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Assessing Dynamism of Urban Built-up Growth and Landuse Change Through Spatial Metrics: A Study on Siliguri and its Surroundings

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ABSTRACT

The process of rapid urban expansion in developing countries has been changing the landuse pattern in the cities and its outskirts, creating adverse effects on the harmony of environment and socio-economic structure on different spatial scale. Siliguri, the largest urban agglomeration in north Bengal, India, has been facing rapid urban growth since three decades that has resulted into continuous decrease of natural land and rapid peri-urban growth. This paper evaluates the landuse and landcover dynamics over three decades and has attempted to quantify the structure of built-up growth in rural-urban gradient. Multi-temporal satellite images were collected for landuse/landcover classification of 1990, 2001 and 2010. Landuse and landcover statistics with landscape metrics were analysed to calculate the impact of urban growth on land fragmentation process. The result shows that intensity of built-up growth is occurring in a rapid pace, whereas, the growth of other landuse classes are dynamic in nature. Agglomeration of built-up patches in the periphery of the city indicates the polycentric urban growth process. The built-up growth process in Siliguri experienced coalescence and infilling growth pattern near the existing patches and the vividness of coalescence is higher near the centre of the city. The present study concludes that spatial metrics is an aid to urban policy makers to understand the composition and configuration of urban landscape. It helps to determine whether the development can take place in a specific landscape and policy can reach a consensus.

Keywords:
Siliguri, landuse and landcover dynamics, landscape metrics, urban growth, rural-urban gradient.

1. Introduction:

The growth of megacities to a saturation point in the global north has propelled the shift of the process of urbanization towards the global south, resulting in 66% urban population growth by 2050 (United Nations, 2014). In the global south, population concentration has steeply increased in the cities with the population less than 1 million (United Nations, 2014). As in the case of India, it has been projected that cities will become centres of strong regional growth by 2030 as a result of a sea-change in its socio-economic conditions; second and third level cities will become the growth centres through infrastructural development and better linkages with hinterlands. Therefore, there is an urgent need to improve of the planning process. But the shortfall of understanding urban planning and the built-up growth pattern in the peri-urban areas lead to hapazard growth in the name of suburbnization (Bhatta, 2009; Maithani, 2010).In light of these issues, remote sensing and GIS tools can render information on land use changes and solutions created by land alteration process (Gupta, 2014). In recent times, most of the researchers have paid attention to the land use changes in the urban area and how land transformation influences the local environment and economy (Choudhury& Das, 2016). Fragmentation of land resource and large-scale conversion of agricultural and forest land to low density

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urban area leads to dispersion of local economy and economic degeneration (Weng, 2002; Yu & Ng, 2007; Dadhich & Hanaoka, 2011). The process of land alteration and urban growth without harmonizing the urban ecosystem posed a serious threat to the natural environment (Deal& Schunk, 2004; Young, 2013). Recently, Du et al., (2014) describes how rapid land use change became significant where built-up development happened at the expense of cropland and thus, threatning the future food security.

There is an enormous differentiation between built-up growth and farmland loss in different regional scales. To render the information of urban land use dynamics, remote sensing and spatial metrics have been used to enhance urban modeling and urban morphological analysis (Chakraborti et al., 2018). In urban studies, spatial metrics have been comprehensively used for its novelity in the landscape analysis. It can address the dynamics of growth process and capture the variability in both intra and inter-city domains (Herold et al., 2005; Chaudhuri & Clarke, 2012). Mas et al. (2012) argued that the transition of land use from one time period to another time period depends on the locational attributes, and patterns of landscape. Landuse modelling depends on the drivers of landuse changes (i.e., population growth, locational advantages, distance from the major transport networks etc.) and amount of changes in the past, but it is unable to capture spatial configuration of landuse classes which is important for the natual resource management and conservation. Thereby, landscape metrics like shape, size, etc come to the forefront to quantify spatial configuration of landuse classes on class and landscape level.

Landscape metrics helps to determine the present status of landscape dynamics in the city level analysis. Different landscape metrics can disclose intra-urban landscape pattern in response to urban growth and its relational aspects with other landscapes. Yeh & Huang (2009) studied city growth process and its outlying area in China by using Edge density (ED), Patch density (PD) and Area Weighted Mean Fractal Dimension (FRAC_AM). They came to the conclusion that though the value has decreased over the study period, fragmentation indices were on the rise; thus having a significant correlation among Shannon's diversity index value (SHEDI) and degree of urbanization. In the study of landscape analysis, Liu et al. (2010) proposed Landscape Expansion Index (LEI), and argued that most of the spatial metrics are characterized by geometric and spatial properties of a categorical map but hardly capture the information of spatio-temporal dynamics change of landscape pattern from multi-temporal satellite images.

Although spatial metrics reveal the spatial characteristics of individual time points they are incapable of capturing integrated information of different time series data. In this context, Landscape Expansion Index (LEI) estimateson two-time-point data, Jiao & Liu (2015) developed Multi-order Landscape Expansion Index (MLEI), to measure the degree of expansion of newly developing urban patches by deliberating their relationships with old patches and their spatial context in the process of urban development. There are significant differences between MLEI and LEI values in the same data in the same period which show that massive urban patches exist in the peripheral zone; a probable sign of future urban growth centre. This can help to characterize the long-term pattern of urban growth, like in-filling, outlying and edge expansion process (Wilson et al., 2003). Sun et al. (2012) demonstrated and outlying growth dominatingin the initial phases of urban growth. Afterwards, distant growth decreased and edge-expansion, in-filling growth became predominant along the major transport networks. Unlike previous studies, Chen et al. (2013) used spatial metrics to determine diffusion and coalescence process of urban growth, proposed by (Dietzel et al., 2005). Metrics are different in their value; one may be range dependent or unitless or reported as a percentage. However, comparing metrics by different value ranges may sometimes be difficult to determine ecologically significant change (Lafortezza et al., 2005). Previously, Principal Component Analysis (PCA) and factor analysis have been used to abbreviate multitude of landscape metrics and sub setting them as per respective applications (Riitters et al., 1995). In this process, (Cushman& Neel, 2008) used 24 independently identified components by using PCA and grouped them to describe universality, strength and consistency of metrics at class and landscape level by which parsimony of landscape metrics are reduced, and actual landscape pattern can be evaluated. This indicator is useful for large scale ecological modelling, but urban like complexes i.e., shape, pattern and configuration may be undermined (Herold et al., 2005). Plexida et al. (2014) suggested to divide a large region into different sub-regions and selected indicator depending on the area size contribution. They also pointed out that Stabilization of metrics values within the proper area size contribute to the right indicator selection process."

Despite the limitation of the applicabilty of spatial metrics, it has been used in Indian cities to understand urban landscape pattern and configuration for better urban mangement (Sudhira et al., 2004; Jatet al., 2008; Punia & Singh, 2012). Jain et al. (2011) computed spatial metrics in Gurgaon to quantify patterns of urban growth in a different direction from the city centre. In newly developed Ranchi City, Jharkhand, evaluation of urban pattern was studied to compare pre-capital and post-capital urban landscape dynamics using different landscape metrics (Sinha et al., 2011). But, few studies have focused on how spatial pattern of urban growth in rural-urban area is important for long term urban mangement in the emerging cities of India. All of these above facts suggested that the application of metrics with the careful choice is useful for various geographical scales. This study focuses on spatial pattern and configuration of landuse classes in an emerging urban landscape and also reveals spatial pattern of newly grown built-up area in rural-urban interface.

2. Study area, database and methodology

2.1 Study area

Siliguri Municipal Corporation (SMC), and its surroundings Census Town (CT) and rural villages are recognized as the study area. SMC is the central urban block, while the surrounding newly formed CT and rural villages are recognised as the peripheral blocks. SMC is the only class 1 city on the bank of river Mahananda, situated at the foothill of the Darjeeling Himalaya, astride in the West Bengal's head. The population of SMC in the current census (2011) is nearly 5 lakh, whereas that of the census town is approximately 3 lakh population and rural area 2lakh. The annual population growth rate of the study area is 5.3 % during 1991-2001 and 2.3 % in 2001-2011. The annual population growth rate of SMC was 11.7% in 1991-2001 and 2001-2011, growth rate is 0.9 %, whereas, annual population growth rate in census town and rural area is 4.3 % and 4.2 % respectively in current census.The growth of Siliguri, and its surroundings is the function of several temporal processes, including rural migration to the urban areas and the city's

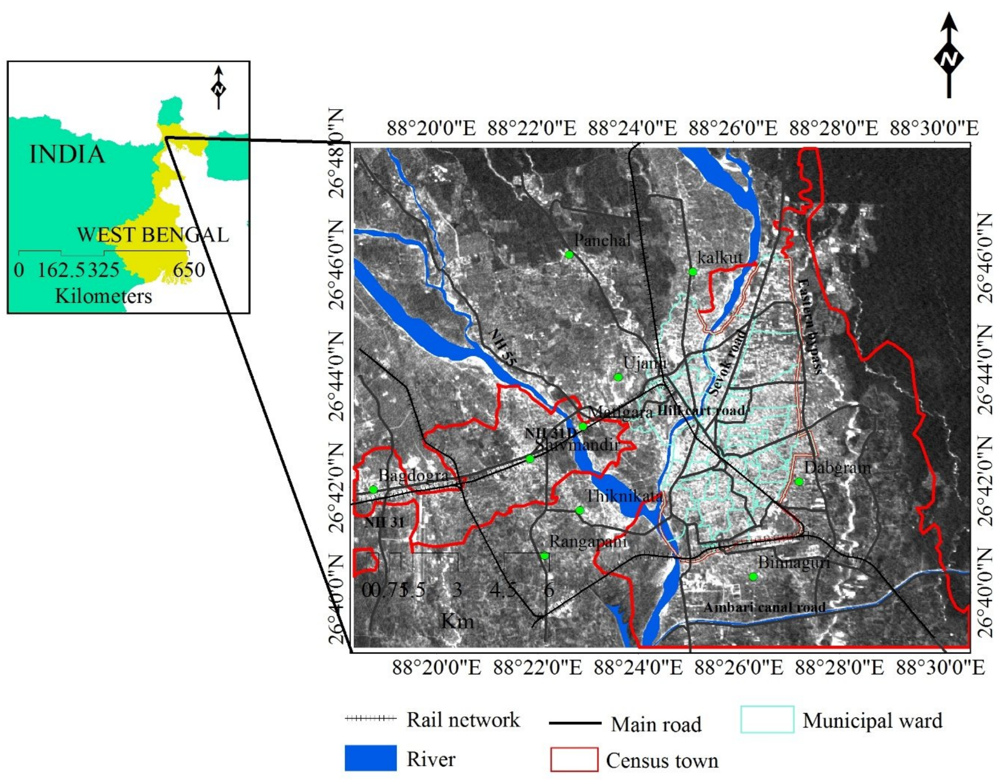

Fig. 1 : Study area map of SMC and surroundings

inherent natural growth, which makes the city vibrant centre for economic development in North Bengal (Gosh et al., 1995). The latitudinal extentof the study area is 26°39'7" N to 26°48'7" N and longitudinal coverage is 88°18'26"E to 88°30'34" E. The total study covers 335 sq. km. Siliguri municipal corporation comprises 40 sq.km, whereas census town and the vast rural area includes 97 km^2 and 198 km^2 respectively (**Fig.1**). The study area is well linked with Sikkim and north-eastern states by National highway and rail networks that make the city a strategically important centre of urban growth in North Bengal.

2.2 Database

Time series Landsat images for the period of 1990, 2001, and 2010 were collected (with minimum cloud cover less than 10 %) based on Path-139 and Row-41. All the images were rectified and resampled to UTM-WGS-84 zone 45N and 30x30m resolution **(Table 1)**. To derive the land use classes, the cloud cover accounting for less than 10% of the satellite images have been removed. Afterwards, atmospheric correction was done in the algorithm predefined in ENVI software using Fast Line of Sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) module. Unique models for each image can be computed using the MODTRAN radiation transfer codes and algorithms on which FLAASH is based (ENVI, 2009). The study area covers 677 columns and 552rows. Several methods have been developed for landuse/landcover classification from the satellite images, mainly Decision Tree (*DT*) (Pal & Mather, 2003), Support Vector Machine (*SVM*) (Huang et al., 2002), Artificial Neural Network (*ANN*) (Civco, 1993), Object based classification (Myint et al., 2011). These classification techniques is superior in homogenous landuse/landcover analysis and outperform in high resolution satellite images. But, in the heterogeneous urban environment, supervised classification with maximum likelihood algorithm extensively used for landuse classification (Bhatta, 2009; Mondal et al., 2017; Sahana et al., 2018). We rendered five broad landuse classes: built-up, water bodies, cropland and open land, sand (sand bar), and greenery and plantation (**Table 2**). Selection of landuse/landcover classes were based on the knowledge of the study area and with the help of landuse map of Siliguri. Training samples of each class were identified by 30n procedure, where n is no of bands. As Siliguri does not have any reliable previous landuse map, therefore, old documents and Google Earth image used to validate the classification images by computing 150 random points. Finally, kappa statistics was calculated to test the level of accuracy of each landuse images. The kappa value for 1990, 2001 and 2010 are 0.81, 0.82 and 0.85% respectively. Brief descriptions of methodology are given in **(Fig.2)**.

Table 1. Descriptions of data source

Sensor	Date of acquired	Spatial reference	Spatial resolution
Landsat 4–5 TM	10-09-1990	WGS 1984 UTM 45 N	30 m
Landsat ETM+	02-10-2001	WGS 1984 UTM 45 N	30 m
Landsat TM	05-09-2010	WGS 1984 UTM 45 N	30 m

Table 2. Descriptions of Landuse and landcover classes

Class Name	Descriptions
Built-up	It includes urban land, high-density urban area, transportation, infrastructure, low-density rural built-up area, impervious area
Water-bodies	Rivers, artificial pond, lakes, canal, etc.
Cropland & current fallow	Agricultural land, non-agricultural land, unused vacant land, fallow land, etc.
Sand (sand bar)	Channel bar, sandy surface, etc.
Greenery & plantation	Reserved forest, tea plantation, manmade forest, vegetation coverage, park, etc.

2.3 Methodology

2.3.1 Landscape metrics, landuse composition and urban form

Pattern and configuration of landuse classes and their changes are important for conservation of natural resources and urban management. Therefore, literature review is the key component for the matrics selection (Dietzel et al., 2005; Herold et al., 2005; Jiang et al., 2007; Yeh & Huang, 2009; Sun et al., 2012). One group consists of three metrics of diversity (i.e., Shannon's diversity index and Shannon's evenness index). The other five metrics comprise of landscape composition and configuration (i.e., Percentage of a landscape (PLAND)), patch density (PD), Mean patch size (AREA_MN), Interspersion and Juxtaposition Index (IJI), and Area weight mean fractal dimension (FRAC_AM). For the purpose of analysing built-up growth pattern in rural-urban interface, gradient analysis was used for this study. There are two principal methods for gradient analysis: one is transect-based analysis, where transect are drawn from different directions, by virtue of which different sampling strategies can be applied to analyse landscape pattern (Schneider et al., 2005; Yu & Ng, 2007) but, directional approaches are quiet inefficient to capture intra-directional variability and another important method is buffer analysis, where buffer

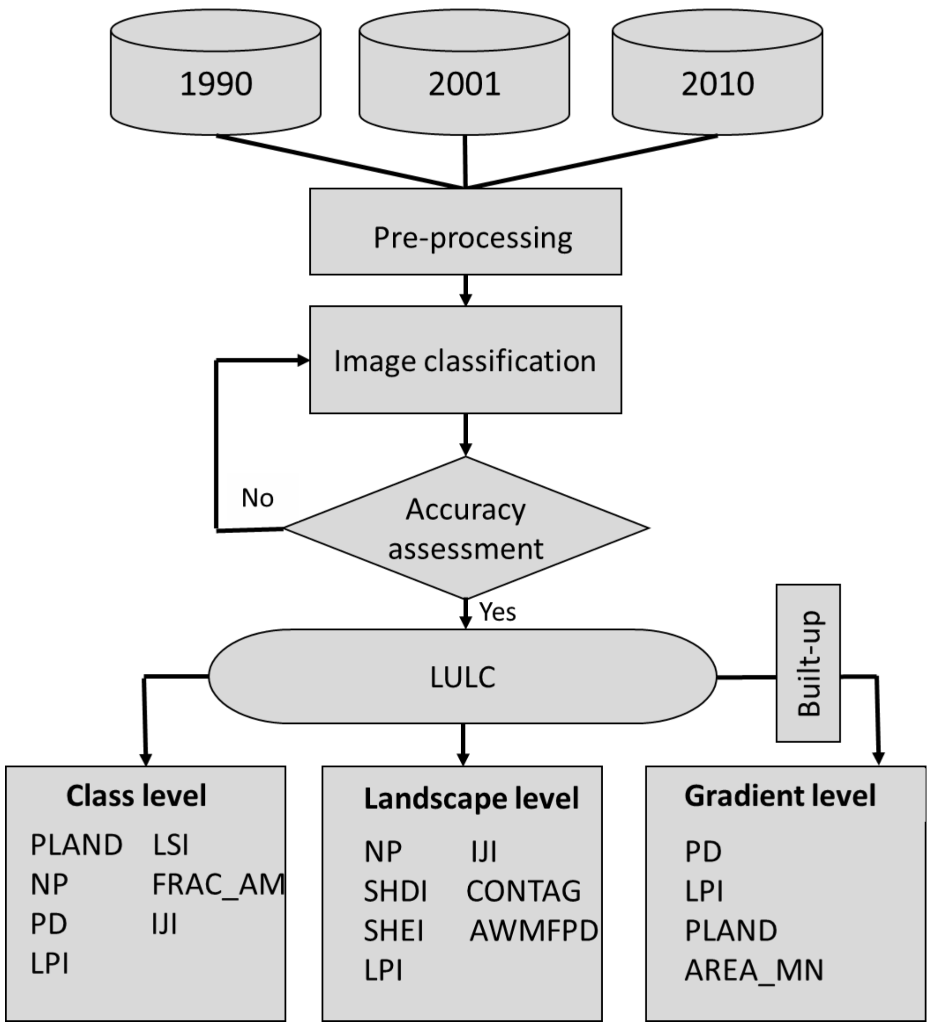

Fig. 2 : Brief methodological flowchart

created from city centre to a uniform distance (Seto & Fragkias, 2005; Wu et al., 2015). In this study, buffer approach was applied and four metrics were selected to quantify the process of built-up growth in rural-urban gradient. The rationality of the metrics selection are sometimes based on the literature review and previous study (Mcgarigal, 2014) Meanwhile, buffers have been created from planner recommended city centre with 500 meter uniform distance that captured dynamics of small patches in the city and the rural areas; 31 buffer covers the whole study regions.

2.3.1.1 Percentage of Landscape (PLAND)

It is a measurement of proportional abundance of landuse classes during 1990, 2001 and 2010. It measured by the total area of the all patches of a particular land use class in respect to the study area in sq. meter. Percentage value is obtained by multiplying it with 100.

$$PLAND = P_i = \frac{\sum_{j=1}^{j} a_{ij}}{A}(100) \quad (1)$$

Where, P_i is the proportion of patch types or classes in the landscape level, a_{ij} is area (m^2) of patch i, j.A is the area of the total landscape

2.3.1.2 Landscape Shape Index (LSI)

It demonstrates the landscape shape of each class in the landscape. It describes the class perimeter and total edge within the landscape divided by the total area. It represents aggregation at the class level or the landscape level.

$$LSI = \frac{e_i}{\min e_i} \quad (2)$$

Where, units: none, range: >1, without limit e_i= total edge length, basically perimeter of each individual class. min e_i is the minimum length of edge of individual class.

2.3.1.3 Number of Patches (NP)

It is an indicator of diversity or richness of the landscape. Number of Patches mainly measures the extension of subdivision of urban area and other land classes. NP is high when the urban landscape experiences rapid growth and hence, landscape becomes more heterogeneous and fragmented.

$$NP = N \quad (3)$$

Where,Units: None, Range: NP$\geq$ 1, without limit, NP=1, when landscape comprises only one single patch.

2.3.1.4 Patch Density (PD)

Intensity of fragmentation in urban units can be measured by patch density. PD varies with its circumference. It may increase or decrease. Substantial growth of patches in the study area is the indication of heterogeneous urban development, which describes landscape is fragmented.

$$PD = \frac{n_i}{A}(10000)(100) \quad (4)$$

Where, n_i = number of patches in the landscape of patch type (class) i, A = total landscape area (m^2), units: number per 100 hectares, Range: PD>0, without limit

2.3.1.5 Interspersion and Juxtaposition Index (IJI) (%)

This metrics is the representation of compactness and dispersion of landcover classes in the landscape level analysis, where it measures patch adjacencies, rather than cell adjacencies. Intermixing is the highest when the value is near 100 that is the interspersion is the highest among the classes.

$$IJI = \frac{-\sum_{i=1}^{m}\sum_{k=i+1}^{m}\left[\left(\frac{e_{ik}}{E}\right)\ln\left(\frac{e_{ik}}{E}\right)\right]}{\ln(0.5[m(m-1)])}(100) \quad (5)$$

Where, units: percent (%), range: $0 \leq IJI \leq 100$, e_{ik} = total length in meter of inter-mediate edge between patches, E = landscape edge in meter, without background. m = a number of classes situated in the landscape.

2.3.1.6 Largest Patch Index (LPI)

It describes the single largest patch in the landscape. This is a relative measurement and can be compared across different regions with different spatial extent. It is a fragmentation index that can describe the relationship of smaller discrete patches with the dominant core. LPI is equal to 0 when patch becomes smaller; it becomes 100 when the entire landscape consists of a single patch. Here, total landscape area(A) includes the background. It's a simple measure of dominance.

$$LPI = \frac{\max(a_{ij})}{A}(100) \quad (6)$$

Where, a_{ij}= area (m^2) of patch i, j; A = total landscape area (m^2), units: percent(%), range: $0 < LPI \leq 100$

2.3.1.7 Mean Patch Area (AREA_MN)

It gives the insight of central tendency of the particular pathches in the landscape. It is the sum of all corresponding patches divided by the total no of patches of the particular class.

$$AREA\_MN = \frac{\sum_{i,j}^{n} x_{ij}}{n_i} \tag{7}$$

2.3.1.8 Area Weighted Mean Fractal Dimension (FRAC_AM)

It is a measurement of patch shape complexity that depicts the convolution and fragmentation of a patch as a perimeter area ratio of 1990, 2001 and 2010. It equals the sum, across all the patches in the landscape, and the fractal dimension values of a corresponding patch can be obtained by multiplication by proportional abundance of the patches. It is logarithm ratio of patch perimeter and patch area.

$$FRAC\_AM = \sum_{i=1}^{m}\sum_{j=1}^{n}\left[\left(\frac{2\ln(.25P_{ij})}{\ln a_{ij}}\right)\left(\frac{a_{ij}}{A}\right)\right] \tag{8}$$

Where, units: none, range: $1 \leq FRAC\_AM \leq 2$

2.3.1.9 Shannon's Diversity Index (SHDI):

It's a relative abundance of patch type in a particular landscape. It is a measurement in the diversity of patch in landscape level. SHDI = 0, when landscape consist only one patch (i.e., no diversity exist). SHDI increases when number of different type (i.e., patch richness).

$$SHDI = -\sum_{i=1}^{m}(P_i * \ln P_i) \tag{9}$$

P_i= proportion of the landscape occupied by patch type (land class, i). Units: None, range: SHDI $\geq$ 0, without limit

2.3.1.10 Shannon's Evenness Index (SHEI):

It represents the uniformity of different patch areas. It describes the proportional abundance of each patch types in the landscape. (MacGarigal et al., 2002).

$$SHEI = \frac{-\sum_{i=1}^{m}(P_i * \ln P_i)}{\ln m} \tag{10}$$

Where, P_i = proportion of the landscape occupied by patch types (class, i). m = number of patch types (classes) present in the landscape, excluding the

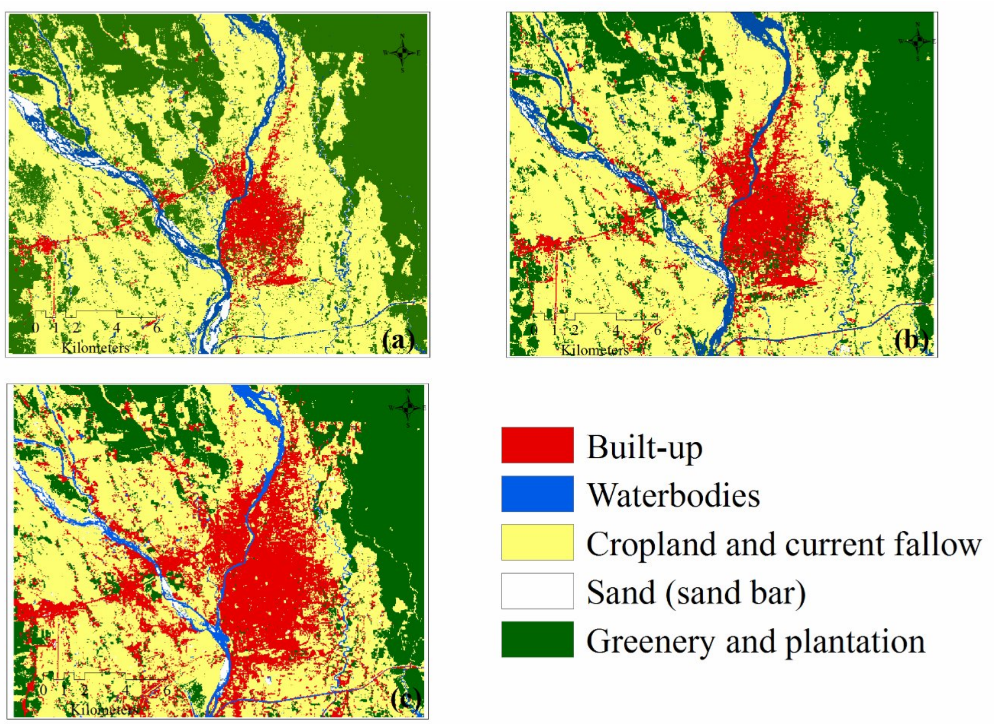

Fig. 3 : Classified landuse and landcover map of (a) 1990, (b) 2001, (c) 2010.

landscape border if present. Units: none and range: $0 \leq SHEI \leq 1$

3. Results and discussion

3.1 Landuse and landcover dynamics and urban growth

Over the last three decades, Siliguri has gone through the overwhelming urbanization process, which can been seen in the output of landuse and landcover maps for 1990, 2001 and 2011(**Figure 3**). **Table. 3** clearly indicates the increasing trend of PLAND value for built up areas and decreasing trend of other landcover pattern. More number of patches of respective classes over the region is clear sign of fragmented pattern of land use and landcover (**Table. 3**).

The scenario of landscape metrics change in the class level of Siliguri, and its surrounding (**Table 3**) clearly show that NP increased remarkably, which finds correspondence withthe patch density for built up class. The number of Patches for built-up areas increased significantly from 920 in 1990 to 2235 in 2001 and 3084 in 2010, which is more than three times growth from 1990 (**Table 3**). A similar indication of increase found in patch density (2.735 in 1990 to 9.169 in 2010) where concentration of a huge number of patches may be due to the rapid rate of urbanization process (Seto & Fragkias, 2005). This might indicate that built up growth in that area is not concentrated rather started to fragment. Considering landscape configuration, it is found that, largest patch index (LPI) and Landscape Shape Index (LSI) both are showing monotonically increasing trend from 3.47% in 1990 to 9.96% in 2010 for built-up (**Table 3**). Sharp growth of LPI point explains that the densification process started both in the already urbanized area and peripheral zone of the leading urban land. LSI is also increased significantly from 1990 (36.508) to 2010 (59.548) (**Table 3**), which denotes that the shape of built up land classes is going to be more complex in future. Values of AWMFD has been remaining same for 1990 and 2001, but slightly decreased by 0.2 points in 2010 (**Table 3**). This confirms that morphology of the urban broader has not become more complex and irregular, indicated by the infilling patches around the existing built-up land in the study area (Kuang et al., 2005). It is an indication of a start with a complex shape but converting to a simpler form in time as a result of an intense urbanization process (Li et al., 2013).

Table 3. Scenario of Landscape metricschange in patch class level of Siliguri and its surroundings

Year	Landuse Types	PLAND	NP	PD	LPI	LSI	FRAC_AM	IJI
1990	Built-up	5.628	920	2.735	3.475	36.508	1.297	58.014
	Water Bodies	5.091	1299	3.862	3.465	42.340	1.307	74.144
	Cropland & current Fallow	51.46	1601	4.760	17.500	47.611	1.326	67.299
	Sand(sand bar)	1.682	326	0.969	0.251	20.547	1.154	29.859
	Greenery& plantation	36.137	2978	8.854	15.878	42.055	1.212	30.945
2001	Built-up	9.951	2235	6.645	6.3751	48.800	1.291	61.382
	Water bodies	4.722	783	2.328	3.6692	34.233	1.327	79.873
	Cropland & current Fallow	56.072	1355	4.028	18.687	44.027	1.313	70.354
	Sand(Sand Bar)	0.718	210	0.624	0.0894	18.653	1.15	28.854
	Greenery& Plantation	28.534	2903	8.631	13.846	42.940	1.210	40.068
2010	Built-up	21.631	3084	9.169	9.9662	59.548	1.278	55.316
	Water bodies	3.445	782	2.325	2.1833	34.026	1.293	83.791
	Cropland & current Fallow	46.631	1677	4.986	10.330	52.501	1.292	70.762
	Sand(Sand Bar)	1.129	590	1.754	0.141	26.469	1.128	69.755
	Greenery& Plantation	27.163	1963	5.836	14.579	31.984	1.193	47.819

Note: PLAND= Percentage of Landscape, NP= Number of Patch, PD= Patch Density, LPI= Largest Patch Index, LSI= Landscape Shape Index, FRAC_AM= Area Weightage Mean Fractal Dimensions, IJI= Interspersion and Juxtaposition Index

On the other hand, NP for water bodies has been decreasing significantly over the period of 1990 (1299) to 2001 (783), but got stability in 2010. PD value also reflects the similar trend (**Table 3**). LPI is an indicator of landscape configuration, dropping from 3.46 in 1990 to 2.18 in 2010 (**Table 3**). However, increase of LPI values indicate that area of waterbodies has been decreasing over the study period. A similar trend has been found in LSI value also, showing a clear indication of certain fall between 1990 (42.340) and 2010 (34.026). LSI and its corresponding value describe patches of water bodies tending to be simpler rather than complex in shape. The increasing value of IJI (74.144 to 83.791 during1990-2010) for water bodies indicate patches being adjunct to each other. Similar trend has been found in AWMFD where the decrease of value between 1990 (1.307) and2010(1.293) establishes the reduction of their regularities of morphology. At the initial phase of urbanization, water-bodies were more disturbed by human intervention. Thus, implementation of regulation on waterbodies reduced human encroachment, hence waterbodies is being less fragmented.

The number of patches for cropland categories decreases during 1990-2001 (246), but the value increases in 2010 (1677) (**Table 3**). It means spatial heterogeneity of farmland increases with the growing disturbance of human intervention. Similar results are also found in the patch density. LPI value continuously declined since 1990, supported the fact of intensified urbanization process over cropland. An increasing trend of LSI value between 2001 (44.027) and 2010 (52.501) implies considerable increase of landscape complexity. AWMFD values (i.e., 1.3) remain same over the periodof 1990 and 2001. But, it slightly decreases in 2010, which shows that the shape of the cropland patch becoming regular. IJI represents similar kind of result indicating that cropland patches are being more adjacent. On the other side, morphology of the sand bar is very dynamic in nature, and it is due to non-perennial shifts of the course of the river from time to time and effects of human intervention. PD value of green space decreases over the study period from 8.85 in 1990 to 5.83 in 2010, this is due to the reduction of number of patch of green space over the study period **(Table 3)**. However, greenery becomes less irregular, and the complexity of shape is reduced due to the removal of the small patches. Another reason is that most of the green place on the eastern side and the northern side comes under the reserved forest category by the implementation of strict govt. rules. The government has given more emphasis on protecting the reserve forest in that particular area, as a result regularities and clumsiness in forest patch (Kowe & Gumindoga, 2014).

3.2 Spatial configuration in landscape level:

As mentioned earlier, different conventional indices have been used for measuring spatial patterns of landscape configuration of all classes at the landscape level (**Fig.4**) which can explain as the intensity of human intervention to change landscape configuration. A higher number of the patches in the landscape level (**Fig. 4(a)**), clearly indicates more fragmentation of landscape (Dewan et al., 2012). Shannon Diversity Index (**Fig. 4(b)**) measures the overall diversity of all the classes at the landscape level, which was 1.092 in 1990 and remained same during the study period till 2001 and started to increase in 2010, which demonstrates that the landscape of the study region began to reduce its diversity. Although it is a relative measurement of landscape patterns of diverseness, the value of Shannon Diversity Index increases if the relative abundance of class increases (Mcgarigal, 2014). The Shannon Evenness Index has not much changed between 1990 and 2001 (**Fig. 4(c)**).This indicates that unit of classes of land use and land cover are not evenly distributed and the size of the landuse and landcover is different. However, the value certainly rose up in 2010, means classes at the landscape level began to distribute uniformly. Uniformity is the accompaniment of dominance and diversity, only achieved when Shannon Evenness Value reaches 1; it is an approach towards the perfect evenness in the landscape level (Sinha et al., 2011; Kowe et al., 2014; Mcgarigal, 2014). LPI value in landscape level was equal in 1990 and 2001 (**Fig. 4(d)**). However, the value started to increase by 5 points in 2010, which means aggregation process of built-up had started in the landscape level. This overview gives a synoptic outlook about patterns and configuration in the landscape level. It depends on the process and response to urbanization. However, this overview cannot be able to conclude spatial pattern and process of built-up growth in rural and urban transect (Yu & Ng, 2007). The next section demonstrates the built up growth pattern in the surrounding land and the dynamics of built up growth along the rural-urban interface.

3.3 Built-up spread and pattern analysis along rural-urban transect

Transect analysis is applied to understand the

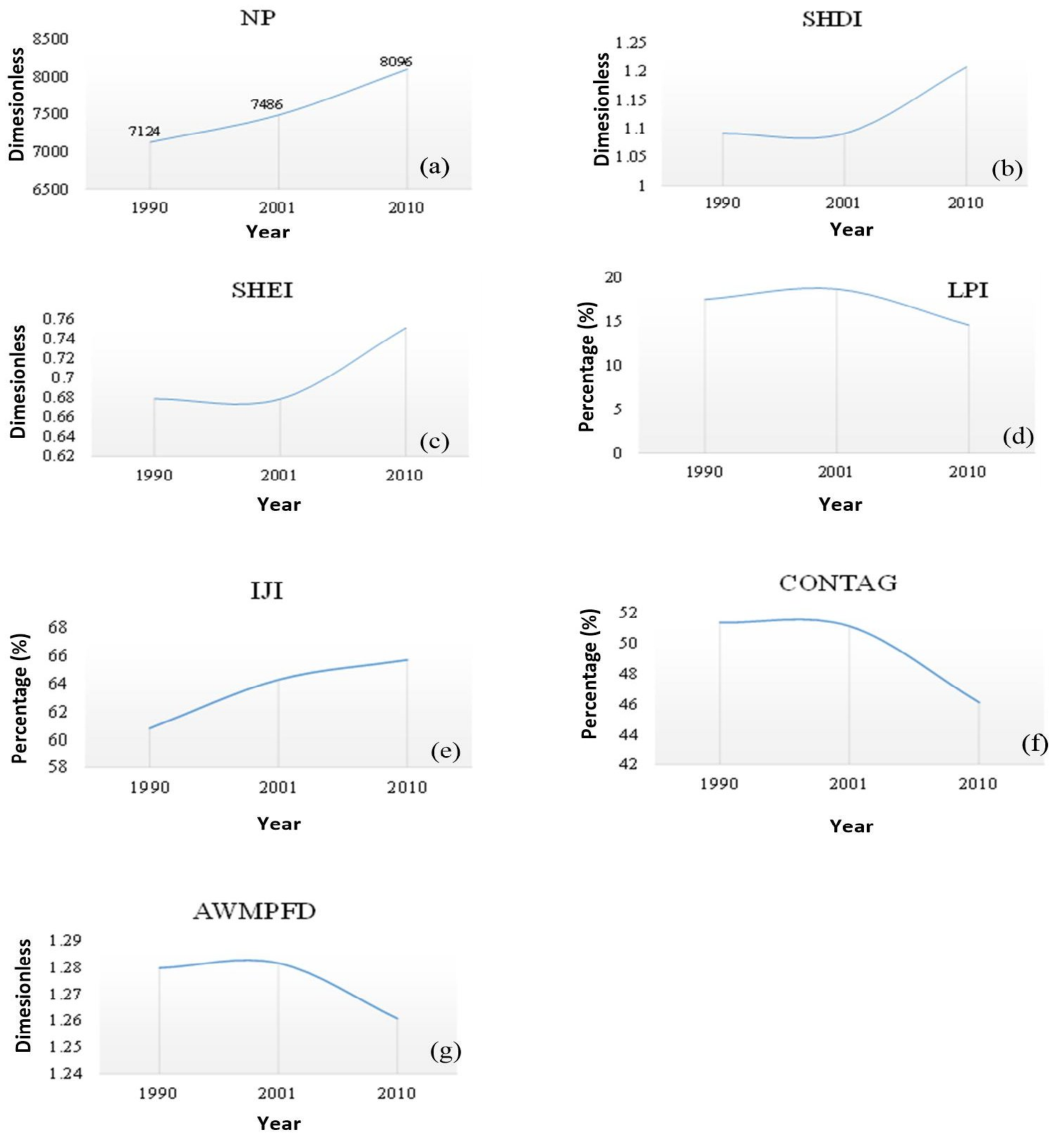

Fig. 4 : Changes in NP (a), SHDI (b), SHEI (c), LPI (d), IJI (e), CONTAG (f), AWMPFD (g) at landscape level.

nomenclature of the spatial pattern of urban growth in the rural area and within the city. Here, we have selected only built-up expansion, as an indicator of urban growth, and some spatial metrics based on literature. The metrics are PLAND, PD, NP, LSI, and LPI. All of these metrics are selected very cautiously to avoid redundancy of landscape metrics. **Fig. 5(a)** illustrate that percentage value of PLAND abruptly decreases from the central city to peripheral zone and gives the trailing shape in 1990. The similar trend followed in 2001 and 2010, when highest built up growth took place within 3 to 5 km from the city centre; which shows built up growth started to converge with the adjacent non-urban land. However, farther than 5 km from the city centre, the percentage share of built up growth decreased. It means that the original urban core started to diffuse from its central to the outward direction. This is happened due to several linkages of transportation node as they are radially expanding outward from the city centre, and

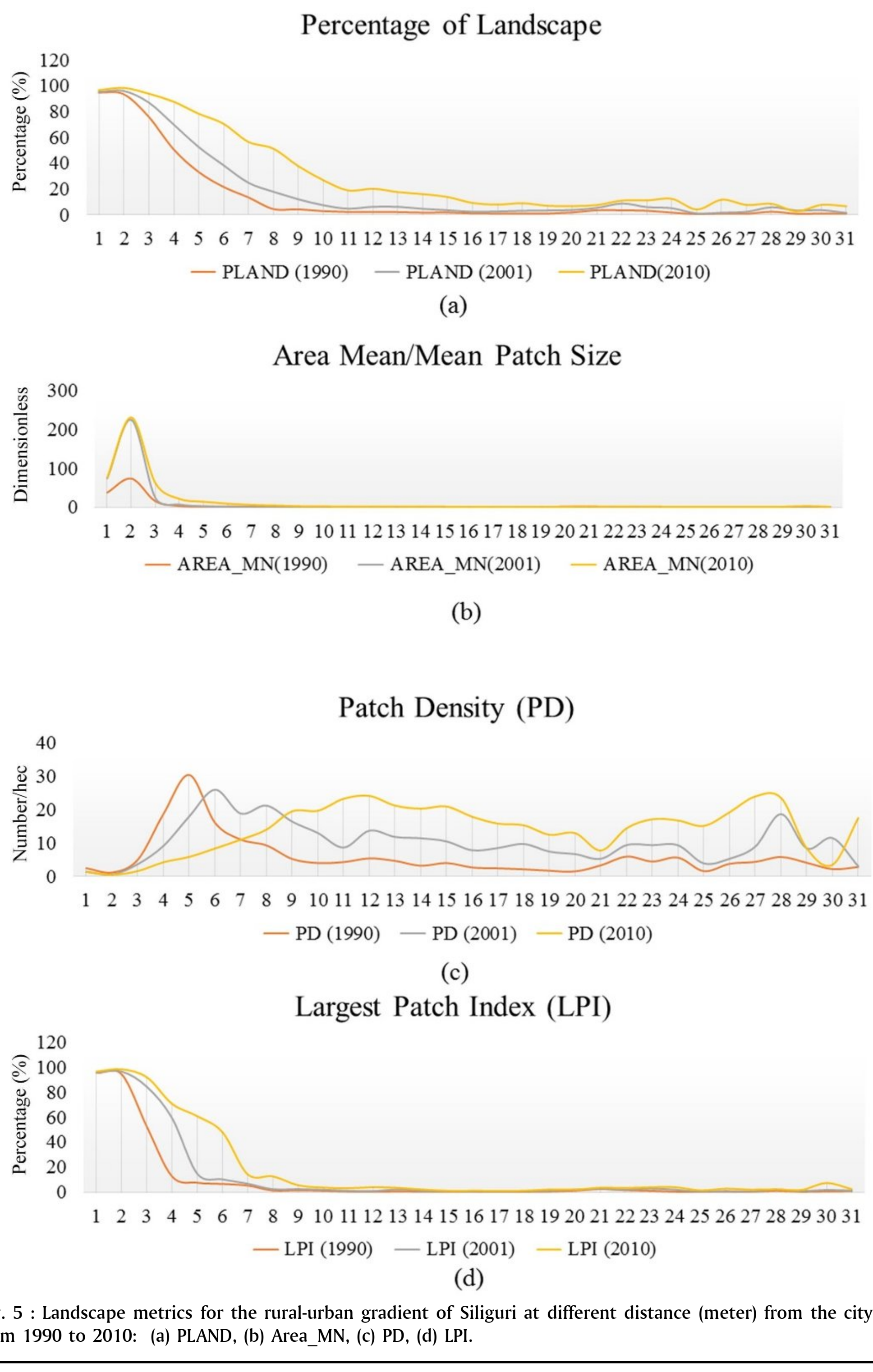

Fig. 5 : Landscape metrics for the rural-urban gradient of Siliguri at different distance (meter) from the city centre from 1990 to 2010: (a) PLAND, (b) Area_MN, (c) PD, (d) LPI.

after certain time of diffusion, they will merge (Dietzel et al., 2005). In Siliguri, major transportation node helps to expand the built-up, afterward minor transportation node helps to join individual patches that ultimately converge to a single patch.

Mean Patch Area (**Fig. 5(b)**) shows that patch size increases from the city core in 1 to 3 number ring buffer in 1990 and 2001; afterwards, it increased in 3 to 6 number buffer . This area covers the high built-up growth area of Ward 41, 43, 36, 37 and part of Dabgram, Kalkut, and Binnaguri. Urban core did not experience a progressive change between 2001 and 2010. It shows gradual decrease in mean patch size over the study period, indicating fragmentation; but increasing trend of mean patch area is responsible for densification and coalescence of the urban area (Taubenböck et al., 2014). PD is another measurement of landscape fragmentation (**Fig. 5(c)**). PD value will increase if the number of patches increases significantly. **Fig. 5(c)** illustrates that PD is growing outward in 2010 and taking an active peak within 5 to 8 km to 14 km from the city center, but the value of PD decreases significantly near the city center between 1990 and 2010, which clearly indicates that landscape fragmentation dropped near the city core and existing urban land within 4 km radius zone. This implies that some patches have grown in an outward direction over time, and they will merge shortly, and this might take a significant role in future urban development in that area. LPI (**Fig. 5(d)**) shows largest patch increase continuously from four to six number buffers between 1990 and 2001, and also expands upto nine number buffer in 2010. This is the denotation of intensified built-up growth pattern near the existing city.

4 Conclusion

Urban agglomeration of Siliguri is one of the largest and thriving phenomena in north Bengal, having great impetus on the regional economic structure. The growth has an unprecedented impact on the surrounding areas of Siliguri. Outward urban growth with the morsel of cropland and green vegetation is constituted as primary problems of Siliguri and its periphery at present. Aggregate studies on urban growth dynamics over the three decades with spatial metrics define two distinct features from 1990 to 2010. The first phase of urban growth started with the small fragmentation of urban core and began to engulf the non-urban land in 2001. Later on, an engrossing trend, higher in the non-urban area with an infilling pattern among the discrete built up patches, formed more aggregative and compact built up growth (illustrated in spatial metrics). If the outlying growth of built-up expansion continuously extends, more urban patches will develop in the outlying area and single core urban area will be converted to multi-core urban expansion (Sun et al., 2012), which has already been seen in the several peaks in 5 km to 15 km in patch density. Thus, it is the major issues to the planner to develop city growth in a compact form that helps to proper service delivery and accomplish the urban mangement.

However, unplanned development of growth centre in the periphery by the expenses of cropland mainly and conversion of plantationis also a serious threat for degradation of environmental conditions.The peripheral growth is happening because of ceiling of land price, population congestion, degrading environmental profile resulted in the declining population growth rate in the central municipal ward.The growth centres emerged in the south-western and western part of the city, covering the areas of Matigarahat, Rangapani, Shiv Mandir and Thiknikata. As opposed to it, the peripheral stemed at the eastern periphery for future, due to the presence of the reserved forest. Whereas, western, south-western extent have the great potentiality of unforeseen growth due to the convergence of numerous service centres. Hence, it creates an onset of spring for the private developers to invest in housing and infrastructural development. However, the ample scope of exception from rules, tax in the suburban area which is not coming into the municipal rules is alluring the interest of real-estate players, and an environment of bountiful nature,good transport system, and access to housing inspiring families to stay outside the city centre, but adjacent to the municipality area.

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