J Indian Soc Remote Sens
DOI 10.1007/s12524-015-0482-0

RESEARCH ARTICLE

ISRS

Visualization of Urban Growth Pattern in Chennai Using Geoinformatics and Spatial Metrics

Bharath H. Aithal[1] · **T. V. Ramachandra**[1,2,3]

Received: 13 May 2014 / Accepted: 13 July 2015

Abstract Urban growth is the spatial pattern of land development to accommodate anthropogenic demand that influences other land uses (e.g.: open spaces, water bodies, etc.). Driven by population increase, urban growth alters the community's social, political and economic institutions with changing land use and also affects the local ecology and environment. India's urban population has increased by 91 million between 2001 and 2011, with migration, the inclusion of new/adjoining areas within urban limits, etc. Evidently, the percentage of urban population in India has increased tremendously: from 1901 (10.8 %) to 2011 (31.16 %). Chennai has an intensely developed urban core, which is surrounded by rural or peri-urban areas that lack basic amenities. Studying the growth pattern in the urban areas and its impact on the core and periphery are important for effective management of natural resources and provision of basic amenities to the population. Spatial metrics and the gradient approach were used to study the growth patterns and status of urban sprawl in Chennai city's administrative boundary and areas within a 10 km buffer, for the past forty years. It is found that though Chennai experiences high sprawl at peri-urban regions, it also has the tendency to form a single patch, clumped and simple shaped growth at the core. During this transition, substantial agricultural and forest areas have vanished. Visualization of urban growth of Chennai for 2026 using cellular automata indicates about 36 % of the total area being converted to urban with rapid fragmented urban growth in the periphery and outskirts of the city. Such periodic land-use change analysis monitoring, visualization of growth pattern would help the urban planner to plan future developmental activities more sustainably and judiciously.

Keywords Urban sprawl · Spatial patterns · Spatial metrics · Cellular automata

✉ T. V. Ramachandra
cestvr@ces.iisc.ernet.in

[1] Energy & Wetlands Research Group, CES TE15, Centre for Ecological Sciences, Indian Institute of Science, Bangalore 560012, India

[2] Centre for Sustainable Technolgies (astra), Indian Institute of Science, Bangalore 560012, India

[3] Centre for infrastructure, Sustainable Transportation and Urban Planning [CiSTUP], Indian Institute of Science, Bangalore, Karnataka 560 012, India

Introduction

Urbanisation is the physical growth of urban areas or the territorial progress of a region as a result of increase in population due to migration or peri-urban concentration into cities. The transition happens from rural to urban in terms of industry structure, employment, living environment and social security (Weber 2001; Bhatta 2009). Urbanisation may be planned with basic infrastructure or organic it occurs as individual, commercial establishment, and the government makes efforts to improve the opportunities for jobs, education, housing, and transportation. Only 14 % of the world's population lived in urban areas in 1900, which increased to 47 % by 2000 (Brockerhoff 2000; Ramachandra et al. 2015b). Specifically if looked at Indian case in 2011, 31.16 % of India's 1.2 billion people lived in urban areas (http://censusindia.gov.in) and this is projected to reach 60 % by 2030. Unplanned urban growth has a considerable impact on the natural resources and has led to urban sprawl: a pressing issue in several metropolitan areas. (Ji et al. 2006; Alsharif and Pradhan 2013; Arsanjani et al. 2013; Ramachandra et al. 2015a).

Urban sprawl refers to the uneven development along the highways, surrounding the city or in the peri-urban region resulting in the destruction of agricultural land and ecological sensitive habitats (Chang 2003; Ramachandra, et al. 2012a). Rapid economic development during the last two decades has resulted in high urban sprawl across India (Ramachandra et al. 2013a). The fragmented urban patches at the fringes originate from multiple nuclei, resulting in urban growth with serious environmental and social issues. Timely and accurate detection of changes to the Earth's surface is vital to understand relationships and interactions between anthropogenic and natural phenomena and thereby promote better decision-making (Sudhira et al. 2004; Lu and Weng 2007; Bhatta 2010; Rahman et al. 2011; Setturu et al. 2012; Ramachandra et al. 2012a, b). This leads to better urban form and a positive relationship between a city and its surrounding areas. As conventional methods of detecting changes are expensive, time consuming and lacks precision (Opeyemi 2008), geo-informatics with temporal–spatial data acquired remotely through space borne sensors have been adopted during recent years to map and monitor specific regions (Jensen 1986; Singh 1989; Ramachandra et al. 2014).

Remote sensing provides vital data for monitoring land-cover changes and its impacts on the environment at local, regional and global scales (Johnson 2001; Kumar et al. 2011a). This aids in monitoring the changes in the region apart from understanding the role of prominent causal factors. Remote sensing is perhaps the only method for obtaining the required data from inaccessible regions on a cost and time-effective basis (Dessì and Niang 2008; Sharma and Joshi 2013). Remote sensing technology with geographic information system (GIS) is ideal to understand the changes in the landscape and help the planners to visualize likely implications with the future developments (Pathan et al. 1991; Epstein et al. 2002; Civco et al. 2002; Herold et al. 2003a; Matsuoka et al. 2004; Yorke and Margai 2007; Yang et al. 2008; Anindita et al. 2010; Kumar et al. 2011b). Spectral and spatial details in the remote sensing data aid in delineating land use categories to understand the surface land characteristics (Ramachandra and Kumar 2008). Landscape dynamics have been understood by implementing empirical studies focusing on monitoring, planning and landscape design which failed to emphasize pattern of growth specifically (O'Neill et al. 1999; Nassauer et al. 1999; Leitao and Ahern 2002; Ramachandra et al. 2012a; Wentz et al. 2014). The land use dynamics can be understood using temporal data acquired remotely through space borne sensors. Land use changes reflect the varied intensity and measure the spatial extent of the urban growth.

The spatial characteristics of land use features are measured using spatial metric, which explains the physical characteristics of the land use (such as urban) forms and its pattern (Herzog and Lausch 2001; Herold et al. 2002; Herold et al. 2003a, b; Chang 2003). Further modelling based on these changes would help in understanding future changes. Models specific to urban growth have been used along with remote sensing data and have proved to be important tools to measure land-use change in peri-urban regions (Clarke and Gaydos 1998; Herold et al. 2003a,b; Mundia and Murayama 2010). Torrens (Torrens 2000) suggests the use of cellular automata (CA) for urban growth modelling and in simulating land use changes as population migration and evolution can all be modeled as automation, while the pixel and its neighbors can account for various changes such as demographic data etc., neighborhoods as part of the city can be simulated by the cells on the lattice based on predefined site-specific rules that represent the local current transitions that are raster-based for modeling urban expansion for discrete time steps (Guan et al. 2008). Further it can be noted that standalone CA models lack the ability to account for the actual amount of change since it cannot account for specific transitions of change in the region. Eastman (Eastman 2009) suggested coupling of Markov chains (MC) and CA. This coupling helps in quantifying future likely changes based on current and past changes which essentially addresses the shortcoming of CA such as spatial allocation and the location of change (Arsanjani et al. 2013). These studies have failed to link agents of changes that are main driving forces (He et al. 2008; He et al. 2013). Further, some studies have used agents or drivers of changes that can be transition potential using multi-criteria evaluation (MCE) techniques. However, this approach failed due to shortcoming in calibration techniques (Eastman 2009). Hence it is necessary to calibrate the model and associate the agents of changes and driving forces in order to understand and develop accurate transition potential maps. Fuzzy-AHP technique of weighing agents was then proposed to obtain such accurate calibrations (Ramachandra et al. 2013a, b). First, fuzzy clustering is used to group the spatial units into clusters based on certain attribute data. Analytical Hierarchal process (AHP) is then used to assign weights to these spatial units thus based on various inputs. Then once the weights are assigned Cellular Markov models with the help of transition probability matrix inherits past states of land use types to predict future state (Praveen et al. 2013). Land use transitions is simulated and validated for the year 2012. Further, prediction for the year 2026 considering City Development Plan [CDP] and without CDP were carried out from the validated data.

The objective of the current communication is to visualize the urban growth patterns in Chennai. Chennai's rapid urbanization has resulted in increased population density, traffic congestion and poor environmental quality, within and surrounding the city. Thus, planners need to understand and visualize future plans to address these problems and ensure that basic infrastructure and amenities are available in the city. The multi-temporal remote sensing data have been used to study the urban structure and its dynamics. The spatial characteristics of the urban pattern is analysed through gradient approach using spatial metrics.

Study Area

Chennai, previously known as "Madras" is the capital city of the Indian state of Tamilnadu and the fourth metropolitan area in India (Dowall and Monkkonen 2008). It lies at 12^0 9′ to13^0 9′ N and 80^0 12′ to 80^0 19′ E at the eastern coast and southern peak of India. The average elevation of the city is about 8 m above the mean sea level. The average temperature ranges from 38^0 to 42^0 C in summer and 18^0 to 20 °C in winter. As per the 1971 census, Chennai's population was 0.3 million, which has increased to more than 8 million (as per census 2011). The population density has increased steadily from 769 persons per sq.km to 1041 (1981), 1315 (1991), 1558 (2001) and 2109 (2011) persons per sq.km. Chennai is one of the more industrialised and economically developed cities in India. Major industries include automobile, software, textiles, and post the 1900s, information technology. Urban growth patterns have been assessed considering the administrative boundary of Chennai with a10 km buffer (Fig. 1) to account for dispersed growth in peri-urban areas.

Materials and Methods

Chennai's urban growth patterns have been assessed using temporal remote sensing data of Landsat satellite downloaded from public domains at Global Land Cover Facility (GLCF) (http://www.glcf.umd.edu/index.shtml) and United States Geological Survey (USGS) Earth Explorer (http://edcsns17.cr.usgs.gov/NewEarthExplorer/). Table 1 describes the data used, including remote sensing data and collateral data. The Survey of India (SOI) topographic maps of 1:50,000 and 1:250,000 scales were used to generate base layers such as the city boundary. Chennai's administrative boundary is digitized from the city administration map obtained from the municipality. Ground control points to register and geo-correct remote sensing data were also collected using hand held pre-calibrated GPS (Global Positioning System) devices, Survey of India topographic maps and Google earth (http://earth.google.com, http://bhuvan.nrsc.gov.in). The method adopted to assess the urban growth patterns includes preprocessing, generation of land cover and land use and a gradient-wise zonal analysis of Chennai, is represented in Fig. 2.

Preprocessing

The remote sensing data obtained was geo-referenced, geo-corrected, rectified and cropped pertaining to the study area. Remote sensing data from different sensors (with different spatial resolutions) was resampled to 30 m in order to maintain uniformity in spatial resolution. The study area includes the Chennai administrative area and 10 km buffer from the administrative boundary.

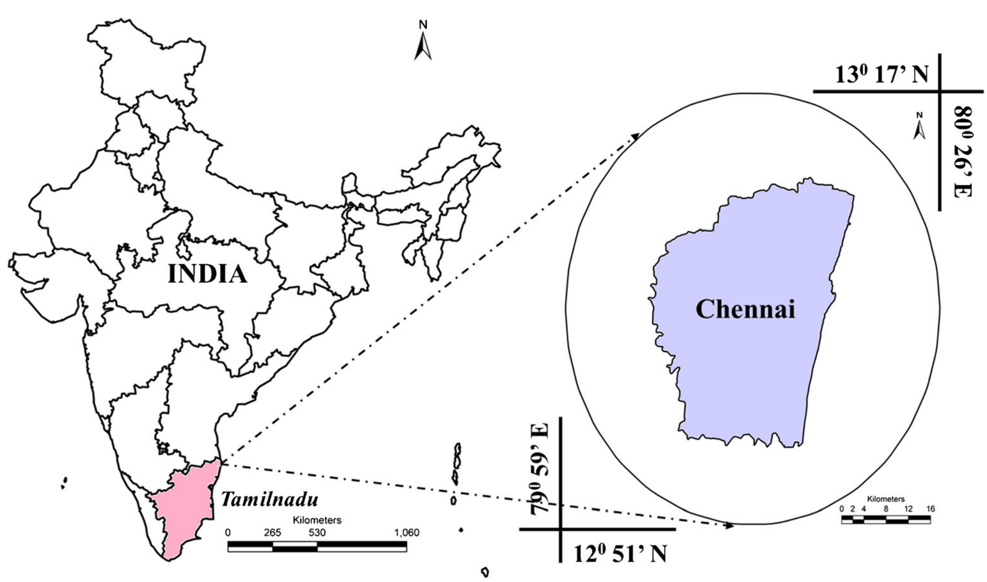


Fig. 1 Study area - Chennai administrative boundary and a 10 km buffer

Table 1 Data used in the Analysis

Data	Year	Purpose
Landsat Series Thematic mapper (28.5 m)	1991, 2000	Land use, Land cover [LULC] analysis, landscape dynamics, urban growth patterns
IRS P6 – LISS III MSS data (23.5 m)	2012	LULC analysis, landscape dynamics, urban growth patterns
Survey of India (SOI) topographic maps of 1:50,000 and 1:250,000 scales		To Generate boundary and Base layer maps.
Field visit data –captured using GPS		For geo-correcting and generating validation dataset
Aster GDEM of *1 arc-second* (30 m) grid	2010	Extraction of Drainage lines, Slope analysis.
City developmental plans, location of various agents	2005, 2015	Extraction of various agents of growth using Google earth and ancillary data

Land Cover Analysis

Land Cover analysis was performed to understand the changes in the vegetation cover during the study period in the study region. Normalized Difference Vegetation Index (NDVI) was found suitable and was used for measuring vegetation cover (Ramachandra et al. 2012a). NDVI values range from −1 to + 1. Very low values of NDVI (−0.1 and below) correspond to

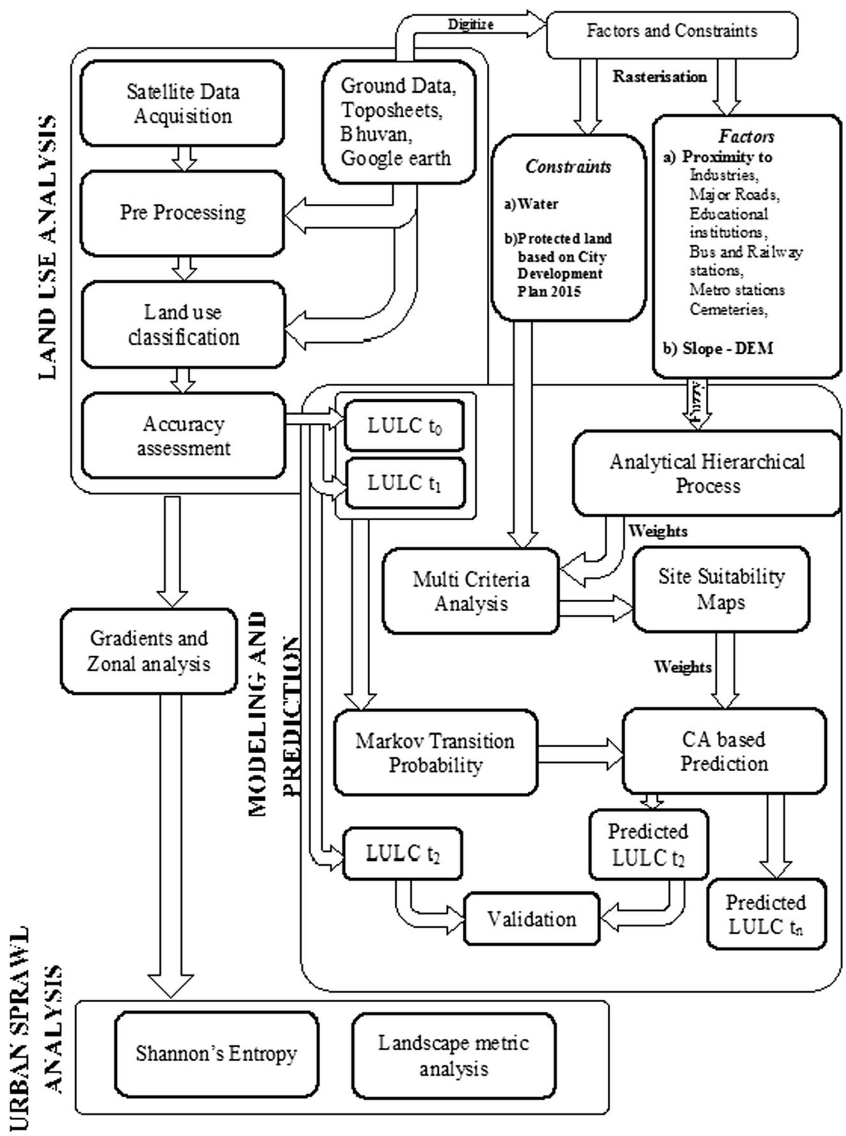


Fig. 2 the procedure adopted for classifying the landscape, computation of metrics and modelling

soil or barren areas of rock, sand, or urban built up. Zero indicates the water cover. Moderate values (0.1 to 0.3) represent low-density vegetation, while high values (0.6 to 0.8) indicate thick canopy vegetation.

Land Use Analysis

Land use categories were classified using supervised technique with Gaussian Maximum Likelihood classifier (GMLC). The spatial data pertaining to different time frame were classified, using signatures from training sites for the land use types listed in Table 2. The training polygons were compiled from collateral data of corresponding time period. Latest data were classified using signatures (training polygons) digitized with the help of Google earth. False color composite of remote sensing data (bands – green, red and NIR), was generated to visualise the heterogeneous patches in the landscape. 60 % of the training data was used for classifying remote sensing data while the balance has been used for validation or accuracy assessment.

Data is classified on the basis of training data through GMLC a superior method that uses probability and cost functions in its classification decisions (Duda et al. 2000; Ramachandra et al. 2012a). Mean and covariance matrices are computed using the maximum likelihood estimator. Land use was analysed using the temporal data retrieved from the open source program GRASS - Geographic Resource Analysis Support System (http://ces.iisc.ernet.in/foss). Signatures were collected from field visit and Google earth. Classes of the resulting image were reclassified and recoded to form four land-use classes (Table 2).

Accuracy Assessment

Accuracy assessment has been done for the classified data to evaluate the performance of classifiers (Ramachandra et al. 2012a). This is done through using kappa coefficients (Congalton et al. 1983). Overall (producer and user) accuracies were computed through a confusion matrix. Assessing overall accuracy and computing Kappa coefficient are widely accepted methods to test the effectiveness of classifications (Lillesand and Kiefer 2002; Congalton and Green 2009).

Table 2 Land use classification categories adopted

Land use Class	Land uses included in the class
Urban	This category includes residential area, industrial area, all paved surfaces (road, etc.) and mixed pixels having major share of built up area.
Water bodies	Tanks, lakes, reservoirs.
Vegetation	Forest, nurseries.
Others	Rocks, cropland, quarry pits, open ground at building sites, un-metaled roads.

Zonal Analysis

The study area (city boundary with 10 km buffer region) is divided into 4 geographic zones based on direction– Northeast (NE), Southwest (SW), Northwest (NW) and Southeast (SE)– as a city or its growth is usually defined directionally. Zones were sub-divided using centroid as a reference (Central Business District). The growth of the urban areas in each zone was studied and understood separately, by computing urban density for different periods.

Gradient Analysis

(Division of zones into concentric circles): To visualise the process of urban growth at local levels and to understand the agents responsible for changes, each zone was divided into concentric circles that are 1 km apart and radiate from the city-center. The analysis of urban growth patterns at local levels help the city administrators and planners identify the causal factors of urbanization in response to the economic, social and political forces and visualizing the forms of urban growth with sprawl.

Urbanisation Analysis

To understand the growth of the urban area in specific zone and determine whether it is compact or divergent, the Shannon's entropy (Sudhira et al. 2004; Ramachandra et al. 2012a) was computed for each zone. Shannon's entropy (Hn), given in Eq. 1, explains the development process and its characteristics over a period of time and indicates whether the growth was concentrated or aggregated.

$$\mathrm{Hn} = -\sum_{i=1}^{n} \mathrm{Pi}\log(\mathrm{Pi}) \qquad (1)$$

Where, Pi is the proportion of the built-up in the i^{th} concentric circle. The lowest value of zero reflects the distribution is maximally concentrated. Conversely, the maximum value equivalent to log n indicates of sprawl with even distribution among the concentric circles.

Computation of Spatial Metrics

Spatial metrics have been used to quantify spatial characteristics of the landscape. Selected spatial metrics were used to anlayse and understand the urban dynamics. FRAGSTATS (McGarigal and Marks in 1995) was used to compute metrics at three levels: patch level, class level and landscape level. Table 3. below gives the list of the metrics along with their description considered for the study.

Table 3 Landscape metrics used in the current analysis (McGarigal and Marks in 1995; Aguilera et al. 2011; Ramachandra et al. 2012a; Ramachandra et al. 2015b)

Indicator	Formula
PLAND	$PLAND = P_i = {\sum_{j=1}^{n} a_{ij}}/{A}$ P_i=proportion of the landscape occupied by patch type i. a_{ij}=area (m^2) of patch ij, A=total landscape area (m^2).
Number of patches (Built-up) - NP	$N=n_i$, Range: NP≥1
Patch Density (PD)	$PD = \frac{n_i}{A}(10,000)(100)$, Range: PD>0
Largest patch Index (Built-up) (LPI)	$LPI = \frac{\max_{j=1}^{n}(a_{ij})}{A}(100)$, Range: 0<LPI≤100
Normalised landscape shape Index (NLSI)	$NLSI = \frac{e_i - \min e_i}{\max\ e_i - \min e_i}$ Range: 0 to 1
Landscape shape Index (LSI)	$LSI = \frac{e_i}{mne_i}$, Range: LSI≥1, without limit.
Interspersion and Juxtaposition Index (IJI)	$IJI = \frac{-\sum_{K=1}^{m}\left(\left[\frac{e\ ik}{\sum_{k=1}^{m} e_{ik}}\right]\ln\left[\frac{e_{ik}}{\sum_{k=1}^{m} e_{ik}}\right]\right)}{\ln(m-1)}(100)$ Range: 0<IJI≤100 eik=total length (m) of edge in landscape between patch types I and k. m=number of patch type present in landscape.
Clumpiness Index (Clumpy)	$CLUMPY = \begin{pmatrix} \left[\frac{G_i - P_i}{P_i}\right] for\ G_i < P_i\ P_i < 5; else \\ \frac{G_i - P_i}{1\ P_i} \end{pmatrix} G_i = \left[\frac{g_{ii}}{\left(\sum_{k=1}^{m} g_{ik}\right) - \min e_i}\right]$ Range: Clumpiness ranges from −1 to 1
Aggregation Index (AI)	$AI = \left[\frac{g_{ii}}{\max g_{ii}}\right](100)$ g_{ii}=number of like adjacencies (joins) between pixels of patch type (class) i based on the single-count method. max-g_{ii}=maximum number of like adjacencies (joins) between pixels of patch type (class) i based on the single-count method.
Percentage of Like Adjacencies (PLADJ)	$PLADJ = (100) * \left(\frac{g_{ij}}{\sum_{k=1}^{m} g_{ik}}\right)$ g_{ii}=number of like adjacencies (joins) between pixels of patch type (class) i based on the *double-count* method. g_{ik}=number of adjacencies (joins) between pixels of patch types (classes) i and k based on the *double-count* method.
Patch Cohesion index	$Cohesion = \left[1 - \frac{\sum_{j=1}^{n} P_{ij}}{\sum_{j=1}^{n} P_{IJ}\sqrt[2]{a_{ij}}}\right]\left[1 - \frac{1}{\sqrt[2]{A}}\right]^{-1} * 100$

Table 4 Agents and constraints considered for modelling

Agents	Industries, proximities to roads, railway stations, metro stations, educational institutes, religious places etc.
Constraints	Drainage lines, slope, water bodies, costal regulated areas, catchment areas etc.

Visualisation of Urban Growth in Chennai by 2026

Agents of urbanisation and constraints (listed in Table 4) with temporal land uses were taken as base layers for modelling and visualisation. Data values were normalized through fuzzification wherein the new values ranged between 0 and 255, 255 indicating maximum probability of change in land

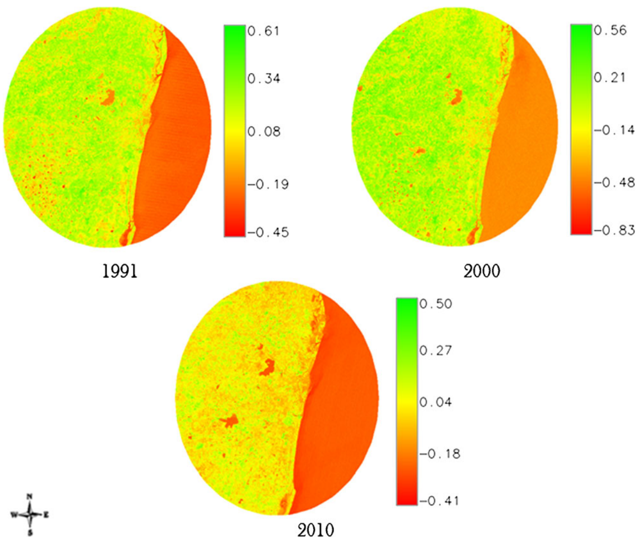


Fig. 3 Temporal land cover analysis using NDVI

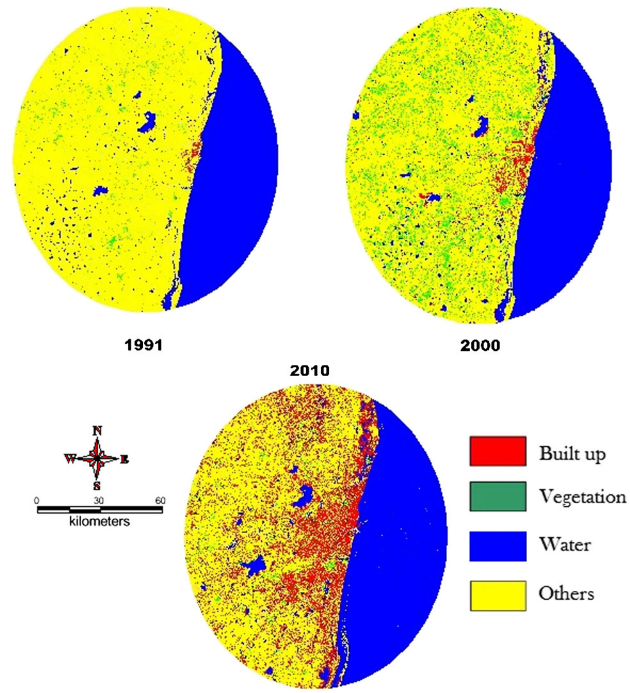


Fig. 4 Output of land use analysis in the study region

use in contrast with 0 for no changes. Fuzzy outputs thus derived are then taken as inputs to AHP for different factors into a matrix form to assign weights. Each factor is compared with another in pair wise comparison followed by enumeration of consistency ratio which should be preferably less than 0.1 for the consistency matrix to be acceptable. Once weights are determined MCE was used to determine the site suitability considering two scenarios i). Restrictions based on City Development Plan (CDP); ii). As usual scenario without CDP. These suitability change maps were considered in the MC-CA model. Considering earlier land uses, transition potentials were computed using a Markovian process. Using and hexagonal CA Filter of 5 × 5 neighborhood with variable iteration at every step until a threshold is reached. Careful model validation through kappa statistics was conducted to assure accuracy in prediction and simulation. Built-up areas were predicted for 2012 were cross-compared with the actual built-up areas in 2012 using classified data. The kappa index of 0.9 shows a good agreement accuracy of the model. Future patterns of urban expansion were then simulated for the years 2026.

Results and Discussion

Land cover (LC) of the region is assessed using the preprocessed temporal remote sensing data using Normalized Difference Vegetation Index (NDVI). Figure 3 depicts the vegetation cover based on NDVI for Chennai region during 1991–2012. Table 5 tabulates the vegetation cover dynamics, which show that the percentage of vegetative cover has drastically reduced by 22 % during the past two decades, with the increase in non-vegetative area (buildings, open space, water, etc.). As per the LC analysis, the current vegetation cover is about 48.18 %. To understand the status of various land use (LU) classes in the region classification of temporal remote sensing data were done using GMLC. LU analysis helps to demarcate the different classes and LC provides only the details of vegetative cover (which might be vegetation and also cropland).

figure 4 depicts land use changes, based on the analysis of temporal remote sensing data using Gaussian Maximum Likelihood Classifier (GMLC). Table 6 provides land use statistics, which reveals that the area under vegetation declined from 70 to 48 % with an increase in urban (paved) surfaces from 1.46 % to about 18.5 %. Table 7 tabulates overall accuracy

Table 5 Vegetation cover changes in Chennai

Year	Vegetation (%)	Non-vegetation (%)
1991	70.47	29.53
2000	56.7	43.27
2012	48.18	51.82

Table 6 Land use in the study region

Land Use category	Built-up Area (%)	Vegetation Area (%)	Water body Area (%)	Others Area (%)
1991	1.46	1.38	27.64	69.52
2000	2.52	0.8	27.25	68.35
2012	18.55	1.51	28.15	51.38

Table 7 Accuracy assessment from confusion matrix and kappa statistics

Category	1991		2000		2012	
	Producer's Accuracy	User's Accuracy	Producer's Accuracy	User's Accuracy	Producer's Accuracy	User's Accuracy
Built-up	92.04	93.02	90.42	97.38	78.23	93.02
Vegetation	99.31	92.49	97.75	99.42	98.98	79.49
Water body	91.50	93.84	91.65	89.52	99.47	93.84
Others	96.28	92.45	92.70	98.82	39.50	76.45
Overall Accuracy	92		91		97	
Kappa	0.92		0.9		0.93	

and kappa statistics obtained for classified images– these results show that the classified and ground truth data are closely related. Overall accuracy and kappa statistics showed a good relation of the classified data with ground truth data.

figure 5 illustrates the urban growth pattern during 1991 to 2012, derived from the classified data.

Shannon's Entropy (Hn)

Shannon's entropy aids in assessing the urbanisation pattern and was calculated for each zone considering the gradients and as shown in Fig. 6. The values closer to 0 indicates of a compact growth, as in 1991. All zones show a compact growth or more concentrated growth towards the central business district as even seen in classified data. The Shannon's entropy values have increased temporally to 0.4 indicating the tendency of dispersed fragmented growth or sprawl in all directions. This indicates a fragmented outgrowth and mostly in North west direction. Increased patches in all zones indicate that the city is heading towards higher fragmented outgrowth and more clumped inner core. Further this pattern is analysed using landscape metrics for better understanding at each gradient and zone.

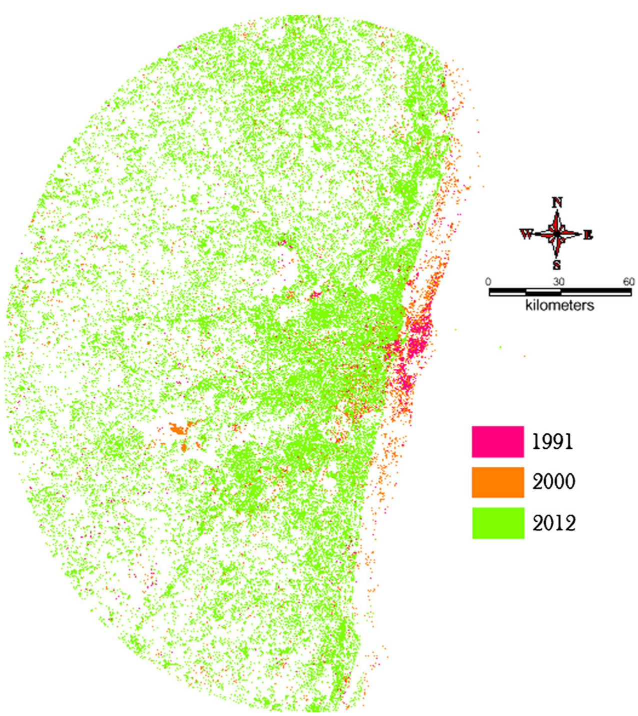


Fig. 5 Urban growth in the study region

Analysis of Spatial Metrics

Results of all metrics are given in Fig. 7a to i; the X-axis represents the gradients considered and Y-axis, the Metric value.

Percentage of Landscape (PLAND)

PLAND equals the proportion of landscape comprised of the corresponding class patches. Built up proportion was computed to understand the ratio of built up in the landscape. The results given in Fig. 7a, reveal that the proportion has increased during the three decades with the tremendous growth in the central circles. The outer gradients show a slight but significant increase, which indicate sprawling development in the periphery and buffer. The NW shows a relatively higher increase as compared to that in the NE and SW.

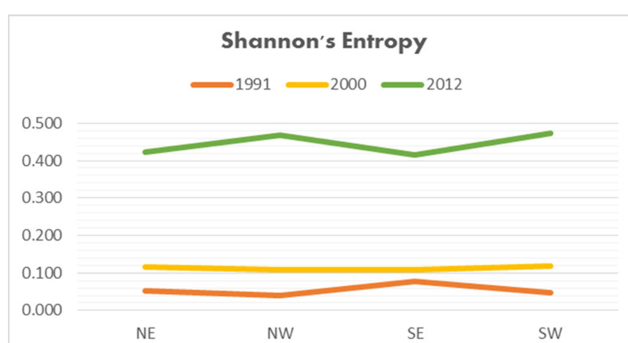


Fig. 6 Shannon entropy

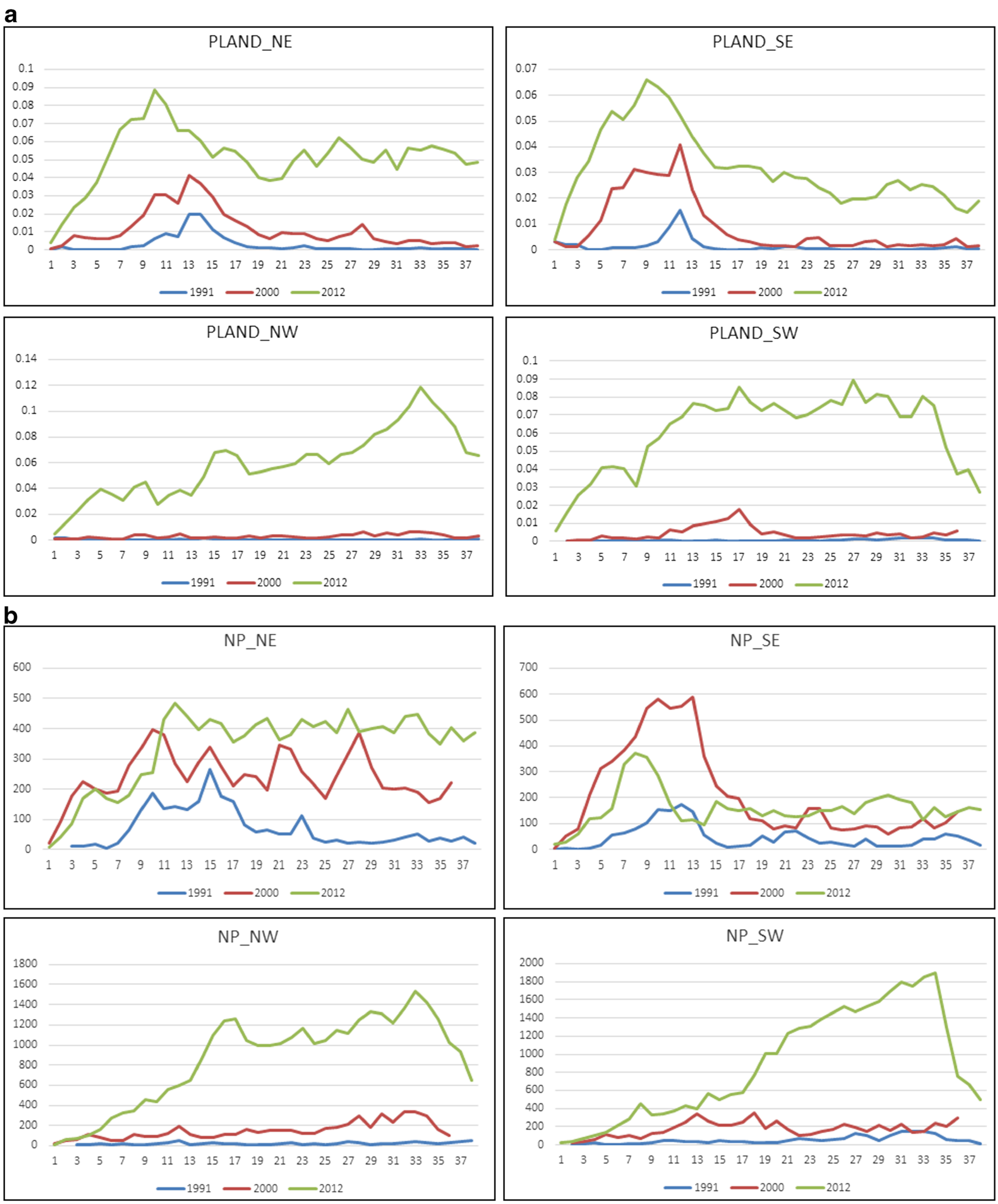


Fig. 7 **a** Percentage of landscape (PLAND). **b**: Number of Patches (NP). **c**: Patch Density (PD). **d**: Largest Patch Index (LPI). **e**: Landscape shape index (LSI) - directionwsie. **f**: Normalized Landscape shape index (LSI). **g**. Clumpiness index (CLUMPY). **h**. Aggregation Index. **i**. Patch cohesion index. **j**. Percentage of like adjacencies metric

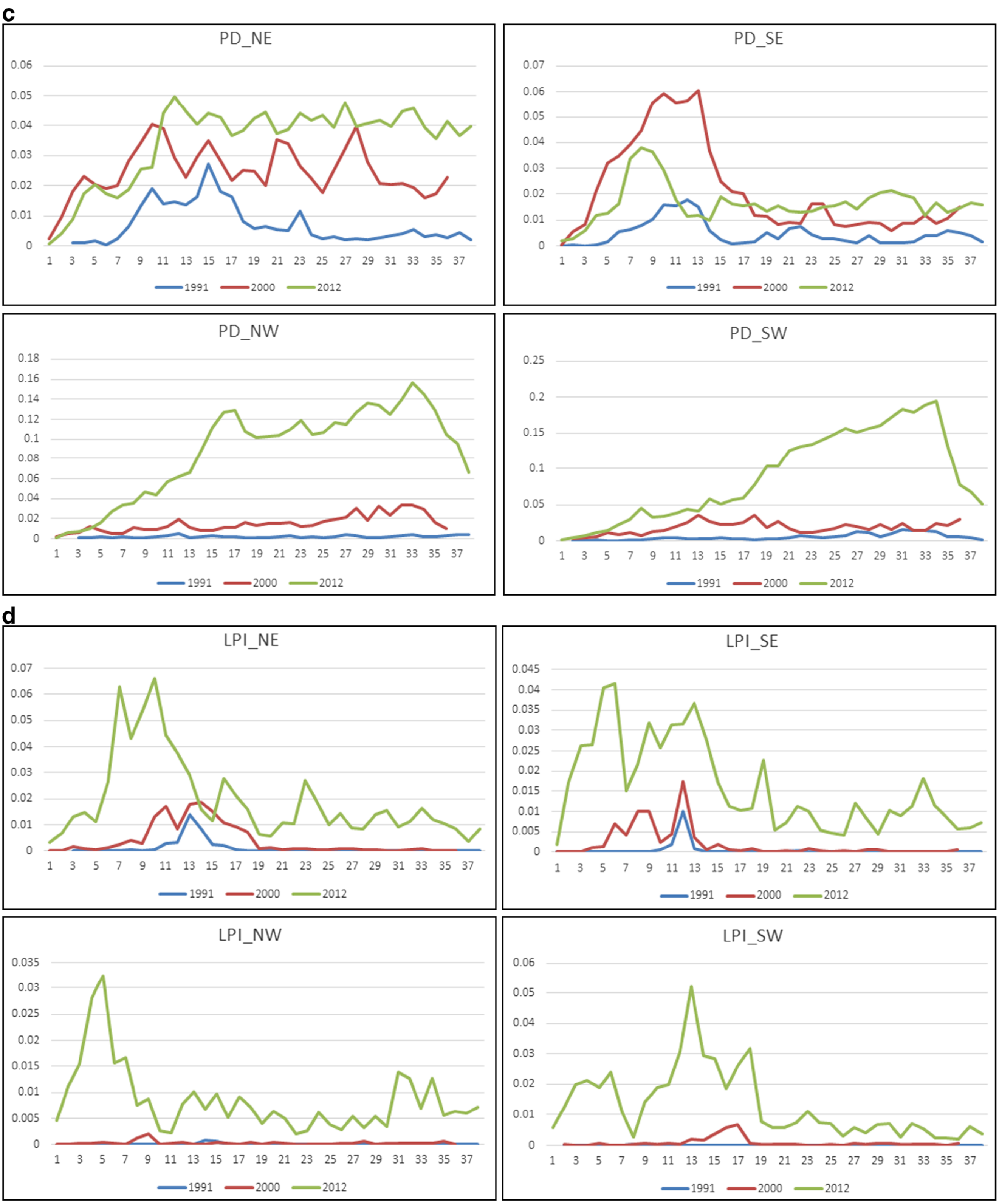


Fig. 7 (continued)

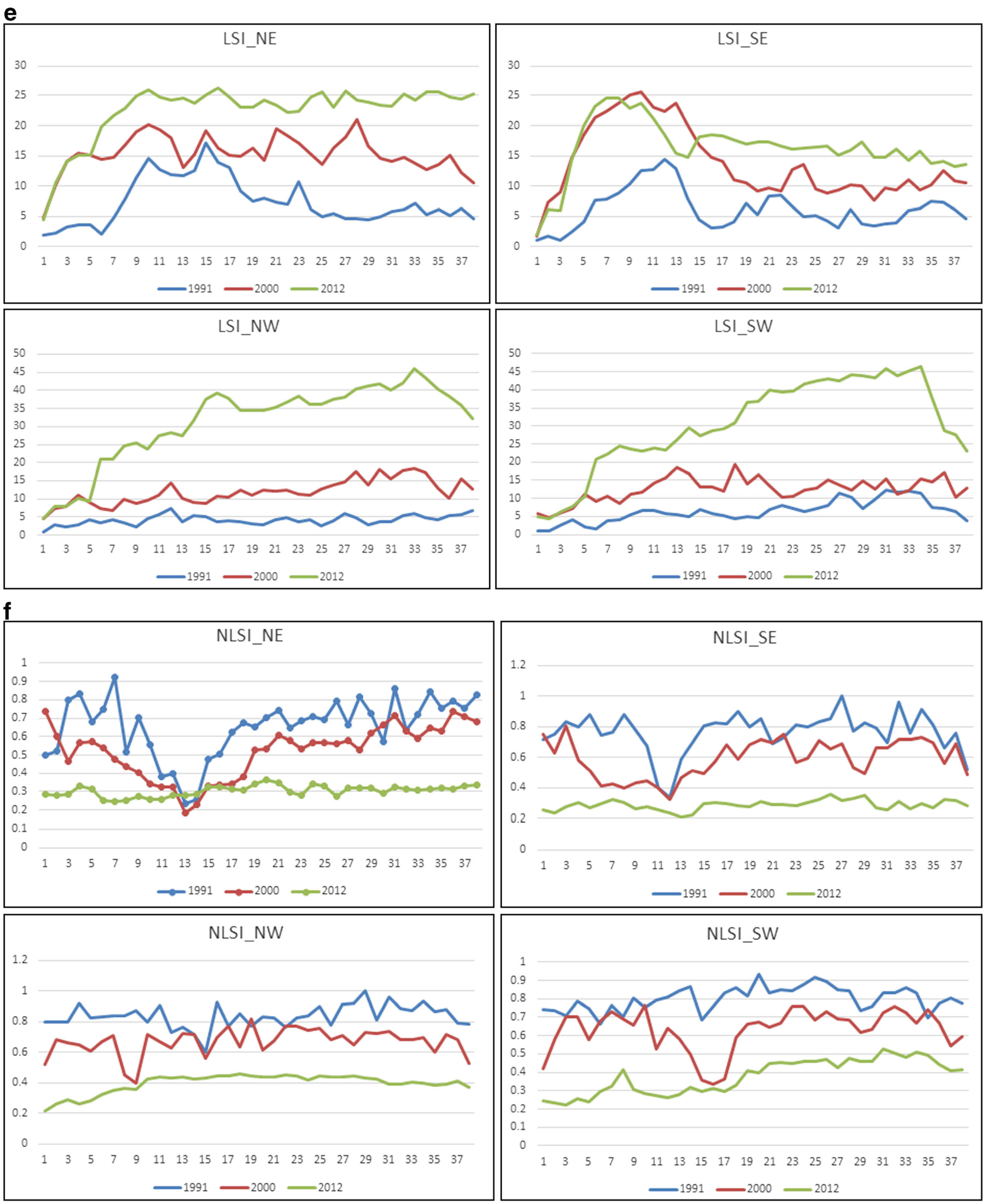
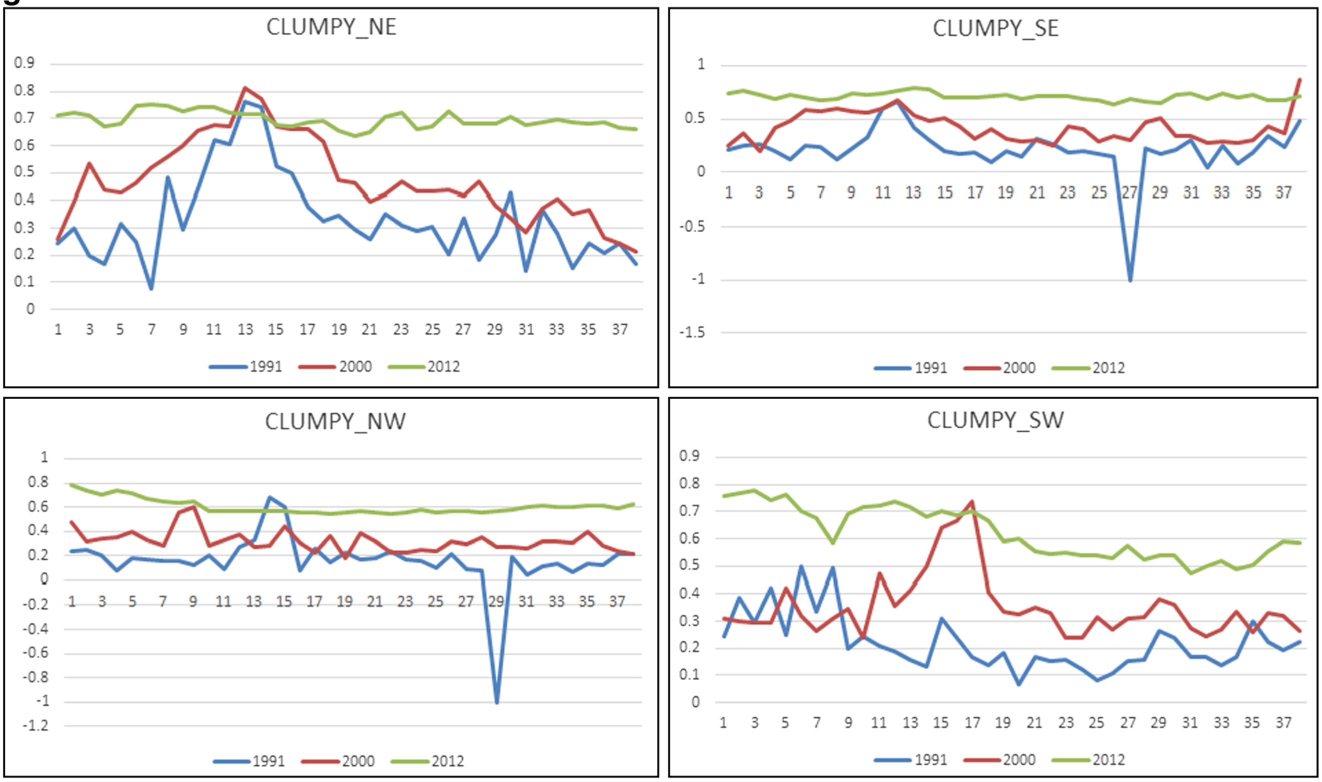


Fig. 7 (continued)

g



h

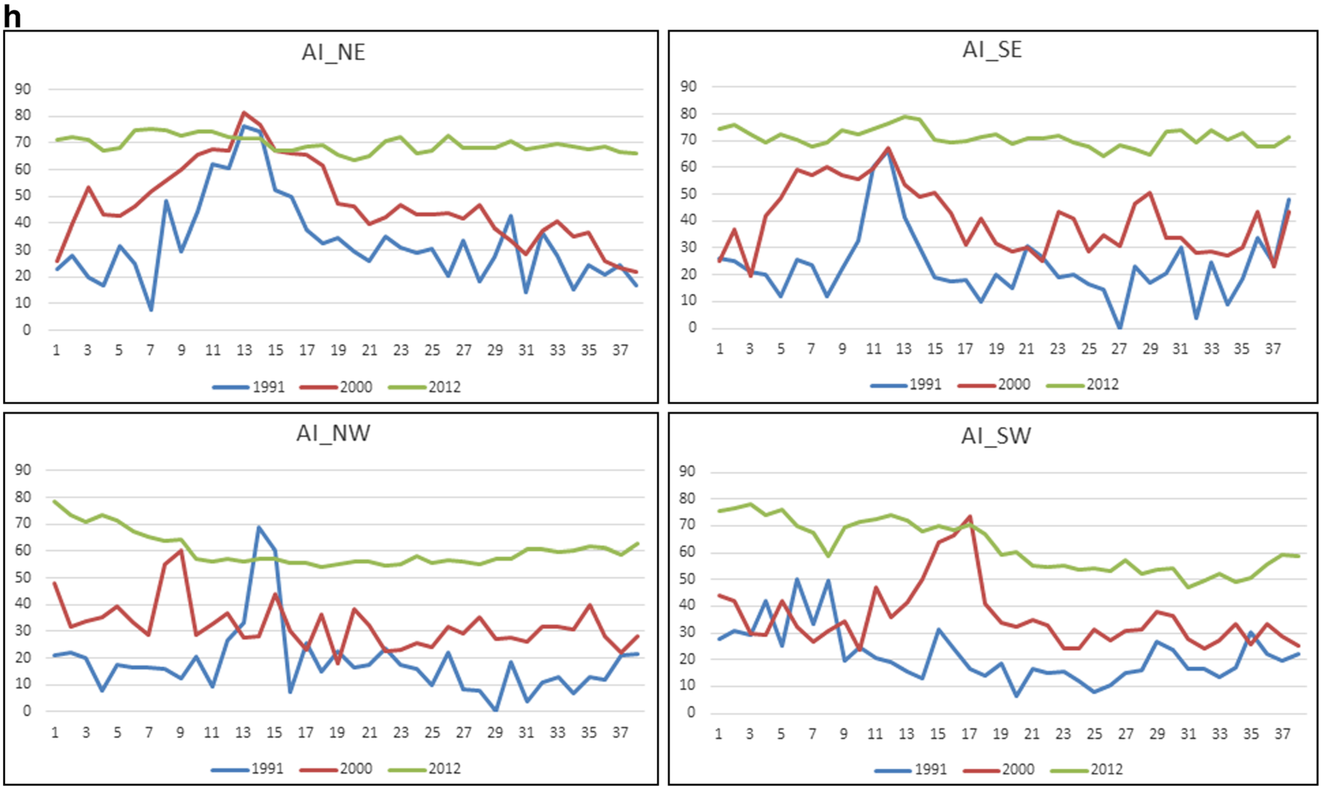
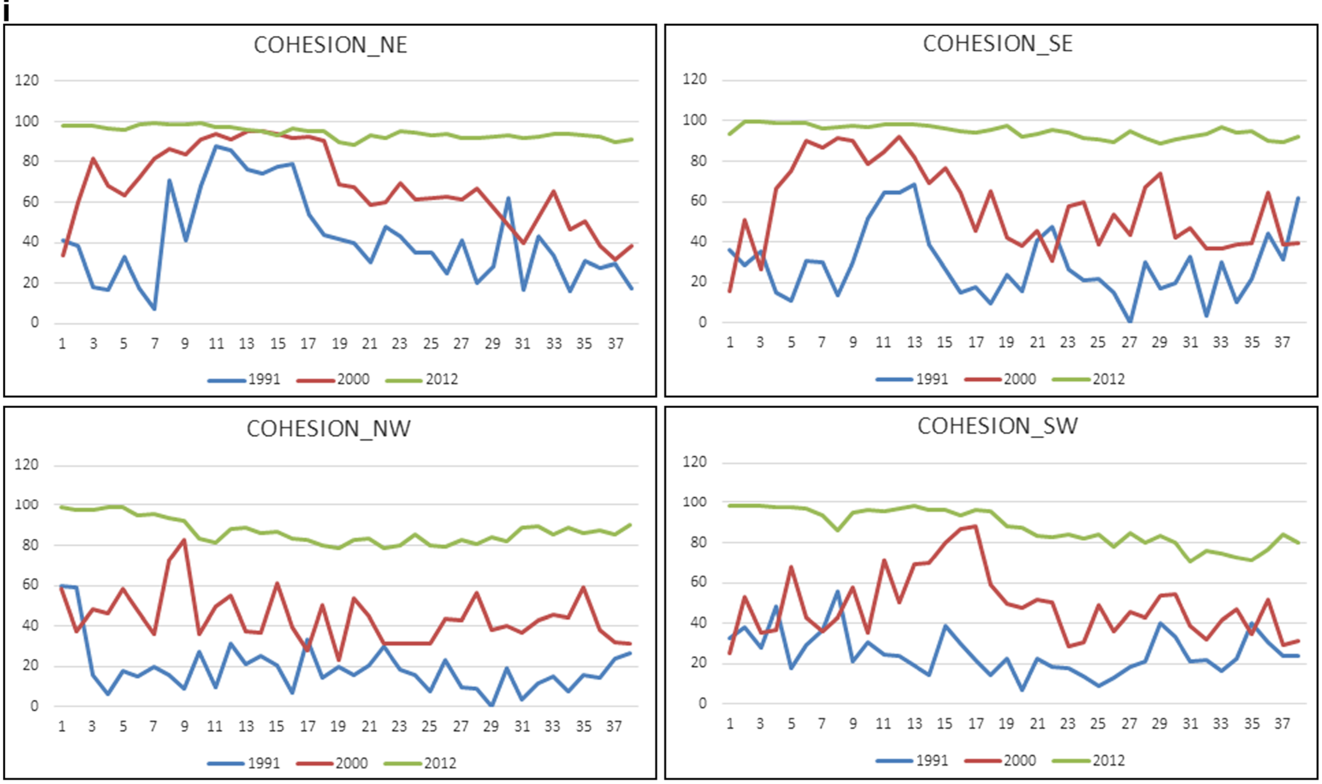


Fig. 7 (continued)

i



j

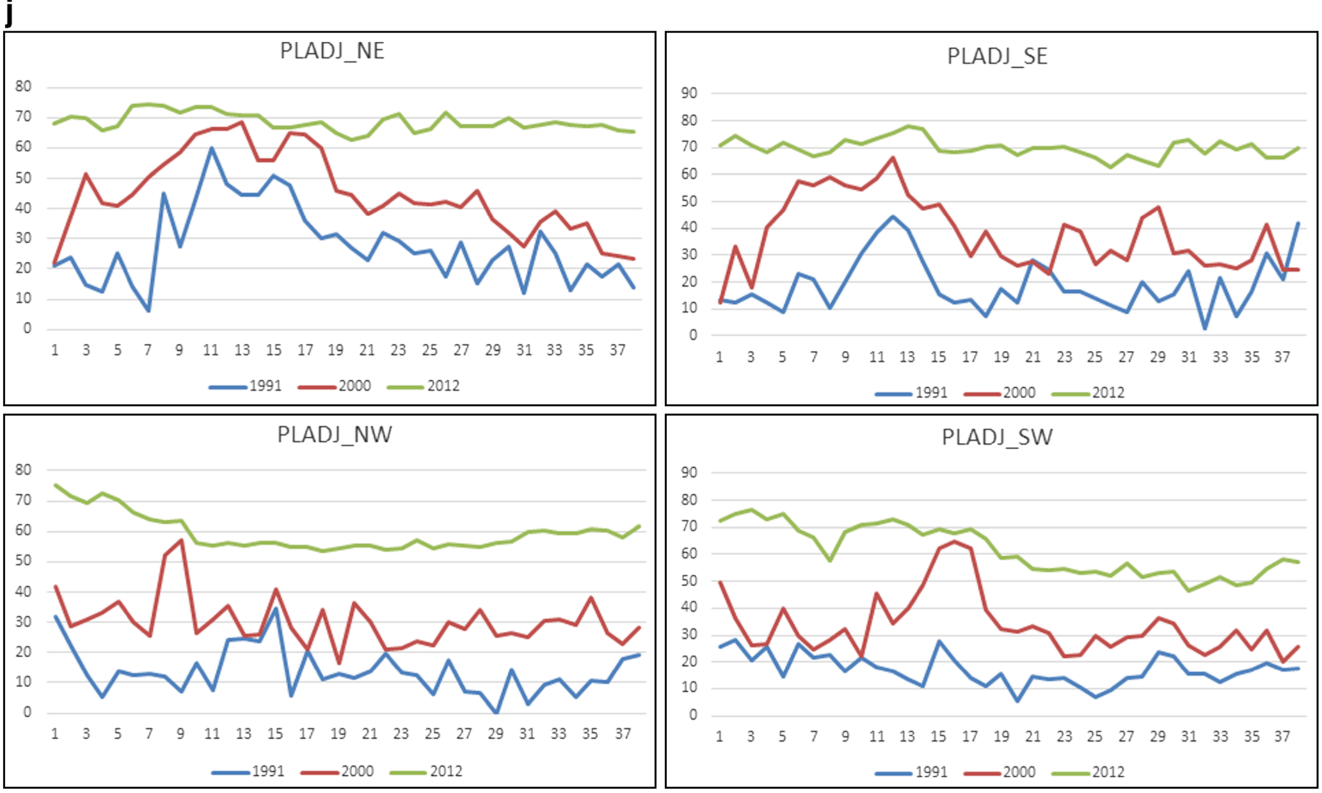


Fig. 7 (continued)

Table 8 Predicted land use statistics for the year 2026

Categories / Year	Predicted 2026 with CDP	Predicted 2026 without CDP
Builtup	36.6	36.5
Vegetation	2.4	2.4
Water	27.9	27.8
Others	33.1	33.3

Number of Patches (NP)

NP equals the number of built up patches in a landscape. It indicates the level of fragmentation in built up landscape. Figure 7b depicts the significant increase in number of urban patches during two decades in all directions in all gradients, indicating the fragmentation of landscape during post 2000. Patches at the city centre are combining to for single clumped dominant patch, whereas in outer gradients is more fragmented.

Patch Density (PD)

Patch density was computed as an indicator of urban fragmentation. As the number of patches increase, patch density increases representing higher fragmentation. Figure 7c shows the trends in patch density and comparable to the number of urban patches i.e., fragmented urban patches towards the fringes in all directions and a clumped patched growth at the center.

Largest Patch Index (LPI)

Largest Patch Index (LPI) was computed to represent the percentage of landscape that contain largest patch. Figure 7d illustrates that gradients at the center are with higher values due to the larger size urban patches indicating compact growth. The declining trends at the gradients away from the city center at fringes or peri urban areas indicates of fragmented urban patches.

Landscape Shape Index (LSI) and Normalized Landscape Shape Index (NLSI)

Landscape shape index provides a simple measure of class aggregation or disaggregation. Aggregation is measured via class edge. Normalized landscape shape index is similar to landscape shape index but this represents the normalized value. figure 7e and f depicts LSI and NLSI respectively indicate that lower values in the gradients at the city center during post 2000 highlights of simpler shapes with compact urban patches compared to the fringes which show complex shape with the fragmented outgrowth.

Clumpiness (CLUMPY) and Aggregation Index (AI)

Clumpiness index represents the status of urban landscape and is the measure of patch aggregation. It measures the clumpiness of the overall urban patches. Clumpiness ranges from −1 to 1 where Clumpy is −1, when the urban patch type is maximally disaggregated, Clumpy is 0 when the patch is distributed randomly and approaches 1 when urban patch type is maximally aggregated. Aggregation Index gives the similar indication as clumpiness i.e., it measures the aggregation of the urban patches, Aggregation index ranges from 0 to 100. An analysis of clumpiness index for the year 1991, explained that the city, except a few patches in the outskirts and buffer, had a simple clumped growth at the center business district with the values close to 0. Analysis for the year 2012 indicated a high fragmented growth or non-clumped growth at outskirts and more clumped growth in the center. The aggregation index showed the similar trend as the clumpiness index. Figure 7h, also revealed that the center part of the city is becoming single homogeneous patch whereas the outskirts

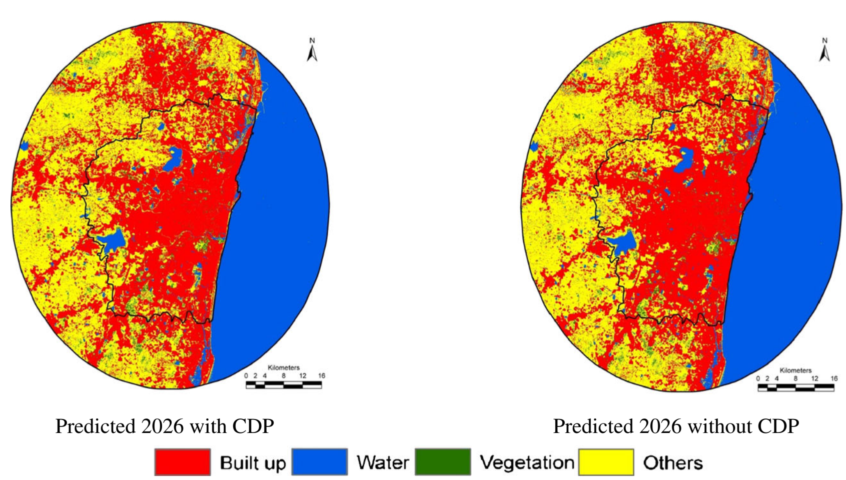


Fig. 8 Predicted land use categories for the year 2026

are growing as fragmented patches of urban area destroying other land uses and forming a single large urban patch.

Patch Cohesion Index

figure 7i measures the physical connectedness of the urban patches. Higher cohesion values in 2012 indicate of higher urban patches while lower values (in 1991) illustrate of fewer urban patches in the landscape.

Percentage of Like Adjacencies (PLADJ)

This indicates the percentage of cell adjacencies of the corresponding patch type. Figure 7j depicts that the urban patches in the landscape are most adjacent to each other in 2012, and were fragmented in 1991 and 2000. This illustrates that urban land use is dominant in 2012 and is in the process of forming a single patch.

Visualisation Using Fuzzy AHP CA-Markov

Prediction for the year 2026 was performed considering both scenarios and agents as specified earlier. Wherein water bodies and coastal regulation areas were kept constant insisting no development at these areas. Subsequently prediction was done without considering CDP. Table 8 shows % land use category change. Built-up areas have been increased two fold, decrease in vegetation and increase in other categories can be observed from 2013 to 2026. Significant changes can be seen in areas which falls within the CMDA boundary such as Korathur and Cholavaram lake bed, Redhills catchment area, Perungalathur forest area, Sholinganallur wetland area etc. as visualized in Fig. 8.

Conclusions

Urban growth is the spatial pattern of land development to accommodate anthropogenic demand, influencing other land uses (open spaces, etc.). Urban growth patterns of Chennai and the sprawl in the surrounding 10 km buffer have been assessed using temporal remote sensing data of four decades and spatial metrics. The spatial characteristics of land use features were measured using spatial metrics to explain the physical characteristics, forms and pattern of the land use. The area under vegetation has declined from 70 % to 48 % with urbanization has increased from 1.46 % to about 18.5 %. The study has demonstrated that urban growth processes, patterns and structures can be quantified and monitored using a combination of remote sensing data, geo-informatics and spatial metrics through gradient approaches. The combination of remote sensing, landscape metrics and gradient analysis provides insights into the multidimensional phenomenon of urbanisation and of dispersed growth– factors essential for urban planning. The spatial metrics reveal a significant increase in number of urban patches in all directions and gradients during two decades, indicating landscape fragmentation post 2000. Patches at the city center are combining to form a single clumped dominant patch, whereas in outer gradients is more fragmented. The analysis of urban growth patterns emphasize the need for judicious land-use transformation, as well as the formulation of urban development policy with an emphasis on the sustainable utilization of natural resources.

Acknowledgments We are grateful to NRDMS Division, The Ministry of Science and Technology, Government of India; ISRO-IISc Space Technology Cell, Indian Institute of Science; Centre for *infrastructure*, Sustainable Transportation and Urban Planning (C*i*STUP), Indian Institute of Science for the financial and infrastructure support. Remote sensing data were downloaded from public domain (http://glcf.umiacs.umd.edu/data). We are also thankful to National Remote Sensing Centre, Hyderabad (http://nrsc.gov.in) for providing the latest data of IRS 1D.

References

Aguilera, F., Valenzuela, L., & Leitao, A. (2011). Landscape metrics in the analysis of urban land use patterns: a case study in a Spanish metropolitan area. *Landscape and Urban Planning, 99*, 226–238.

Alsharif, A. A. A., & Pradhan, B. (2013). Urban sprawl analysis of Tripoli metropolitan city (Libya) using remote sensing data and multivariate logistic regression model. *Journal of the Indian Society of Remote Sensing, 42*(1), 149–163.

Anindita, D., Kumar, U., & Ramachandra, T. V. (2010). Urban Landscape analysis through spatial metrics, In the proceedings of the Conference on Infrastructure, Sustainable Transportation and Urban Planning, C*I*STUP@CISTUP2010, JN Tata Auditorium, Indian Institute of Science, Bangalore. 18–20 October, 2010.

Arsanjani, J., Helbich, M. W., Kainz, & Darvishi, A. (2013). Integration of logistic regression, Markov chain and cellular automata models to simulate urban expansion - the case of Tehran. *International Journal of Applied Earth Observation and Geoinformation, 21*, 265–275.

Bhatta, B. (2009). Analysis of urban growth pattern using remote sensing and GIS: a case study of Kolkata, India. *International Journal of Remote Sensing, 30*, 4733–4746.

Bhatta, B. (2010). *Analysis of urban growth and sprawl from remote sensing data*. Berlin: Springer.

Brockerhoff, M. P. (2000). An urbanizing world. *Population Bulletin, 55*, 3–44.

Chang, C. Y. (2003). Landscape structure and bird's diversity in the rural areas of Taiwan. *Journal of Environmental Sciences, 15*, 241–248.

Civco, D. L., Hurd, J. D., Wilson, E. H., Arnold, C. L., & Prisloe, S. (2002). Quantifying and describing urbanizing landscapes in the northeast United States. *Photogrammetric Engineering and Remote Sensing, 68*, 1083–1090.

Clarke, K. C., & Gaydos, L. (1998). Loose-coupling a cellular automaton model and GIS: long-term urban growth prediction for San Francisco and Washington Baltimore. *International Journal of Geographical Information Science, 12*, 699–714.

Congalton, R. G., & Green, K. (2009). *Assessing the accuracy of remotely sensed data: Principles and practices*. Boca Raton: CRC Press Taylor & Francis Group.

Congalton, R. G., Oderwald, R. G., & Mead, R. A. (1983). Assessing Landsat classification accuracy using discrete multivariate analysis

statistical techniques. *Photogrammetric Engineering and Remote Sensing, 49*, 1671–1678.
Dessì, F. G., & Niang, A. J. (2008) Thematic mapping using quickbird multispectral imagery in Oung El-Jemel area, Tozeur (SW Tunisia). In *Desertification and risk analysis using high and medium resolution satellite data* (207–212) by Springer.
Dowall, D. E., & Monkkonen, P. (2008). Chennai urban land market assessment. *International Real Estate Review, 11*(2), 142–165.
Duda, R. O., Hart P. E., & Stork, D. G. (2000). *Pattern classification*, A Wiley-Interscience Publication, Second Edition, ISBN 9814-12-602-0.
Eastman, J. R. (2009). *IDRISI Taiga, guide to GIS and remote processing. Guide to GIS and remote processing*. Worcester: Clark University.
Epstein, J., Payne, K., & Kramer, E. (2002). Techniques for mapping suburban sprawl. *Photogrammetric Engineering and Remote Sensing, 68*, 913–918.
Guan, D. J., Gao, W. J., Watari, K., & Fukahori, H. (2008). Land use change of Kitakyushu based on landscape ecology and Markov model. *Journal of Geographical Sciences, 18*, 455–468.
He, C. Y., Okada, N., Zhang, Q. F., Shi, P. J., & Li, J. G. (2008). Modelling dynamic urban expansion processes incorporating a potential model with cellular automata. *Landscape and Urban Planning, 86*, 79–91.
He, J., Liu, Y., Yu, Y., Tang, W., Xiang, W., & Liu, D. (2013). A counterfactual scenario simulation approach for assessing the impact of farmland preservation policies on urban sprawl and food security in a major grain-producing area of China. *Applied Geography, 37*, 127–138.
Herold, M., Scepan, J., & Clarke, K. C. (2002). The use of remote sensing and landscape-metrics to describe structures and changes in urban land uses. *Environment and Planning, 34*, 1443–1458.
Herold, M., Goldstein, N., & Clarke, K. (2003a). The spatio-temporal form of urban growth: measurement, analysis and modeling. *Remote Sensing of Environment, 85*, 95–105.
Herold, M., Goldstein, N. C., & Clarke, K. C. (2003b). The spatiotemporal form of urban growth: measurement, analysis and modeling. *Remote Sensing of Environment, 86*, 286–302.
Herzog, F., & Lausch, A. (2001). Supplementing land-use statistics with landscape metrics: some methodological considerations. *Environmental Monitoring and Assessment, 72*, 37–50.
Jensen, J. R. (1986). *Introductory digital image processing, a remote sensing perspective*. Englewood Cliffs: Prentice-Hall.
Ji, W., Ma, J., Twibell, R. W., & Underhill, K. (2006). Characterizing urban sprawl using multi-stage remote sensing images and landscape metrics. *Computers, Environment and Urban Systems, 30*, 861–879.
Johnson, M. P. (2001). Environmental impacts of urban sprawl: a survey of the literature and proposed research agenda. *Environment & Planning A, 33*, 717–735.
Kumar, A., Pandey, A. C., Hoda, N., & Jeyaseelan, A. T. (2011a). Evaluating the long-term urban expansion of Ranchi Township. India using Geospatial Technology. *Journal of Indian Society of Remote Sensing, 39*(2), 213–124.
Kumar, A., Pandey, A. C., Hoda, N., & Jeyaseelan, A. T. (2011b). Evaluation of urban sprawl pattern in tribal dominated cities of Jharkhand State, India. *International Journal of Remote Sensing, 32*, 7651–7675.
Leitao, A. B., & Ahern, J. (2002). Applying landscape ecological concepts and metrics in sustainable landscape planning. *Landscape and Urban Planning, 59*, 65–93.
Lillesand, T. M., & Kiefer, R. W. (2002). Remote sensing and image interpretation, Fourth Edition (215–216). Wiley ISBN 9971-51-427-3.
Lu, D., & Weng, Q. (2007). A survey of image classification methods and techniques for improving classification performance. *International Journal of Remote Sensing, 28*, 823–870.
Matsuoka, M., Hayasaka, T., Fukushima, Y., & Honda, Y. (2004). Analysis of the land cover and its change over yellow river basin using satellite data. *The International Archives of the Photogrammetry Remote Sensing and Spatial Information Sciences, 35*, 836–839.
McGarigal, K., & Marks, B. J. (1995). FRAGSTATS: spatial pattern analysis program for quantifying landscape structure. USDA Forest Service General Technical Report PNW-351.
Mundia, C. N., & Murayama, Y. (2010). Modeling spatial processes of urban growth in African cities: a case study of Nairobi city. *Urban Geography, 31*, 259–272.
Nassauer, J. I., Corry, R. C., & Cruse, R. M. (1999). The landscape in 2025 alternative, future landscape scenarios: a means to consider agricultural policy. *Journal of Soil and Water Conservation, 57*, 44–53.
O'Neill, R. V., Ritters, K. H., Wichham, J. D., & Jones, K. B. (1999). Landscape pattern metrics and regional assessment. *Ecosystem Health, 5*, 225–233.
Opeyemi, Z. (2008). Monitoring the growth of settlements in Ilorin, Nigeria (a GIS and remote sensing approach). *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 37*, 225–232.
Pathan, S. K., Shukla, V. K., Patel, R. G., & Mehta, K. S. (1991). Urban land use mapping - A case study of Ahmedabad city and its environs. *Journal of the Indian Society of Remote Sensing, 19*(2), 95. **I 12**.
Praveen, S., Kabiraj, S., & Bina, T. (2013). Application of a hybrid cellular automaton – Markov (CA-Markov) Model in land-use change prediction: a case study of saddle creek drainage Basin, Florida. *Applied Ecology and Environmental Sciences, 1*(6), 126–132.
Rahman, Y., Kumar, S., Fazal, S., & Bhaskaran. (2011). Urbanization and quality of urban environment using remote sensing and GIS techniques in East Delhi-India. *Journal of Geographic Information System, 3*, 61–83.
Ramachandra, T. V., & Kumar, U. (2008). Wetlands of Greater Bangalore, India: automatic delineation through pattern classifiers. *Electronic Green Journal, 26*, https://escholarship.org/uc/item/3dp0q8f2#page-3
Ramachandra, T. V., Bharath, A. H., & Durgappa, D. S. (2012a). Insights to urban dynamics through landscape spatial pattern analysis. *International Journal of Applied Earth Observation and Geoinformation, 18*, 329–343.
Ramachandra, T. V., Bharath, A. H., & Sreekantha, S. (2012b). Spatial metrics based landscape structure and dynamics assessment for an emerging Indian Megalopolis. *International Journal of Advanced Research in Artificial Intelligence, 1*(1), 48–57.
Ramachandra, T. V., Bharath, H. A., Vinay, S., Kumar, U., & Joshi, N. V. (2013a).Modelling urban revolution in Greater Bangalore, India, In the proceedings of 30th Annual In-house Symposium on Space Science and Technology, 7–8 November 2013, ISRO-IISc Space Technology cell, Indian Institute of Science, Bangalore
Ramachandra, T. V., Bharath, A. H., & Sowmyashree, M. V. (2013b). Analysis of spatial patterns of urbanisation using geoinformatics and spatial metrics. *Theoretical and Empirical Researches in Urban Management, 8*(4), 5–24.
Ramachandra, T. V., Bharath, H. A., & Sowmyashree, M. V. (2014). Urban structure in Kolkata: metrics and modeling through geo-informatics. *Applied Geomatics, 6*(4), 229–244.
Ramachandra, T. V., Bharath, H. A., & Shreejith, K. (2015a). GHG footprint of major cities in India. *Renewable and Sustainable Energy Reviews, 44*, 473–495.
Ramachandra, T. V., Bharath, H. A., & Sowmyashree, M. V. (2015b). Monitoring urbanization and its implications in a mega city from space: spatiotemporal patterns and its indicators. *Journal of Environmental Management, 148*, 67–91.

Setturu, B., Bharath, H. A., Durgappa, D. S., & Ramachandra, T. V. (2012). Landscape dynamics through spatial metrics, Proceedings of India GeoSpatial Conference, Epicentre, Gurgaon, India, 7–9 February, 2012.

Sharma, R., & Joshi, P. K. (2013). Monitoring urban landscape dynamics over Delhi (India) using remote sensing (1998–2011) inputs. *Journal of the Indian Society of Remote Sensing, 41*(3), 641–650.

Singh, A. (1989). Digital change detection techniques using remotely sensed data. *International Journal of Remote Sensing, 10*, 989–1003.

Sudhira, H. S., Ramachandra, T. V., & Jagdish, K. S. (2004). Urban sprawl: metrics, dynamics and modelling using GIS. *International Journal of Applied Earth Observation and Geoinformation, 5*(1), 29–39.

Torrens, P. M. (2000). How cellular models of urban systems work, CASA Centre for Advanced Spatial Analysis, University College London, Working paper 28, URL http://www.casa.ucl.ac.uk/working_papers/paper28.pdf (accessed 15th May 2015)

Weber, C. (2001). Remote sensing data used for urban agglomeration delimitation. In J. P. Donnay, M. J. Barnsley, & P. A. Longley (Eds.), *Remote sensing and urban analysis* (pp. 155–167). London: Taylor and Francis.

Wentz, E. A., Anderson, S., Fragkias, M., Netzband, M., Mesev, V., Myint, S. W., Quattrochi, D., Rahman, A., & Seto, K. C. (2014). Supporting global environmental change research: a review of trends and knowledge gaps in urban remote sensing. *Remote Sensing, 6*(5), 3879–3905.

Yang, X., Ren, L., Yong, B., & Jiao, D. (2008). Remote sensing-based land use and land cover change in Shalamulun catchment. *IEEE Computer Society, 2*, 504–507.

Yorke, C., & Margai, F. (2007). Monitoring land use change in the Densu river basin, Ghana using GIS and remote sensing. *African Geographical Review, 26*, 87–110.