ANALYZING SPATIAL AND GEOMETRICAL PATTERNS OF TIRUCHIRAPPALLI AND TIER-URBAN CENTERS USING SPATIAL METRICS

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ABSTRACT

Understanding spatial and geometrical patterns of urbanization is crucial in tackling associated problems. As urbanization progresses through various stages of development, it reflects different forms, patterns, and interactions based on its physical and functional aspects. Spatial metrics is a well-acclaimed technique for quantifying urban morphological characteristics. The current study was conducted for Tiruchirappalli and six tier-urban centers located within a 40-kilometers radius to comprehend the comparative growth and spatial patterns. The urban centers are divided into eight zones based on direction for more precise quantification. The study employed Landsat 5 and 8 satellite images to classify land use/cover for the periods 1996, 2008, and 2020. FRAGSTAT is the software application used to analyze spatial metrics, at patch, class, and landscape levels. The study generated a significant amount of data about spatial and geometric patterns of growth. Area, edge, and aggregation metrics indicated that zones in Manachanallur, Manapparai, Musiri, Thiruverumbur, and Thuraiyur had protrusive urban growth during the study period. Transport networks have been the instrumental factor for such growth. Diversity metrics revealed Tiruchirappalli and Thiruverumbur have abundant patches of various classes in many of their zones since they retain patches like open, vegetation, and water bodies extensively. Shape metrics across all urban centers during the period 1996-2008 were more irregular in shape; it has become significantly smooth during 2008-2020 due to infill developments on the fringe areas. The period 1996-2008 recorded a huge transition of open areas into built-ups, attributing to infill development, especially inside the urban centers; similarly, during the period 2008-2020, edge expansion has been recorded widely across the urban centers. The current study is a significant contribution to urban research in understanding relative spatial and geometric patterns of urbanization.

Keywords: Urbanization, spatial and geometrical pattern, spatial metrics, FRAGSTAT.

INTRODUCTION

Urban growth has been the most active process that continues to change the landscape. Eventually, the urban landscape has become a permanent structure. Which sometimes affects the stability of the ecosystem surrounding it. The landscape also has a deep impact on the socio-behavioral characteristics of people (Palmer, 2004). Major urban centers would not sustain growth without the mutual coexistence of surrounding subordinate tier-urban centers. At times, the major urban centers may encounter barriers or slowdown in spatial growth that could lead to urban collapse due to multiple factors such as housing, employment, and social equality (Berg *et al.*, 1982; Fol *et al.*, 2010; Pirisi *et al*., 2014). Subordinate tier-urban centers can be promoted as an alternative growth center and relieve the accumulating urban problems. The objective of the current study is to quantify the spatial growth of Tiruchirappalli urban center and other subordinate urban centers. The study provides insights into 1) morphological characteristics 2) barriers to spatial growth, and 3) planning and promotion of subordinate tier-urban centers.

Urbanization converts the natural environment into a space for the accumulation of people, and this affects the natural systems and their functions (Chen *et al*., 2016; Yang *et al.*, 2021; Ankur *et al*., 2022), unless managed properly (Rath *et al.*, 2022). Hence, it is essential to manage the growth in every stage (Berg *et al*., 1982; Geyer et al., 1993). Urbanization in tier-II cities across the world is becoming proportionately equal as compared to some of the leading metropolitan cities (Ramachandra *et al*., 2011, 2012; Dhanaraj *et al.*, 2022), as a result of people's increased choice of housing in the urban fringes due to the extensive developments in the availability of infrastructure, telecommunication, transport networks and cheap land value (Shaw, 1999). Unmanaged urban growth leads to improper land use patterns (Liu *et al.*, 2011; Satir *et al*., 2016); which proceeds to the fragmentation of the urban landscape and its neighborhood areas; landscape fragmentation often results in disruptions to the urban centers (Jaeger *et al*., 2000; Abedini *et al.*, 2020). Much like fragmentation, urban sprawl is another form of urban growth resulting from improper planning that decays the surrounding environment (Fang *et al*., 2007). However, fragmentation and sprawl can be managed with prior guidelines and plans to ensure sustainable growth (Wang *et al*., 2019).

General urban growth studies lack many quantitative and morphological aspects, from which comprehensive sustainable development plans cannot be drawn (Shukla *et al*., 2019, Chettry., *et al*. 2021). In many cases, a detailed urban study can ultimately help to improve the quality of life, economy, and ecosystems (Li, 2021; Ai *et al*., 2016; Najafabadi *et al*., 2015). There are numerous studies related to urban growth to quantify its structural characteristics. Landscape metrics have been widely used as a tool to quantify spatial heterogeneity (McGarigal *et al*., 1995). Landscape metrics have evolved rigorously during the past three decades; through the years, plenty of mathematical methods were included to study urban morphology. Incorporating spatial characteristics in the landscape metrics has further expanded the application of metrics into multiple disciplines (Frazier *et al*., 2017; McGarigal *et al*., 1995; Bhatta *et al*., 2010). Originally developed for use in ecological studies; in recent years, they are widely implemented in various other domains, like urban studies; in which, landscape metrics are referred to as spatial metrics (Herold *et al*., 2005). Plenty of research has stated the use of landscape metrics in urban studies has benefitted both the living and non-living natural ecosystems and has ensured sustainable growth (Turner, 2005; York *et al*., 2011; Dai *et al*., 2018; Dhanaraj *et al*., 2022).

Spatial metrics are applied widely to understand urban growth dynamics (Sinha *et al*., 2011; Imchen *et al.*, 2020) concerning its morphological characteristics like area, density, edge, shape, and diversity (Hargis *et al*., 1998; Dahal *et al.*, 2016; Tagil *et al*., 2018) and other spatial heterogeneity (Rahimi *et al*., 2022). Changes in urban fringes led by urbanization are better studied using metrics (Baez *et al*., 2021); It quantifies the diversity, pattern, and interactions among the land fragments (Aimaiti *et al*., 2016; Dai *et al.*, 2018). Alternatively, the metrics can also be used to study urban and various other associated sub-components like open and green spaces (Nasehi *et al.,* 2020).

Data and approaches are crucial factors in the delivery of an impactful study on the urban environment (Aimaiti *et al.*, 2016; Zhao *et al.*, 2021). Hierarchical classification is one of the most widely accepted approaches to classifying satellite images (York *et al*., 2011; Maselli *et al*., 2021). On a spatial scale, urban growth and pattern do not proceed similarly, it depends on the place and its economic functions. An urban growth pattern can be anyone of 1) infill 2) edge expansion or 3) outlier types (Wilson *et al*., 2003; Sun *et al*. ,2013). Describing the landscape using metrics is a cumbersome process (Soleimani *et al*., 2020), yet it is important to carry out further analysis using various statistical functions to understand the intricate characteristics (Abbas *et al*., 2022; Bosch *et al*., 2020) and simulate urban growth for the future (Yang *et al*., 2016).

Urbanization largely affects the rural areas surrounding them. Studies on urban-rural gradients seem to be an impactful method of investigation to reveal the intrinsic characteristics of mutual growth (Weng, 2007). Urban-rural gradient studies quantify various spatiotemporal patterns of growth along the transect path (Xie *et al*., 2006). Spatial metrics are powerful quantifications enabled by GIS programs to investigate the complex structures of urban growth (Turner, 1990; 2005). FRAGSTAT provides substantial metrics that are very unique in investigating landscape structures (McGarigal *et al.*, 2018; Wang *et al*., 2021), this helps planners to make reliable decisions. Urban landscapes are determined by many influencing factors like administration, functions, physical setup, etc. These factors have been constantly changing concerning the functional characteristics of the urban (Uuemaa *et al*., 2009). Additionally, metrics can also be studied by splitting the study area into directional zones, radial circles, or moving windows for a much deeper understanding (Das *et al*., 2021) also, these metrics can be applied particularly to an urban or include other classes as well (Azareh *et al*., 2021). For sustainable urban growth and the environment, all the factors must be continuously monitored and maintained at balance by the urban planners and policymakers (Hiremath *et al*., 2013; Effati *et al*., 2021; Akın *et al*., 2020; Jain *et al*., 2011).

STUDY AREA, DATA AND METHODOLOGY

The study area is in Tamil Nadu state, India (Figure 1). There are six urban centers within a radius of 40 kilometers from Tiruchirappalli urban, all of which have more than 25,000 thousand people (Census of India, 2011). The highest elevation point in the study area is located on the Pachamalai hills, which is 545 meters above Mean Sea Level (MSL) and the lowest point is 29 meters, located on the river Cauvery. The study area experiences a tropical climate with no major variation between summer and winter; summer is generally hot and winter is warm and pleasant. The temperature decreases with the onset of the southwest monsoon in the month of June; maximum rainfall occurs between October and December.

Tiruchirappalli is one of the most prominent cities throughout history. The city is well known to some of the most notable historians like Ptolemy of the 1st century for several hundreds of years. According to the census of India – 2011, Tiruchirappalli Municipality Corporation is the largest urban with a population of 8,47,387, followed by Manapparai with a population of 40,510. The least populated urban is Viralimalai with a population of 10,883. Tiruchirappalli has grown at a comparatively less rate than other important cities like

Chennai, Coimbatore, Madurai, and Salem despite its historical prominence. This can be attributed to its fewer industrial establishments and natural and environmental factors.

Tiruchirappalli urban was not very active concerning built-up growth like other cities in Tamil Nadu until early 2000. Until the economic liberalization, agriculture and trading has been the major economic activity of Tiruchirappalli with fewer industries; later, the international trade agreements played a crucial role in the setup of industries. Since then, urbanization has been accelerated and urban areas are continuously becoming denser and expanding.

The present study used level-1 processed Landsat 5 (Thematic Mapper, December 1996, and May 2008) and 8 satellite (Operational Land Imager Sensor, March 2020) images to extract land use/cover classes (Table 1). The satellite images are 30 meters in spatial resolution, which is optimum to identify built-up classes.

Table 1: Details of the satellite images used in the study

Year of Acquisition	Image ID	Path/Row
1996	LT05_L1TP_143052_19961203_20170101_01_T1 LT05_L1TP_143053_19961203_20170101_01_T1	143/052 & 053
2008	LT05_L1TP_143052_20080510_20161031_01_T1 LT05_L1TP_143053_20080510_20161031_01_T1	143/052 & 053
2020	LC08_L1TP_143052_20200306_20200309_01_T1 LC08_L1TP_143053_20200306_20200309_01_T1	143/052 & 053

Fig. 1: Study area – Tiruchirappalli and subordinate tier-urban

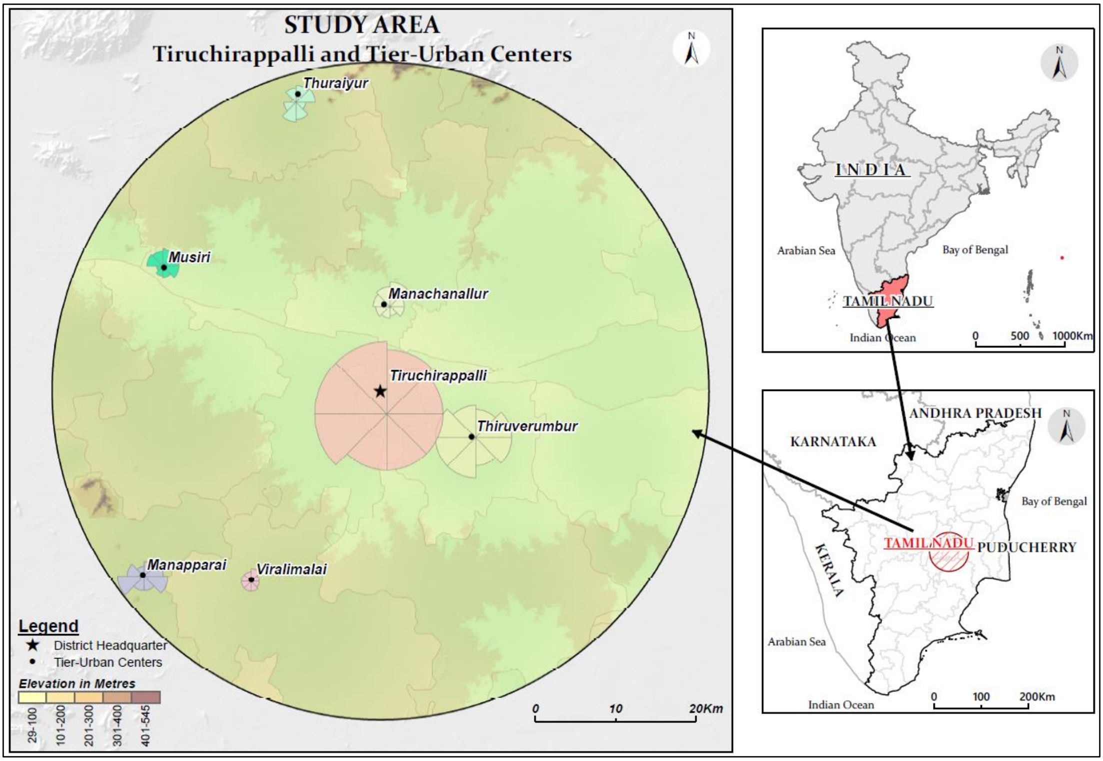
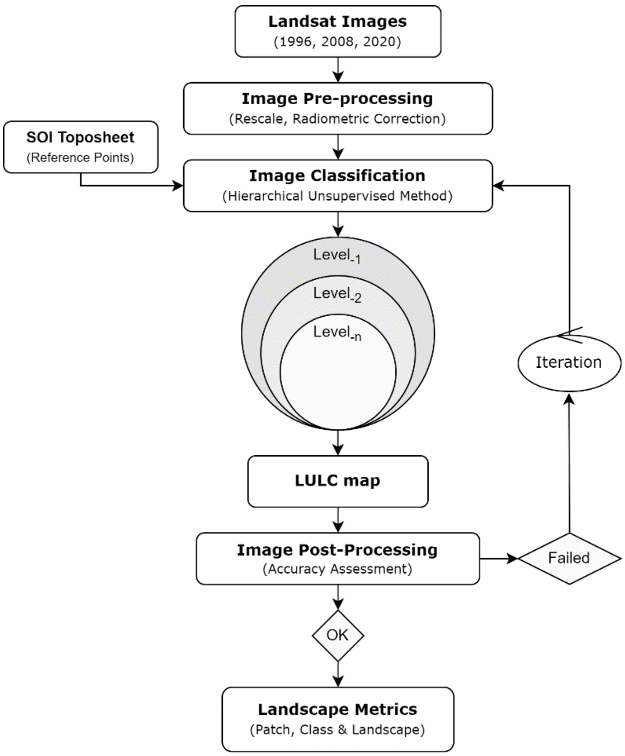


Image Classification: Spatial resolution is a determining factor of the results in the study of landscapes (Huang *et al*., 2018). The spectral similarity between classes could lead to uncertainty in making solid decisions for clustering. To overcome this, a hierarchical unsupervised classification technique has been adopted. Hierarchical unsupervised classification is a promising technique applied to cluster similar pixels (Lee, 2004). Multiple studies have shown improved accuracy in identifying and grouping pixels based on hierarchical classification (Du *et al*., 2016; Alshehhi *et al*., 2017; Mao *et al*., 2020). The methodological framework of the present study has shown in Figure 2. The images are classified in a four-step processing viz 1) Image Pre-processing: radiometric corrections (rescale tool) are performed to balance the brightness of the images. 2) Level-I classification: NRSC, India classification system has been followed for classifying the Land use/cover. At level-I, major classes were identified. 3) Level-II classification: at level-II classification all the major classes were masked separately to avoid pixel mixing and further sub-classification processes were carried out until the desired classes were classified. 4) Post-processing: image classification creates stranded pixels which have no relevance to the ground truth data. The stranded pixels are eliminated using clump and eliminate tools.

Fig. 2: Methodology of the study



Spatial Metrics: The habitat in which the organisms live develops a structure and pattern in conjunction with the environment. Unlike any other organisms, anthropogenic activities can disrupt the integrity of the environment and the structure, in some cases they can also facilitate to grow. To ensure environmental stability, landscape studies have been carried out to understand the relationship between form, pattern, and process. Spatial metrics are a comprehensive method to quantify the structural aspects of urban (Turner, 1990). FRAGSTAT is one of the well-acclaimed applications for analyzing landscape metrics. Apart from its wide range of metrics, the application supports multiple data formats and offers a seamless GUI (McGarigal *et al*., 2013).

Metrics are computed at three levels *1) Patch metrics:* are analyzed at individual patches, and characterize the spatial patterns in the context of patches. *2) Class metrics:* are integrated over all the patches of a given type or class. *3) Landscape metrics*: integrates all the patch types or classes over the full extent of the data (i.e., the entire landscape). The metrics are further grouped into six different aspects according to the property it represents viz Area and edge, shape, aggregation, and diversity metrics. The present study utilized 13 metrics to understand the geometric characteristics of urban growth; few of the selected metrics are common at the metrics level since we expect it could reveal varying results at each level and infer much detail.

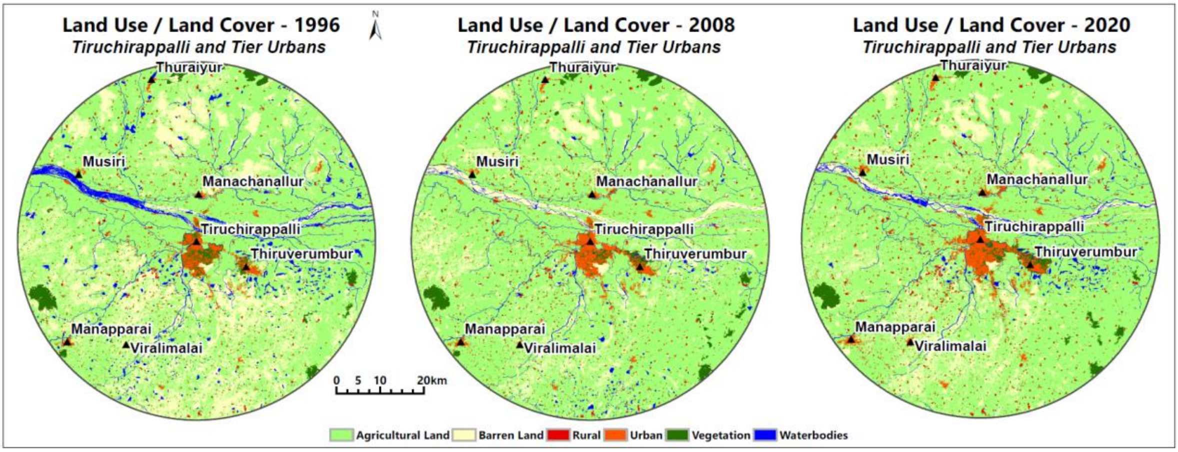
Table 2: List of Spatial metrics used in the study. (Adopted from McGarigal *et al.*, 1995)

Metrics Type (Spatial configuration)	Metrics	Formula	Description
Class Metrics (Area and Edge metrics)	1. Total Class Area (CA)	$CA = \sum_{j=1}^{n} a_{ij} \left[\frac{1}{10{,}000}\right]$	The class area is a measure of landscape composition; specifically, how much of the landscape is comprised of a particular patch type.
	2. Mean Patch Area	$Area_{mn} = \frac{\sum_{j=1}^{n} X_{ij}}{n_i}$	Mean equals the sum, across all patches of the corresponding patch type, of the corresponding patch metric values, divided by the number of patches of the same type.
	3. Largest Patch Index (LPI)	$LPI = \frac{\max(a_{ij})}{A}(100)$	LPI quantifies the percentage of the total landscape area comprised by the largest patch. As such, it is a simple measure of dominance.
	4. Percentage of Landscape (PLAND)	$PLAND = \frac{\sum_{j=1}^{n} a_{ij}}{A}(100)$	PLAND quantifies the proportional abundance of each patch type in the landscape.
Class Metrics (Aggregation metrics)	5. Clumpiness Index (CI)	$Given\ G_i = \left(\frac{g_{ii}}{(\sum_{k=1}^{m} g_{ik}) - mine_i}\right)$ $CLUMPY = \begin{bmatrix} \frac{G_i - P_i}{P_i}\ for\ G_i < P_i \text{ and } P_i < .5; \\ else \\ \frac{G_i - P_i}{1 - P_i} \end{bmatrix}$	Clumpiness index is calculated from the adjacency matrix, which shows the frequency with which different pairs of patch types appear side-by-side on the map. It equals the proportional deviation of the proportion of like adjacencies involving the corresponding class from that expected under a spatially random distribution.
	6. Landscape Shape Index (LSI)	$LSI = \frac{.25 \sum_{k=1}^{m} e * ik}{\sqrt{A}}$	LSI provides a standardized measure of total edge or edge density that adjusts for the size of the landscape.
	7. Number of Patches (NP)	$NP = n_i$	NP equals the number of patches of the corresponding patch type (class). NP of a particular patch type is a simple measure of the extent of subdivision or fragmentation of the patch type.
	8. Patch Density (PD)	$PD = \frac{n_i}{A}(10{,}000)(100)$	PD has the same basic utility as the number of patches as an index, except that it expresses a number of patches on a per unit area.
Landscape Metrics (Aggregation metrics)	9. Aggregation Index (AI)	$AI = \left[\sum_{i=1}^{m} \frac{g_{ii}}{max \to g_{ii}} * P_i\right](100)$	At the landscape level, AI is computed simply as an area-weighted mean class aggregation index, where each class is weighted by its proportional area in the landscape.
Landscape Metrics (Diversity metrics)	10. Patch Richness (PR)	$PR = m$	PR is perhaps the simplest measure of landscape composition, but it does not reflect the relative abundances of patch types.
	11. Shannon's Diversity Index (SHDI)	$SHDI = -\sum_{i=1}^{m} (P_i \ln P_i)$	Shannon's diversity index is a popular measure of the diversity of landscapes.
Patch Metrics (Aggregation metrics)	12. Proximity Index (PROX)	$PROX = \sum_{s=1}^{n} \frac{a_{ijs}}{h_{ijs}^2}$	The proximity index considers the size and proximity of all patches whose edges are within a specified search radius of the focal patch.
Patch Metrics (Shape metrics)	13. Shape Index (SHAPE)	$SHAPE = \frac{.25\ P_{ij}}{\sqrt{a_{ij}}}$	SHAPE is the simplest and perhaps most straightforward measure of shape complexity.

RESULTS

The hierarchical unsupervised classification technique produced high accurate land use land cover map with six classes following the level-II classification system of the National Remote Sensing Centre (NRSC), India. Tiruchirappalli is the largest urban center in the study area, influences the surrounding urban centers in providing major administrative, health, and educational services in addition to its employment opportunities (Figure 3). The study area is generally a vast plain topography suitable for agriculture. Agricultural land in the study area was observed with constant increase in terms of area. In the year 1996, it was observed with 65.7 % of the area, which increased to 73.8 % in the year 2020. A significant land under the barren class was transitioned into agricultural land during the study period (Table 3).

Fig. 3: Land use and land cover for the years 1996, 2008, and 2020



Both rural and urban classes have recorded constant growth over the study period; however, urban growth is overwhelming since in the year 2020, it matched with the rural built-up area and is expected to outrun the rural built-up growth in the future as well. The presence of vegetation is very limited in the study area; the foothills of Pachamalai on the north and Thogaimalai on the southwest are the two major patches with dense vegetation. However, the vegetative area was observed to decrease during the study period; it was 99.5 hectares in the year 1996 and it was reduced to 91.8 in the year 2020. The water body is a crucial resource of the study area since its use in agricultural purposes. It is noteworthy that the study area receives only a small quantity of water through rainfall and its major need is met by river and groundwater systems. The Cauvery is the chief river for surface water supply, apart from which the study area has numerous ponds and lakes. Water bodies in the study area are volatile to the rainfall in the catchment areas.

Table 3: Spatial distribution of Land use land cover (Area in sq. km)

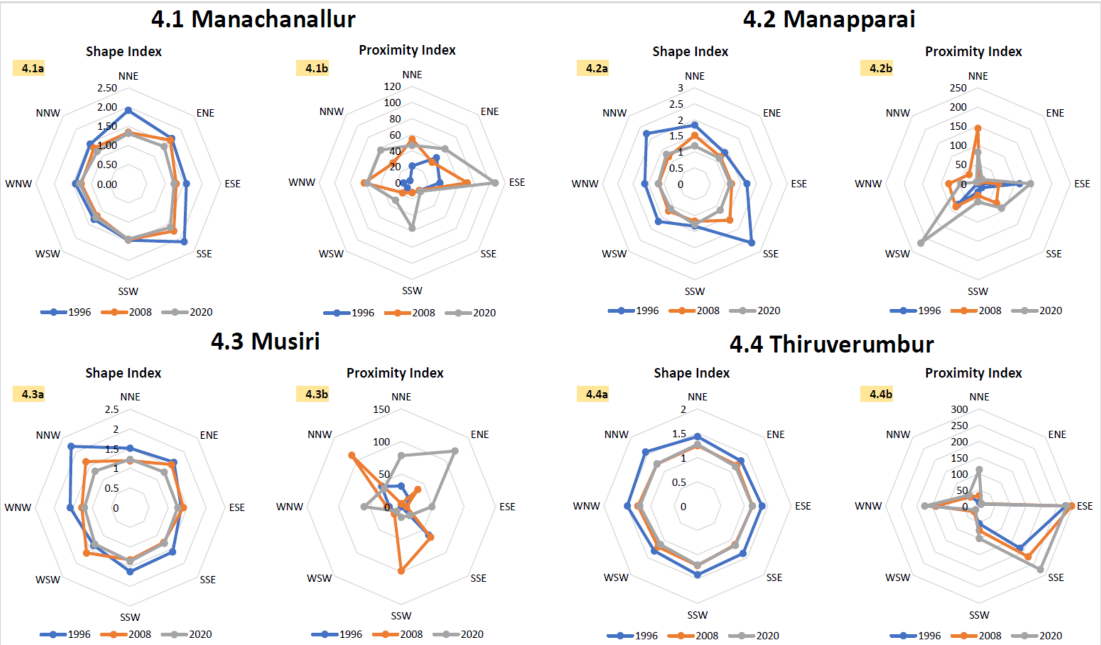
Class	1996	Area in %	2008	Area in %	2020	Area in %	2035	Area in %	2050	Area in %
Agricultural	3473.3	65.7	4066.5	76.9	4016.7	76.0	3957.6	74.9	3901.1	73.8
Barren	1272.6	24.1	749.7	14.2	716.9	13.6	716.7	13.6	716.7	13.6
Rural Built-up	111.8	2.1	129.7	2.5	153.5	2.9	184.4	3.5	211.8	4.0
Urban Built-up	78.3	1.5	105.2	2.0	139.3	2.6	174.9	3.3	209.3	4.0
Vegetation	99.5	1.9	100.9	1.9	104.5	2.0	97.0	1.8	91.8	1.7
Water Bodies	249.1	4.7	132.6	2.5	153.8	2.9	154.0	2.9	153.9	2.9

A group of 13 crucial metrics were selected across patch, class, and landscape levels to investigate the structural patterns. The results yield vital information to understand the spatial patterns and to plan a sustainable urban.

Patch Metrics: The patch is the smallest spatial unit selected for the current investigation. It is an isolated group of cells of a class. Patches are at the minimum scale to represent urban structures and patterns for better investigation. The study computed two important metrics from patch metrics viz. shape index and proximity index, and the results are shown in Figure 4.

Shape Index (SHAPE): In general, the polar graph forms a smooth circle across all the zones indicating an identical pattern of patches found in all the urban centers. Manapparai, Thuraiyur, and Viralimalai (Fig. 4.2, 4.5, 4.7) have more irregular patches causing the graph to stretch disproportionately. Shape irregularities have been showing a decreasing trend for the years 1996, 2008, and 2020 across all the urban centers except Tiruchirappalli urban (Fig. 4.6), where the shape index has increased during 2020 than the previous year 2008.

Fig. 4.1. – 4.4: Displays zonal-level Patch Metrics. Prepared based on the FRAGSTAT results

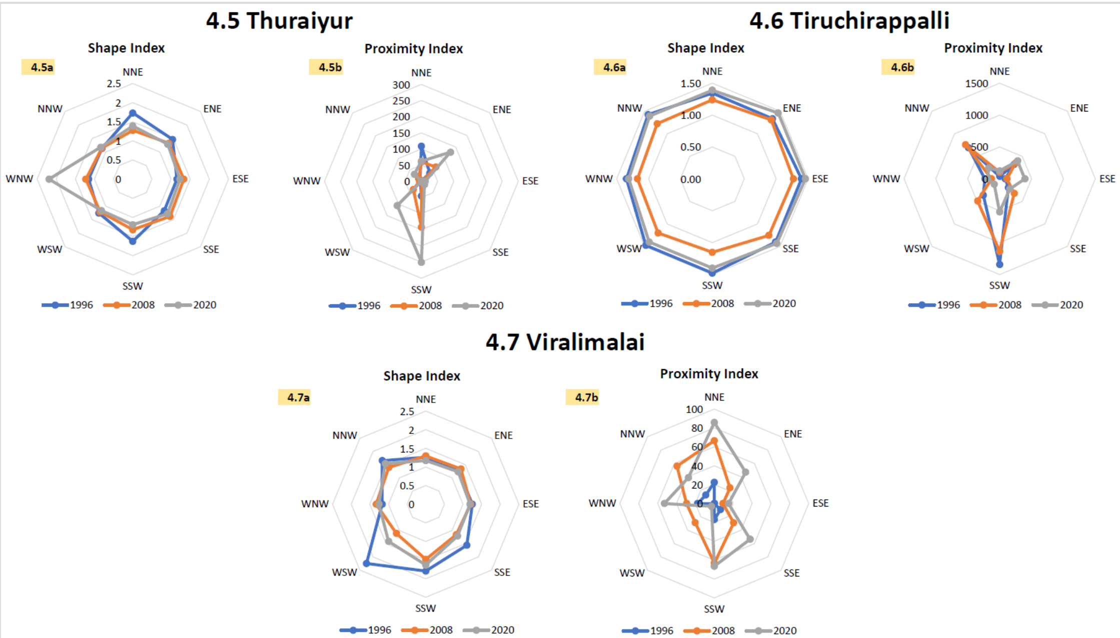


Edge expansion is the vital factor for the increase in shape index value due to the dispersed nature of the development of built-ups. Zones with a high shape index value and a high number of patches indicate inadequate planning of plots and a lack of supply of necessary infrastructure like road networks; these patches might need quick attention and rapid measures for proper development. Ideally, uniformity in the graph line also denotes equal growth and proper management of land during the study period across the zones (Example: Thiruverumbur); however, it is constrained by natural and man-made factors.

Proximity Index (PROX): Proximity value for most of the zones in urban centers has increased from 1996 to 2020 due to firstly, many of the other class patches being dissolved into built-up patches and secondly, comparatively a smaller number of new patches of built-up classes were developed. This phenomenon was observed more commonly in the tier urban centers while zones like WNW of Manapparai, NNW, SSW zones of Musiri, ESE, SSW, WSW of Tiruchirappalli urban, NNW, WSW of Viralimalai (Fig. 4.2a, 4.3a, 4.6a, 4.7a) have reported a decrease in the proximity value since the rate of new built-up developments is higher than the rate of dissolve which resulted in increased fragmentation.

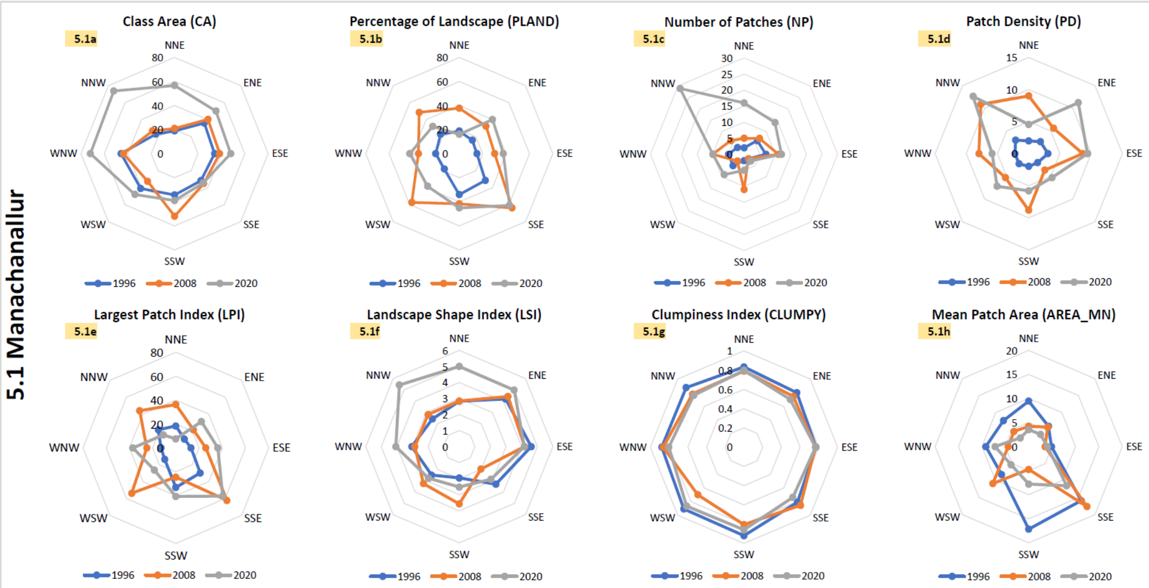
Fragments are a concern for the planners to ensure sustained growth of the fragments, otherwise, these fragmented patches of built-ups suffer multiple urban problems like service inadequacy. Between the period 1996 and 2008, a stage of abrupt transitions was observed in many urban centers causing the graph line to rise and fall across the zones; however, this was not observed in Thiruverumbur and Tiruchirappalli urban centers (Fig 4.4b, 4.6b). Apart from these observations, fragmentation is a good indication when handled with proper planning for sustainable development.

Fig. 4.5. – 4.7: Displays zonal-level Patch Metrics. Prepared based on the FRAGSTAT results (Continued figure)



Class Metrics: Class metrics are the aggregate metrics of the patches that belong to a particular class. However, class metrics provide more capability to investigate class-level properties in association with other classes.

Fig. 5.1 – 5.2: Displays the zonal level Class Metrics. Prepared based on the FRAGSTAT results



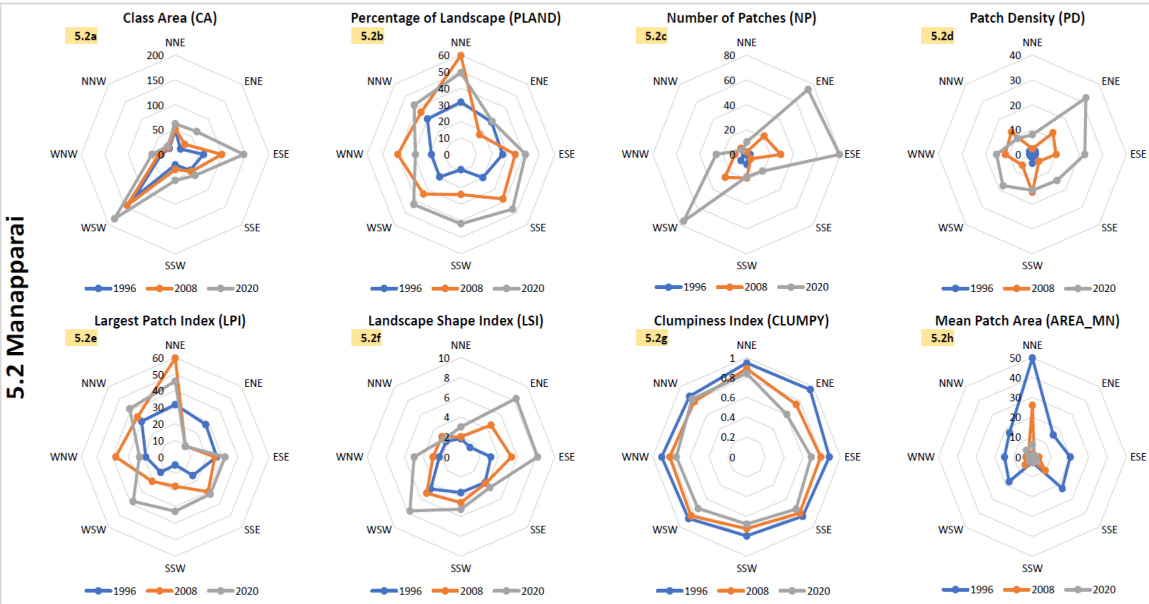
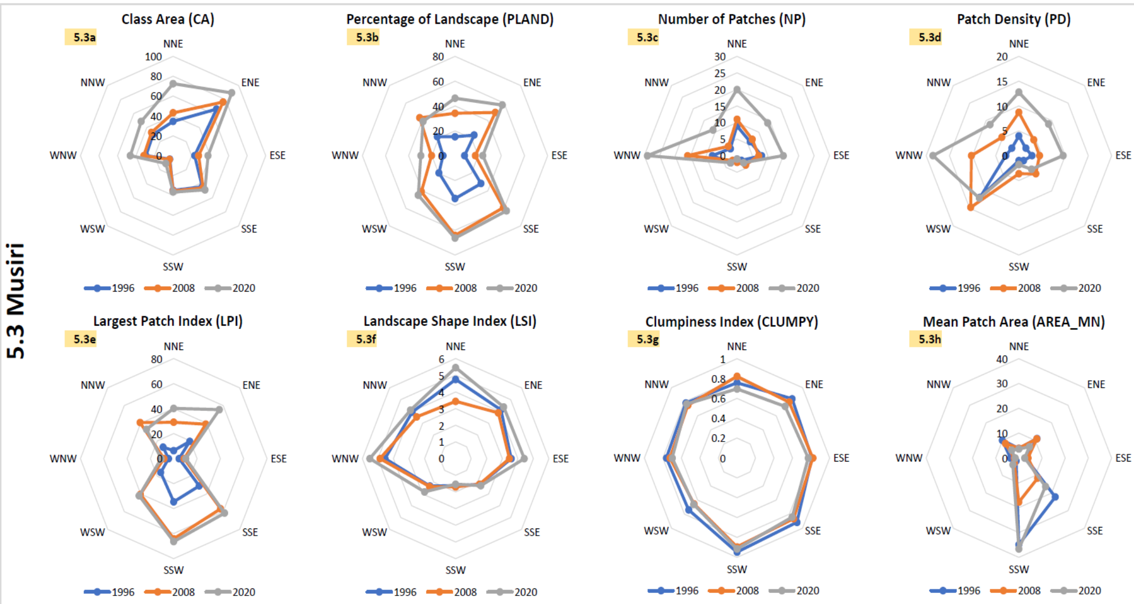


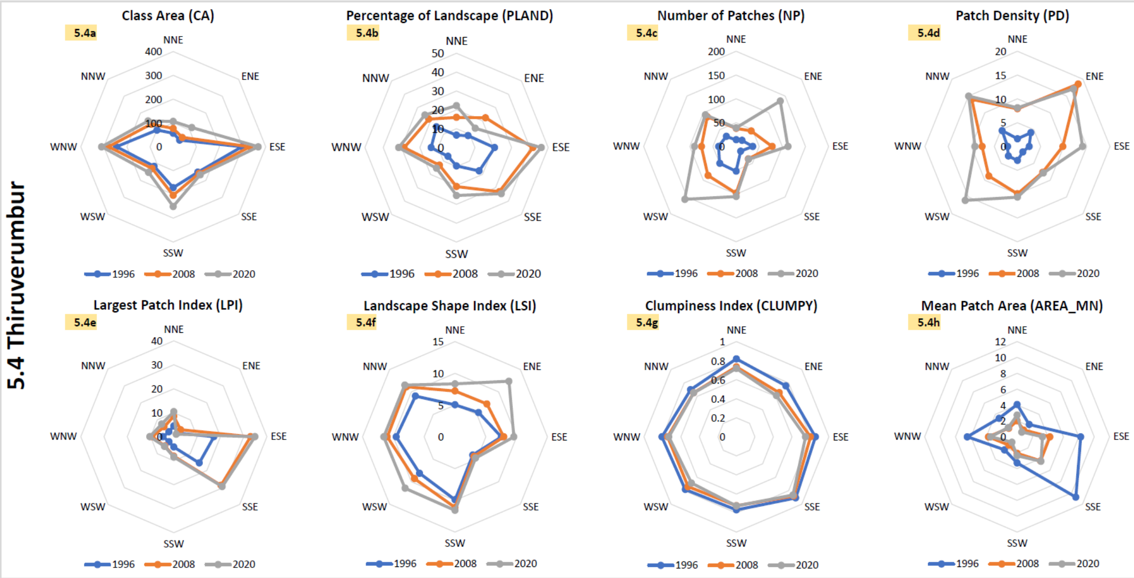
Figure 5 shows various class metrics computed in the study. *Class area (CA)* is the total area under built-ups measured in hectares. In terms of class area for the year 2020, Tiruchirappalli has the largest class area (around 1400 hectares) in the NNW zone and Viralimalai has the smallest area (around 25 hectares) in the SSE zone (Fig. 5.6a, 5.7a).

Between 1996 and 2008, the class area recorded a positive transition that implies the existence of stable policies and planning. In the later part of that period, major changes in funding and land acquisition were made to boost the real estate and construction sector; sequentially, numerous infrastructure and residential projects were taken place across the country until the global economic recession. During the years 2008 to 2020, the class area has grown exponentially in multiple zones of Manachanallur, Musiri, Tiruchirappalli and Viralimalai (Fig. 5.1a, 5.3a, 5.6a, 5.7a).

Percentage of Landscape (PLAND): PLAND is highly dependent on how the zones are demarcated for an urban center; this is essentially important because an urban center cannot grow equally on all sides hence the zonal size varies within an urban. From the polar graphs, a circular graph represents a proportional composition of classes and a stretched graph shows a disproportionate composition of classes. During the year 1996, most of the urban centers has been marked with a stretched graph due to the presence of numerous fragmented patches at remote locations; these fragmented patches coalesced in the following periods making the graph more circular. Manachanallur, Musiri, Thiruverumbur and Tiruchirappalli display a stretched graph (Fig. 5.1b, 5.3b, 5.4b, 5.6b); however, in a broader sense, a stretched graph means no adverse urban growth.

Fig. 5.3. – 5.4: Displays the zonal level Class Metrics. Prepared based on the FRAGSTAT results (Continued figure)

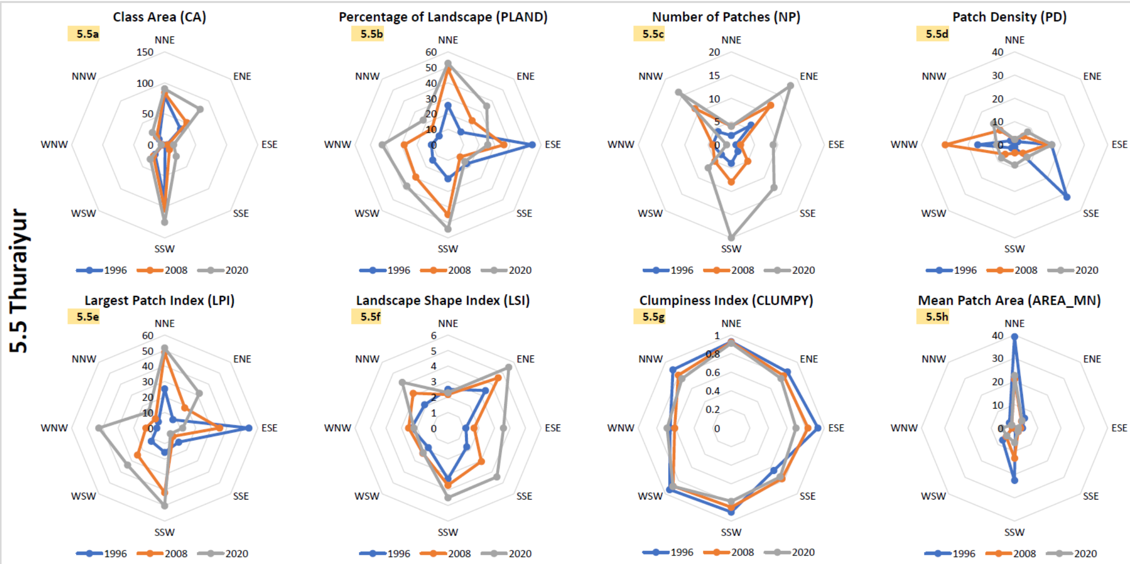


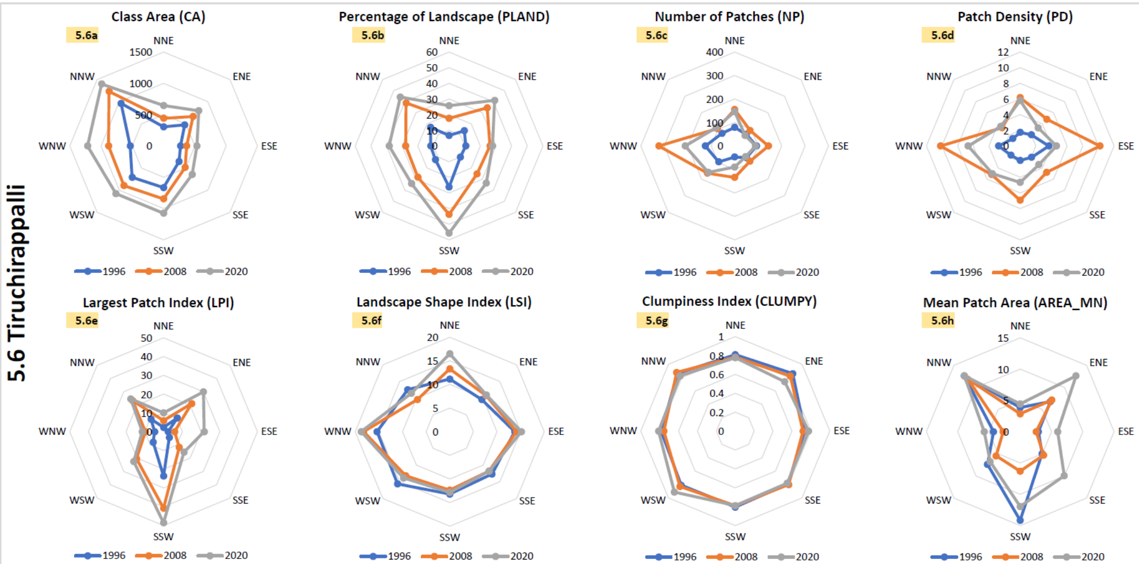


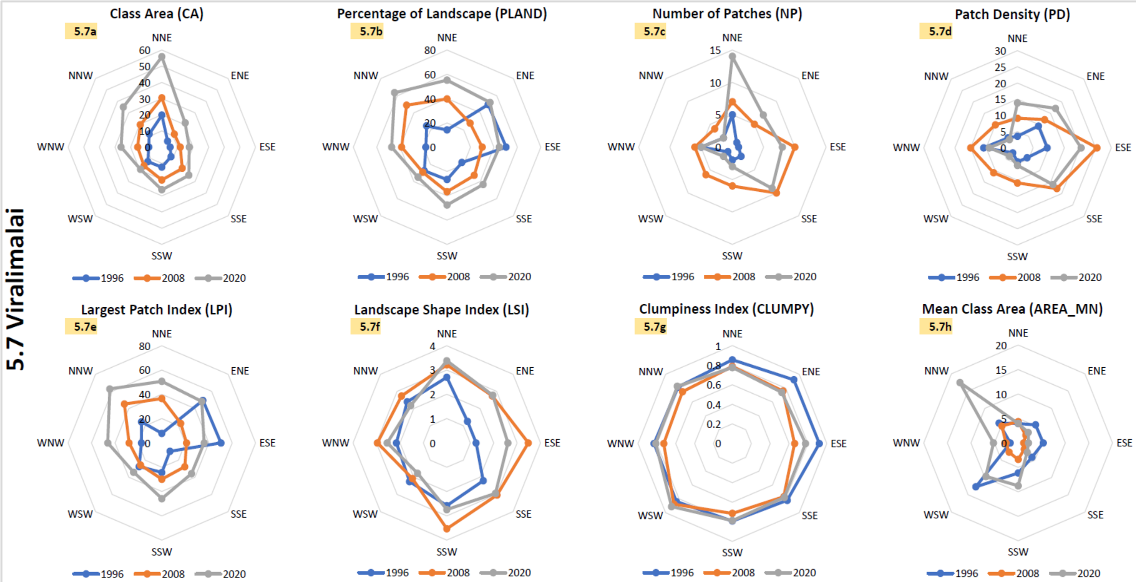
Number of Patches (NP) NP is the raw fragmentation level of the area studied and it is used as a variable in the calculations of many other metrics. In temporal studies, NP reports the rapidness of urban spatial growth in terms of new patches developed. NP provides a dynamic value in every period of investigation by the number of active developments at the patch level. NP reveals the active patch development in an urban center for a particular period. From the polar graph, it is understood that most of the tier urban centers have developed new patches of urban class which is marked by increased NP value during 2008-2020, whereas Tiruchirappalli urban has marked with a decreased NP value which is in fact, plenty of existing patches coalesced and new patches were developed however not as much as the patches coalesced (Fig. 5.6c). Another important aspect of the NP metric is that most of the increments were reported in the northern zones than the southern zones of the urban centers; road pattern has the vital factor for the peculiar orientation of NP value during the period 2008-2020.

Patch Density (PD) has a less inferential value since the numerator represents a number, not an areal unit whereas the denominator is an areal unit; it has some significance to understanding the patches at the class level. PD is a volatile value that varies with the development of new patches in a select unit of area. During the years 1996, 2008 and 2020, PD has increased substantially in all the tier urban centers and only Tiruchirappalli has not reported an increment during 2020, which confirms there is comparatively less development of new patches meanwhile, existing patches have expanded to a larger extent (Fig. 5.6d). Development of new patches was heavily influenced by transport networks; hence PD has a strong similarity with the plots of NP in multiple zones across the urban centers especially in the year 2020, for the rest of the years the area and the number of patches has been different thus low similarity was found.

Fig. 5.5. – 5.7: Displays the zonal level Class Metrics. Prepared based on the FRAGSTAT results (Continued figure)







Largest Patch Index (LPI) computed for different periods reveals the temporal pattern and transition of land use and its dominance over other classes. At the same time, it is a vital indicator to relatively measure the coexistence of other components as well. The complete dominance of built-ups poses serious issues relating to the environment and biodiversity. ENE, SSE, SSW zones of Musiri, NNE, ESE, SSW, WNW of Thuraiyur and ENE, and SSW of Tiruchirappalli have urban patches that cover more than 50 % of the zonal area (Fig. 5.3e, 5.5e, 5.6e). This can be sorted out with the proper development of other classes. Other urban centers have patches that are less than 50 % of the zonal area, where patches of agriculture and vegetation classes dominate the zone. The dominance of built-up land can be compromised easily on the urban fringe while maintaining a balance in the inner urban area need proper policies and management.

Landscape Shape Index (LSI) observed that most of the zones in Manachanallur, Manapparai, Musiri, Thiruverumbur, and Thuraiyur with an increasing trend and higher margins of LSI from 1996 to 2008 and 2020, which affirms the increasing shape irregularity (Fig. 5.1f, 5.2f, 5.3f, 5.4f, 5.5f). In support of that, these urban centers have shown stretched graphs, indicating the patches have not grown equally across the zones. Since LSI is directly influenced by the total landscape area, the value range reveals the relative zonal level size of the urban center; Tiruchirappalli tops the list with a value range from 0-20, and Viralimalai, at the bottom, ranges from 0-4.

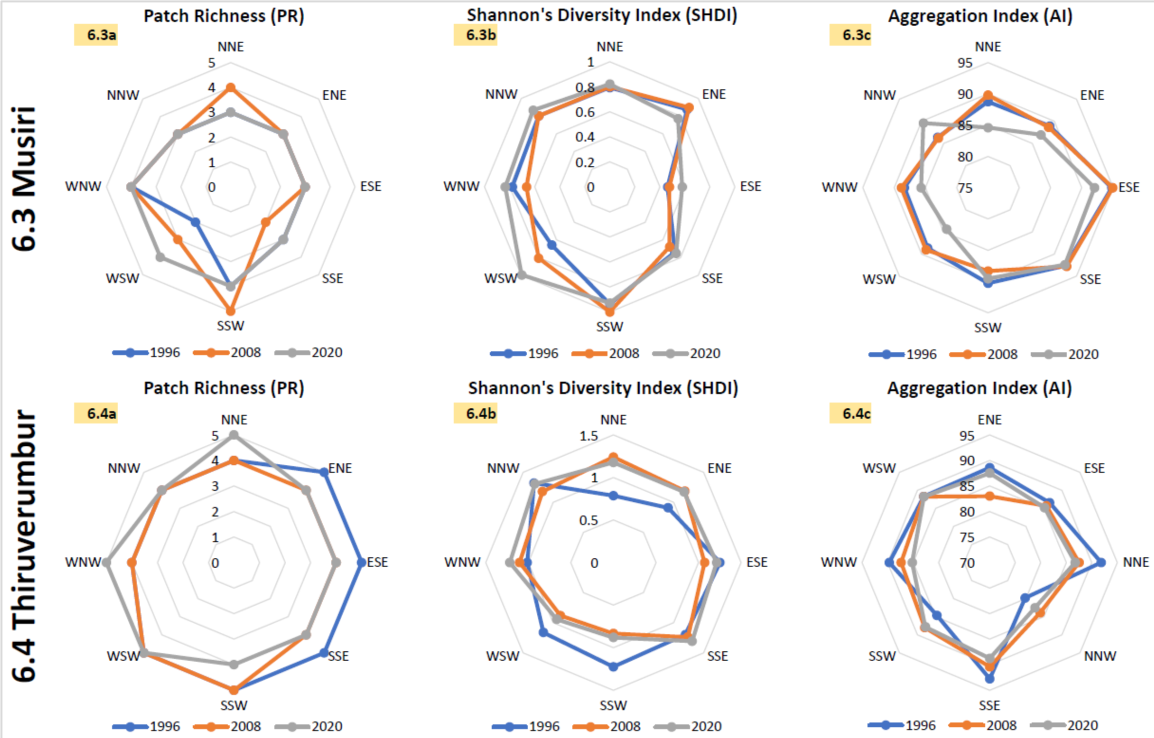
Clumpiness Index (CLUMPY) value across the zones of all the urban centers was close to 0.8, marking that the urban patches are highly aggregated with no common trend in transition between 1996, 2008, and 2020. Adjacency is an important indicator to understand the pattern of the class under investigation. Since all the urban centers have high aggregation of built-ups, the current study emphasizes monitoring the spatial growth of built-ups and ensuring the preservation of necessary components like vegetation, open land, waterbody, etc.

Mean Patch Area (AREA_MN) is a volatile value based on the numerator and denominator values irrespective of the size of the urban. Hence, Manachanallur, Manapparai, Musiri, Thuraiyur, and Viralimalai have higher AREA_MN (Fig. 5.1g, 5.2g, 5.3g, 5.5g, 5.6g) despite their relatively smaller total area than Tiruchirappalli and Thiruverumbur urban. High AREA_MN among the tier urban centers indicates the patches are highly aggregated while the numbers of patches are comparatively less than Tiruchirappalli and Thiruverumbur urban. Though this phenomenon was found to be common in tier urban centers at the current rate of urban growth, however, it must be carefully monitored for sustained growth.

Landscape Metrics: Landscape metrics integrates patches and classes over the full extent of the data. The significance of the landscape-level study is that it reveals the broad pattern of the landscape with the use of metrics like Patch Richness (PR), Shannon Entropy (SHDI), and Aggregation Index (AI) as shown in Figure 6.

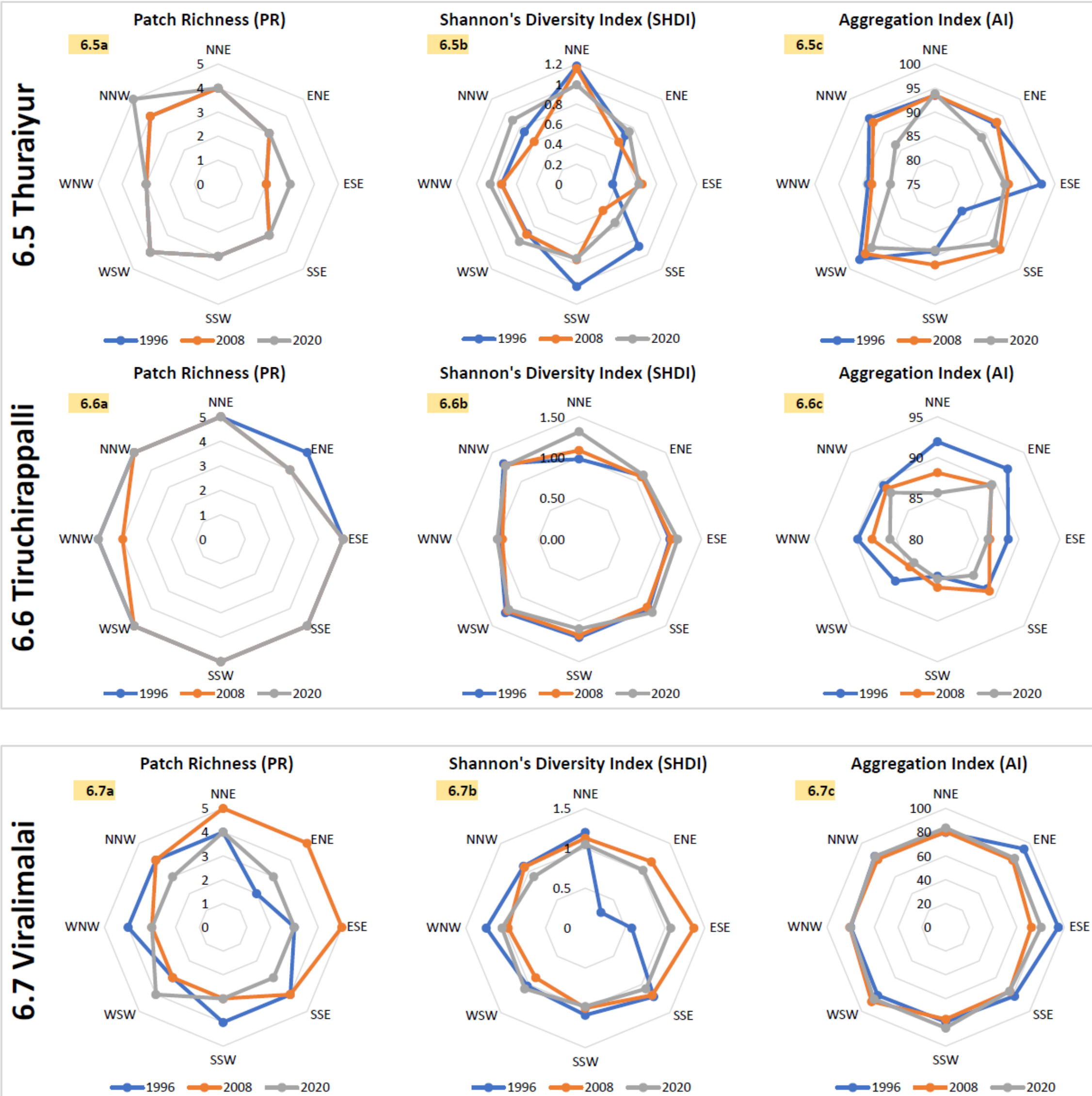
Patch Richness (PR) is the simplest measure of the composition of classes present in the landscape. A decrease in the PR value during 2020 indicates the zone is losing on diverseness thereby a particular class could become a dominant feature in the zone. Uncontrolled urban sprawl is the chief factor for the loss of the diverse environment surrounding an urban center. Zones like SWS, SSW, SSE of Manapparai, NNE, SSW of Musiri, ENE, ESE, SSE, SSW of Thiruverumbur, ENE of Tiruchirappalli and all the zones except WSW of Viralimalai urban centers were observed with decreased PR value during the period 2020, which is a concern for urban planners (Fig. 6.2a, 6.3a, 6.4a, 6.6a, 6.7a). Manachanallur, Musiri, Thuraiyur, and Tiruchirappalli urban centers have retained their classes in the majority of their zones.

Fig. 6.1 – 6.4: Displays the zonal level Landscape Metrics. Prepared based on the FRAGSTAT results



Shannon's Diversity Index (SHDI) is a significant measure of homogeneity (abundance of a particular class) or heterogeneity (includes other classes as well). The maximum SHDI value observed in Thiruverumbur, Tiruchirappalli and Viralimalai urban centers was 1.4, and the least value observed in Musiri is 1.0 (Fig. 6.3b, 6.4b, 6.6b, 6.7b). The diversity was transitioned without much variation from the year 1996 and thereafter. A peculiar phenomenon observed in the study is that major urban centers like Tiruchirappalli and Thiruverumbur have high diversity value than the smaller urban centers; this is resulted due to the abundance of patches on the fringe areas and the proportional size of patches being equally distributed. Whereas, in the smaller urban centers the number of patches is relatively less since the newer developments are mostly in the form of expansion rather than isolated patches.

Fig. 6.5 – 6.7: Displays the zonal level Landscape Metrics. Prepared based on the FRAGSTAT results (Continued figure)



Aggregation Index (AI) Manapparai and Viralimalai are the most aggregated urban centers as revealed from the AI (Fig. 6.2c, 6.6c); since most of the zones in these urban centers have closely located patches of the same class. Manachanallur, Musiri, Thiruverumbur, Thuraiyur and Tiruchirappalli have comparatively less AI than the aforesaid urban centers. Interestingly, AI in these urban centers also decreased during 2020 than the year 2008; which implies there are numerous new urban patches developed on the urban fringe in a disaggregated pattern. Another important fact is that AI has been highly varying among the zones of these urban centers and shows discrete growth patterns.

DISCUSSION

Like many urban centers in developing countries, Tiruchirappalli urban area also encounters issues related to internal morphological systems and the depletion of surrounding ecosystems. The present study aims to examine and quantify spatial changes in a cluster of urban centers surrounding the Tiruchirappalli urban area. To achieve a comprehensive understanding, the study utilizes satellite images spanning the past 25 years to analyze urban dynamics through GIS techniques, resulting in a substantial volume of data concerning the geometrical characteristics of urban growth. The significance of the study lies in the inclusion of surrounding urban centers to assess their geometrical characteristics, which can aid in urban planning (Dahal *et al*., 2016) and promote the sustainable development of tier-urban centers (Wang *et al*., 2021).

Table 4: Accuracy Report (PA-Producer's Accuracy; UA-User's Accuracy

	1996		**2008**		**2020**	
	Overall Accuracy: 92.9 **Overall Kappa: 0.86**		**Overall Accuracy: 92.8** **Overall Kappa: 0.86**		**Overall Accuracy: 89.0** **Overall Kappa: 0.88**	
	PA	UA	PA	UA	PA	UA
Water bodies	92%	92%	93%	93%	93%	88%
Vegetation	100%	80%	100%	86%	86%	67%
Barren land	83%	92%	76%	90%	84%	90%
Cropland	98%	93%	98%	92%	98%	96%
Urban	80%	100%	86%	100%	80%	100%
Rural	100%	100%	100%	100%	88%	100%

The hierarchical image classification technique has demonstrated its efficiency (Du *et al*., 2016) and generated a classified map with the expected accuracy (Table 4). The classified map was employed for landscape analysis to investigate geometric characteristics. While high-resolution images offer detailed patches, they may lead to cumbersome results, whereas low-resolution images may encompass similar patches. Pixelation poses a concern with raster images as it can lead to erroneous outcomes. The study employed the Erdas application for pre-processing, image classification, and post-processing, utilizing clump and eliminate tools to merge stranded pixels.

The study focuses on zones and rings for analysis. The center point of the urban area was selected based on the urban extent, not the Central Business District (CBD), to eliminate directional polarization errors. The optimal ring width was determined to minimize the number of rings created. Spatial metrics analyze patterns and processes of various land components using mathematical functions; however, the accuracy of results depends on image resolution and the geometric complexities of urban structures. Metrics hold significant implications for understanding urban growth patterns.

The study utilized metrics from class, patch, and landscape levels, which are widely accepted in urban studies. The shape index at the patch level indicates shape irregularities, particularly in outlier developments with large clusters of built-ups. Monitoring the shape index is essential for addressing urban form-related issues. Many urban centers showed a decreasing trend in the shape index from 2008 to 2020. The proximity index measures the distance between patches of the same class, indicating patch fragmentation. An increase in the proximity value suggests less fragmentation. Tiruchirappalli exhibited a decreased proximity value in 2020 compared to 2008, indicating higher rates of outlier growth.

At the class level, eight metrics were implemented to quantify urban growth. CA represents the aggregation of patch areas in a class within a zone, while AREA_MN provides deeper insights into the mean area of patches in a class. PLAND and LPI measure the proportional abundance of the class, emphasizing the importance of coexistence with other elements like vegetation and water bodies for the sustainable development of urban areas. Maintaining balanced green and public spaces, clean water bodies and the environment are some of the crucial elements drafted in the eleventh Agenda for Sustainable Development - 2030.

PLAND and LPI consistently increased from 1996 to 2020 across most zones, raising concerns for urban planners. Separating the urban area based on directions produced similar PLAND and LPI values, as it includes the core urban area. However, separation into rings yielded different values. Most metrics aligned with previous study periods, while only a few metrics contradicted previous values in some zones. NP and PD are simple metrics that report numerical properties at the class level. PD provides an inferential value and describes the proportional abundance of a class in a specific zone. Results for both of these metrics depend on the kernel window size and the exclusion of noise/stranded pixels. The study used 8 window kernels and cleaned raster data to eliminate pixelated patches for accurate metric computation.

LSI calculates standardized shape irregularities, indicating edge density in a zone. LSI correlates with zones having significant development of built-ups along road transport lines, such as Manachanallur, Manapparai, and Thuraiyur. CLUMPY measures the proportion of like-adjacencies, indicating patch aggregation or disaggregation. Area_MN represents the mean area of patches in a class, indirectly denoting patch maturity. Smaller values suggest numerous newly developed patches that may require careful planning for sustained expansion. PR considers only numerical values, indicating uniform growth across all zones in a zonal-based study. SHDI measures patch diversity relative to their abundance in a landscape, showing a positive relationship with PR. Both PR and SHDI significantly improved in all urban centers from 1996 to 2020. AI is similar to CLUMPY, which considers the number of like adjacencies but not proportional ones. AI at the landscape level considers classes for adjacency matrix calculation, unlike CLUMPY which uses patches. The AI graph for the urban class reveals high aggregation in Manapparai and Viralimalai zones, indicating faster coalescence with neighboring patches compared to other urban centers.

CONCLUSION

The primary objective of this study was to employ spatial metrics to quantify the urban spatial growth of subordinate urban centers surrounding the Tiruchirappalli urban area. Spatial metrics are widely used in urban studies to analyze the spatial and geometric characteristics of urban areas, providing valuable insights into their morphology and growth patterns. The study focused on three distinct levels of analysis: patch, class, and landscape, examining various area and edge metrics, aggregation metrics, diversity metrics, and shape metrics.

At the class level, metrics such as CA, AREA_MN, LPI, and PLAND were utilized to gain a deeper understanding of area and edge characteristics. The analysis revealed that certain urban centers exhibited unpredictable values in specific zones, indicating uneven distribution. Aggregation metrics, including CI, LSI, NP, PD, AI, and PROX, demonstrated a highly polarized distribution in certain urban centers. Ensuring equitable promotion of urban growth across all zones is essential for providing fair access to urban services.

The study thoroughly investigated spatial and geometric characteristics using vital metrics, yielding valuable insights into the patterns of urban growth. However, it was observed that metrics like PLAND and LPI were influenced by the dominance of core urban areas due to direction-based zoning. To mitigate this issue, a ring-based approach could be adopted, but this necessitates a minimum urban area and sufficient rings for effective separation. Additionally, the study noted similarities in results between metrics like PLAND and LPI across all urban centers, which could be addressed by incorporating more diversified analytical methods.

Diversity metrics, represented by PR and SHDI, showcased the abundance of urban patches relative to other land cover classes. Tiruchirappalli displayed a dominant presence of urban patches, while other centers exhibited a more balanced distribution. However, the preponderance of urban patches could pose challenges to sustainable urban growth if it overlooks the integration of natural and organic elements. This is reported in the AI for Manapparai and Viralimalai, which have shown an increasing trend in the aggregation of urban patches at the landscape level. It indicates the rate, that built-ups replacing the other classes is higher. Continuing at this rate, these urban centers would lose vegetation, open space, and other natural elements from the urban.

Spatial and geometric characteristics play a crucial role in facilitating sustainable urban growth, significantly impacting the development of physical and functional elements within urban areas. The study effectively quantified various urban characteristics using metrics, offering valuable information for policy formulation and decision-making. However, a notable limitation is the absence of established threshold values for the metrics, which are essential for effectively implementing urban policies. Another major concern is about the selection of ring based or direction-based approach to study and compare the growth; the direction-based method covers the maximum urban area, yet, the area differs from one direction to another; while the ring-based approach covers an equal area around the urban center which would be preferred in some studies over the direction-based approach. Further research could focus on determining threshold values and spatial extents to guide more informed and evidence-based policy decisions. Based on the threshold metrics values, suggestions, and policies can be drawn to make the urban areas more sustainable.

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CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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