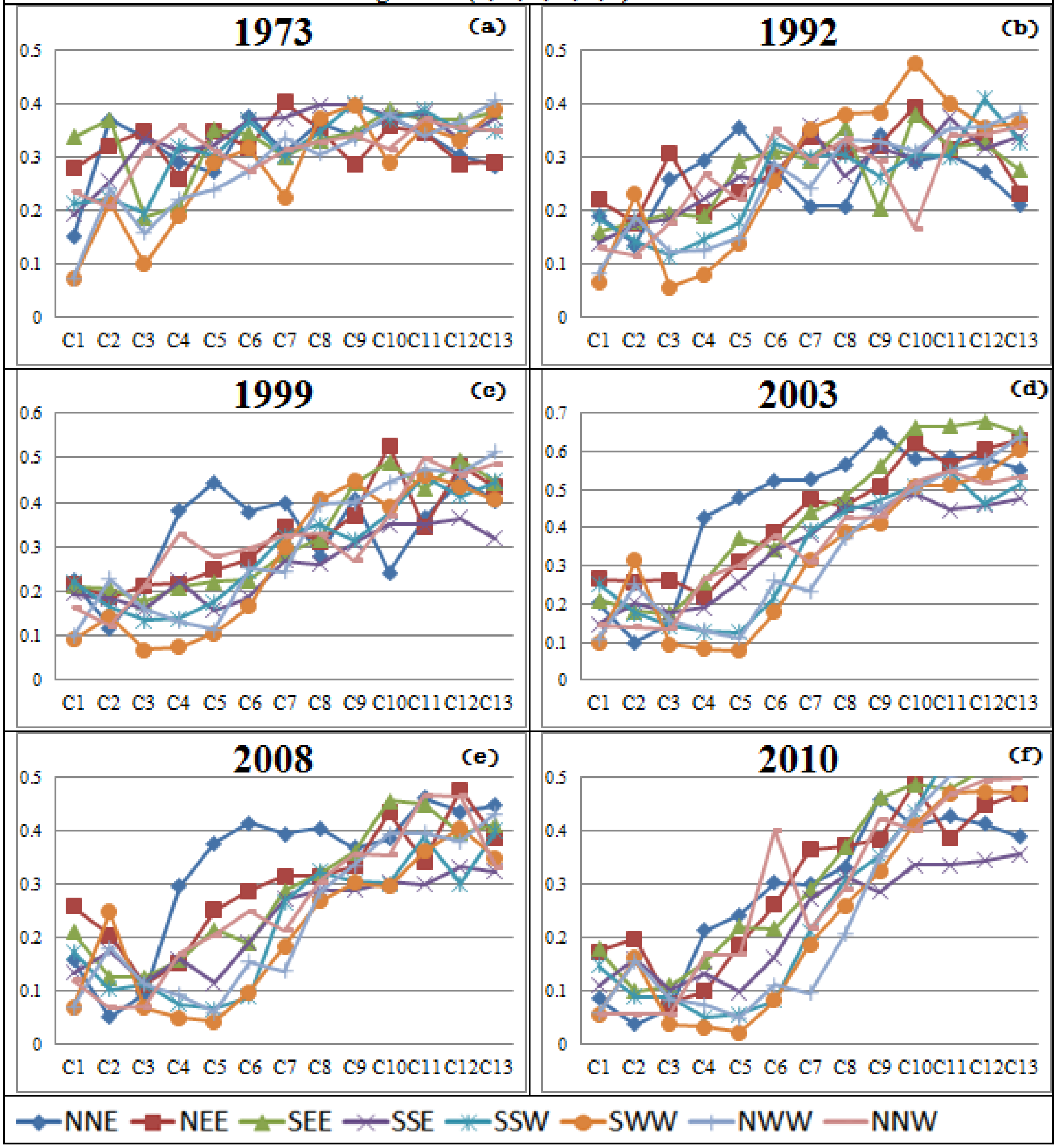
Figure 11and Figure12 shows MSI (Mean Shape Index) & NLSI (Normalized Landscape Shape Index) explain shape complexity. In the year 1973 shape complexity in all directions is simple. But the shape complexity increases as we move on 1973 to 2010.

Figure 11 (a, b, c, d, e, f): MSI



X axes: Circles of 2km radius; Y axes: Mean Shape Index.

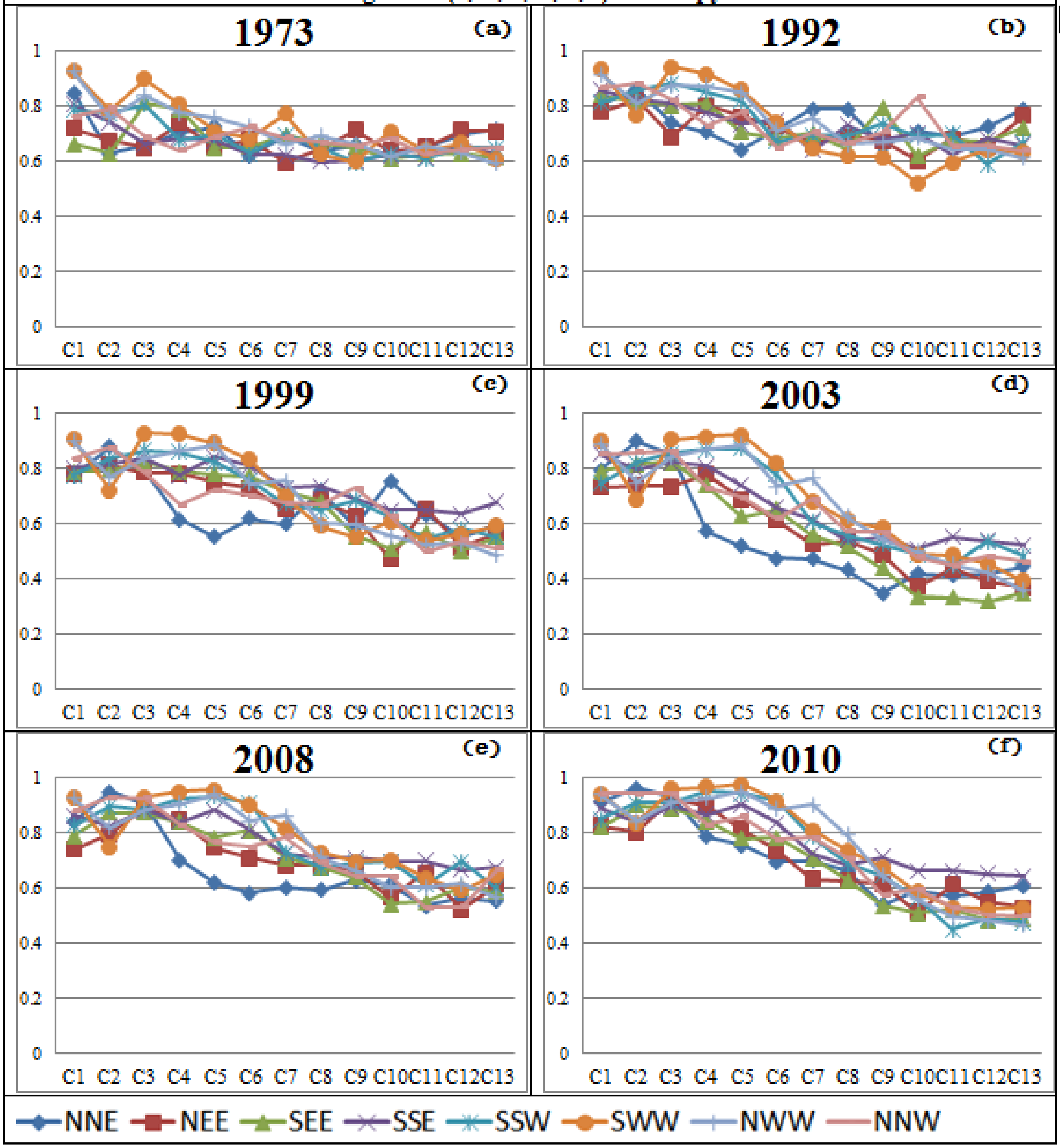
Figure 12 (a, b, c, d, e, f): NLSI



X axes: Circles of 2km radius; Y axes: Normalized Landscape Shape Index.

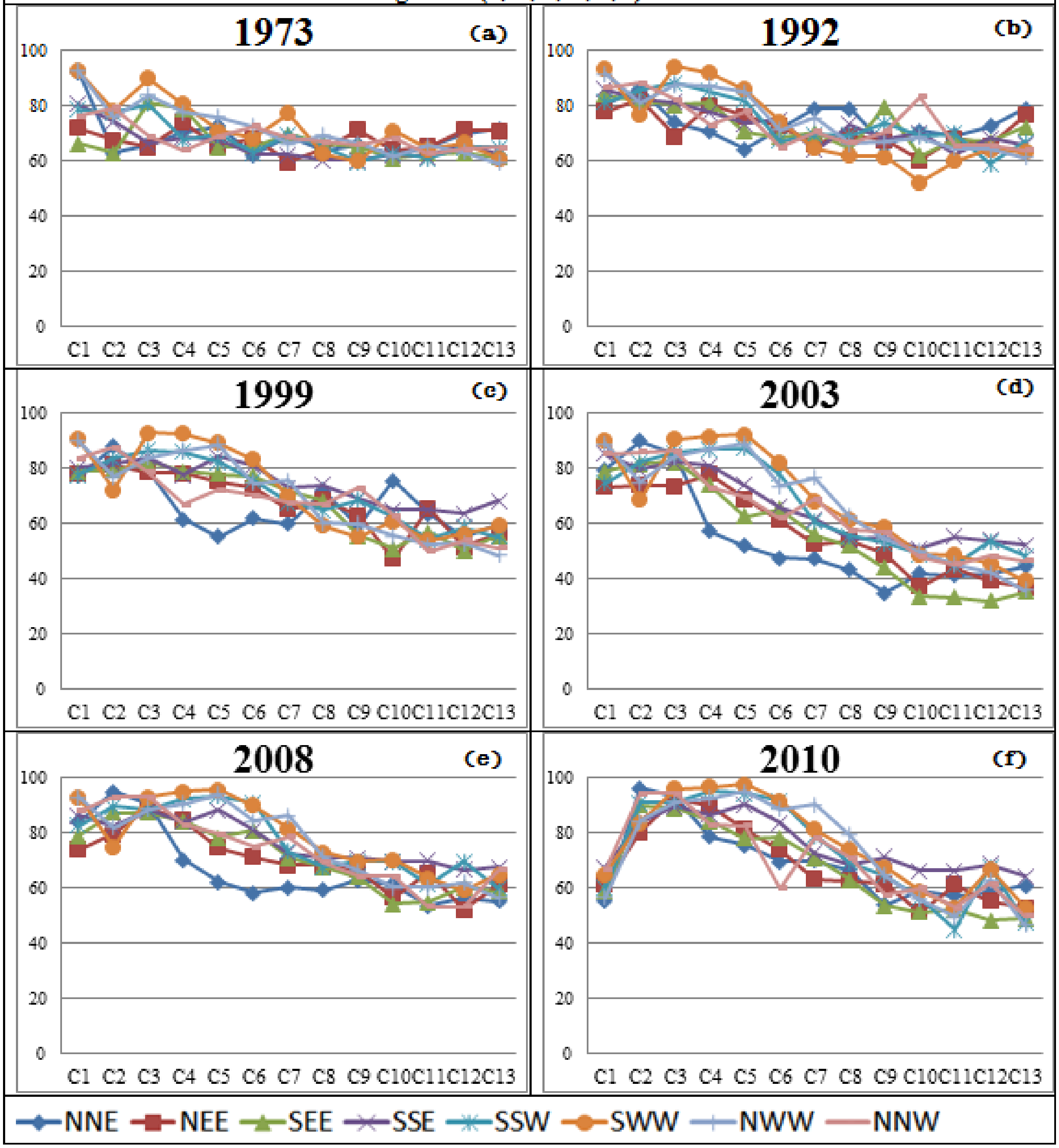
Figure 13and Figure14 shows Clumpy Indexand AI (Aggregation Index). The city is more clumped/aggregated in the center with respect to all the directions(i.e. aggregation) but towards periphery it is showing the patches are disaggregated for all the years indicating that the regions towards periphery in experiencing a kind of growth in which small fragments are formed and then each fragments join to form a single fragment (many to one) this clearly indicates urban sprawl happening in this region.

Figure 13(a, b, c, d, e, f): Clumpy



X axes: Circles of 2km radius; Y axes: Clumpiness Index.

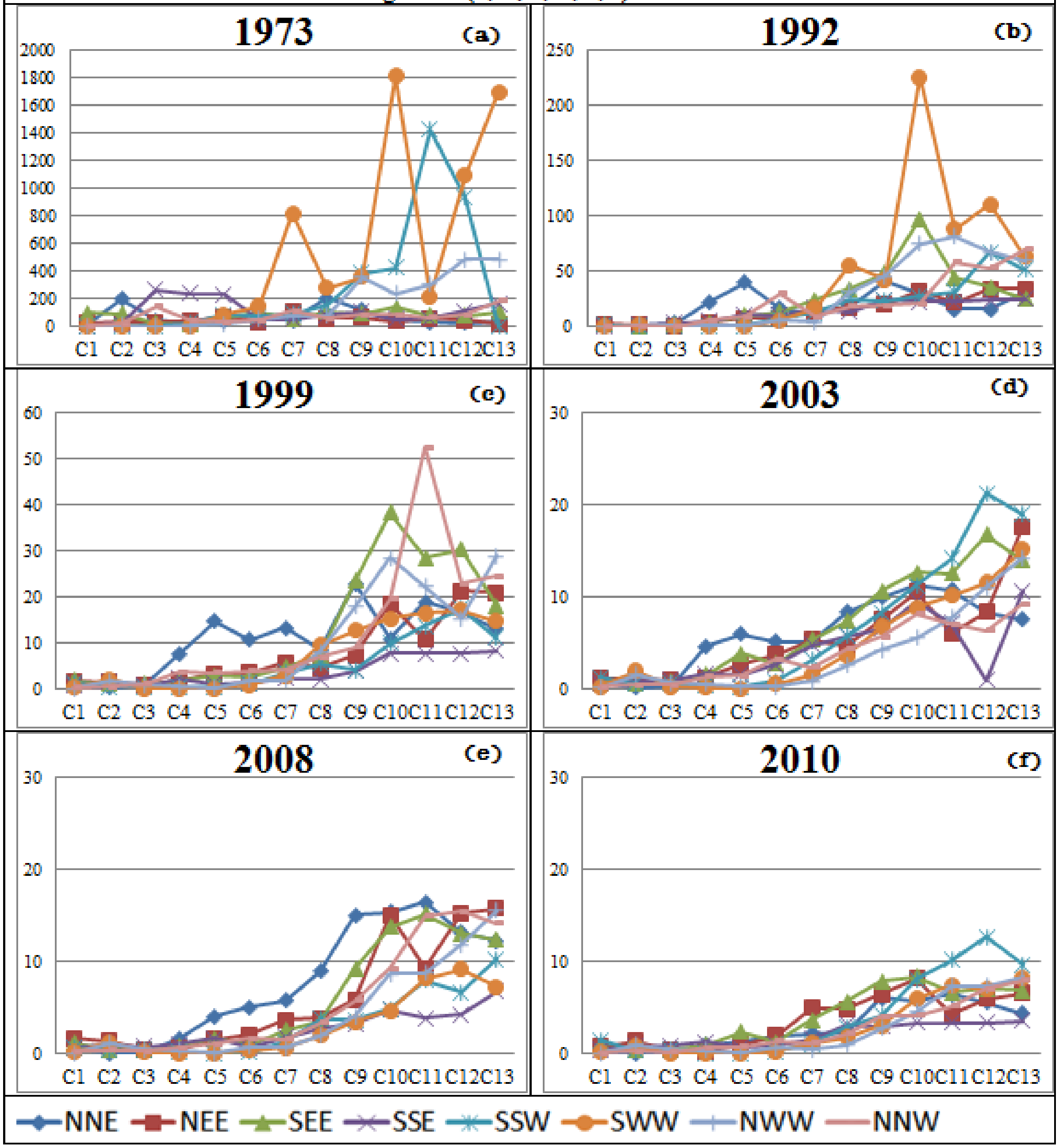
Figure 14(a, b, c, d, e, f): AI



X axes: Circles of 2km radius; Y axes: Aggregation Index.

Figure 15shows Ratio of Open Space (ROS) index. This Index explains the contribution of open spaces in urban region, which is necessary to understand the growth of urban region and its connected dynamics.ROS was more in 1973 with respect to all the directions, especially in the periphery of 10km boundary. ROS decreases in the later years and reaches low values in 2010 indicating that the urban patch dominates the open area which causes limits spaces and congestion in the urban area

Figure 15(a, b, c, d, e, f): ROS



X axes: Circles of 2km radius; Y axes: Ratio of open space Index.

6. Conclusion

The study shows that Bangalore is rapidly expanding with a significant increase in built-up area i.e., 28.7% and decrease in open space (water bodies and vegetation). This study also identifies the potential utility of common landscape metrics in the identification of the spatio–temporal pattern of landuse change in response to the process of urbanization.The results substantiate the utility of spatial metrics for metropolitan land use planning. The study concludes that urban patches in Bangalore are clumped together near the urban center, but fragmented towards the periphery due to new urban patches developed at the edge.Shannon’s entropy and landscape metrics have been computed which helped in understanding the form of urban sprawl and its spatial pattern. Urban sprawl is taking place continuously at a faster rate in outer areas, bringing more area under built-up category as revealed by metrics (dispersed growth). Shannon entropy is indicating the increase in the value from 1973 to 2010 and reaching towards the critical (reference) value showing the most prominent growth in the urban area. Current research results can be further be improved in detail by incorporating ecological, social, political, and economic factors with higher resolution data. This Analysis suggest that there has to be a planned growth and must be monitored and maintained, which will help in avoiding unplanned upsurge in the outskirts.

7. Acknowledgement

We are grateful to NRDMS Division, The Ministry of Science and Technology, Government of India and Centre for *infrastructure*, Sustainable Transportation and Urban Planning (C*i*STUP), Indian Institute of Science for the financial and infrastructure support.

References:

1. Barney,Cohen., 2006. Urbanization in developing countries: Current trends, future projections, and key challenges for sustainability, Technology in Society, 28 (1-2), pp. 63-80.

2. DiBari, J., 2007. Evaluation of five landscape-level metrics for measuring the effects of urbanization on landscape structure: the case of Tucson, Arizona, USA. Landscape and Urban Planning. 79, pp. 308–313.

3. Dietzel, C., Herold, M., Hemphell, 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), pp. 175-195.

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

5. 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., pp. 517–554).

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

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

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

9. 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, pp. 293–303.

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

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

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

13. Li, X. and Yeh, A.G.O., 2000. Modelling sustainable urban development by the integration of constrained cellular automata", International Journal of Geographical Information Science, 14(2), pp. 131-152.

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

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

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

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

18. 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, pp. 198–207.

19. RaffaellaFrondoni, Barbara Mollo, Giulia Capotorti, 2011. A landscape analysis of land cover change in the Municipality of Rome (Italy): Spatio-temporal characteristics and ecological implications of land cover transitions from 1954 to 2001, Landscape and Urban Planning, 100 (1-2), pp. 117-128.

20. 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.

21. 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

22. Roy, P.S., Tomar, S., 2001. Landscape cover dynamics pattern in Meghalaya. Int. J. Remote Sens. 22, pp. 3813–3825.

23. 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, pp. 201–216.

24. Small, C., 2001. Scaling properties of urban reflectance spectra, Proceedings of AVIRIS Earth Science and Applications Workshop, 27 February—02 March, Palo Alto, California, (NASA) Jet Propulsion Laboratory, Pasedena, California.

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

26. 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, pp. 29–39.

27. Tanguay, A., Lefebvre, J.F., Lanoie, P., 2010. Measuring the sustainability of cities: an analysis of the use of local indicators. *Ecological Indicators*, 10, pp. 407–418.

28. Taubenböck, H.M., Wegmann, Roth, A., Mehl, H., Dech, S., 2009. Urbanization in India – Spatiotemporal analysis using remote sensing data Original Research Article Computers, Environment and Urban Systems, 33 (3), pp. 179 -188.

29. UNPD, 2005. World Urbanization Prospects: The 2005 Revision. United Nations Population Division, New York.

30. 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.

31. 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), pp. 761–782.

32. 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 Sensensing. 69, pp. 1003–1010.

33. 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), pp. 83–90.

34. 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), pp. 1075–1092.

35. Zhou, Z., 2000. Landscape changes in a rural area in China. Landscape and Urban Planning. 47, pp. 33–38.