DOI: 10.2478/jlecol-2022-0020 Journal of Landscape Ecology (2022), Vol: 15 / No. 3

ASSESSMENT OF URBAN EXPANSION AND IDENTIFICATION OF SPRAWL THROUGH DELINEATION OF URBAN CORE BOUNDARY

SRIDHAR M. B. [1*], SATHYANATHAN R. [2]

[1]*Assistant Professor, Department of Civil Engineering, SRM Institute of Science and Technology, Kattankulathur – 603203, Tamil Nadu, India*
[2]*Associate Professor, Department of Civil Engineering, SRM Institute of Science and Technology, Kattankulathur - 603203, Tamil Nadu, India*
E-mail: sathyanr5@srmist.edu.in;
**Corresponding author email: sridharb@srmist.edu.in*

Received: 19th June 2022, **Accepted:** 25th October 2022

ABSTRACT

Cities are spatially expanding rapidly, leading to urban sprawl. This study aims to understand the nature of the urban expansion of Chennai city, located on India's southeastern coast, by determining the urban growth pattern and identifying the urban sprawl areas. The urban growth pattern and sprawl areas between 1998 and 2019 are identified using remote sensing data through the delineation of the Urban Core Boundary (UCB). The urban areas were extracted from the Land Use Land Cover (LULC) classification using combined classification technique to delineate the UCB. All the findings were validated using ground truth information. LULC classification performed with an accuracy of more than 90 % for urban land cover revealed an increase in urban cover by 71.77% from 1998 to 2009 and 36.91 % from 2009 to 2019. The delineated UCB's peripheral distance was measured from the city centre in an anticlockwise direction from 0˚ to 360˚ at every 10˚ interval. It is observed that the urban core boundary expanded to a maximum of 16.02 km along 240˚ and 11.93 km along 220˚ from the city centre, and the lands in the vicinity of the National Highway (NH 32), which is situated between these sectors, experienced maximum urban development. The study also pinpointed the sprawl areas during the study period, revealing that the urban sprawl occurs along the highways, around designated special economic zones, and industrial corridors.

Keywords: Urban sprawl; Urban core boundary; Urban growth; Landcover classification.

INTRODUCTION

Urbanization is the socio-economic and land use transformation from rural to urban. The agricultural lands, forests, and surface water bodies are irretrievably transformed into houses, industries, commercial buildings, and other infrastructure (Bhatta, 2009; Grand *et al*., 2018). Cities are expanding spatially at an unprecedented rate due to urban population growth and economic development (Mahtta *et al*., 2022). According to the World Bank (2020; source: https://data.worldbank.org/indicator/SP.URB.TOTL.IN.ZS), the global urban population has increased from 34.124 % in 1961 to 55.714 % in 2019, whereas in India, the urban population has increased from 17.924 % in 1960 to 34.472 % in 2019. However, India has one of the least urban population percentages compared to other countries, indicating scope for further urbanization. As of 2021, there are more than two hundred countries whose urban population percentage is more than India (world bank report 2021; source: https://data.worldbank.org/indicator/SP.URB.TOTL.IN.ZS). India is an economically developing country with its Gross Domestic Product (GDP) increasing from 421.35 billion dollars in 1998 to 2.83 trillion dollars in 2019 (world bank 2021; source: https://data.worldbank.org/indicator/NY.GDP.MKTP.CD?locations=IN).

Remote sensing and Geographic Information System (GIS) techniques have been adopted globally to analyze Land Use Land Cover (LULC) and model urban growth (Sahana *et al.*, 2018; Taubenböck *et al.*, 2009). Data from sources such as Landsat Thematic Mapper (TM), Enhanced Thematic Mapper (ETM+), Multi-Spectral Scanner (MSS), and MODIS data are analyzed using a variety of approaches like including maximum likelihood classification, support vector machine, artificial neural network, and decision trees, to evaluate the LULC cover (Dixon & Candade, 2008; Pandey *et al.*, 2021).

In rapidly urbanizing cities, urban planning is needed to avoid uncontrolled urban landscape conversion (Gavrilidis *et al.*, 2019; Mohammadi *et al.*, 2012; Weng, 2001). It is known that systematic urban growth, i.e., without affecting the agricultural farmland, water bodies, and other environmental features, is not considered a threat. However, uncontrolled urban growth (urban sprawl) is considered a threat to the environment and sustainable development. Various researchers define urban sprawl in different ways (Triantakonstantis & Stathakis, 2015). Unclear definitions and varying characterization have made it difficult to quantify the sprawl (Bhatta *et al.*, 2010). The geographical extension of the cities characterized by low-density settlements and scattered development without proper urban planning was considered urban sprawl (Schneider & Woodcock, 2008). Sprawl was described as real estate development that produces low-density, scattered, discontinuous urban patches (Hayden, 2004). Sprawl was considered an extension of sub-urban development into agricultural lands and increased traffic congestion (Bourne, 2001). Sprawl was also described as an excessive spatial expansion of city areas as the population grew (Brueckner, 2000). In this study, the urban area that is discontinuous and scattered from the urban core area is considered urban sprawl.

Researchers have made several efforts to quantify sprawl. Shannon's entropy was employed to determine the extent of sprawl in Tripoli, Libya (Alsharif *et al.*, 2015), Urmia City, Iran (Mohammadi *et al.*, 2012), Tabriz city, Iran (Parvinnezhad *et al.*, 2021), Mumbai, India (Ramachandra *et al.*, 2014), along the national highway from Mangalore to Udupi city, India (Sudhira *et al.*, 2004), Dongguan City, China (Yeh & Li, 2001). Several researchers used landscape metrics to understand sprawl in various cities such as Ajmer city, India (Jat et al., 2008) and Idaho, United States of America (Dahal *et al.*, 2018). Although Shannon's entropy, which is widely used to determine sprawl, provides a radial extent to which compact urban development happens, it does not provide the exact location of sprawl and fails to quantify the extent of urban growth. The urban sprawl of Shanghai city, China, was determined by urban boundary delineation using fractal methods (Zhao *et al.*, 2021). Urban boundary delineation methods have been utilized in urban growth boundary studies (Long *et al.*, 2013; Tayyebi *et al.*, 2011). The urban growth boundary is a demarcated administrative boundary to contain the urban developments within it. The urban growth boundaries (UGB) are tools used in some urban agglomerations or states like Oregon, USA but are not employed in the Indian cities.

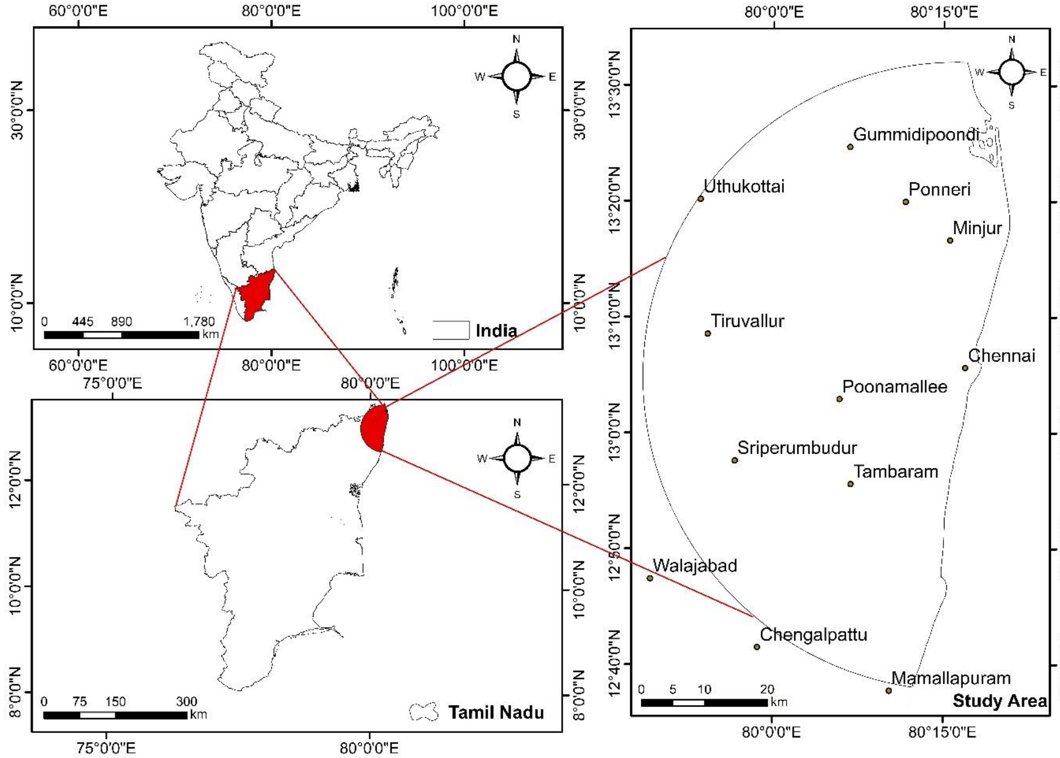
The urban growth patterns of the Kolkata urban agglomeration, India, were studied by determining the areas of the urban primary core, secondary core and suburban fringes (Sahana *et al.*, 2018). Spatial metrics were integrated with Renyi entropy to model the urban sprawl of Chennai city (Padmanaban *et al*., 2017). The urban growth of 25 cities across the world was compared using urban area change and patch density (Schneider & Woodcock, 2008). The urban pattern of the Pune metropolis was analyzed by classifying the pixels as core, fringe, ribbon or scattered (Kantakumar *et al*., 2016). The urban expansion of cities in the form of infill, edge expansion and leapfrog development was studied in the Guangdong province, China (Liu *et al*., 2010). Numerous attempts have been made to simulate urban growth and examine spatial patterns in cities using a variety of algorithms (Sahana *et al*., 2018), including cellular automata (Bharath *et al*., 2018; Ke *et al*., 2016; Maithani, 2010), artificial neural networks (Pijanowski *et al*., 2009; Tayyebi *et al*., 2011), Markov chain (Arsanjani *et al*., 2013; Ozturk, 2015; Shafizadeh Moghadam & Helbich, 2013), geographical weighted regression (Mondal *et al*., 2015). The urban growth expansion was quantitatively determined for the city of Dhanbad, India, using the spatial metrics for eight compass headings (N, E, S, W, NE, NW, SW and NW) from the city centre (Lal *et al*., 2017). Similarly, spatial metrics were calculated for the city of Gurgaon, India, along sixteen compass headings (N, NNE, NE, ENE, E, ESE, SE, SSE, S, SSW, W, WNW, NW, NNW) from the city centre (Jain *et al*., 2011).

Understanding the spatial extent and determining the magnitude of urban growth would help city planners to plan and eradicate the problems associated with increasing urban growth (Ramachandra *et al*., 2015; Zhao *et al*., 2021). There is a need for a method to reliably quantify and visualize the extent of urban growth and to compare the past urban boundaries of the city. This study proposes an integrated method to identify the urban sprawl areas and to determine the magnitude of urban growth by extending the urban core boundary (UCB) delineation method proposed by (Tayyebi *et al*., 2011). Spatially continuous urban pixels are grouped, and the outlining polygon boundary forms the UCB. The utilization of UCB facilitates measuring urban growth in any specific direction. In this study, the urban expansion is measured at a uniform interval of 10° in all directions from the city centre. The study is carried out for Chennai city, India, whose urban expansion has outgrown its administrative boundary, making it essential to understand its urban growth dynamics. Furthermore, to investigate the urban growth dynamics, the study constitutes the following objectives: i) Determining the LULC by using a combined classification method, ii) Identifying spatial temporal urban growth pattern (1998, 2009 & 2019) by UCB delineation, iii) Demarcating and validating the urban sprawl areas.

STUDY AREA

Chennai is the capital of Tamil Nadu state, India. It is situated on the east coast of India at a latitude and longitude of 13° 4' 2.7804" N and 80° 14' 15.4212" E, respectively. Established as Madras corporation in 1688, Chennai is the oldest municipal body in India. According to the 2011 census, the urban agglomeration, which includes the city and its suburbs, was home to approximately 8.9 million people, making it the fourth most populous metropolitan area in the country and the 31st largest urban area in the world. The city is home to 4.68 million people, making it the sixth most populous city in India. With an extraordinary expansion of industry and infrastructure, Chennai is also one of India's most important business centres (Raman & Sathiya Narayanan, 2008). Chennai is a rapidly expanding urban city (Gowri *et al*., 2008), resulting in uncontrolled urban growth with detrimental effects on air pollution, housing shortage, overpopulation, encroachment, slums, unregulated waste disposal, growing water scarcity, and pollution (Jayaprakash *et al*., 2015). Chennai's urban areas have outgrown the administrative district boundary; hence, a 50 km buffer area from the city centre is considered for the study. The 50 km radius is selected based on the exploratory survey, which found that most of the urbanized area connected to Chennai is covered in this radius. The ocean areas covered in the buffer area were clipped, and only the study area's land portion was considered for the study. Fig. 1 shows the study area of Chennai with a 50 km radial buffer from the city centre. The study area covers 4088 sq km, bounding Pullicat town in the north, Madathukuppam village in the west, and Pattipulam village in the south. Taking a circular buffer is necessary to give equal importance to assessing urban sprawl in all directions.

Fig. 1: Study area of Chennai with 50 km buffer from city centre



DATA SOURCES AND METHODOLOGY

The study analyses spatio-temporal LULC using temporal remote sensing data from the years: 1998, 2009, and 2019. The satellite data were downloaded from the United States Geological Survey (USGS) public domain in GeoTIFF format. Description of the satellite data such as path, row, band combination, month and year of data acquisition considered for this study are given in Table 1. The retrieved satellite images of different time intervals (1998, 2009, and 2019) were transformed to Universal Transverse Mercator (UTM) having datum WGS 1984 and subjected to coordinate system Zone 44 N. For all the three-time periods considered in the study, cloud-free satellite images were procured for February and

March. These images were clipped with the study area boundary using the spatial analyst tool available in ArcGIS 10.5 software.

Table 1: Details of satellite images

Year	Month	Path, row	Satellite	Band combination
1998	17th February	142, 51	LANDSAT 5	4, 3, 2
2009	15th February	142, 51	LANDSAT 5	4, 3, 2
2019	31st March	142, 51	LANDSAT 8	5, 4, 3

LANDSAT 5 (bands 4, 3, 2) and LANDSAT 8 (bands 5, 4, 3) were used for the LULC analysis. Initially, the satellite images were enhanced by performing edge enhancement to facilitate an accurate classification. Consequently, combined classification is performed to identify the LULC in the study area during the study period. Unsupervised classification is initially carried out in the combined classification method to categorize the 256-pixel groups into 100-pixel groups in ERDAS 15. Each group is selected manually, and its pixels from the different parts of the study area are compared with the ground truth data through the google earth engine. Based on the comparison with the ground truth data, each group is categorized into one of the five classes considered for the study, viz., water bodies, urban, vegetation, agriculture, and barren land. Once all the 100 groups of pixels are categorized, they are recoded into one of the five classes. If urban areas were present along with pixels of other groups, urban pixels were manually selected and classified as urban (Angel *et al*., 2005; Kantakumar *et al*., 2015, 2016; Xu *et al*., 2007). As urban areas are significant for the study, preference was given for categorizing the urban pixels. During automatic classification, some urban pixels were grouped with other classes; for example, railway lines were grouped along with the pixels of the vegetation class. Similarly, the roof of the old buildings, which had dark green coloured deposits on them, were classified along with vegetation pixels, and the river beds were classified along with urban pixels. The pixels were manually screened and recoded to their respective classes to rectify this.

An equalized random distribution method was employed for selecting 50 reference points under each LULC class (Tang *et al*., 2006). The ground truth land cover of these reference points were obtained through field visits, and the google earth engine for accuracy assessment. This combined classification method results in a higher user's accuracy of above 90 % for urban class, thereby facilitating its use for further analysis.

The urban pixels from the LULC of each year were extracted separately. The pixels of water bodies, vegetation, agriculture, and barren land were recoded as zero, whereas the urban pixels were recoded as one. If a pixel is connected to another pixel on any eight sides, they are considered contagion pixels. The outer polygonal boundary of the largest patch of contagion urban pixels encompassing the central city is considered an Urban Core Boundary (UCB) in this study, and it was extracted by digitizing it in vector format (Tayyebi *et al*., 2011). This UCB delineation process was carried out for the urban extracted images of 1998, 2009 and 2019. The generated UCB delineated maps were utilized to assess the urban growth of Chennai city by measuring the distance from the city centre in all directions. Radially outward projecting lines were drawn at 10˚ intervals from the city centre until the exterior edge of each urban core boundary. The distance between the city centre and the urban boundary was measured. The direction in which maximum urban growth is happening is determined using the formula

$$\text{Max } d_{x\text{-}y} = \text{Max } (d(i)_y - d(i)_x)$$

where,

i = angle of measurement, varies from 0˚ to 360˚ in an anticlockwise direction with an interval of 10˚

$d(i)_x$ = distance between the city centre and the urban growth boundary of the x^{th} year at an angle i

$d(i)_y$ = distance between the city centre and the urban growth boundary of the y^{th} year at an angle i

Newly developed urban areas were determined by finding the difference between the urban pixels of the two time periods. Thereby, newly developed pixels were extracted between 1998 and 2009 and between 2009 and 2019.

The urban sprawling areas were identified by extracting the newly developed urban pixels between 1998 and 2009 present outside the UCB of 1998. Similarly, the newly developed urban pixels between 2009 and 2019 were extracted from the UCB of 2009. Finally, these identified urban sprawling areas are validated with the ground information.

RESULTS

The combined classification was carried out for the satellite images of 1998, 2009 and 2019, and LULC for all five classes was computed. Fig. 2 illustrates LULC for 1998, 2009, and 2019. It has been observed that urban area has increased drastically while the area covered by water bodies shrunk at an alarming rate. The study revealed that urban areas grew by 71.77 % between 1998 and 2009 and 36.91 % between 2009 and 2019. At the same time, the area of water bodies declined by 17 % between 1998 and 2009 and 45.39 % between 2009 and 2019. Over time, the percentage of land covered by vegetation, agricultural, & barren terrain also decreased, and they were converted into urban areas. For the LULC of 1998, 2009, and 2019, overall accuracy was 84 %, 88 %, and 92 %, respectively. The user's accuracy for urban land cover was 90 %, 93 %, and 94 % for 1998, 2009, and 2019 respectively. The kappa statistics for the classification were 0.80, 0.86 and 0.90 for 1998, 2009, and 2019 respectively.

Table 2: Land use land cover of Study area

Land class/Year	1998 (km^2)	2009 (km^2)	2019 (km^2)	1998 (%)	2009 (%)	2019 (%)
Water bodies	357.31	295.48	161.35	8.74	7.23	3.95
Urban	363.63	624.62	855.18	8.89	15.28	20.92
Agriculture	1323.66	1543.04	1189.66	32.37	37.74	29.10
Vegetation	976.09	617.22	862.84	23.87	15.10	21.10
Barren land	1067.95	1008.29	1019.63	26.12	24.66	24.94
Total	4088.65	4088.65	4088.65	100	100	100

Fig. 2: (a) LULC 1998, (b) LULC 2009, (c) LULC 2019

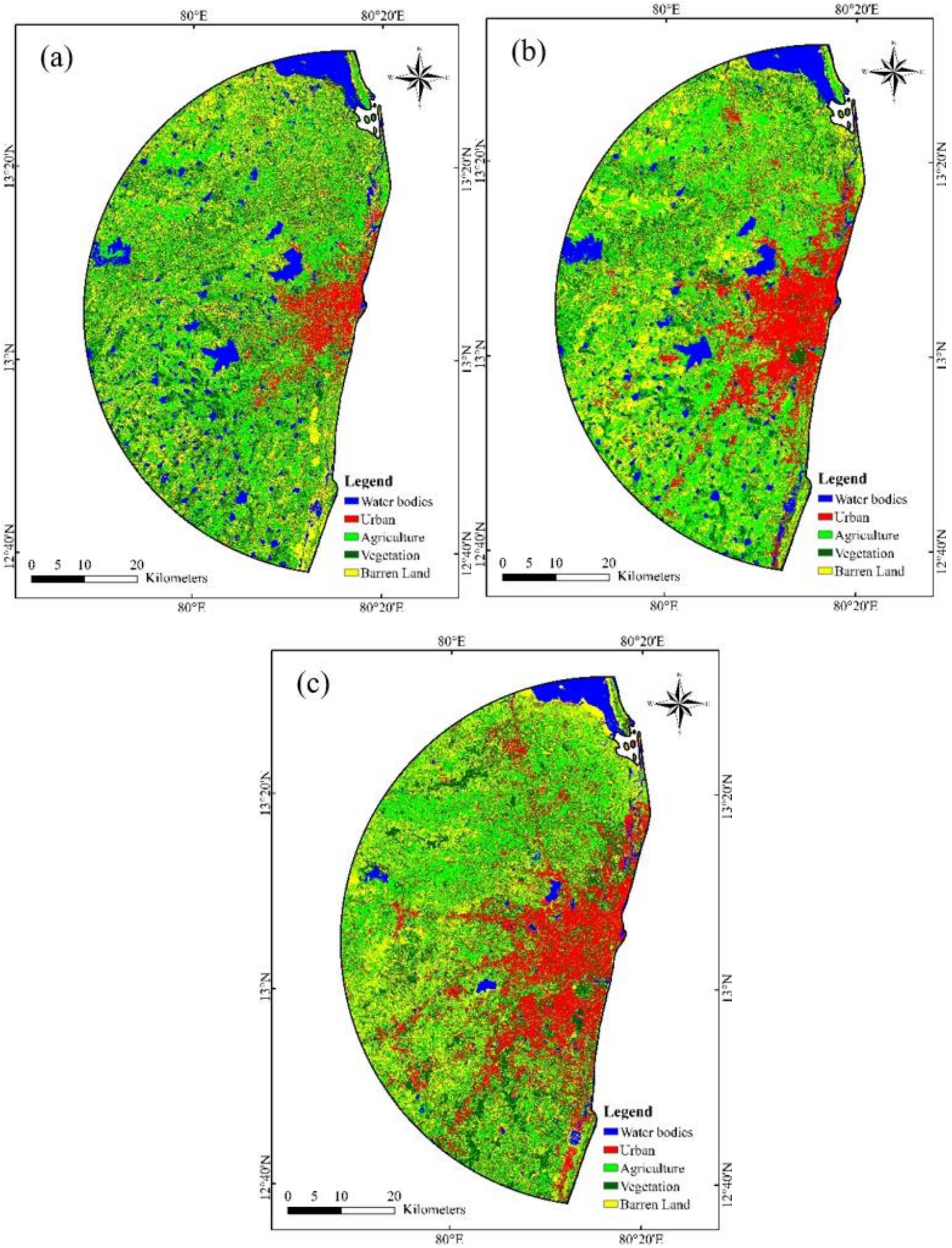
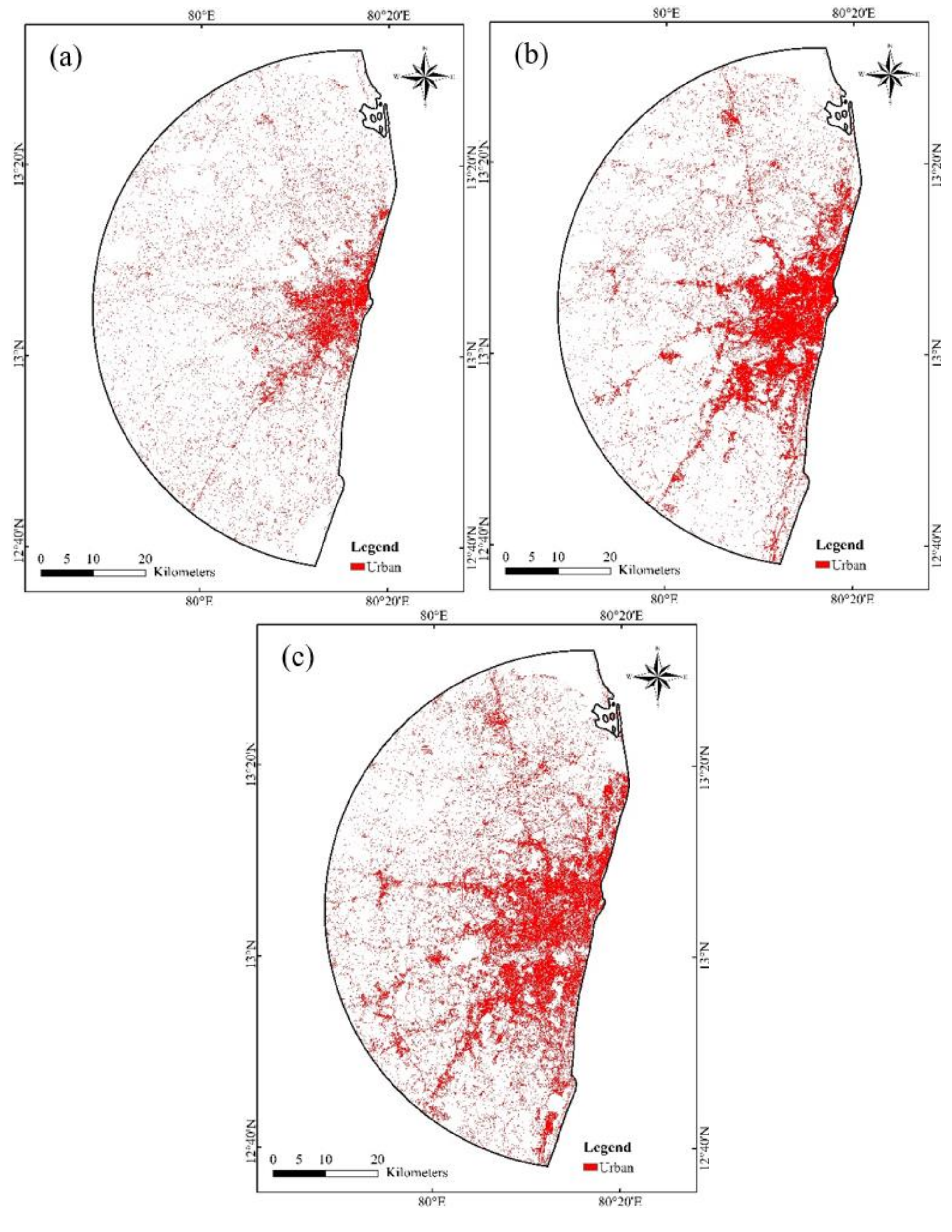


Fig. 3: (a) Urban areas of 1998, (b) Urban areas of 2009, (c) Urban areas of 2019



Furthermore, the urban pixels were extracted separately; the red pixels in Fig. 3 show urbanized areas for 1998, 2009, and 2019. Then, the contagion urban pixels were grouped, and the largest patch was vectorized to form a UCB. The UCB was delineated for 1998, 2009 and 2019, shown in Fig. 4. The UCB covered an area of 198.22 km^2 in 1998, 387.917 km^2 in

2009 and 585.817 km^2 in 2019, which increased by 95.7 % between 1998 and 2009, 51.01 % between 2009 and 2019. Therefore, it is distinct that urban areas grew faster between 1998 and 2009 than in 2009 and 2019. The distance for every 10 degrees in the anticlockwise direction was measured and represented in Table 3.

Fig. 4: (a)UCB of 1998, (b)UCB of 2009 (c)UCB of 2019 and (d) radial lines to measure the urban growth

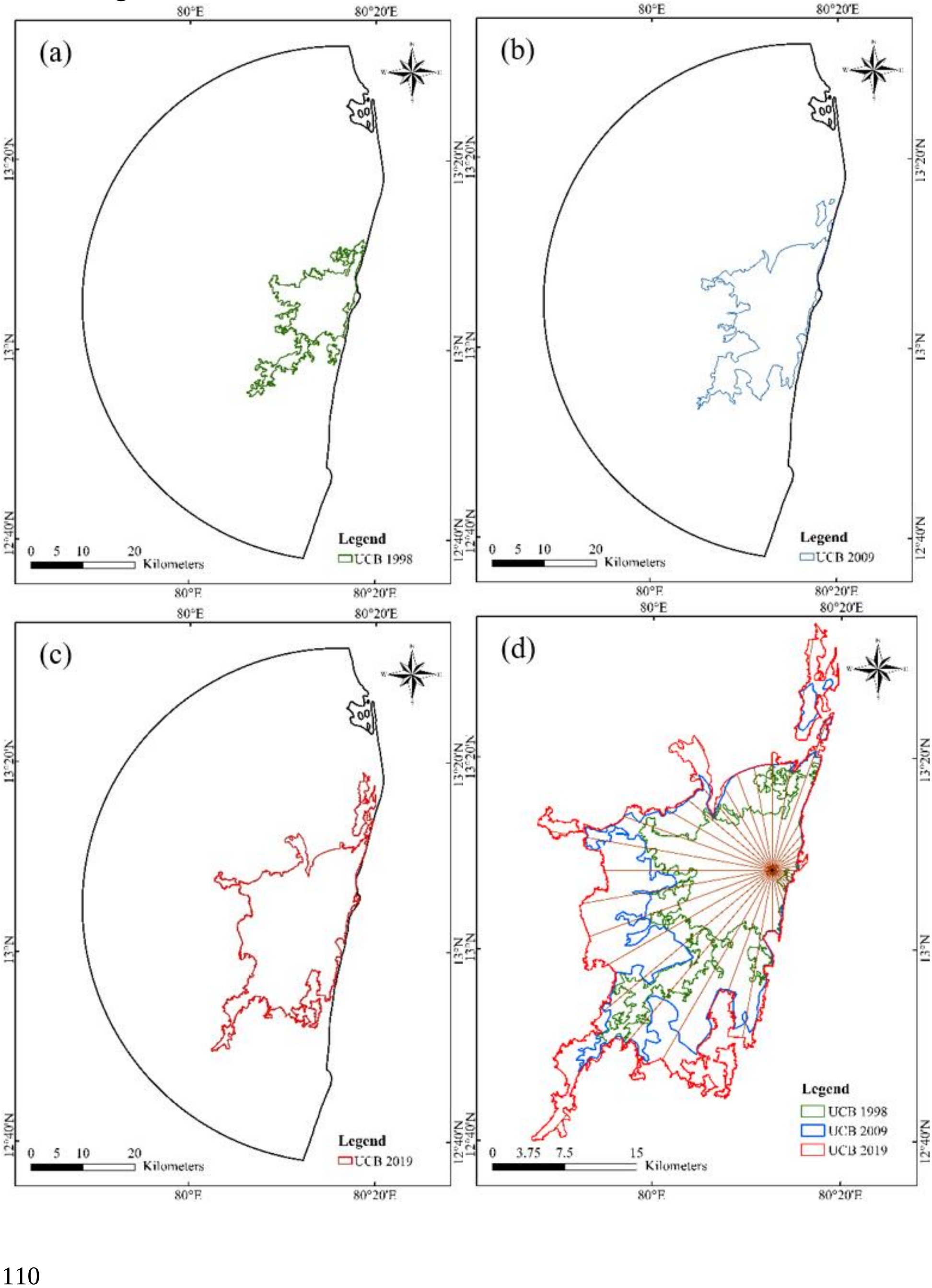
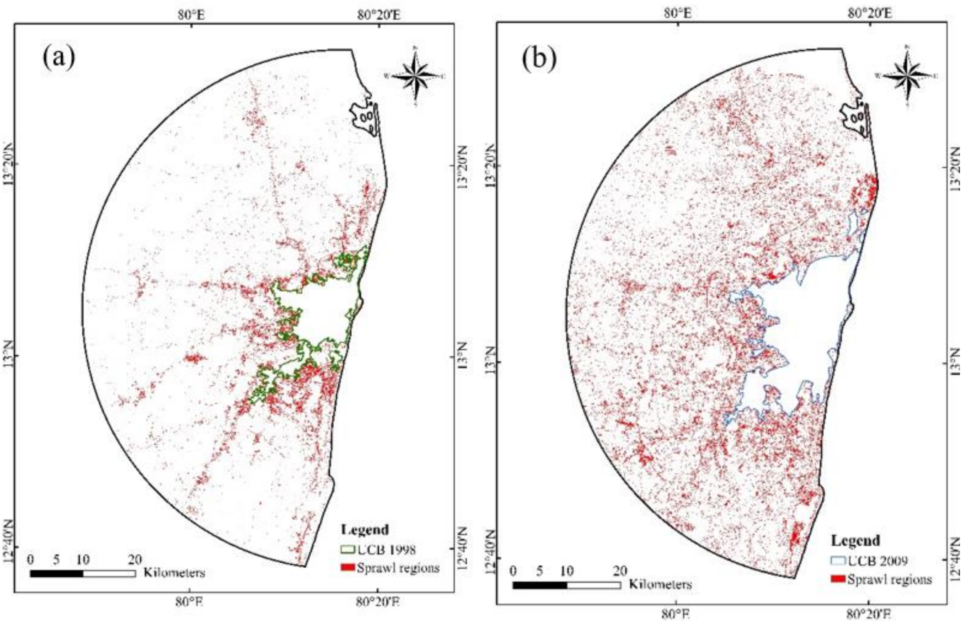


Table 3: Distance of urban growth boundary from the city centre

Angle of measurement	Distance from the city centre (km)		
	1998	2009	2019
0˚	2.13	2.54	2.71
10˚	2.59	2.77	3.40
20˚	2.74	2.74	3.09
30˚	3.07	3.15	3.34
40˚	4.10	4.17	4.24
50˚	4.72	4.72	4.86
60˚	5.62	5.80	6.07
70˚	12.98	15.29	16.34
80˚	8.76	12.22	16.99
90˚	7.20	11.06	12.25
100˚	6.66	10.90	10.92
110˚	6.82	10.68	10.72
120˚	6.36	9.85	12.05
130˚	6.72	9.86	11.89
140˚	9.25	11.41	11.56
150˚	8.79	12.03	12.76
160˚	11.20	16.26	16.46
170˚	12.69	15.42	21.50
180˚	9.68	12.64	17.45
190˚	10.73	12.52	20.04
200˚	11.00	15.59	20.27
210˚	10.41	12.55	19.72
220˚	11.71	17.41	23.63
230˚	16.06	21.27	26.80
240˚	6.85	19.57	22.87
250˚	6.22	13.33	14.66
260˚	10.14	15.48	17.73
270˚	6.26	6.44	7.82
280˚	4.95	5.31	5.37
290˚	3.47	3.54	3.68
300˚	2.31	2.82	2.88
310˚	1.30	2.31	2.39
320˚	1.21	2.14	2.16

Angle of measurement	Distance from the city centre (km)		
	1998	2009	2019
330˚	1.75	2.29	2.45
340˚	1.94	2.20	2.24
350˚	2.09	2.24	2.32

Fig. 5: (a) Sprawling areas from 1998 to 2009 (b) Sprawling areas from 2009 to 2019



The city's core boundary has increased the most along 240˚, 250˚, 220˚, and 260˚ by a length of 12.72, 7.11, 5.71, and 5.34 kilometres, respectively, between 1998 and 2009. Between 2009 and 2019, the UCB had increased by a length of 7.52, 7.17, 6.22, and 6.08 kilometres along 190˚, 210˚, 220˚, and 170˚ from the city centre, respectively. From 1998 to 2019, the city had grown 16.02, 11.93, 10.75 and 9.31 km along 240˚, 220˚, 230˚, and 190˚ from the city centre, respectively. The maximum urban development occurred between 220˚ and 240˚, followed by the area between 190˚ and 210˚. As Chennai is situated along the coast, the urban expansion is curtailed between 270˚ and 60˚. The UCB in northern parts of Chennai from 70˚ to 160˚ has extended for a mean distance of 4.71 km for the study period. On the other hand, the western and southern parts, from 160˚ to 260˚, have extended for a mean distance of 9.92 km for the same period.

The urban sprawl areas identified in the study area are depicted in Fig. 5, and their validation with the ground data is represented in Fig. 6. The sprawl areas are determined by extracting the newly developed pixels lying outside the UCB. The urban sprawl areas from 1998 to 2009 (Fig. 5 a) show that most development happens encompassing the existing urban areas. It is apparent that sprawling is happening along the six stretches. On examination with the ground reality using google earth, it is observed that National

Highways (NH) and major roads are running along the stretches, which point to ribbon development characterized by the urban development of lands along major transportation corridors (Barnes *et al*., 2001).

The urban sprawling areas from 2009 to 2019 (Fig. 5 b) show a scattered and widespread sprawl. Sprawling areas have increased and scattered, which is a cause for concern. The determined sprawl areas are inspected with the ground truth data with randomly selected areas across the study area (open rectangles A, B, C, and D in Fig. 6). The shapefile for the selected areas (A, B, C, and D Fig. 6) were imported into the google earth engine and inspected for decadal changes (1998-2009 and 2009-2019; Fig. 6).

Fig. 6: Validation of sprawl areas with ground truth (a) 1998 – 2009 (b) 2009 – 2019

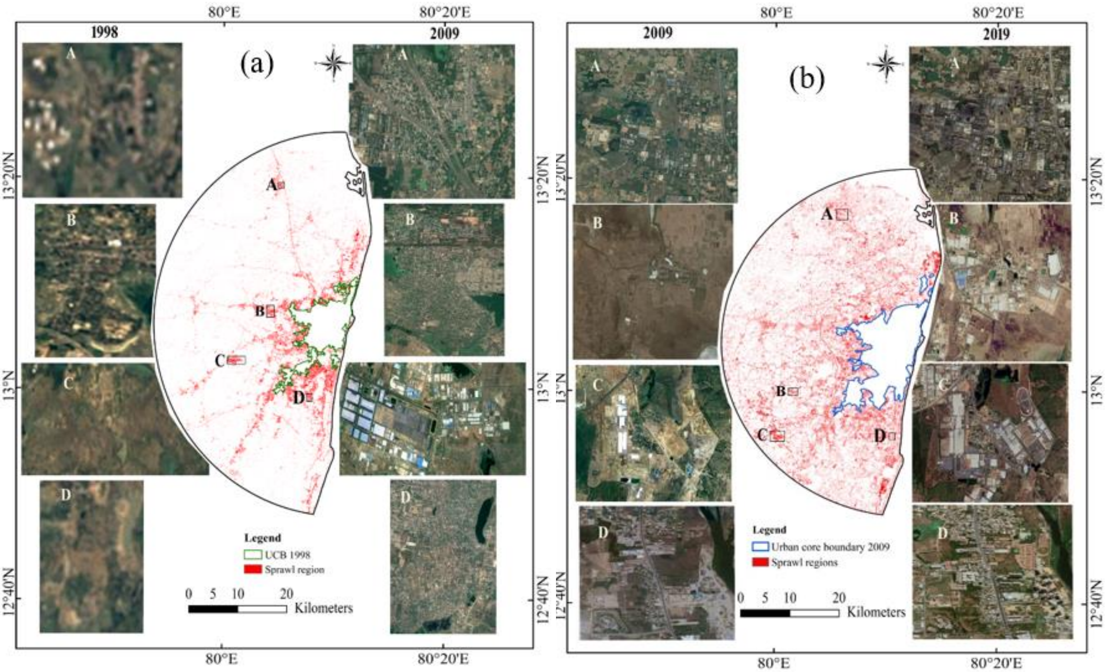


Figure 6a depicts the ground truth images of 1998 and 2009 on the left and right sides, respectively. The images depict the dramatic transformation of the uninhabited landscapes of 1998 into sprawling urban areas of 2009. Box A depicts the town of Gummudipoondi's transformation from a few urban parcels in 1998 to a widespread urban landscape in 2009, with the development of National highways and the emergence of several industries. Due to the establishment of heavy vehicle factories and educational institutions, Box B displays significant changes in urban development in the Avadi municipal corporation. The urban development of Irungattukottai village, as depicted in box C, represents the transformation of a barren landscape into a fully industrialized area. A Special Economic Zone (SEZ) established for the footwear industries and the establishment of industries by multinational automobile manufacturers are credited as the primary causes of the landscape change. The landscape change of Vengaivasal village, devoid of any urban structures in 1998, is depicted in box D, dominated by residential settlements in 2009.

Figure 6b compares the landscape change in the areas between 2009 and 2019. Box A demonstrates that the urban parcels of 2009 in Gummudipoondi town have expanded further in 2019. New urban developments were observed in Anakaputhur town, depicted in box B, primarily due to the emergence of industries in the region. Box C depicts the additional urban structures constructed alongside older ones in the Vattambakkam village. The depiction of Sholinganallur, a Chennai IT hub, in Box D demonstrates that urban sprawl has filled the vacant spaces. The results demonstrated that identification of sprawl areas using UCB is adequate and precise.

DISCUSSION

The combined classification method utilized in the study improved the accuracy of classification. The classification had an overall accuracy of more than 84 % for all three years, while the user's accuracy of the urban class was more than 90 %. The arrived accuracy of the classification follows the findings in other studies of LULC in different geographical regions with data from other satellite systems (Hong *et al*., 2014; Stefanski *et al*., 2014).

The study witnessed an increase in urban land cover of 363 km^2 from 1998 to 624.62 km^2 in 2009 and 855.18 km^2 in 2019. During this period, India's economy saw a seven-fold increase in GDP (world bank 2021). The economic revival resulted in the establishment of several industries and institutions in the vicinity of the cities, which attracted the settlements of people migrating from rural areas, thereby increasing the urban landscape. The urban land cover of the Chennai study area increased 2.5-fold between 1998 and 2019, from 363.63 km^2 to 855.18 km^2. Comparing the results of similar studies, land cover in the Delhi metropolitan area increased by 326 % between 1990 and 2018 (Naikoo *et al*., 2020). The urban growth expansion analysis of the Pune metropolitan area from 1992 to 2013 (Kantakumar *et al*., 2016) revealed that the built-up area occupied 6.5 % (107.5 km^2) of the Pune metropolitan area in 1992, 9.9 % (162.4 km^2) in 2001, and nearly doubled to 19.7 % in 2013. (322.9 km^2). The LULC analysis of Chennai with a 10 km buffer from the administrative boundary from 1991 to 2016 revealed a threefold increase in urban cover (Padmanaban *et al*., 2017).

This study using UCB, quantitatively determined the urban growth at 10˚ intervals from the city centre and found that the core city has expanded to a maximum of about 27 km along 230˚ from the city centre in the year 2019. The urban core area increased from 198 km^2 in 1998 to 585 km^2 in 2019. Comparatively, the urban core area of the Pune metropolitan area increased from 72.6 km^2 in 1992 to 227 km^2 in 2013 (Kantakumar *et al*., 2016). In previous studies (He *et al*., 2019; Kantakumar *et al*., 2016), urban growth was measured quantitatively by calculating the area, while in this study, the area is quantified, and the distance of urban growth along all directions is also arrived. Landscape metrics were utilized (Yue *et al*., 2013) to quantify urban growth patterns; however, these metrics are influenced by the extent of the study area considered. For example, the value of the Largest Patch Index (LPI), a metric that quantifies the percantage of the largest urban built-up patch area to the total build-up land area, depends on the spatial extent of the study area considered. Similarly, Shannon entropy (Mohammadi *et al*., 2012; Ramachandra, *et al*., 2014; Rastogi & Jain, 2018) is influenced by the extent of the study area considered. Therefore the current study gains significance in quantifying growth assessment values, which remain constant irrespective of the extent of the study area. Therefore, the difficulties in fixing the extent of the study area are averted, especially for cities whose urban expansion has extended beyond the administrative boundaries.

Relative Shannon entropy (Alsharif *et al*., 2015; Sridhar & Sathyanathan, 2022) was used to determine the radial distance from the city centre to understand the urban expansion as compact if it falls within the radial boundary, whereas in reality, the cities do not expand symmetrically in all the direction. Therefore this study gains significance in quantitatively determining the direction specific urban growth and its ability to identify sprawling areas.

The newer urban expansions in Chennai are witnessed near the existing urban core boundaries, and this trend was also observed in other cities of Nanjing, China (Xu *et al.*, 2007), Pordenone, Italy (Martellozzo & Clarke, 2011) and Romania (Grigorescu *et al.*, 2021). Several industries and SEZs have been established on the outskirts of Chennai in recent decades. Owing to the larger area needed for setting up these facilities, the availability of larger vacant lands with relatively reduced land values influenced the setting up of these hubs in the periphery of the city, as depicted in Fig. 6. Several educational institutions have also developed in the last decades which has led to the urban conversion of the landscape. The other prominent factors influencing urban sprawl in the study area are transportation accessibility, ease in regulatory practices and reduced congestion. Similar factors causing urban sprawl were also observed in other studies, such as land prices (Brueckner & Fansler, 2006; Habibi & Asadi, 2011), societal considerations (Brueckner, 2000), transit options (Christiansen & Loftsgarden, 2011), the geography of the landscape (Anguluri & Narayanan, 2017), technological advancements, demographic trends (Yue *et al.*, 2013), ease in regulatory practices (Ewing *et al.*, 2007) and globalization (Gavrilidis *et al.*, 2019).

The comparability of the UCB in the study area for different periods makes it a valuable tool in urban growth monitoring. The corridor between 220˚ and 240˚ witnessed maximum urban growth from 1998 to 2019, with NH 32 and a suburban railway line traversing in the middle of the corridor. Additionally, this corridor also has an airport terminal. The enhanced transportation connectivity and other infrastructure facilities, coupled with economic development in the region, have led to maximum urban growth. North Chennai is the old city and was the first part of the city to develop, having space limitations, whereas southern Chennai was recently developed. North Chennai's urban growth has concentrated around the port and industrial zones of Ambattur and Avadi. On the other hand, South Chennai witnessed rapid urban growth in the last 20 years by developing new infrastructure facilities and services.

CONCLUSION

In this study, urban growth assessment and identification of the sprawl areas were carried out by utilizing UCB for Chennai city. From 1998 to 2019, the UCB has expanded to a maximum of 16.02 km along 240˚ and 11.93 km along 220˚ from the city centre and the maximum urban growth is witnessed between these sectors. The urban growth assessment reveals the direction in which urban expansion is profound; therefore, urban planners can have an additional focus on that direction. Visualizing and comparing past urban boundaries enable determining a city's growth rate over time, making it feasible to compare the growth rates along different directions. This approach is ideal for comparing urban growth among different cities. The results of this quantifiable method do not vary depending on the extent of the study area considered, and it will be helpful for the government agencies in deciding on direction specific extension of the city administrative boundary. The UCB delineation also helps accurately identify the sprawl areas over the study period, which was validated with the ground truth information. However, this method has certain challenges, such as the accuracy of the urban land cover classification and natural barriers such as lakes, rivers, and mountains between urban areas, which may cause the urban pixels to become isolated polygons by rupturing their continuity. In such cases, manual intervention is required to determine whether this isolated polygon should be considered part of the core city. Though there are various classification of sprawl, the study limits to the identification of the spatial location of sprawl areas. Future studies should focus on integrating techniques for assessing the urban expansion of multi-nuclei cities and determining the type of sprawl.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

REFERENCES

Alsharif, A. A. A., Pradhan, B., Mansor, S., & Shafri, H. Z. M. (2015). Urban expansion assessment by using remotely sensed data and the relative Shannon entropy model in GIS: A case study of Tripoli, Libya. *Theoretical and Empirical Researches in Urban Management*, *10*(1), 55–71.

Angel, S., Sheppard, S. C., & Civco, D. L. (2005). The Dynamics of Global Urban Expansion. *The World Bank*, *September*, 205. http://www.citiesalliance.org/sites/citiesalliance.org/files/CA_Docs/resources/upgrading/urban-expansion/worldbankreportsept2005.pdf

Anguluri, R., & Narayanan, P. (2017). Role of green space in urban planning: Outlook towards smart cities. *Urban Forestry and Urban Greening*, *25*, 58–65. https://doi.org/10.1016/j.ufug.2017.04.007

Arsanjani, J. J., Helbich, M., Kainz, W., & Boloorani, A. D. (2013). Integration of logistic regression, Markov chain and cellular automata models to simulate urban expansion. *International Journal of Applied Earth Observation and Geoinformation*, *21*(1), 265–275. https://doi.org/10.1016/j.jag.2011.12.014

Barnes, K., Morgan, J., Roberge, M., & Lowe, S. (2001). Sprawl Development: Its Patterns, Consequences, and Measurement. *Annals of Physics*, *54*, 24. http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:No+Title#0

Bharath, H. A., Chandan, M. C., Vinay, S., & Ramachandra, T. V. (2018). Modelling urban dynamics in rapidly urbanizing Indian cities. *Egyptian Journal of Remote Sensing and Space Science*, *21*(3), 201–210. https://doi.org/10.1016/j.ejrs.2017.08.002

Bhatta, B. (2009). Modelling of urban growth boundary using geoinformatics. *International Journal of Digital Earth*, *2*(4), 359–381. https://doi.org/10.1080/17538940902971383

Bhatta, B., Saraswati, S., & Bandyopadhyay, D. (2010). Urban sprawl measurement from remote sensing data. *Applied Geography*, *30*(4), 731–740. https://doi.org/10.1016/j.apgeog.2010.02.002

Bourne, L. S. (2001). Myths , Realities and Hidden Agendas. *Plan Canada*, *41*(4), 26–28.

Brueckner, J. K. (2000). Urban sprawl: Diagnosis and remedies. *International Regional Science Review*, *23*(2), 160–171. https://doi.org/10.1177/016001700761012710

Brueckner, J. K., & Fansler, D. A. (2006). The Economics of Urban Sprawl: Theory and Evidence on the Spatial Sizes of Cities. *The Review of Economics and Statistics*, *65*(3), 479. https://doi.org/10.2307/1924193

Christiansen, P., & Loftsgarden, T. (2011). *Drivers behind Urban Sprawl in Europe* (Issue May). https://www.toi.no/getfile.php/Publikasjoner/TØI rapporter/2011/1136-2011/1136-2011-el.pdf

Dahal, K. R., Benner, S., & Lindquist, E. (2018). Analyzing Spatiotemporal Patterns of

Urbanization in Treasure Valley, Idaho, USA. *Applied Spatial Analysis and Policy*, *11*(2), 205–226. https://doi.org/10.1007/s12061-016-9215-1

Dixon, B., & Candade, N. (2008). Multispectral landuse classification using neural networks and support vector machines: One or the other, or both? *International Journal of Remote Sensing*, *29*(4), 1185–1206. https://doi.org/10.1080/01431160701294661

Ewing, R., Pendall, R., & Chen, D. (2007). Measuring Sprawl and Its Transportation Impacts. *Transportation Research Record: Journal of the Transportation Research Board*, *1831*(1), 175–183. https://doi.org/10.3141/1831-20

Gavrilidis, A. A., Niță, M. R., Onose, D. A., Badiu, D. L., & Năstase, I. I. (2019). Methodological framework for urban sprawl control through sustainable planning of urban green infrastructure. *Ecological Indicators*, *96*(October), 67–78. https://doi.org/10.1016/j.ecolind.2017.10.054

Gowri, V. S., Ramachandran, S., Ramesh, R., Pramiladevi, I. R. R., & Krishnaveni, K. (2008). Application of GIS in the study of mass transport of pollutants by Adyar and Cooum Rivers in Chennai, Tamilnadu. *Environmental Monitoring and Assessment*, *138*(1–3), 41–49. https://doi.org/10.1007/s10661-007-9789-9

Grand, J., DeLuca, W. V., McGarigal, K., Compton, B. W., Plunkett, E. B., & Willey, L. L. (2018). Modeling non-stationary urban growth: The SPRAWL model and the ecological impacts of development. *Landscape and Urban Planning*, *177*(October 2017), 178–190. https://doi.org/10.1016/j.landurbplan.2018.04.018

Grigorescu, I., Kucsicsa, G., Popovici, E. A., Mitrică, B., Mocanu, I., & Dumitraşcu, M. (2021). Modelling land use/cover change to assess future urban sprawl in Romania. *Geocarto International*, *36*(7), 721–739. https://doi.org/10.1080/10106049.2019.1624981

Habibi, S., & Asadi, N. (2011). Causes, results and methods of controlling urban sprawl. *Procedia Engineering*, *21*, 133–141. https://doi.org/10.1016/j.proeng.2011.11.1996

Hayden, D. (2004). A field guide to sprawl. WW Norton & Company.

He, Q., Zeng, C., Xie, P., Tan, S., & Wu, J. (2019). Comparison of urban growth patterns and changes between three urban agglomerations in China and three metropolises in the USA from 1995 to 2015. *Sustainable Cities and Society*, *50*(April), 101649. https://doi.org/10.1016/j.scs.2019.101649

Hong, G., Zhang, A., Zhou, F., & Brisco, B. (2014). Integration of optical and synthetic aperture radar (SAR) images to differentiate grassland and alfalfa in Prairie area. *International Journal of Applied Earth Observation and Geoinformation*, *28*(1), 12–19. https://doi.org/10.1016/j.jag.2013.10.003

Jain, S., Kohli, D., & Rao, R. M. (2011). *Spatial Metrics to Analyze the Impact of Regional Factors on Pattern of Urbanization in Gurgaon , India*. *39*(June), 203–212. https://doi.org/10.1007/s12524-011-0088-0

Jat, M. K., Garg, P. K., & Khare, D. (2008). Monitoring and modelling of urban sprawl using remote sensing and GIS techniques. *International Journal of Applied Earth Observation and Geoinformation*, *10*(1), 26–43. https://doi.org/10.1016/j.jag.2007.04.002

Jayaprakash, M., Senthil Kumar, R., Giridharan, L., Sujitha, S. B., Sarkar, S. K., & Jonathan, M. P. (2015). Bioaccumulation of metals in fish species from water and sediments in macrotidal Ennore creek, Chennai, SE coast of India: A metropolitan city effect. *Ecotoxicology and Environmental Safety*, *120*, 243–255. https://doi.org/10.1016/j.ecoenv.2015.05.042

Kantakumar, L. N., Kumar, S., & Schneider, K. (2015). Spatiotemporal urban expansion in

Pune metropolis , India using remote sensing. *Habitat International*, *51*, 11–22. https://doi.org/10.1016/j.habitatint.2015.10.007

Kantakumar, L. N., Kumar, S., & Schneider, K. (2016). Spatiotemporal urban expansion in Pune metropolis, India using remote sensing. *Habitat International*, *51*, 11–22. https://doi.org/10.1016/j.habitatint.2015.10.007

Ke, X., Qi, L., & Zeng, C. (2016). A partitioned and asynchronous cellular automata model for urban growth simulation. *International Journal of Geographical Information Science*, *30*(4), 637–659. https://doi.org/10.1080/13658816.2015.1084510

Lal, K., Kumar, D., & Kumar, A. (2017). Spatio-temporal landscape modeling of urban growth patterns in Dhanbad Urban Agglomeration, India using geoinformatics techniques. *Egyptian Journal of Remote Sensing and Space Science*, *20*(1), 91–102. https://doi.org/10.1016/j.ejrs.2017.01.003

Liu, X., Li, X., Chen, Y., Tan, Z., Li, S., & Ai, B. (2010). A new landscape index for quantifying urban expansion using multi-temporal remotely sensed data. *Landscape Ecology*, *25*(5), 671–682. https://doi.org/10.1007/s10980-010-9454-5

Long, Y., Han, H., Lai, S. K., & Mao, Q. (2013). Urban growth boundaries of the Beijing Metropolitan Area: Comparison of simulation and artwork. *Cities*, *31*, 337–348. https://doi.org/10.1016/j.cities.2012.10.013

Mahtta, R., Fragkias, M., Güneralp, B., Mahendra, A., Reba, M., Wentz, E. A., & Seto, K. C. (2022). Urban land expansion: the role of population and economic growth for 300+ cities. In *npj Urban Sustainability* (Vol. 2, Issue 1). https://doi.org/10.1038/s42949-022-00048-y

Maithani, S. (2010). Cellular Automata Based Model of Urban Spatial Growth. *Journal of the Indian Society of Remote Sensing*, *38*(4), 604–610. https://doi.org/10.1007/s12524-010-0053-3

Martellozzo, F., & Clarke, K. C. (2011). Measuring urban sprawl, coalescence, and dispersal: A case study of Pordenone, Italy. *Environment and Planning B: Planning and Design*, *38*(6), 1085–1104. https://doi.org/10.1068/b36090

Mohammadi, J., Zarabi, A., & Mobaraki, O. (2012). Urban Sprawl Pattern and Effective Factors on Them : the Case of Urmia City , Iran. *Geography*, *IV*, 77–89.

Mondal, B., Das, D. N., & Dolui, G. (2015). Modeling spatial variation of explanatory factors of urban expansion of Kolkata: a geographically weighted regression approach. *Modeling Earth Systems and Environment*, *1*(4), 1–13. https://doi.org/10.1007/s40808-015-0026-1

Naikoo, M. W., Rihan, M., Ishtiaque, M., & Shahfahad. (2020). Analyses of land use land cover (LULC) change and built-up expansion in the suburb of a metropolitan city: Spatio-temporal analysis of Delhi NCR using landsat datasets. *Journal of Urban Management*, *9*(3), 347–359. https://doi.org/10.1016/j.jum.2020.05.004

Ozturk, D. (2015). Urban growth simulation of Atakum (Samsun, Turkey) using cellular automata-Markov chain and Multi-layer Perceptron-Markov chain models. *Remote Sensing*, *7*(5), 5918–5950. https://doi.org/10.3390/rs70505918

Padmanaban, R., Bhowmik, A. K., Cabral, P., Zamyatin, A., Almegdadi, O., & Wang, S. (2017). Modelling urban sprawl using remotely sensed data: A case study of Chennai city, Tamilnadu. *Entropy*, *19*(4). https://doi.org/10.3390/e19040163

Pandey, P. C., Koutsias, N., Petropoulos, G. P., Srivastava, P. K., & Ben Dor, E. (2021). Land use/land cover in view of earth observation: data sources, input dimensions, and classifiers—a review of the state of the art. *Geocarto International*, *36*(9), 957–988.

https://doi.org/10.1080/10106049.2019.1629647

Parvinnezhad, D., Delavar, M. R., Claramunt, C., & Pijanowski, B. C. (2021). A modified spatial entropy for urban sprawl assessment. *Geocarto International*, *36*(16), 1804–1819. https://doi.org/10.1080/10106049.2019.1678676

Pijanowski, B. ., Tayyebi, A., Delavar, M. R., & Yazdanpanah, M. J. (2009). Urban expansion simulation using geospatial information system and artificial neural networks. *International Journal of Environmental Research*, *3*(4), 495–502.

Ramachandra, T. V., Aithal, B. H., & Sowmyashree, M. V. (2014). Urban structure in Kolkata: metrics and modelling through geo-informatics. *Applied Geomatics*, *6*(4), 229–244. https://doi.org/10.1007/s12518-014-0135-y

Ramachandra, T. V., Bharath, A. H., & Sowmyashree, M. V. (2015). Monitoring urbanization and its implications in a mega city from space: Spatiotemporal patterns and its indicators. *Journal of Environmental Management*, *148*, 67–81. https://doi.org/10.1016/j.jenvman.2014.02.015

Ramachandra, T. V, Bharath, H. A., & Sowmyashree, M. V. (2014). Urban footprint of Mumbai - the commercial capital of India. *Journal of Urban and Regional Analysis*, *6*(1), 71–94. https://www.scopus.com/inward/record.uri?eid=2-s2.0-84904006635&partnerID=40&md5=55006c6860115bd88f73dbda359dfb78

Raman, N., & Sathiya Narayanan, D. (2008). Impact of solid waste effect on ground water and soil quality nearer to pallavaram solid waste landfill site in Chennai. *Rasayan Journal of Chemistry*, *1*(4), 828–836.

Rastogi, K., & Jain, G. V. (2018). Urban Sprawl Analysis Using Shannon'S Entropy and Fractal Analysis: a Case Study on Tiruchirappalli City, India. *ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XLII–5*(November), 761–766. https://doi.org/10.5194/isprs-archives-xlii-5-761-2018

Sahana, M., Hong, H., & Sajjad, H. (2018). Analyzing urban spatial patterns and trend of urban growth using urban sprawl matrix: A study on Kolkata urban agglomeration, India. *Science of the Total Environment*, *628–629*, 1557–1566. https://doi.org/10.1016/j.scitotenv.2018.02.170

Schneider, A., & Woodcock, C. E. (2008). Compact, dispersed, fragmented, extensive? A comparison of urban growth in twenty-five global cities using remotely sensed data, pattern metrics and census information. *Urban Studies*, *45*(3), 659–692. https://doi.org/10.1177/0042098007087340

Shafizadeh Moghadam, H., & Helbich, M. (2013). Spatiotemporal urbanization processes in the megacity of Mumbai, India: A Markov chains-cellular automata urban growth model. *Applied Geography*, *40*, 140–149. https://doi.org/10.1016/j.apgeog.2013.01.009

Sridhar, M. B., & Sathyanathan, R. (2022). Spatiotemporal Patterns of Urbanization in Chennai City, Tamil Nadu, India Using Remote Sensing Data. *Lecture Notes in Civil Engineering*, *191*, 23–34. https://doi.org/10.1007/978-981-16-5839-6_3

Stefanski, J., Kuemmerle, T., Chaskovskyy, O., Griffiths, P., Havryluk, V., Knorn, J., Korol, N., Sieber, A., & Waske, B. (2014). Mapping land management regimes in western Ukraine using optical and SAR data. *Remote Sensing*, *6*(6), 5279–5305. https://doi.org/10.3390/rs6065279

Sudhira, H. S., Ramachandra, T. V., & Jagadish, K. S. (2004). Urban sprawl: Metrics, dynamics and modelling using GIS. *International Journal of Applied Earth Observation and Geoinformation*, *5*(1), 29–39. https://doi.org/10.1016/j.jag.2003.08.002

Tang, J., Wang, L., & Yao, Z. (2006). Analyzing urban sprawl spatial fragmentation using multi-temporal satellite images. *GIScience and Remote Sensing*, *43*(3), 218–232. https://doi.org/10.2747/1548-1603.43.3.218

Taubenböck, H., Wegmann, M., Roth, A., Mehl, H., & Dech, S. (2009). Urbanization in India - Spatiotemporal analysis using remote sensing data. *Computers, Environment and Urban Systems*, *33*(3), 179–188. https://doi.org/10.1016/j.compenvurbsys.2008.09.003

Tayyebi, A., Pijanowski, B. C., & Tayyebi, A. H. (2011). An urban growth boundary model using neural networks, GIS and radial parameterization: An application to Tehran, Iran. *Landscape and Urban Planning*, *100*(1–2), 35–44. https://doi.org/10.1016/j.landurbplan.2010.10.007

Triantakonstantis, D., & Stathakis, D. (2015). Examining urban sprawl in Europe using spatial metrics. *Geocarto International*, *30*(10), 1092–1112. https://doi.org/10.1080/10106049.2015.1027289

Weng, Q. (2001). A remote sensing?GIS evaluation of urban expansion and its impact on surface temperature in the Zhujiang Delta, China. *International Journal of Remote Sensing*, *22*(10), 1999–2014. https://doi.org/10.1080/713860788

Xu, C., Liu, M., Zhang, C., An, S., Yu, W., & Chen, J. M. (2007). The spatiotemporal dynamics of rapid urban growth in the Nanjing metropolitan region of China. *Landscape Ecology*, *22*(6), 925–937. https://doi.org/10.1007/s10980-007-9079-5

Yeh, A. G. O., & Li, X. (2001). Measurement and monitoring of urban sprawl in a rapidly growing region using entropy. *Photogrammetric Engineering and Remote Sensing*, *67*(1), 83–90.

Yue, W., Liu, Y., & Fan, P. (2013). Measuring urban sprawl and its drivers in large Chinese cities: The case of Hangzhou. *Land Use Policy*, *31*, 358–370. https://doi.org/10.1016/j.landusepol.2012.07.018

Zhao, C., Li, Y., & Weng, M. (2021). A fractal approach to urban boundary delineation based on raster land use maps: A case of shanghai, china. *Land*, *10*(9). https://doi.org/10.3390/land10090941