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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.

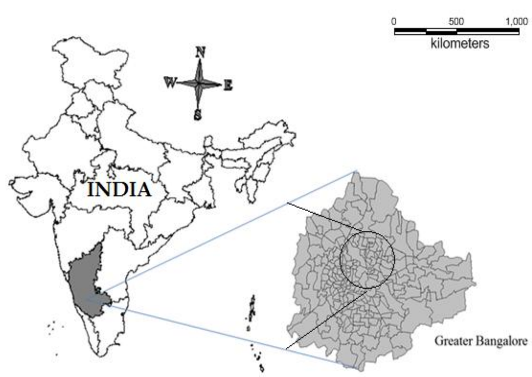


Fig. 1. Study Area: Greater Bangalore.

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

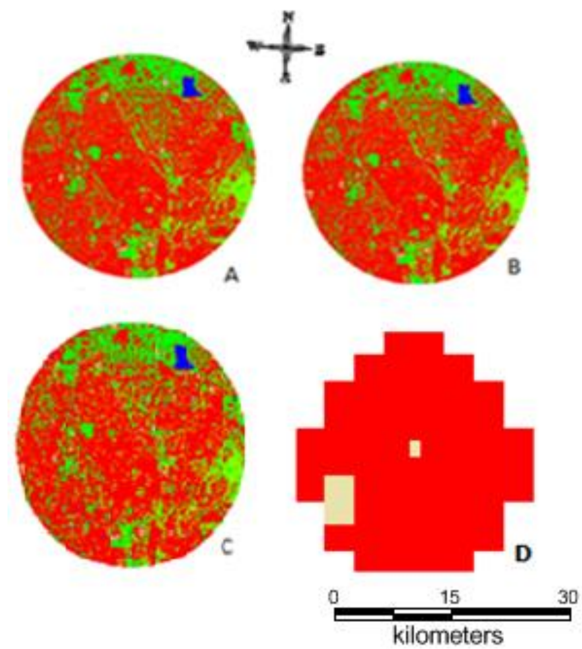


Figure 2: Land use statistics a). Ikonos 4m, b).IRS-P6 5 m, c). Landsat-30m, d). Modis-500m.

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.

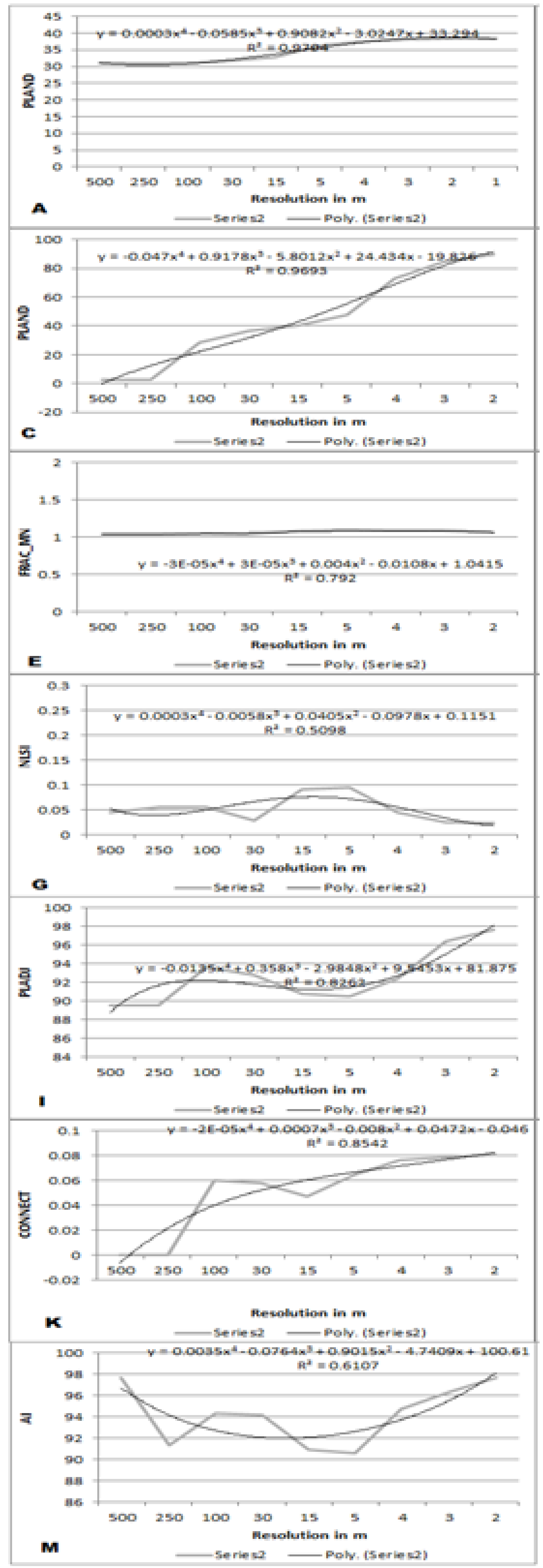
Percentage of Landscape (PLAND) and Number of Patches (NP) as tabulated in table 3, Indicates the level of fragmentation. The results highlight the dependence on spatial resolutions evident from the refinement of values with finer spatial resolutions. PLAND indicates that the urban patches in this region 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.



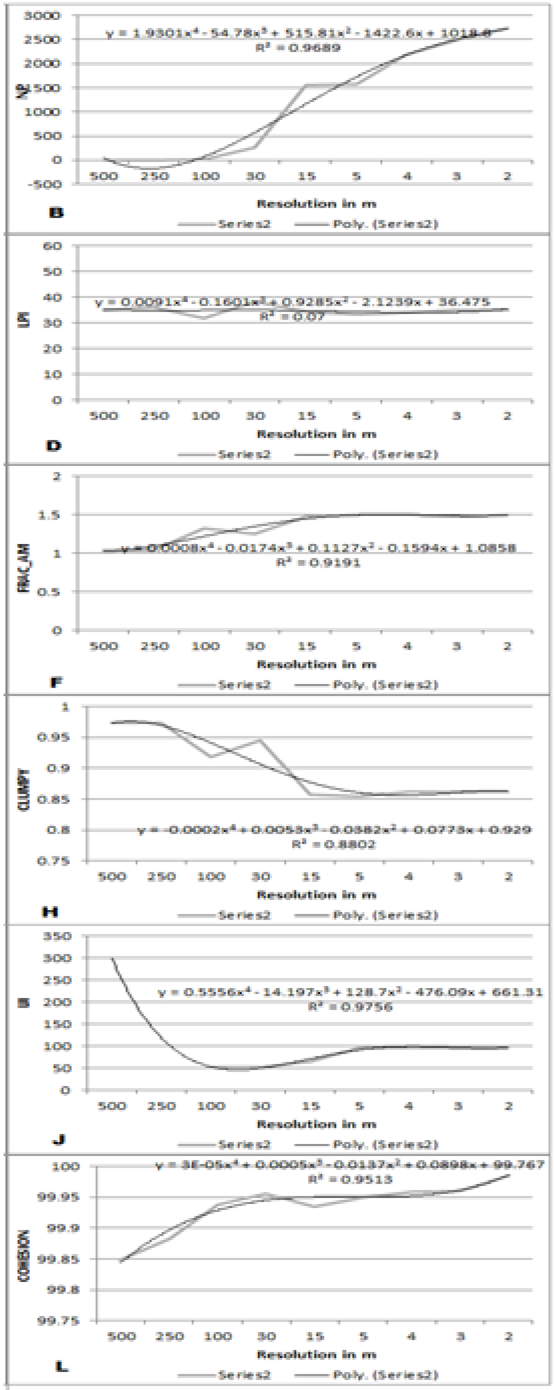


Figure 3: Correlation of spatial Matrices with resolutions of the data

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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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	$$IJI=\frac{-\sum_{i=1}^{m}\sum_{k=i+1}^{m}\left[\left(\frac{e_{ik}}{E}\right).\ln\left(\frac{e_{ik}}{E}\right)\right]}{\ln\left(0.5\left[m(m-1)\right]\right)}(100)$$ 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.	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	$$COHESION=\left[1-\frac{\sum_{j=1}^{n} p_{ij}}{\sum_{j=1}^{n} p_{ij}\sqrt{a_{ij}}}\right]\left[1-\frac{1}{\sqrt{A}}\right]^{-1}\cdot(100)$$	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)