



Analyzing the Fragmentation of Urban Footprints in Eastern and Southern Indian Cities and Driving Factors

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Abstract

Rapid urbanization in combination with poor planning processes and/or policies give rise to dispersed and fragmented patches. Small pockets of urban sprawl forming fringes, secondary cores, or satellite towns in the peri-urban space hinder city sustainability. The current study comprehends the magnitude of fragmentation in terms of urban spatial dynamics over the cities of eastern and southern India. A total of eight cities considered, those are existing metropolises or possess the strong potential to become one shortly. Satellite-derived land use and land cover (LULC) information is used to study the urban expansion by adopting the LULC change assessment, entropy, and spatial metrics approach for detailed understanding of urban dynamics. A novel approach using spatial difference of night-time light (NTL) is carried out to nullify the NTL image saturation and amplify the minute changes to make new urban built-up patches identifiable. The results show a heterogeneous growth pattern and sprawling for different cities with overall expansion, infill, and outlying type of growth. Entropy analysis reveals the aggregation and dispersive nature of the selected cities. An increase in night-time anthropogenic activity noticed within the newly developed urban patches rather than densely populated areas. This analysis also discovered the existing gaps between the scientific and technological advancements and relevant policies while materializing the urban development plans for Indian urban agglomerations.

Keywords Fragmentation · Urbanization · Sprawl · Spatial metrics · Entropy · NTL

Introduction

Urbanization can bring economic, scientific, technological, and sociological advancement for a country (Bertinelli & Black, 2004; Chen et al., 2014; Liang & Yang, 2019). In the process of urbanization, the city boundaries keep on expanding with time to accommodate population inflow. Cities, generally, comprise of an urban core and associated peri-urban and neighboring rural areas. A semi-urban or surrounding rural area can gradually be included in the main development boundary that subsequently blends with the core urban area seamlessly. Most of the time, the process of seamless inclusion of peri-urban areas within the city, leads to the interpenetration of built-up areas and the

open spaces in and around them. Interpenetration causes fragmentation of urban landscapes, which is a key attribute of the spatial structure of cities that hinders the overall economic growth for a country (Bloom et al., 2008). In the modern urban landscape, both city and rural area fragment each other in the process of urban transition.

Urban landscape studies suggest that fragmentation is an inherent part of the urban transition process (Angel et al., 2012; Zambrano et al., 2019). Urban fragmentation caused by sprawling is a major constraint for a sustainable society rising as a global threat from the last century. It is being intensified at lightning speed since the last few decades. This is the consequence of uncontrolled development along the highways, surrounding the city, or in the suburban region (Bhatta et al., 2010; Oloke et al., 2021). Fragmentation of urban landscape exhausts natural resources, reduces open spaces, increases traffic congestion, and deteriorates air quality (Ji et al., 2006; Aithal & Ramachandra, 2016). Characterization of urban fragmentation of a city can be done based on how the sprawl

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exhibits around the central business district (CBD) with time. Previous studies have attributed sprawls based on (1) the spread of the planning boundary beyond the walkable range, (2) rapid consumption of land resources in the outskirts of the CBD, (3) the rise of suburbanization outside the city limits increasing the population density in the neighborhood while suppressing the population inside the core city, (4) reducing contiguity of infrastructures inside the city while creating open spaces in and around them, and (5) compaction of cities in between their ribbon developments (Angel et al., 2007). Sustainable answers for urban fragmentation can include green buildings, balanced job to housing ratio, walkability to services, mixed-land use pockets, greenways, and open spaces, an alternative source of energy such as solar and wind, and green transportation alternatives.

Sprawlification, as a result of the fragmented urban landscape, can occur depending upon transportation network, proximity to amenities, and associated topographic and socioeconomic factors (Li et al., 2010; Kiran & Joshi, 2013; Li et al., 2020). However, the degree of dispersion of sprawl depends on the favoring factors of urban growth (Punia & Singh, 2012). Shannon's entropy approach is adopted to analyze the urban growth pattern in different concentric buffer zones around the CBD (Sudhira et al., 2004; Sekhar, 2004; Lata et al., 2001; Ramachandra et al., 2012; Sumari et al., 2020; Zachary & Dobson, 2020). Shannon's entropy can capture the randomness of patch distribution at a macroscale considering the whole landscape. Effective analysis of urban fragmentation can be done by using spatial metrics along with the entropy to understand the structural and functional aspects of the urban landscape (Bosch et al., 2020; Jain et al., 2016; Kantakumar et al., 2016; Sahana et al., 2018). These metrics are numeric measurements that quantify spatial patterning of land cover patches, classes, and the entire landscape, and quite helpful for planning and management decisions (Hai & Yamaguchi, 2008; Pham et al., 2011). Study of landscape structure helps to put forward the development of landscape, to assess the fragility and required for determining the relations among structural features, landscape functions, and changes (Jaeger, 2000). Hence, quantifying the structural characteristics of the landscape is necessary for the sustainable planning of the urbanized area (Bhatta et al., 2010; Kong et al., 2007; Terfa et al., 2020). For this purpose, open-source fragment statistics package, i.e., FRAGSTATS (McGarigal et al., 2002), is used for the characterization of urban expansion, sprawl, and fragmentation analysis (Aithal & Ramachandra, 2016; Dasgupta et al., 2009; Ramachandra et al., 2015; Sun et al., 2015; Terfa et al., 2020; Toosi et al., 2012).

Further, analyzing urban sprawl using night-time light (NTL) imageries as proxy data is one of the novel

approaches (Hu et al., 2020; Small et al., 2018) to understand the sprawl dynamics. These images depict the unique pattern of urbanized landscapes, which help in the identification and validation of newly developed patches, urban boundaries, dynamics of urban patches (Ma et al., 2015; Pandey et al., 2013), population estimation (Amaral et al., 2006; Zhou et al., 2017; Xu et al., 2021), mapping of transitions, air quality, GDP growth, and other socioeconomic activities (Castrence et al., 2014; Ma et al., 2014).

The growth pattern of Indian cities is relatively different from most of the developed countries in the world. Most of the Indian cities are growing abruptly due to improper planning and inadequate management practices (Aithal & Ramachandra, 2016). Many industrial corridors/townships are constructed, attracting population inflow from surrounding areas in search of employment and better livelihood (Jain & Sharma, 2018; Moghadam & Helbich, 2013). It is encouraging the demand for affordable houses, consequently resulting in budding suburban areas surrounding the central city. These suburb infrastructures are often lacking in proper amenities and transportation since they are far from the limits of CBD. This process leads to fragmentation nearby the core city; eventually, the city planning boundaries expanded to accommodate the sprawled population at the cost of less sustainable cities (Bhatta et al., 2010). During the last three decades, several studies helped in understanding the existing urban dynamics of Indian cities in terms of fragmentation and landscape composition by evaluating LULC change, spatial metrics, Shannon's entropy by adopting remote sensing and Geographic Information System (GIS) techniques (Rahman et al., 2011; Kumar et al., 2011; Ramachandra et al., 2012; Moghadam & Helbich, 2013; Kantakumar et al., 2016; Jain et al., 2016; Jain & Sharma, 2018; Sahana et al., 2018; Das & Angadi, 2020; Hasnine & Rukhsana, 2020).

The current study focuses on analyzing the fragmentation of the urban footprints by utilizing approaches of LULC change, Shannon's entropy, spatial metrics analysis, population growth, and NTL analysis for an in-depth understanding of urban expansion and the sprawl pattern over eight tier-I and tier-II cities in the eastern and southern parts of India. The considered cities include the ones listed in the Government of India's smart city project and the existing megacities. Unlike the traditional thresholding approach, this study adopts a novel method called 'spatial difference (SD)' to validate the findings of LULC analysis regarding the spatial growth pattern of the cities. The present study provides a comprehensive and updated illustration of the urban growth and dynamics and can be directly helpful in policy/decision making for the sustainable city development process.

Study Area

The study area consisting of urban agglomerations of eastern and southern India includes Bhubaneswar–Cuttack (Odisha), Chennai (Tamil Nadu), Bengaluru (Karnataka), Hyderabad (Telangana), Ranchi (Jharkhand), Kolkata (West Bengal), Visakhapatnam (Andhra Pradesh), and Coimbatore (Tamil Nadu), i.e., four cities each from tier-I and tier-II (Table 1; Fig. 1). The choice of these cities is made based on the region of interest, population densities, inclusion in the smart city project, and diverse climatic/geographical settings. The changes in urban built-up and growth dynamics are studied using spatial metrics and discussed in Sect. 4. The topographical maps of the cities are illustrated in Fig. 1 with their locations indicated on the map of India as the asterisk sign.

Data and Methodology

The data used for the current study include pre-processed remote sensing images from BHUVAN portal (http://bhuvan.nrsc.gov.in/bhuvan_links.php) of National Remote Sensing Centre (NRSC), ISRO (for the years 2005, 2010, and 2015), and the LULC thematic layers (for the years 1985 and 1995) from the decadal classification project of National Aeronautics and Space Administration (NASA) at 30 m spatial resolution (Roy et al., 2016). The overall classification accuracy of these data is 90.07%, with a range of 86–95% in different states. The decadal LULC datasets were prepared using IRS and Landsat images, and overall mapping accuracy of 94.46% was achieved with the Kappa accuracy of 0.9445 (Roy et al., 2016). Notably, the imageries taken from decadal LULC datasets (from NASA) are initially of 100 m resolution and resampled to 30 m to maintain the consistency. Thus, land use (LU) data from NASA is of relatively poor resolution than that of BHUVAN. Therefore, while considering both the datasets for LU change analysis, entropy, and spatial metrics, the

results may vary significantly from the year 1995 to 2005. Therefore, the decadal LU datasets are not considered for the spatial metrics analysis.

The location map is prepared from Shuttle Radar Topography Mission (SRTM) 30 m resolution data, available from the United States Geological Survey (USGS). Apart from this, the gridded population of the world (GPW-v4) and NTL images from Visible Infrared Imaging Radiometer Suite-Day/Night Band (VIIRS-DNB) were also used. The flowchart of the methodology is illustrated briefly in Fig. 2.

Urban growth patterns can be statistically summarized and represented through Shannon's entropy (Jat et al., 2008). It is a metric calculation technique to study spatiotemporal changes in the urbanized landscape. Shannon's entropy indicates the degree of compactness of CBD and urban sprawl in all directions of the city:

$$H_n = \sum_{i=1}^n P_i * \ln \frac{1}{P_i}$$

where H_n = Shannon's Entropy and P_i = probability of variable in the i^{th} zone. The absolute Shannon's entropy (ASE) values vary between zero and $\ln(n)$. Zero entropy value indicates that built-up areas have densely aggregated, whereas entropy nearer to $\ln(n)$ shows very high dispersion (Thomas, 1981). An evenly dispersed distribution among the zones gives a maximum value of $\ln(n)$.

Urbanized development is mirrored in the economic, environmental, technological, and sociocultural changes of cities over the years, yet all are driven by evolving the urban landscape configuration. Quantification of the spatial characteristics of city's landscape using spatial metrics is carried out by FRAGSTATS v4.2 (McGarigal et al., 2002), developed by Oregon State University, USA, to represent the structure and pattern of the landscape (Table 2).

Table 1 Details of the cities considered in the study

Sl. No	City name	Latitude		Longitude		Area(km ²)
		From	To	From	To	
1	Bhubaneswar–Cuttack	20° 12' N	20° 23' N	85° 44' E	85° 54' E	~ 745
2	Chennai	12° 50' N	13° 17' N	79° 59' E	80° 20' E	~ 1160
3	Bengaluru	12° 45' N	13° 11' N	77° 23' E	77° 48' E	~ 1280
4	Hyderabad	16° 57' N	17° 54' N	85° 12' E	85° 31' E	~ 7000
5	Ranchi	23° 13' N	23° 29' N	85° 12' E	85° 31' E	~ 680
6	Kolkata	22° 19' N	23° 01' N	88° 04' E	88° 33' E	~ 1765
7	Visakhapatnam	17° 29' N	18° ° 11' N	82° 56' E	83° 31' E	~ 1700
8	Coimbatore	10° 48' N	11° 14' N	76° 45' E	77° 14' E	~ 1302

Elevation of selected cities (in meters)

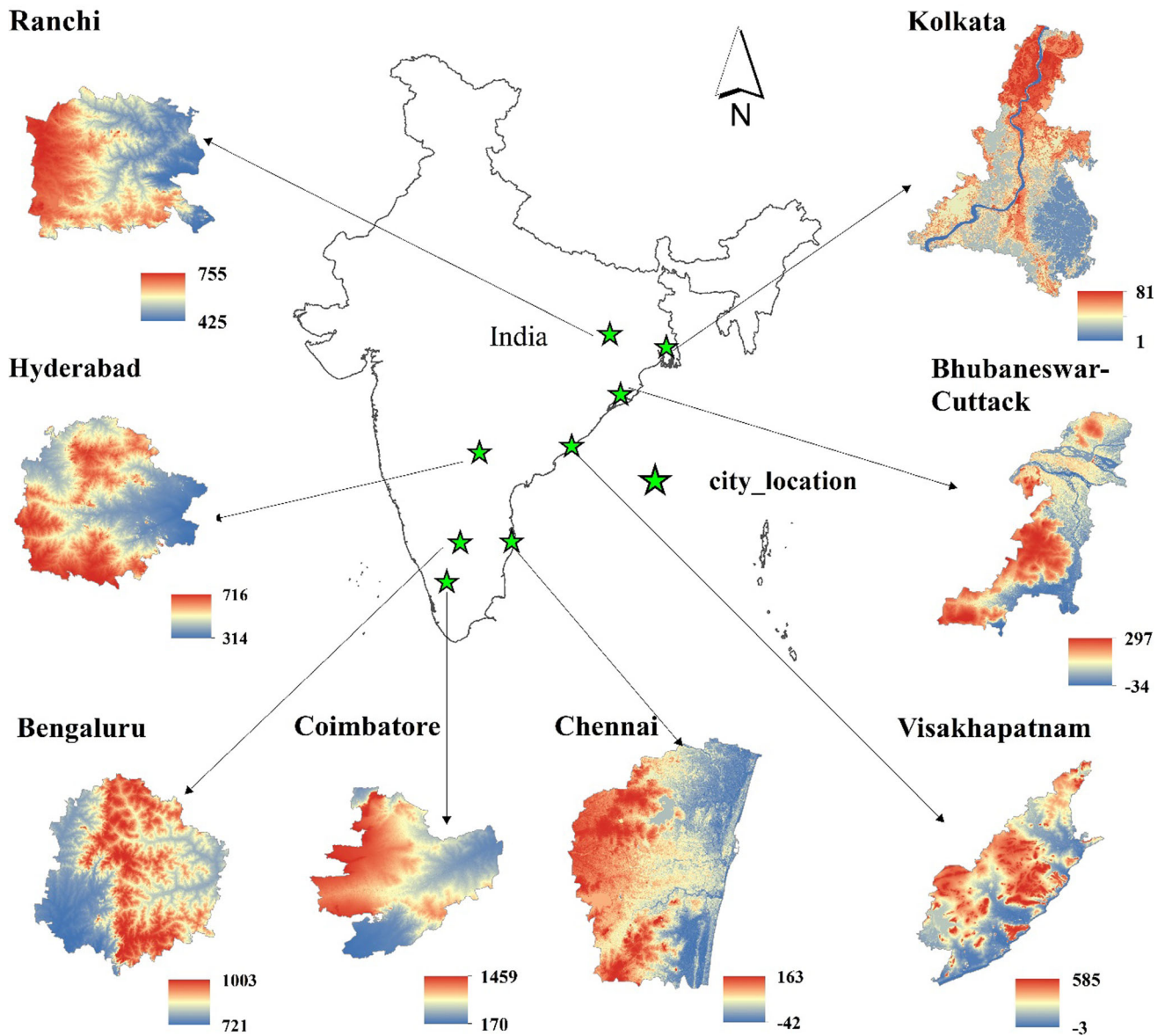


Fig. 1 Geographical location with elevation maps of the study area

Urban Growth Analysis

The LULC thematic images obtained from ISRO and USGS consist of 20 and 24 classes, respectively. These images are masked according to the prepared city boundaries and reclassified to 5 classes, i.e., built-up, waterbody, forest, agriculture, and barren land. For the LU analysis, these five classes are re-categorized as urban and non-urban (waterbody, forest, agriculture, and barren land) category. During the analysis of the temporal thematic maps from USGS (1985 and 1995), some discrepancies were

found in the concerned classes. These errors were corrected by referring to the historical images of ‘Google Earth.’ Comparatively, the later year ISRO images were found to be of suitable quality for the analysis. The temporal changes in urban extent are shown in Fig. 3, for the cities of interest (Kolkata, Chennai, Bengaluru, Hyderabad, Bhubaneswar–Cuttack, Ranchi, Visakhapatnam, and Coimbatore). The spatial patterns of urban growth for Bhubaneswar–Cuttack and Hyderabad, as a representative for tier-II and tier-I city, respectively, are computed by considering a circular area of 2000 m radius (Fig. 4). Here,

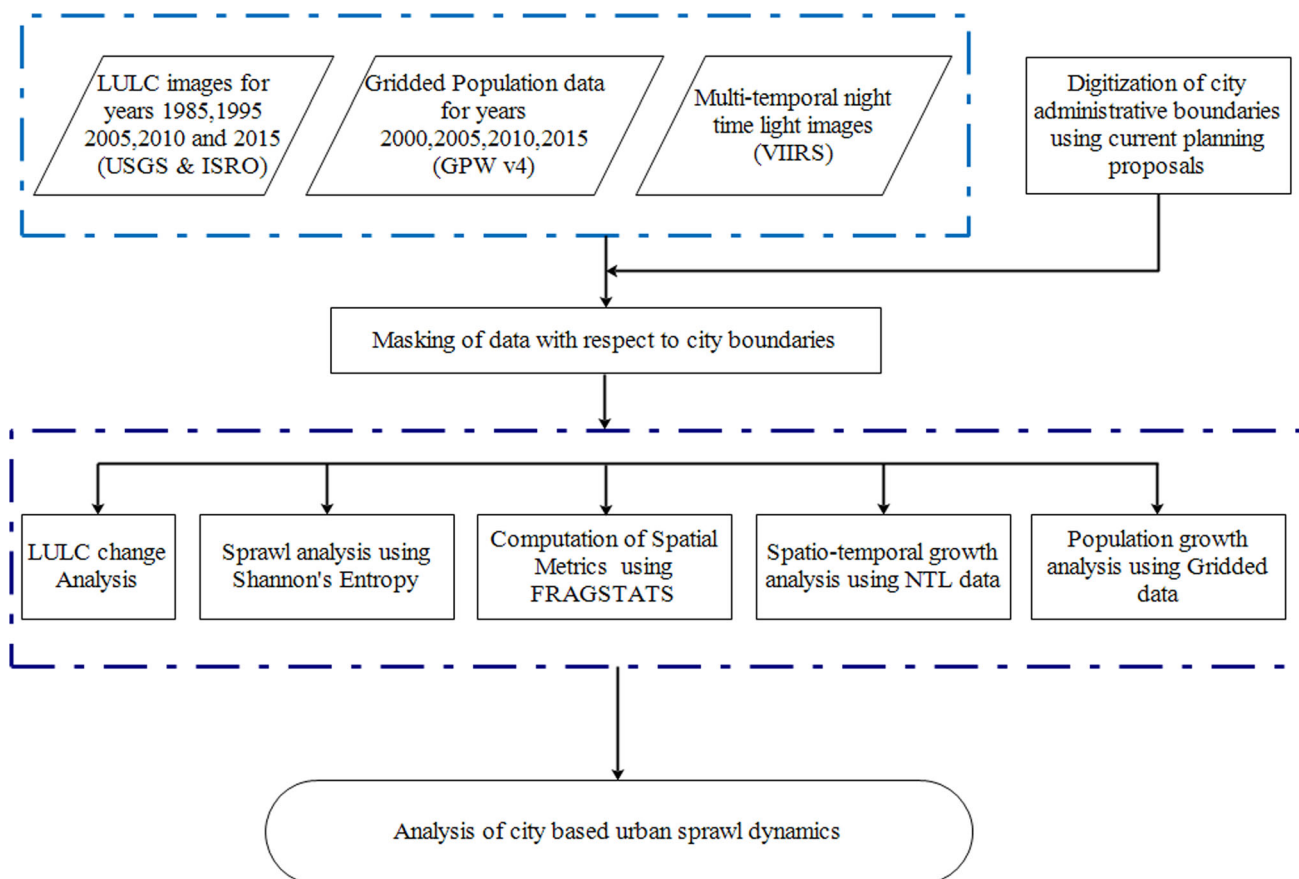


Fig. 2 Flowchart of methodology adopted for the study

the morphological pattern of urban growth for the selected cities computed considering the built-up density within the circle. Figure 5 illustrates the Percentage of Land (PLAND) occupied by each LULC class in all the cities from the year 1985 to 2015. The industrial revolution started in India during the early 2000s, which resulted in the rapid alteration of LULC of the cities. Thus, most of the cities show a significant increase in urban land cover from 1995–2005.

Bhubaneswar–Cuttack urban complex experienced an increase of $\sim 95\%$ in the built-up area during the last three decades. Establishment of numerous satellite towns along the highways is seen in Bhubaneswar–Cuttack urban complex and Coimbatore by the conversion of barren and agriculture land (Fig. 5). The core area of Coimbatore is dominated by the infill type of growth and fringe expansions along the highways connecting the eastern and northern side of the city with an overall 200% increase in the built-up area within the last three decades (Fig. 3). The north and northwestern part of Bhubaneswar–Cuttack was covered by agricultural land and a prominent green cover, which gradually transformed into residential, industrial, and commercial establishments and ‘New Bhubaneswar’

area, respectively (Fig. 5). These results bear partial similarity with those observed by Swain et al., (2017). Further analysis is done for the urban spatial pattern over tier-II cities, showing similar developments. For instance, patterns of urbanization over Bhubaneswar–Cuttack can be broadly categorized into four types, shown in the encircled areas (Fig. 4). Circles ‘A’ and ‘B’ represent primary and secondary core with 96.5% and 87.1% urban pixels, respectively. Fringe development can be seen within the circle ‘C’ with 31% urban pixels along the NH 5. Circle ‘D’ shows scattered sprawl with 6.7% built-up pixels. Ranchi shows an increase of $\sim 30\%$, and Visakhapatnam city added $\sim 109 \text{ km}^2$ ($\sim 47\%$ increase) of urban built-up land to its planning boundary during the study period. Both of the cities show scattered impervious patches depicting leapfrog developments (Fig. 3). Essentially, Visakhapatnam experiences infill growth and spread along the east coastline of India. A secondary urban core is found to be growing toward the northern corner of the city (Fig. 3). The analysis also suggests a decrease in the forested area over the eastern part of Ranchi, similar to the observations of Kumar et al., (2011). A substantial decrease in barren land is found in all four tier-II cities,

Table 2 Types of spatial metrics selected for this study

Sl. no	Type	Spatial metrics	Description	Range	Unit
1	Area and edge metrics	Class area (CA)	Sum of the areas of all patches of the corresponding patch type	$CA > 0$, without limit	Hectare (ha)
2		Percentage of land (PLAND)	Percentage the landscape comprised of the corresponding patch type	$0 < PLAND \leq 100$	%
3		Total edge (TE)	The sum of the lengths (m) of all edge segments	$TE \geq 0$, without limit	Meters
4		Mean patch size (MPS)	The average area of all patches in the landscape	$MPS \geq 0$	Hectare (ha)
5		Largest patch index (LPI)	The largest patch of the corresponding patch type divided by total landscape area (m^2)	$0 < LPI \leq 100$	%
6	Shape metrics	Perimeter–Area Fractal dimension (PAFRAC)	Describes the power relationship between perimeter and area and measures the change in shape complexity of the group patches	$1 \leq PAFRAC \leq 2$	None
7	Aggregation metrics	Number of patches (NP)	The number of patches of the corresponding patch type (class)	$NP \geq 1$, without limit	None
8		Contagion index (CONTAG)	An information theory-based index that measures the extent to which patches are spatially aggregated in a landscape	$0 < CONTAG \leq 100$	%
9		Aggregation index (AI)	Measures aggregation of similar patch type using adjacency matrix	$0 \leq AI \leq 100$	%
10	Diversity metrics	Shannon's diversity index (SHDI)	Measures diversity of patches in the landscape	$SHDI \geq 0$, without limit	None
11		Shannon's evenness index (SHEI)	Measures distribution of patch types in the landscape. Evenness is the complement of dominance	$0 \leq SHEI \leq 1$	None

complementing the increase in cropping land or built-up area.

Chennai shows $\sim 108 \text{ km}^2$ increase in the urban built-up area, with the rate of expansion gradually decreasing in the last two decades ($\sim 22\%$ from 2005 to 2010 and $\sim 1\%$ until 2015). Bengaluru added more than twofold ($\sim 112\%$) built-up area in the last three decades, while Hyderabad shows an increase of $\sim 88\%$ in urban built-up during 2005; overall, there is an increase of $\sim 100\%$ in an urban area since 1985. Chennai, Bengaluru, and Hyderabad, the IT (Information and Technology) hubs of India, show fringe developments along the major highways, mostly due to the conversion of barren lands (Fig. 5). During 1990–2000, due to the establishment of IT industries, the rate of development seems to be the highest ($\sim 66\%$ for Bengaluru) within and around the city premises (Fig. 5). Chennai and Bengaluru also experience core infill along with the radial expansion of the sprawled built-up, whereas a decentralized leapfrog development is realized in Hyderabad during the study period, similar to the findings of Taubenböck et al. (2009) and Aithal and Ramachandra (2016). Spatial variability for Hyderabad Metropolitan represents the pattern of urbanization of tier-I cities (Fig. 4). Here, circle 'A' represents the primary core of the city with 97.8% of built-up pixels; circle 'B' shows one of the planned satellite towns growing outskirts of the

city with 83% built-up pixels. A linear fringe and scattered developments can be prominently identified within circles 'C' and 'D' with 30% and 9.4% built-up pixels, respectively, so as the case of other tier-I cities. In the case of Kolkata, $\sim 10\%$ increase in the urbanized area predominating infill growth is reported (Fig. 3) along with a decrease in open space and waterbody from 2005 to 2015. New urban patches are found on the eastern side of Kolkata, with an overall decrease of barren land. Urban expansion is seen outside the core urban periphery of Kolkata, similar to the observations by Bhatta (2009).

Urban Dynamics During the Last Decade

Analysis of Urban Sprawl: Shannon's Entropy Approach

Shannon's entropy is used as a precise indicator for analyzing urban sprawl. It is an area computation method using multiple concentric buffer zones having 2 km interval (Jha et al., 2008; Deka et al., 2012; Kiran & Joshi, 2013). The consideration of a 2 km buffer zone for calculating Shannon's entropy in the present study is based on the size and extension of the city from the CBD and carried out for each city to determine ASE, where the maximum

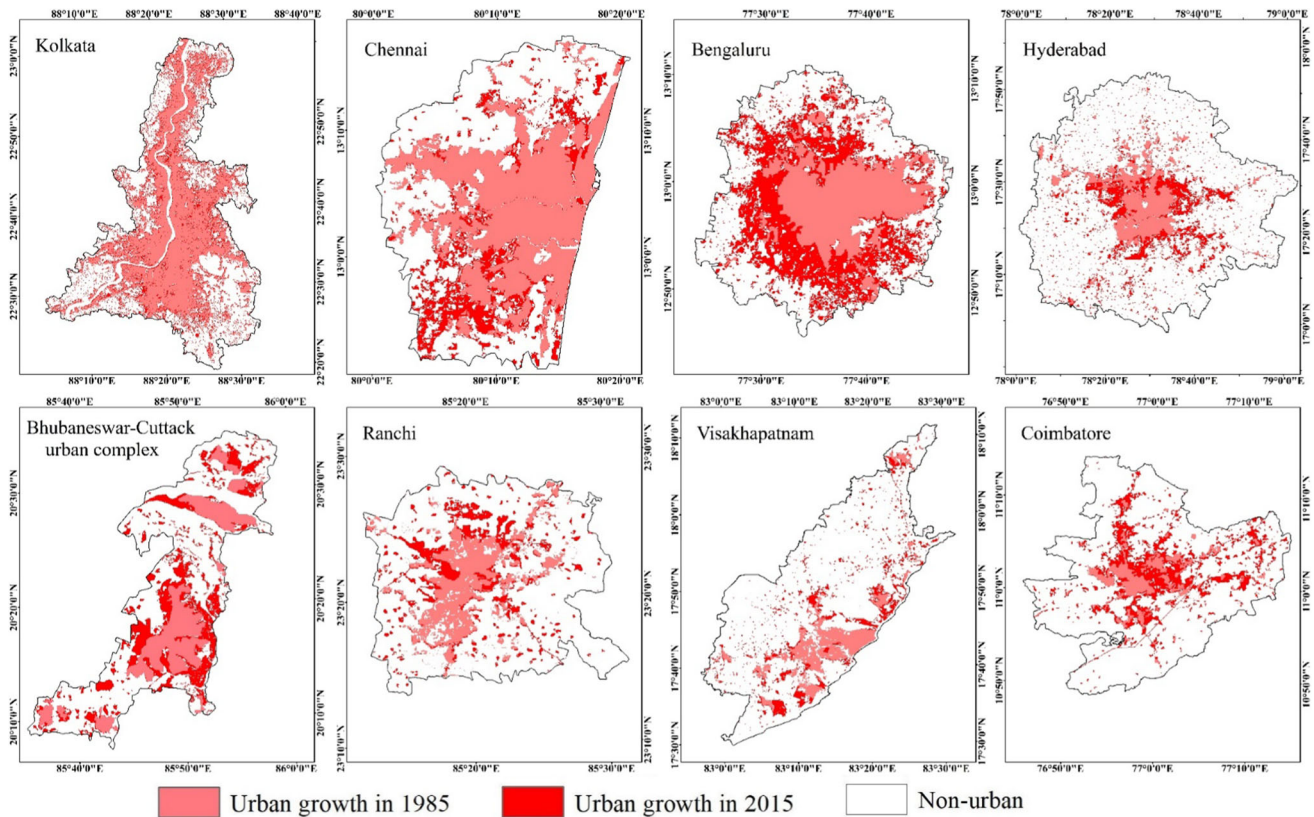


Fig. 3 Urban transition map of considered cities from 1985–2015 and for Kolkata from 2005–2015

value, i.e., ‘ $\ln(n)$,’ represents the logarithmic function of the total number of buffer rings. It quantifies the highest fragmentation possible in that particular urban agglomeration. Thus, as the entropy value pushes toward $\ln(n)$, more spreading of patchiness is seen in the metropolitan area.

Bhubaneswar–Cuttack urban complex, Chennai, and Bengaluru exhibit roughly similar trends of fragmentation (Table 3). During the study period (1985–2015), the increase in entropy is 0.16, 0.08, and 0.086 for Chennai, Bhubaneswar, and Bengaluru, respectively. From 1985 to 1995, all three cities experienced more dispersed growth; gradually, a moderate increase in fragmented development is seen in the last decade. However, the cities are facing rapid urbanization and an absolute demand for LU alteration for the growing population. A similar trend in entropy is seen for Hyderabad metropolitan area (Table 3) with a significantly higher value. It is probably due to the establishment of small satellite towns around the city almost in all directions.

Visakhapatnam shows relatively high variation in entropy value during the study period (Table 3). With high $\ln(n)$ value (i.e., 3.466), the city has a tremendous opportunity to grow with sustainable planning and management. In the case of Coimbatore, the least entropy is found to be in 1985, and the maximum (2.512) is in 2005. This trend

indicates that the compact older city of Coimbatore experienced fragmented growth peaking toward 2005. By 2010, a slight decline in entropy is found due to the slow infill growth. The rapid urbanization in recent years resulted in slightly higher entropy value in 2015. Kolkata shows a mostly compact growth pattern from 2005 to 2015. Budding of many small suburbs along the major highways and all around the city leads to higher entropy value in the case of Kolkata. Unlike other cities, Ranchi has a very stagnant trend of urbanization during these thirty years (1985–2015). The results indicate that, even though the variation of entropy is very less among different years, the degree of randomness is quite high while dispersed growth taking place all around the city center.

For most of the cities, the year 2005 is showing relatively higher entropy. This is primarily due to the ten years gap between the datasets from 1995 to 2005. It may also be attributed to the industrial revolution leading to rapid urbanization during the late 90 s, which resulted in sprawling in and around the cities.

Characterization of Urban Fragments

The increase of urban land use (LU) is an inevitable process, irrespective of the growth rate depending upon the

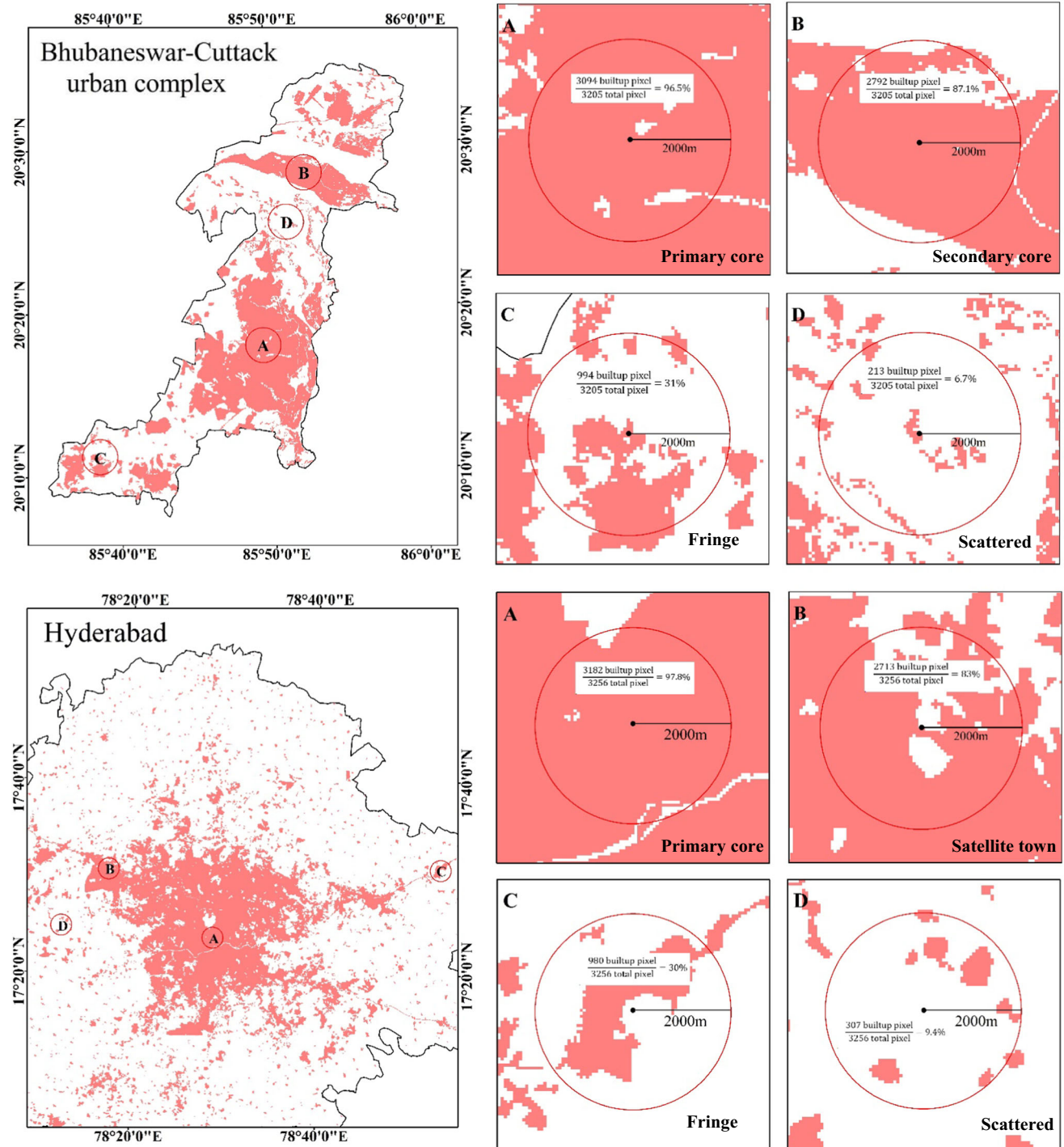


Fig. 4 Map showing the urban spatial pattern for a tier-II (Bhubaneswar–Cuttack) for **A** Primary core, **B** Secondary core **C** Fringe and **D** Scattered and a tier-I (Hyderabad) city for **A** Primary core, **B** Satellite town **C** Fringe and **D** Scattered development

economic development of each city. But the main question arises regarding the pattern of arrangement of these patches and how they are spatially distributed within the city landscape. The answer lies in the spatial metrics, which quantifies the spatial arrangement of the patches of urban class or the whole landscape of the core and peri-urban

area. In this study, four categories of metrics based on (1) area-edge, (2) shape, (3) aggregation, and (4) diversity of landscape are considered for studying the fragmentation of cities. These metrics can evaluate the edginess, mono-centrism in terms of nuclearity dimension, shape complexity, connectivity between similar/different patches,

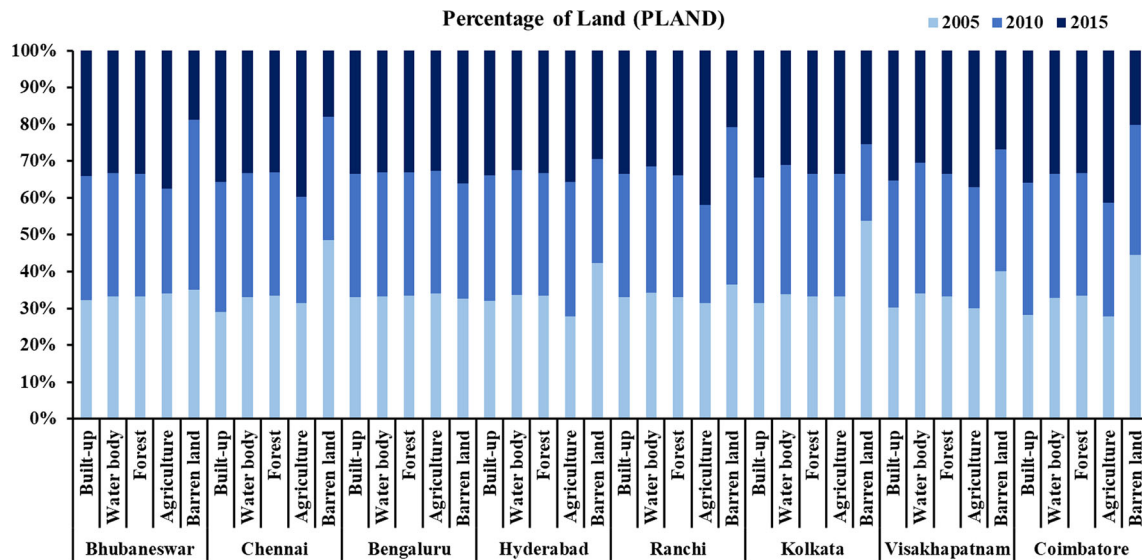


Fig. 5 Spatial metric Percentage of Land (PLAND) for land use classes of different cities

Table 3 Absolute Shannon’s entropy for all the cities

City/year	1985	1995	2005	2010	2016
Bhubaneswar	2.163	2.127	2.242	2.243	2.244
Chennai	2.350	2.370	2.512	2.510	2.509
Bengaluru	2.316	2.316	2.393	2.394	2.402
Hyderabad	2.160	2.358	2.512	2.467	2.469
Ranchi	2.832	2.838	3.029	3.038	3.039
Kolkata	N.A	N.A	2.825	2.840	2.837
Vishakhapatnam	2.016	2.037	2.012	2.012	2.009
Coimbatore	2.492	2.601	2.955	2.949	2.935

aggregation of both the dispersed and interspersed patches, and degree of diversity and evenness of the whole landscape.

Area-Edge Metrics

The ‘class area (CA)’ metric determines the total area coverage of all patches for the selected class, i.e., built-up. This metric shows exponential growth for Chennai with a massive rise of ~ 10700 ha of impervious layer, followed by Kolkata, Hyderabad, Coimbatore, and Visakhapatnam (Fig. 6a). A class-based metric Mean Patch Size (MPS) averages out the patches of an individual class (i.e., urban class) within the entire city landscape. It shows the exponential rate of growth for Chennai, Coimbatore, and moderate growth in the case of Bengaluru, Hyderabad, and Bhubaneswar–Cuttack. The least increase in urban spreading is found for Ranchi, which is mainly due to the dominance of infill growth rather than dispersed type. In

terms of the size of the patch, Kolkata and Visakhapatnam contain a dispersed and interspersed pocket of tiny urban fragments (Fig. 6a). The measure of Total Edge (TE) of all the patches combined for urban cover depicts the degree of fragmentation in terms of connectivity and physical continuity of the landscape. For all the selected cities, TE decreases over 15 years. However, Kolkata shows a peculiar pattern by an increase in 330.32 km edge length of the built-up area from 2005 to 2010. The reason behind such peculiarity might be coming up of new patches, namely Barrackpur, Sarodapalli, Parbungla, Budge Budge, Hind motor development area, and Pratiraksha Nagar. Chennai shows the maximum decrease in edge length, and the minimum is found in Ranchi (Fig. 6a). Largest Patch Index (LPI), which generally signifies the mono-centrism of a particular patch type (of an individual class), is found to be growing in all the cities over the study period, except for Coimbatore. Coimbatore shows a slight drop in the LPI value for 2015 after a sharp rise in 2010 and indicates the modification of graininess of the landscape approaching patch fragmentation. However, the overall increase of the urban patch dominance ranges from less than one to nearly 5%, but Chennai shows a significant increase of approximately 10% in the urban patch (Fig. 6a). If we look at the bigger picture of LPI, the index values are very less for most of the cities consist of merely 10–20% of the whole cityscape. However, Bengaluru comprises the largest urban patch representing the large core of the city (Fig. 7) with a ~ 50% built-up layer. The extremely fragile and miniature city core is found for Visakhapatnam with the lowest LPI value.

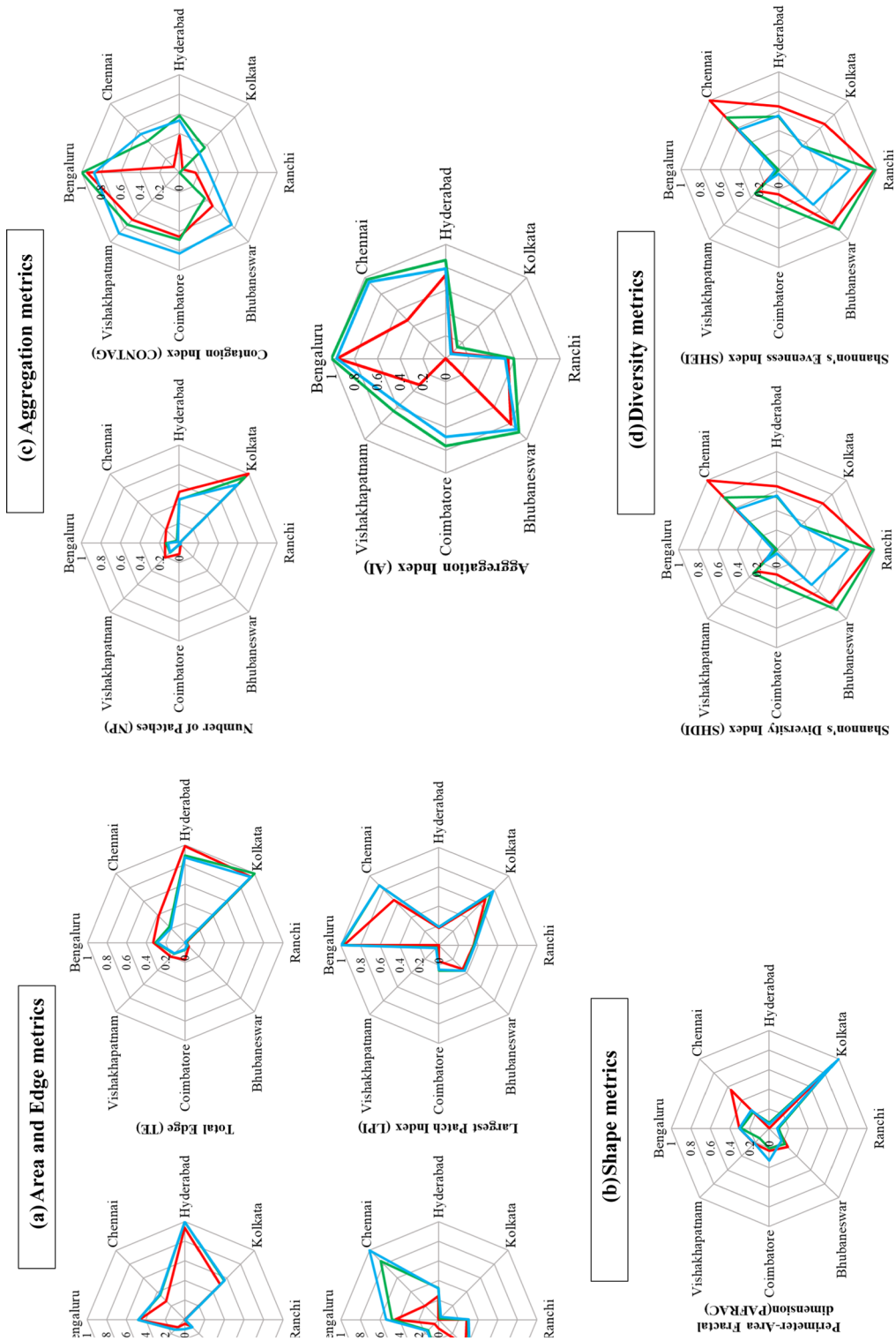


Fig. 6 Spatiotemporal variation of **a** Area and Edge metrics (CA, TE, MPS, and LPI) **b** Shape metrics (PAFRAC), **c** Aggregation metrics (NP, CONTAG, and AI) and **d** Diversity metrics (SHDI and SHEI) for selected cities

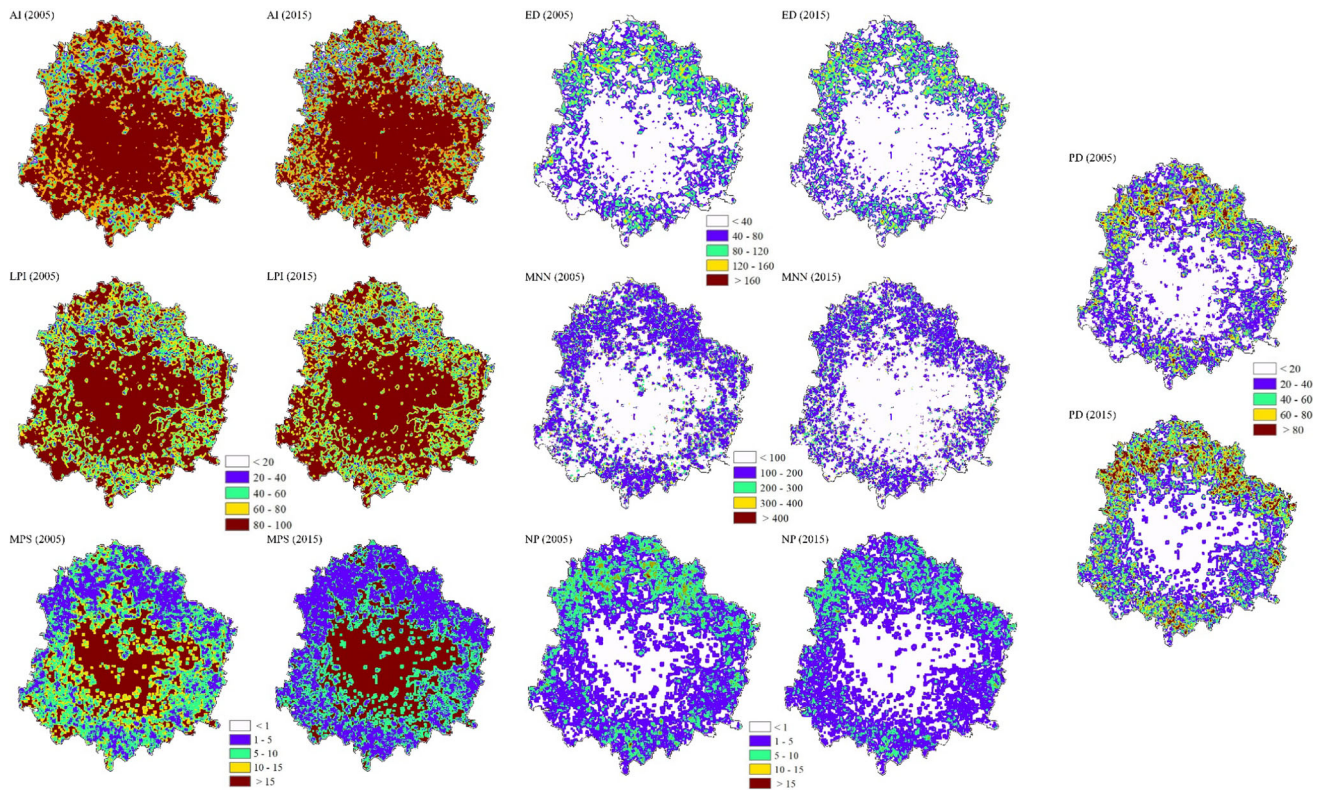


Fig. 7 Spatiotemporal variation of selected metrics for tier-I city Bengaluru

Shape Metrics

The geometric complexity of a patch or a cluster of patches for a selected class can be expressed by ‘shape metrics’ in terms of the degree of compactness. The shape geometry has the potential to decipher the magnitude of fragmentation in an urban pocket. The shape of the patches plays a vital role in influencing the inter-patch processes establishing the connectivity among the neighboring patches (Buechner, 1989). If the shape of the patches is regular and well distributed, then that is more of a planned urban pocket; but the sporadic expansion of urban patches is a symbolic representation of the unplanned growth and can be termed as the bad sprawl. The bad sprawl may hinder the developmental process for both the interspersed land cover types and demand much more energy and resource consumption but unable to access it properly due to breakage of the resource-economy-feedback cycle within the city core. In most of the selected cities, such complex-shaped patches are found in the surrounding of the central core in metropolitans in the form of fringes and scattered patches, especially within the medium-sized cities such as Coimbatore, Visakhapatnam (Fig. 6b). Notably, shape metrics are extremely unit-sensitive. If the unit varies, the value may vary drastically. PAFRAC illustrates the power relationship of the perimeter–area ratio expressing the

interdependency of both the variables in terms of per unit change. This index gives higher value when the patches are of complex shapes, indicating that the perimeter varies rapidly with a unit increase in patch area. Among all the shape metrics, this index gives the best quantification for a larger spatial scale, e.g., class level or landscape level. Kolkata shows the highest value with maximum complexity, and Hyderabad shows the opposite. In the case of Chennai, the values drop drastically from 2005 to 2015, showing lessening of fragmentation effects and more of simple Euclidean-shaped urban patches (Fig. 6b). The star-shaped fringed growth in Coimbatore pushes the level of complexity for urban cover in later years (toward 2015). Few cities are showing a declining trend, and others a gradual rise. The pattern is unclear and capricious and confirms the slow and steady approaching trend of sprawling in the cities.

Aggregation Metrics

Aggregation metrics illustrate the measure of patch distribution in the landscape and summarizes the sub-division, isolation, dispersion, and interspersion properties of landscape configuration (McGarigal, 2015). This study considers a set of a total of four aggregation metrics to scrutinize the complex morphology of the selected Indian

cities. Among them, two metrics, i.e., the number of patches (NP) and TE, show a high correlation with each other. Theoretically, within a unit area, with an increase in NP, the rise in TE is noticed due to numerous small urban fragments. For most of the cities, these metrics decline either drastically or steadily from 2005 to 2015 (Fig. 6c). Nevertheless, a slight increase in the values is observed from 2010 to 2015 for Hyderabad, Bhubaneswar–Cuttack, and Coimbatore. Both Hyderabad and Bhubaneswar–Cuttack are under rapid LU transformation phase with new urban covers are coming up each year, which is well captured by the steady decrease in NP (Fig. 6c). Ranchi extensively follows infill development within the study period (2005–15), and the existing scattered patches serve as the seed nuclei for urban expansion.

CONTAG has the capability to quantify the textural aspect of the landscape and provides a brief understanding of the maximum clumpiness of urban patches. It is highly correlated with the shape index/fractal dimension of the patch types. Chennai, Coimbatore, and Visakhapatnam exhibit a rising continuum of contagion characterized by aggregated patch development and also supports the findings of NP metric. Remaining tier-I cities, i.e., Bengaluru (Fig. 7), Hyderabad, and Kolkata, show a slight increase in the metric value toward 2010, followed by a declining trend in 2015, which is contradictory in the case of tier-II cities like Ranchi and Bhubaneswar–Cuttack (Fig. 6c). The primary reason could be the excess load on the urban

landscape in megacities leads to a higher rate of fragmentation and this rapidity now passes over to the tier-II group of cities. Although sprawled urbanization dominates earlier in these cities, 2010 onwards, they are experiencing more of an overall infill growth pattern.

Aggregation Index (AI) shows the maximal increase for Chennai and Coimbatore due to the exponential rate of patch aggregation. Several new mixed-use patches have been developed in Chennai since 2005 following the highway network connecting nearby cities and boosting the city's economy. The mixed LU comprises of the industrial corridors, institutional blocks, commercial complexes, and huge chunk of residential plots in the southwestern side of the city and necessitates careful planning and design for future years. In order to achieve the 'compact theory of sustainability,' Coimbatore is approaching toward a magnificently clumped CBD with arterial fringes (Fig. 8). In the eastern half of the city, the linearly grown urban clusters are also gradually getting intact with industrial patch development, and the residential land cover dominates the western side of the landscape in recent years as per the proposed master plan. Except for these two cities, all the other cities are following a similar trend for this metric, showcasing a steady rise followed by even a slower drop in the values (Fig. 6c). The fragmented urban patches with a relatively higher degree of dispersion affect the configuration of Ranchi's landscape as reflected by continuously deteriorating AI values.

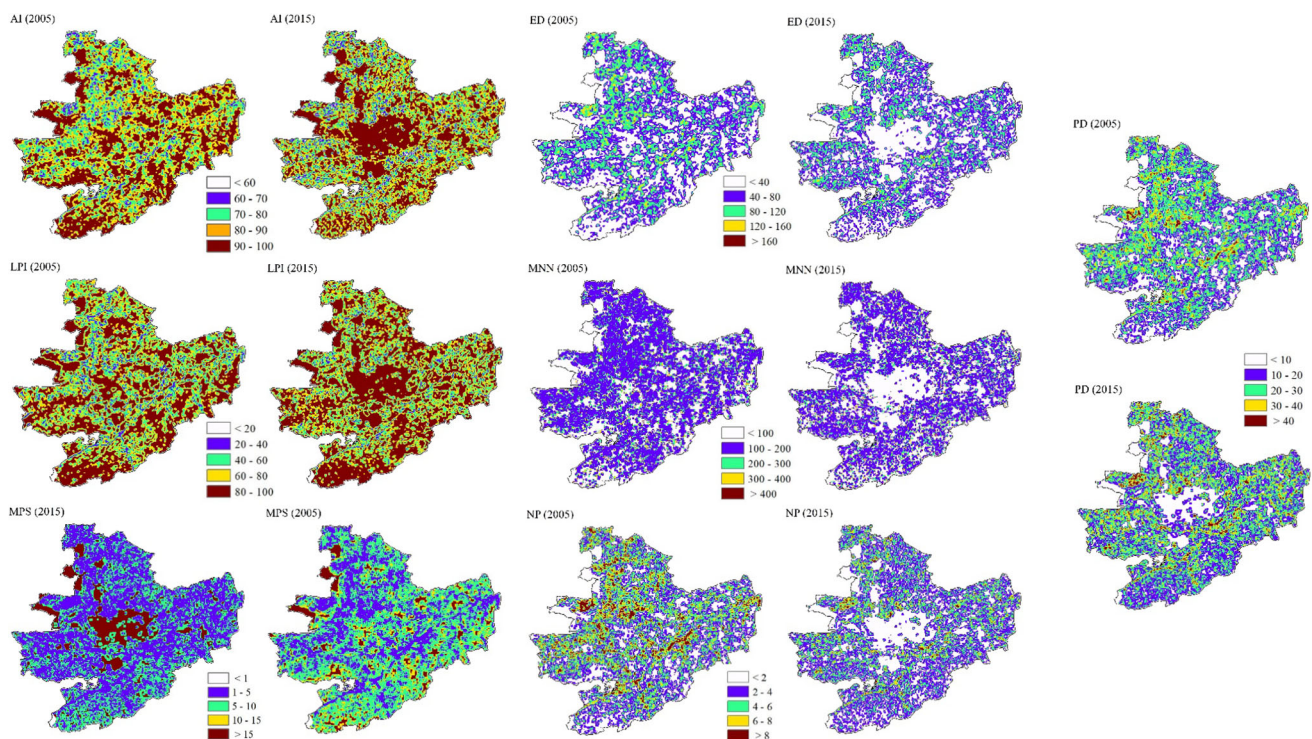


Fig. 8 Spatiotemporal variation of selected metrics for tier-II city Coimbatore

Dispersion and interspersed of the urban patches affect the contiguity, edginess, and functionality of the landscape on a large scale. More fragmented land pieces require more attention, hanging on the silver lining of losing the connectivity with the mainland (i.e., CBD), disproportionate the balance of housing–job ratio. It increases the length of the driveway, multiplies the demand for more private vehicles, and creates more pollution, traffic congestion. Different groups of patches require a different set of amenities and move forward in the direction of exploitation of the resources. Thus, summing up all the aggregation metrics, higher the fragmented growth more pushing away the sustainable development goals, a large patch with less degree of scatteredness a step closer toward a sustainable city environment.

Diversity Metrics

Shannon's diversity index (SHDI) computes the diversified patch arrangement within a certain landscape, and the index value increases with the increase in patch richness. A large single patched area is considered to null diversity (i.e., SHDI = 0). However, the evenness of the patch distribution can be calculated by Shannon's evenness index (SHEI). Both the diversity metrics are found to be decreasing for Chennai and Kolkata, indicating the homogeneity of the urban land cover in the city landscape. Ranchi, Bhubaneswar–Cuttack, and Coimbatore experienced a higher degree of fragmentation with rising SHDI and SHEI in 2010 and followed by a more or less singularity of the patch types acquired by a declining trend of both the metrics (Figs. 6d and 8). In the case of Bengaluru (Fig. 7), Hyderabad, and Visakhapatnam, the trend seems to be opposite with an increasing abundance and evenness in distribution of different patch types and drop the values in the recent year, i.e., 2015 (Fig. 6d). Such type of growth suggests the rapid urbanization in those cities, which resulted in the occurrence of several clusters of urban patches due to irrational human intervention and the connectivity among those patches established by infill and edge development around them.

Population and Urban Dynamics Using NTL

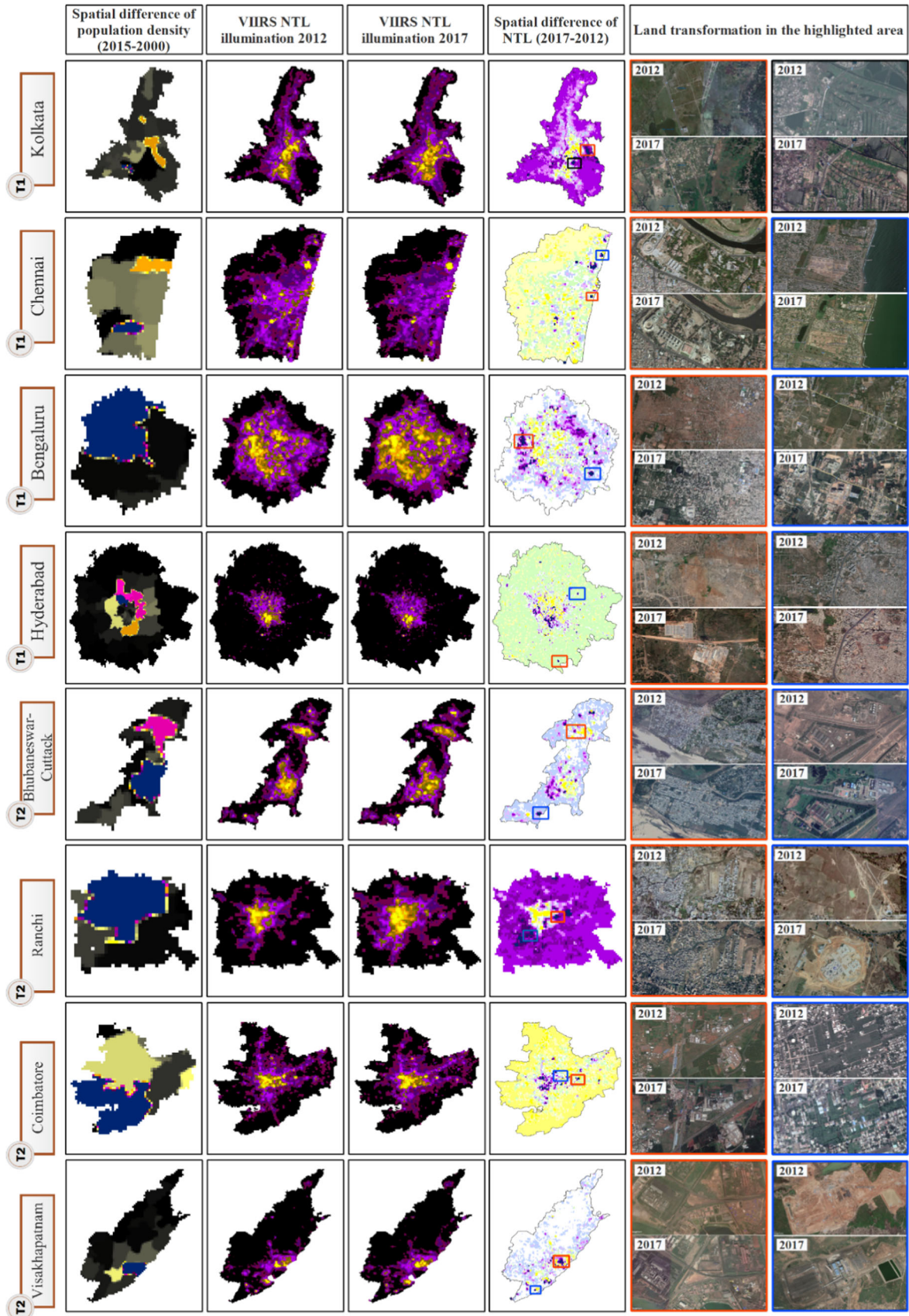
Apart from the direct methods of urban area identification and sprawl analysis using satellite imageries, several studies emphasized on proxy-based approach using gridded population database and NTL images (Sudhira et al., 2003; Gallo et al., 2004; Shi et al., 2014; Ma et al., 2015; Xiao et al., 2014; Xie & Weng, 2016; Levin & Zhang, 2017; Li & Zhou, 2017; Small et al., 2018). The studies over the Indian region are very few, particularly in this direction.

One such studies like Pandey et al. (2013) identified urban areas using NTL images and vegetation data. Similarly, Small et al. (2018) analyzed the spatial distribution of population and development over Asian cities. In the present study, population density data for 2000 and 2015 and NTL images for the years 2012 and 2017 are used for computation of population distribution and a dimensionless quantity called 'spatial difference (SD).'

NTL and Population

While some studies provided a plausible explanation of NTL as a surrogate of the urban population (Operti et al., 2018), others fail to explain the possible co-relation between them, though considered the socioeconomic factors influencing population distribution (Pozzi et al., 2003). Thus, a densely populated pocket not necessarily indicates an economically developed urban center. NTL cannot differentiate between a planned patch and a sprawled region. Metropolitan cities of India elucidate both high economically developed areas and sprawling. Kolkata holds a dense population in the older city centers, while the increasing population density in the north and eastern parts (New Kolkata) of the city is seen with a high SD of NTL (Fig. 9). New urban patch development and infill growth over northern and southern parts adjacent to the core of Chennai are noticed with dense population growth and isolated NTL differences. Bengaluru shows one-sided growth in population density over the northwestern part of the city, whereas the SD of NTL mainly illustrates overall developments outside the city core. NTL found to be evolving uniformly over the newly formed built-ups (Fig. 9), starting from the outskirts and extends toward the city boundary. A significant increment in Hyderabad's population density is seen over the outer periphery of the city core. A similar trend can be seen with the SD of NTL (Fig. 9) over the southern, eastern, and northwestern parts of the old city.

Bhubaneswar–Cuttack shows a high population density over the core of old Bhubaneswar, while the SD of NTL is found evolving over the western periphery of the city (Fig. 9). Ranchi population density shows a similar one-sided distribution, like Bengaluru. However, the NTL evolved over the same area only, unlike the overall development seen for Bengaluru. For Coimbatore, the population density found distributed over the western part while the higher values of NTL seen over industrially developed eastern part of the city. Visakhapatnam shows a higher population density in the southern part and increasing density over central and the southeastern part of the city. NTL evolutions are found quite similar to the population density distribution (Fig. 9).



◀ **Fig. 9** Evaluation of urban extent for the selected cities using spatial difference of population density, NTL illumination for 2012 and 2017, spatial difference of NTL and land transformation in high-lighted areas (T-I and T-II refer to tier-I and tier-II, respectively)

The high NTL seen inside tier-I cities indicates a re-urbanization process while, over the outskirts, specify new isolated developments. However, tier-II cities in India mostly show a lower value in the city core and higher NTL over the outskirts. There is good correlation noticed between areas with planned human activity or intervention with NTL illumination, whereas densely populated areas are less likely to show high night time activity.

NTL and Urban Dynamics

The NTL images have more potential to identify the urbanization pixels on the ground correctly and to trail the spatial pattern of a city expansion using multi-temporal images. Greater the urbanization-induced activities, brighter the NTL pixels would be; whereas the higher SD value demonstrates newer developments and lower value highlights the city core.

Infill growth is dominated in Chennai and can be seen along the coastline of the city. A bright yellow corridor is found in the southwest corner of Chennai, representing the intersection of major roads and highways. The curvilinear feature in the northwestern side provides evidence of fringed growth following a newly built transportation network within the city. In the case of Hyderabad and Bengaluru, both the highest and lowest values of NTL difference are mainly confined to the central buffer area around the city core (Fig. 9). The lowest values in the core depict the CBD, whereas the highest values indicate infill growth in the form of new commercial complexes. The brighter pixels around the city core show aggregated development due to the addition of new urban patches in recent years, and the sparse patches near the boundary confirm leapfrog development, which is seen in multi-temporal LULC images (Fig. 3) too. The sprawling fringes along transportation networks can be seen for NH-9 (Mumbai–Hyderabad–Vijayawada Highway), NH-202 (Hyderabad–Warangal Highway), and NH-7 (Hyderabad–Bengaluru Highway) in Hyderabad and NH-7, NH-4 (Bengaluru–Tirupati Highway), and NH-209 (Bengaluru–Dindigul Highway) in Bengaluru. The CBD area of Kolkata can be detected by the lower NTL values and a linear discontinuous fringe along the river Hooghly that shows the older urban areas of Kolkata (Fig. 9). A cluster of relatively higher SD of NTL pixels in the vicinity of the city boundary supports complex leapfrogged and infill development with the addition of new patches.

The city core is distinctly represented by the lowest values of SD (blue pixels) surrounded by newer additions in the Bhubaneswar–Cuttack urban complex. Satellite towns are seen in the northern and southern corners of the urban complex, and linear fringes found along the NH-5 corridor. Unlike others, relatively compact city core can be seen from the SD of NTL image of Coimbatore, from which radially expanded transportation networks are spread across the city in the east and west direction. Addition of new urban patches seen mainly in the southern part of Visakhapatnam and several fragmented patches are identified within the city premise. For Ranchi, the older city can be spotted with the lowest SD at the central urban patches in Fig. 9 and dispersed newer patches around the core. The LULC analysis supports the fragmented growth of the city identified from NTL images.

Role of Policies on Urbanization in India

Usually, a specific group of policies governs the urbanization process in a city/region. Those policies are mainly driven by international/domestic migration, affordable housing affecting population distribution, sociocultural interaction, employment, and developmental process-related (Gnaneshwar, 1995). Migration policies of India are very lenient, unlike other countries, which causes immigration from countries around the world. Domestically, the major sector of employment, i.e., industries, is located mainly around big urban agglomerations that create a huge pool of opportunities. However, there are no city-specific policies for migrating population control in any part of India. The advanced educational and medical facilities and attractive lifestyle of city dwellers lure people from smaller towns to bigger cities. Due to the changing climate and increased frequency of devastating calamities such as famine, flood, and cyclone, the people from agricultural-based areas are migrating to the cities in search of alternative employment, food, and shelter as well.

Most of the cities considered in this study are the capital regions of respective states, thereby enabling them as an administrative hub, attracting the migrant population for better employment opportunities and quality living. Cities like Ranchi and Bhubaneswar encounter massive population inflow and enormous demand for land transformation being the highly developed area of the respective state. Since sprawling cannot be avoided entirely, it may redirect toward a sustainable urban environment to diminish the adverse effects. With the initiatives and/or schemes like Smart Cities, AMRUT, HRIDAY by the government of India, (<http://mohua.gov.in/cms/schemes-or-programmes.php>) this planning process is intensified, especially for tier-

II cities. The process of change takes time to meet the gap between technology and policy to take effect.

Summary and Conclusions

Urbanization is an extremely complex process intermingled with its nonlinear attributes. Intensive characterization of this phenomenon gives a brief idea about the spatial growth of the city, the direction of land expansion, and the drivers of urban expansion. Quantitative analysis of a cityscape provides valuable information regarding whether the city is developing compact or fragmented, and in the case of later one, the degree and structure of fragmentation need to be evaluated. LULC assessment shows the distribution of LU categories within city premises and plays a major role in natural resource management as well. India-specific urbanization studies are mostly limited to broader scales due to the unavailability of relevant data, and heterogeneity and inconsistency in city-level database. The current study renders the comprehensive analysis of urban growth for a prolonged period of thirty years along with dynamics of urbanization using entropy and multiple spatial indices besides using NTL images and population density datasets for eastern and southern Indian cities. The urban areas considered in this study are the existing megacities (tier-I cities) of Chennai, Kolkata, Bengaluru, and Hyderabad with expanded planning boundaries and those which have tremendous potential to grow as a future megacity (tier-II cities included in the Smart city project), i.e., Ranchi, Bhubaneswar–Cuttack urban complex, Visakhapatnam, and Coimbatore.

The combination of remote sensing technique and spatial metrics provides an effective method to study urban growth and can be useful for supporting urban planning and associated management processes. The concerned cities experienced a massive load of population inflow, industrialization, and economic development. Since all these cities have higher growth potential, there is an urge to assess the current scenario of urban sprawl dynamics for the careful design for planning and policymaking. Tier-I cities like Chennai and Hyderabad experience the spreading of the city core, but Kolkata and Bengaluru mostly show infill growth. These cities show compact development up to ~ 25–35 km radius and mushrooming of satellite townships. Ribbon developments along the expressways are found connecting to the nearby small towns. Among the tier-II cities, Visakhapatnam developed a secondary core and expanding rapidly than the central core, while Ranchi shows the highest degree of sprawling. Fanning and fringe development are predominant for Coimbatore city. In Bhubaneswar, a peri-urban area in the southern part is found to be expanding, and both Cuttack

and Bhubaneswar are approaching each other to form a single metropolitan.

There is an overall increment of population density in all cities, and new patches of the densely populated areas observed near the peripheral areas of the cities. SD of NTL images showed higher illuminations over the newly built areas. Interestingly, the densely populated area does not always show a high SD of NTL values. It is because all populated areas are not economically developed. However, planned human intervention found to be positively correlated to the NTL illuminations and with the population density increment. Higher NTL values found to be associated mostly with administrative buildings, oil storages, industries, stadiums, and international airports of the concerned city. SD of NTL also picked out the core city and newer developments within the premise depicting the growth pattern of tier-I and tier-II cities, which supports the findings of LULC analysis.

Indian conurbations are prone to urban sprawl in the process of the expansion of the city. The sprawling influenced by the vast population and lack of prior planning to accommodate them. Several summits are being organized for improving city health at the global level by IPCC, UNESCO, etc., by creating goals to tackle such problems. However, the rate of implementation is found to be relatively slow, even in developed countries. The developing countries, including India, should contingent upon the identification of their specific sprawling pattern and its root causes and characteristics so that they can design their policies accordingly. There should be coordination among the leaders, policy makers, and city planners to understand the key issues and resolve them to combat the local problems by incorporating the scientific findings into relevant policies (Gnaneshwar, 1995). Public awareness plays a vital role in planning and policy to take effect.

Effective use of such type of analysis, along with the existing master plan, can be helpful for the sustainable development of these cities. Real-time availability of satellite image-derived high-spatial-resolution LULC datasets will be of much help in updating this knowledge on yearly basis. Use of novel remote sensing and GIS techniques along with artificial intelligence and machine learning approaches can be used to improve the results of the current findings. Extensive future studies using NTL datasets are also necessary for a better understanding of urban hotspots.

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Declarations

Conflict of Interest The authors declare no potential competing or conflict of interest in between whether it is scientific, financial, or personal.

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