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Modelling the growth of two rapidly urbanizing Indian cities

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Abstract: Sustainable urban planning requires an understanding of the spatial and temporal patterns of urbanization with insights to the sprawl. Indian cities have been experiencing a rapid urbanization consequent to globalization and relaxations in market economy during the past three decades. This has posed challenges to the policy makers and necessitated appropriate urban policies taking into account sensitiveness of a region and dynamic changes. Availability of remote sensing data at regular intervals with Geo-informatics has proved to be highly efficient in identifying, measuring and quantifying spatio-temporal patterns of urban growth. This communication quantifies the changes in two rapidly urbanizing landscapes in India. This involved analysis of (i) land cover and land use changes, (ii) spatial patterns of urbanisation through zone wise density gradients. Tier I cities namely Hyderabad and Chennai, emerging IT giants in India were chosen for the analysis. Computation of Shannon's entropy and spatial metrics aided in assessing the sprawl and spatial patterns of urbanisation in a landscape. Modelling and prediction of likely changes in the land use was done using an integrated approach with fuzzy, analytical hierarchical process (AHP), cellular automata (CA) and Markov chain. Results of land use analysis revealed an increase in urban area from1.46% (1991) to 18.81% (2013) for Chennai region and 1.75% (1989) to 22.19% (2014) for Hyderabad region. The spatial analysis through prioritized eight metrics reveal a fragmented or dispersed growth in the outskirts and compact growth in the core area. Modelling was performed considering a set of agents and constraints with two scenarios- implementation of city development plan (CDP) and without CDP. Modelling of urban growth in 2025 reveals urbanized landscapes of 36.6% and 51% in Chennai and Hyderabad respectively. Periphery of the major roads and outside the city jurisdiction limits are favorable areas of urban growth with land use changes from agriculture or others category to built-up category. Modelling and visualisation of urban growth equip regional decision making to provide basic amenities and appropriate infrastructure considering the likely demand with urbanisation.

Keywords: Urbanisation, Cellular automata, Markov chain, AHP, Fuzzy

1. Introduction

Urban growth is a form of metropolitan growth occurs when local patches of settlement agglomerate in response to various economic, social, and political forces and to the physical geography of an area. Urban area constitute predominantly of built up or paved surfaces with transitions from forest patch, agricultural fields or rural landscapes (Dupont, 2005). Earlier civilizations consisted of small colonies adjacent to rivers. This eventually led to the formation of villages, towns, cities and at present many are settled in complex urban ecosystems also reflected by population growth. Thus urban areas are formed through progressive concentration of population. Statistics indicate that today 54% of the global population and 34.16% of Indian population reside in urban areas (World Urban Prospects, 2014). Urban areas are expected to house 40% of India's population with increasing urbanisation trend, which is expected to contribute to 75% of India's GDP with serious erosion in food production by 2030.

Unplanned urbanisation has impacted on the regional environment evident from fragmentation of natural landscape due to changes in landscape patterns with a complex irreversible socio-economic phenomenon (Jat et al., 2008; Bharath et al., 2012). Unprecedented and irreversible urban growth and concentration of urban region in the city core, has led to escalation in land prices leading to sprawl in peri-urban regions across the city boundary. The buffer region or zone of transition exists between a rural landscape and urban pockets (Pryor, 1968). Prior visualization of this dynamic zone of rural-urban continuum aid in the effective decision making. Sprawl thus refers to dispersed or the scattering of new developments on isolated tracts, separated from other land uses

(Ottensmann, 1977). Also referred as the pattern of low-density expansion near urban areas, mainly into the surrounding rural regions having urban rural transitions. Urbanisation in these regions are patchy, scattered and strung out, with discontinuity and lack basic amenities such as treated water, sanitation, etc., These kind of unplanned growth have a tendency of attenuating natural resources as a consequence of large land use change (conversion of green lands, water bodies etc.) affecting directly on human health and quality of life (Alberti, 2005; Ramachandra et al., 2009). Government agencies and planners often neglect rural-urban transition land which leads to unsustainable development. Sprawl regions in most metropolitan regions have been posing serious challenges with respect to electricity, water, sanitation, waste management and other basic amenities, necessitating prior visualization of spatial patterns of urban growth. Agents of urban growth are geography of a region, economic progression, population growth and migration, industrialization, transportation, way of living etc. (Barnes et al., 2001; Yang and Lo, 2003; Bruckner and Kim, 2003).

The growth of Indian urban centers in an unprecedented rate has often led to deterioration of balance in natural ecology, while impacting ambient environment due to spurt in greenhouse gas (GHG) emissions, leading to global warming and consequents changes in the climate (Ramachandra and Kumar, 2010; Ramachandra et al., 2015). Unplanned urbanisation is resulting in urban sprawl with escalated vehicle and traffic density (Ewing et al. 2002), impacts on the biodiversity, environment and ecosystem (Xian et al., 2007; Li et al., 2010), land use fragmentation, human-animal conflicts (Hotton, 2001) and most importantly the rapid changes in hydrological cycle with changing rainfall patterns and flooding regimes (McCuen et al., 2003). Mitigation of the consequences of climate change and environmental degradation necessitates an understanding of spatial patterns of urbanisation, quantification and visualization of urban growth and sprawl.

Sustainability of natural resources entails planning and stewardship in management by the government and other agencies considering population growth and urban expansion. This is possible only with the inventorying, mapping and monitoring of urbanisation process through land use and land cover dynamics analysis (Ramachandra et al., 2013). Recent advancements in remote sensing technologies and Geoinfomatics have further boosted efforts to analyze growth (Bharath S, et al., 2012; Ramachandra et al., 2014a). Space borne sensors assists in inventorying, mapping and monitoring earth resources. Geographic Information System (GIS) aids in capture, store, query, analyze and display geo-spatial data (Chang, 2006). Remote sensing is cost effective and technologically reliable, and is therefore, increasingly being used for urban sprawl analysis (Bharath, H.A. et al., 2014; Ramachandra et al., 2014; Vishwanatha et al., 2015). Availability of temporal data acquired through space borne sensors drives remote sensing techniques better for its ability to characterize spatiotemporal trends of urban sprawl that forms a basis for projecting future urbanization processes.

Spatial metrics aid in assessing the spatial patterns of urbanisation through spatial heterogeneity of patches, classes of patches, or entire landscape mosaics of a geographic area (O'Neill et al., 1988, Herold et al., 2005). There are numerous metrics to quantify spatial patterns and the selection of spatial metrics depends upon the study region (Irwin and Bockstael, 2007; Furberg and Ban, 2012) and earlier studies (Wu, 2006; Hepinstall-Cymerman et al., 2013). Zone wise (based on directions), gradient analysis of a particular region helps in viewing the growth scenario at micro scale and also helps to identify drivers or catalysts of urbanisation. Gradient analysis, earlier implemented to analyze vegetation (Whittaker, 1975), has been used to study the effects of urbanisation on plant distribution (Kowarik, 1990; Sukopp, 1998), green spaces (Kong and Nakagoshi, 2006) and ecosystem properties (Zhu and Carreiro, 1999). This communication focuses on combining temporal remote sensing data, GIS with spatial metrics analyses along density gradients helps to understand urban land-use changes at local levels.

Prediction of likely land uses is essential to provide vital inputs for urban planning, which will help to ensure sustainability and balance in the natural ecosystem. Modelling refers to the data acquired to calibrate, validate, verify and predict future urban trends (Batty, 1997, 1998). Various models available for analyzing urban growth based on allocation of different land use activities within a region are cellular automata (CA), Markov chain, analytical hierarchical process (AHP), slope, land use, exclusion, urban extent, transportation and hill shade (SLEUTH), artificial neural network (ANN) and decision making tool such as multi criteria evaluation (MCE).

Recently, the Government of India (GoI) has embarked on 'Smart City' concept to boost economy, infrastructure and improve quality of living in emerging urban regions in India. The objective needs to be towards enabling E-governance for efficient management of natural resources, including urban mobility and housing, waste management, etc. to ensure sustainability at the same time maintaining ecological balance. GoI programme of 100 smart cities (Smart cities, 2015) includes Chennai and Greater Hyderabad, two rapidly growing metropolitan cities. Chennai also figures in one among 35 global mega cities (population greater than 10 million people). Advance visualisation of urban growth help in this regard to identify growth poles and provide appropriate infrastructure and basic amenities. Models based on CA and Markov chain aided by analytical hierarchal process (AHP) and fuzzy to account agents with the weightages of influences. This involved estimation of Eigen vectors or priority vectors followed by measure of consistency using consistency ratio (Khwanruthai and Yuji, 2011). Decision support tool MCE is adapted to evaluate choice between alternative factors. This process is necessary for CA models to generate site suitability maps for future land use predictions. CA is a discrete two dimensional dynamic systems with local interactions among components generate global changes in space and time (Wolfram, 2002). CA follows a “Bottom-up” approach, in which the future state of the pixel depends on its past and current state with a set of specified transition rules. Finally, CA-Markov chain analysis provides the transition probability matrix and transition area matrix. CA are thus not just a framework for dynamic spatial modelling but provide insights about complex spatial-temporal phenomena and constitute an experimental laboratory for testing ideas. Predication of urban dynamics using CA model is flexible due to easy integration with GIS (Wagner, 1997). CA has been adopted earlier to simulate land use changes (Lau and Kam, 2005; Stevens and Dragicevic, 2007) and also by considering spatial agents (Loibl and Toetzer, 2003), transition rules (Almeida et al. 2005), neighborhood functions (White and Engelen, 2000; Yuzer, 2004) and mapping urban and non-urban states (Cheng and Masser, 2004; He et al. 2006; Li et al. 2008). CA coupled with Markov chain helped to demonstrate quantify the states of conversion between land-use types, especially from forest, agriculture, wetland and other landuse categories to urban landuse (Mukunda et al. 2012; Praveen et al. 2013; Hossein and Marco, 2013).

The main objectives of this research are (i) quantify urbanization and urban sprawl process with the help of temporal remote sensing data, density gradient and spatial metrics and (ii) predict land use dynamics in 2025 for Chennai and Hyderabad through an integrated modelling framework considering geographic, topographic and socio-economic factors.

2. Study area and data

Chennai is capital city of Tamilnadu state, India. It is located between two major rivers i.e. Coovum and Adayar and at the eastern coast - Coromandel Coast line also known popularly as “Gateway to South India”. Chennai is known as “Detroit of India” due to the presence of a wide array of automobile industries. Chennai has tropical wet and dry climate with temperatures ranging from 15˚- 40˚C. The jurisdiction of the Chennai (city) Corporation was expanded from 174 sq. km (2001) to 426 sq.km in 2011. Chennai Metropolitan Area (CMA) has an area of 1189 km2 comprising Chennai city district and partially extending to two districts Kancheepuram and Tiruvallur. Chennai is presently fourth most populous city in India with 4.68 million (2011), whereas CMA population shows an increase of 1.86 million considering 2001 and 2011 census.

Hyderabad is a capital of Telangana state and Andhra Pradesh (after partition in 2014). The city is located along the banks of river Musi and surrounded by many lakes like Himayat Sagar, Hussain Sagar, etc. It has very old history since 1500’s under Nizam’s rule. Hyderabad is the largest contributor to the gross domestic product. With creation of special economic zones at Gachibowli, Pocharam, Manikonda etc. dedicated to have encouraged companies from across India and around the world to set up operations. Erstwhile Hyderabad urban development authority (HUDA) was expanded in 2008 to form Hyderabad metropolitan area (HMA) covering 7100 km2 and population of 7.74 million (2011). HMA covers a total of 5 districts namely Hyderabad, Rangareddy, Medak, Mehaboobnagar and Nalgonda. Chennai and Hyderabad are at the verge of attaining “Mega city” status (urban agglomerations greater than10 million inhabitants), while India already has 3 mega cities namely Mumbai, Delhi and Kolkata (United Nations, 2012).

The geographical bounds of the two study cities are given in table 1.

Table 1: Geographical extents of Chennai and Hyderabad metropolitan area

City	Latitude values (N)		Longitude values (E)	
Chennai	12˚51’04’’	13˚17’29’’	79˚59’45’’	80˚20’16’’
Hyderabad	17˚12’51’’	17˚42’26’’	78˚12’34’’	78˚45’29’’

3. Data acquisition

Temporal data of Landsat 5 (TM), Landsat 7 (ETM+) and Landsat 8 (OLI-TIRS) satellites were downloaded from the public archive of USGS Earth Explorer. IRS LISS-III data was procured from the National Remote Sensing Centre (NRSC) for the year 2012. A circular buffer zone of 10 km from an administrative boundary (centroid as central business district) as in figure 1 was considered to account for likely growth or sprawl at outskirts or peri-urban regions. Data used land cover and land use analyses and for transition rules are listed in table 2.

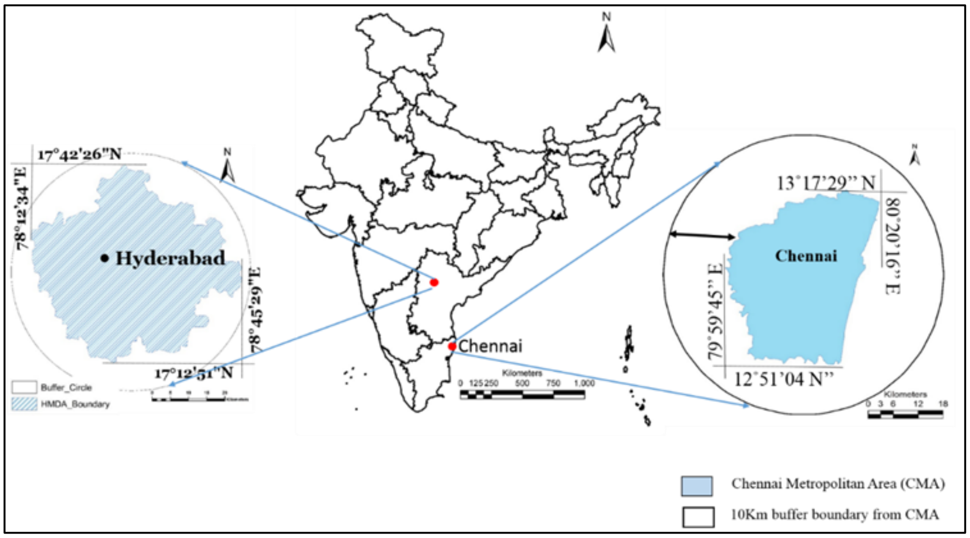

Figure 1: Location of Chennai and Hyderabad

Table 2: Data used for the analysis

DATA	YEAR	PURPOSE
Landsat 5 TM (30m)	1989,1991 and 1999	Land use and land cover analysis
Landsat 7 ETM+ (30m)	2000 and 2009	
Landsat 8 OLI-TIRS (30m)	2013 and 2014	
IRS LISS-III (23.5m)	2012	
Aster GDEM	2010	Extraction of drainage lines, slope analysis
Google earth		Geo-correction, classification and validation. Collection of point, line and polygon data
Boundary maps and raster layers		To create agents and constraints data sets based on city development plans
Survey of India Topographic maps, online portals (Google and Bhuvan data)		Base layers of the administrative boundary
Field data – using GPS		Geo-correction, training data and validation data

4. Method

Preprocessing: This involved geo-referencing of data, done with the help of known location points (compiled from the Survey of India topographic maps and also from field using pre-calibrated GPS – Global Positioning System). Remote sensing data were cropped corresponding to study regions with ten km buffer. Co-ordinates of known locations such as road intersections, edges of huge permanent structures like dams, bridges etc. were compiled using GPS and online high resolution data (Google-earth) at inaccessible places. Further, resampling was performed to maintain the spatial resolution uniformity across temporal remote sensing data. Histogram equalization was performed wherever enhancement was necessary to maintain the dynamic range. Landsat and IRS LISS-III images were co-registered to WGS 1984 and UTM zone 44.

Land cover analysis: Land cover refers to the original earth surface features that are formed naturally in the form of vegetation, water body, etc. (Ramachandra et. al., 2013). Land cover analysis helps to understand the changes of the vegetation cover over the study area at different time periods. It is obtained by performing normalized difference vegetation index (NDVI). NDVI value ranges from -1 to +1. Values consisting of -0.1 and below indicates soil, barren land, rocky outcrops, built up/urban cover, whereas water bodies are indicated by zero values. Low density vegetation is indicated in the range +0.1 to +0.3 while high density vegetation or thick forest canopy is given in the range +0.6 to +0.8.

Land use analysis: Land use analysis starts with generation of false colour composite (FCC)of 3 bands (Green, Red and NIR). Creation of FCC directly helps in identifying heterogeneous patches in the landscape (Ramachandra et al., 2014). Training polygons are digitized based on the distinguishable heterogeneous features in FCC, covering at least 15% and uniformly distributed across the entire study area. These polygons and its coordinates with GPS and attribute information is compiled with respect to corresponding land use type (ground truth data). Training polygons were supplemented with the data available at Google earth for classification. 60% of these training polygons were used for classification purpose while the rest 40% for validation and accuracy assessment. Supervised Gaussian maximum likelihood classification (GMLC) was employed to assess quantitatively land uses in the region. GMLC algorithm considers cost functions as well as probability density functions and proved to be efficient among other classifiers (Duda et al., 2000). It evaluates both variance and co-variance of the category while classifying an unknown pixel (Lillesand et al., 2012). Land use classification under four categories (table 3) using GRASS.

Accuracy assessment: Possible errors during spectral classification are assessed by a set of reference pixels collected by ground data collection. Based on the reference pixels, statistical assessment of classifier performance including confusion matrix, kappa (κ) statistics and producer and user's accuracies were calculated. These accuracies relate solely to the performance of spectral classification. Entire method followed has been summarized in figure 2.

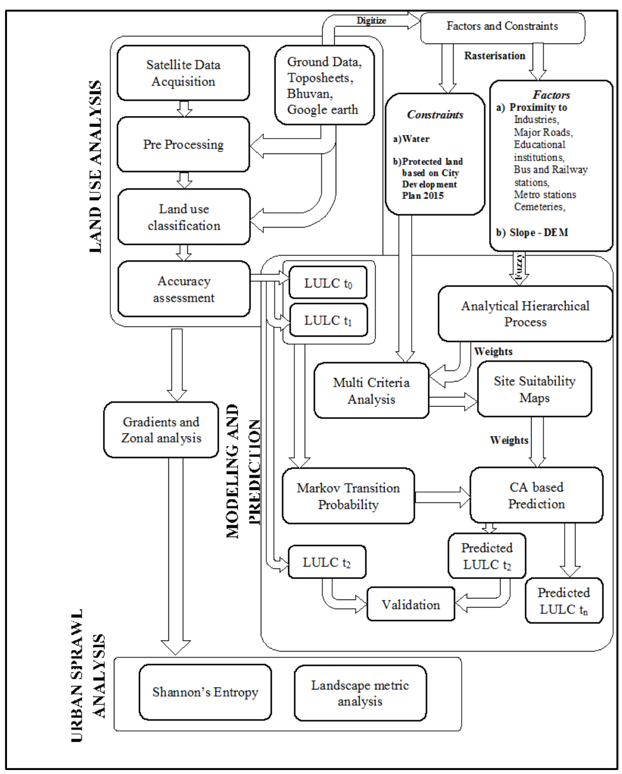

Figure 2: Method adopted to understand, quantify and model urban growth

Table 3: Land use categories

Category	Features involved
Builtup	Houses, buildings, road features, paved surfaces etc.
Vegetation	Trees, gardens and forest
Water body	Sea, lakes, tanks, river and estuaries
Others	Fallow/barren land, open fields, quarry site, dry river/lake basin etc.

Density gradient and zonal analysis: Earlier investigations of spatial patterns of urbanisation were restricted to political boundaries (Taubenbock et al., 2009; Deng et al., 2009; Sadhana et al., 2011). In order to understand the growth at local levels, specific to neighborhood, the entire study area was divided based on directions into four zones (i.e. North East (NE), North West (NW), South East (SE) and South West (SW) and concentric circle with the central business district as centroid and incrementing radii of 1km. The zone wise concentric circle based analyses was performed helped to interpret, quantify and visualize forms of urban sprawl pattern (low density, ribbon, leaf-frog development) and agents responsible in urbanization at local levels spatially (Ramachandra et al., 2014b).

Spatial patter analysis: Shannon's entropy (Hn) is computed (equation 1) to determine whether the growth of urban areas is compact or dispersed growth. Dispersed growth is also known as 'urban sprawl' This analyses gives a better understanding of degree of spatial concentration or dispersion of geographical variables among "n" concentric circles across four direction zones. Also, the regions undergoing sprawl needs decision makers' attention to provide appropriate infrastructure and adequate basic amenities.

$$H_n = -\sum_{i=1}^{n} P_i \log (P_i) \quad \ldots\ldots\ldots\ldots\ldots \quad (1)$$

where, Pi is the proportion of the built-up in the ith concentric circle. Shannon's Entropy, values ranges from 0 to log n. 0 if the distribution is maximally concentrated whereas log n indicates sprawl.

Spatial metrics: Metrics pertaining to spatial heterogeneity of patches, classes of patches, or entire landscape mosaics of a geographic area (O'Neill et al., 1988, Herold et al., 2005) give quantitative description based on the composition and configuration of the urban pixels in a landscape. Spatial metrics were computed for urban class through FRAGSTATS (McGarigal and Marks, 1995) for each zone and density gradients. Table 4 lists prioritized (based on our earlier work (Ramachandra et al., 2012, Ramachandra et al., 2015) six metrics to characterize urban growth.

Modelling: Urban growth during 2025 is predicted considering agents with constraints (listed in table 5) and base layers of historical land uses (based on the classified temporal remote sensing data). Data values were normalized (between 0 and 255) through fuzzyfication wherein 255 indicates maximum probability of land use 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 are to be <0.1 for the consistency matrix to be acceptable (Saaty, 1980).

Constraints were assigned considering city development plan (CDP), Digital elevation model and slope data. Drainage lines were delineated using ASTER DEM and a buffer of 30m from drains were assigned constraint to restrict development as per the guidelines of the regional metropolitan development authority. Constraints and factors were fed to multi criteria evaluation (MCE) (Table 5). The MCE approach combines various criteria into a single index that indicates the site suitability of specific land use of each location in the study area. Markovian transition estimator provided bi-temporal land use data to estimate transition and predict future likely land uses. Probability distribution map was developed through Markov process. First-order Markov model based on probability distribution over next state of the current cell that is assumed to only depend on current state. CA was used to obtain a spatial context and distribution map. Transition suitability areas and matrix, iterations to be performed and filter stipulations are carried out by CA coupled with Markov chain to predict future land use. Validation of predicated data was done by comparing reference (classified) image versus the predicted image for the same year (in this case 2014). Various kappa indices of agreement and related statistics were calculated. Further, Land use is predicted for 2025.

Table 4: Spatial metrics used

	Indicators	formula	Range
1	Number of patches-NP	NP = n (no. of patches in landscape)	NP>0
2	Normalised landscape shape index-NLSI	NLSI = $\frac{\text{ei} - \text{min ei}}{\text{max ei} - \text{min ei}}$ e_i= total length of edge (or perimeter) of class i in terms of number of cell surfaces; includes all landscape boundary and background edge segments involving class i. min e_i = minimum total length of edge. Maximum e_i = maximum total length of edge.	$0 \leq \text{NLSI} \leq 1$
3	Clumpiness-CLUMPY	$\frac{\text{Gi}-\text{Pi}}{\text{Pi}}$ for $G_i<P_i$ and $P_i<5$; else $$\frac{\text{Gi}-\text{Pi}}{1-\text{Pi}}$$ where, $G_i = \frac{\text{gii}}{(\sum_{k=1}^{m} gik) - \text{min } ei}$ g_{ii}= number of like adjacencies between pixels of patch type (class) i based on double count method. g_{ik}=number of like adjacencies between pixels of patch type (class) i and k based on double count method. min ei=minimum perimeter of patch type (class) i for maximally clumped class. Pi= proportion of the landscape occupied by patch type (class) i.	$-1 \leq \text{CLUMPY} \leq 1$
4	Aggregation index – AI	$$AI = \left[\sum_{i=1}^{m}\left(\frac{g_{ii}}{\max \to g_{ii}}\right)P_i\right](100)$$ g_{ii}=number of like adjacencies between pixels of patch type P_i=proportion of landscape comprised of patch type	$0 \leq \text{AI} \leq 100$
5	Largest patch index – LPI	LPI = $\frac{\max aij}{A} * (100)$ Where, a_{ij}=area (m^2) of patch ij. A=total landscape area (m^2).	$0 < \text{LPI} \leq 100$
6	Interspersion and Juxtaposition – IJI	$$IJI = \frac{-\sum_{i=1}^{m}\sum_{k=i+1}^{m}\left[\left(\frac{e_{ik}}{E}\right).\ln\left(\frac{e_{ik}}{E}\right)\right]}{\ln\left(0.5\left[m(m-1)\right]\right)}(100)$$ eik=total length (m) of edge in landscape between patch types (classes) i and k. E: total length (m) of edge in landscape, excluding background . m=number of patch types (classes) present in the landscape, including the landscape border.	$0 \leq \text{IJI} \leq 100$

Table 5: 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, regulated regions for non-development, Protected areas, coastal regulated areas, sensitive regions in a catchment, etc.

5. Results and discussion

Land cover analysis: This analysis helps in delineating regions under vegetation and non-vegetation. Vegetation cover analysis was done through NDVI. Figure 3, 4 and table 6 indicates the land cover changes of different time periods for Chennai and Hyderabad regions respectively. In Chennai, vegetation cover has dramatically decreased from 70.47% (1991), to 35.53% in 2013, whereas the non- vegetation i.e. built up, paved areas, bare soil etc. have increased 29.53% in 1991 to 64.47% in 2013. Hyderabad also shows similar trend with decrease in vegetation from 95.64% (1989), 93.28% (1999), 82.67% (2009) and 61.15% (2014). Land use analyses was performed to understand the transitions across land use categories like built up, forests, water bodies, etc., Vegetation cover and water bodies aids in moderating local climate and also help in mitigating floods, etc.

Land use analysis and Accuracy assessment: Figure 5 and 6 represents land use dynamics for the study regions during the past four decades. Results revealed the steep increase of 72% in built up areas in Chennai at Ponneri, Pattabiram, Sriperumbudur, Tambaram, etc. during 1991-2000 and 646% during 2000-2013. Areas such as Malakpet, Madapur, Bollaram, Kukkatpally, Cherlapally, etc. Hyderabad showed an increase in built-up area by 93% during1989-1999, 319% (during 1999-2009) and 56% (2009-2014). It is important to notice that both the study regions show significant increase during the years 2000-2010 with emergence of various industrial sectors such as automobile, hardware manufacturing as well as information technology parks. Others category (mainly open spaces) has consistently reduced from 69.5% to 50.5% (1991-2013) in Chennai and 90.5% to 72.6% (1989-2014) in Hyderabad region indicating a large scale conversion to urban land use type. Water bodies of Hyderabad shows a very critical decrease which indicates either these land uses are converted or they have been dried up. Decline from 3.75% to 1.84% during 1989-2014, highlight the grave situation in the region and the need to restore and rejuvenate water bodies which aid as a lifeline of the society. Table 7 summarizes the land use details for Chennai and Hyderabad respectively.

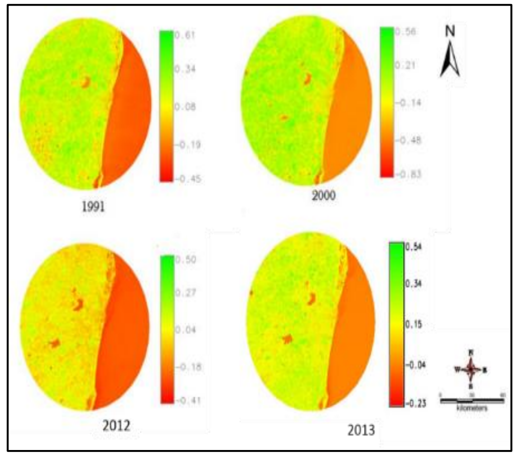

Figure 3: Land cover changes 1991-2013, Chennai region

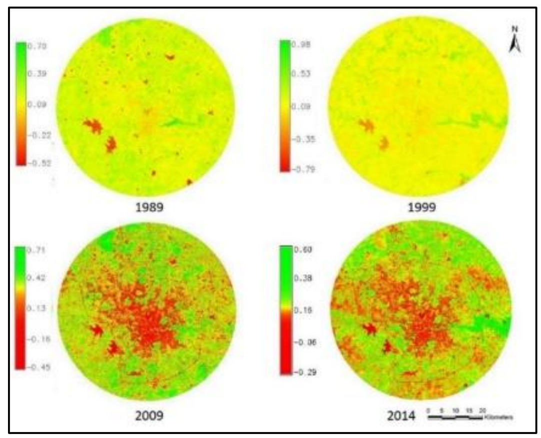

Figure 4: Land cover changes during 1989-2014 in Hyderabad region

Table 6: Temporal land cover details for Chennai and Hyderabad

CHENNAI			HYDERABAD		
Year	**Vegetation (%)**	**Non-Vegetation (%)**	**Year**	**Vegetation (%)**	**Non-Vegetation (%)**
1991	70.47	29.5	1989	95.64	4.36
2000	56.7	43.27	1999	93.28	6.72
2012	48.18	51.85	2009	82.67	17.4
2013	35.53	64.47	2014	61.15	38.85

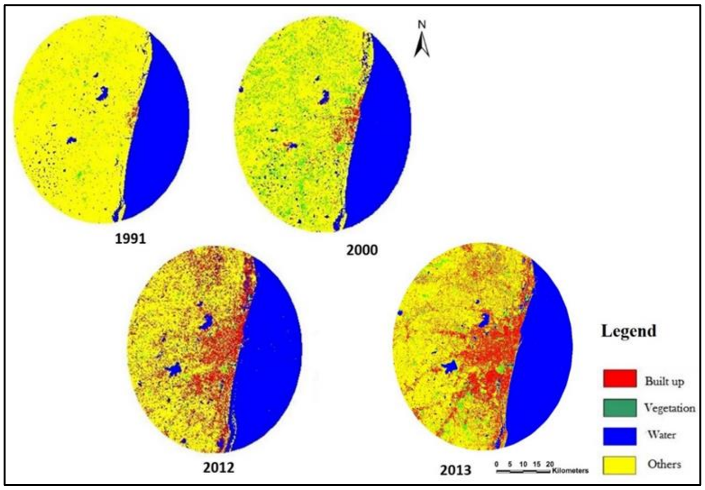

Figure 5: Land use dynamics during 1991 to 2013 in Chennai metropolitan area

Table 7: Land use dynamics in Chennai and Hyderabad

	Chennai					Hyderabad				
Year	**1991**	**2000**	**2012**	**2013**	**2016**	**1989**	**1999**	**2009**	**2014**	**2016**
Urban	1.46	2.52	18.55	18.81	22	1.75	3.39	14.21	22.19	24.18
Vegetation	1.38	0.8	1.51	2.76	1.83	4	3.53	3.83	3.38	2.43
Water	27.64	27.25	28.15	27.92	28.34	3.75	2.89	2.46	1.84	0.64
Others	69.52	68.35	51.38	50.51	47.83	90.5	90.19	79.5	72.59	72.76

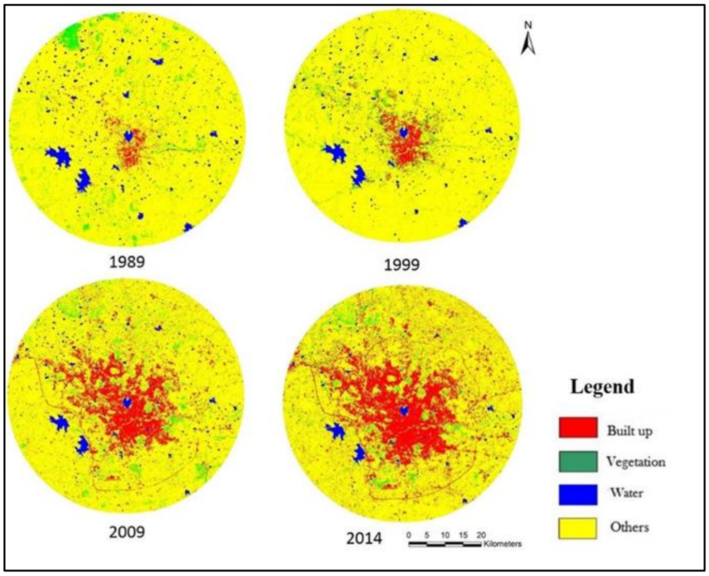

Figure 6: Land use dynamics in Hyderabad

Table 8 lists overall accuracy and Kappa statistic for land use classified information for Chennai and Hyderabad. Overall accuracy for Chennai varied from 86% to 97% and for Hyderabad 87% to 94% highlights the agreement of classified information with the field data.

Table 8: Accuracy assessment of Chennai and Hyderabad regions

CHENNAI			HYDERABAD		
Year	**Overall Accuracy (%)**	**Kappa**	**Year**	**Overall Accuracy (%)**	**Kappa**
1991	92	0.92	1989	94	0.73
2000	91	0.9	1999	87	0.85
2012	97	0.93	2009	90	0.90
2013	86	0.78	2014	91	0.76

Urban sprawl analysis: Shannon's entropy is calculated direction wise considering the proportion of built-up/paved urban area in the gradient and results are listed in table 9. Shannon's entropy values ranges from 0 (concentrated growth) and log n (dispersed growth or sprawl). 'n' indicates the number of circles /gradients in the respective direction. Analysis highlights the tendency of urban sprawl during 2000 and 2012 for Chennai and 2009 and 2014 for Hyderabad. Higher entropy values of 0.444 (NE), 0.396 (NW), 0.409 (SE) for Chennai and 0.442 (SW); 0.352(NE), 0.422 (NW), 0.444 (SE) and 0.355 (SW) in for Hyderabad shows of dispersed growth. The sprawl phenomenon is evident in figures 5 and 7.

Quantifying spatial patterns of urbanization through metrics: Six metrics were computed using FRAGSTATS for each gradient, zone wise to understand the spatial patterns of urban growth.

- Number of patch (NP): Figures 7 and 8 gives NP for Chennai and Hyderabad. Patches shows rapid growth in all the directions pointing out fragmentation during 2009, 2012, 2013 and 2014. During 2013 and 2014, core city area (circles 1-9 in Chennai and circles 1-11 in Hyderabad), each patch has agglomerated into a single large urban patch i.e. there is a saturated urban landscape with no other land uses (Egmore, Nugambakkam in Chennai and Abids, Secunderabad, Narayanaguda, Somajiguda, etc. in Hyderabad). Sprawl is evident with higher number of patches in NW, SW directions (Chennai) and NE, SE, SW directions (Hyderabad).

- Normalized landscape shape index (NLSI): This metrics provides measure of class aggregation. All four zones show lesser value of NLSI in 2013 and 2014 compared to 1991 and 1989 (reflected in figures 9 and 10 for Chennai and Hyderabad). The minimum values (NLSI < 0.5) especially in CBD areas (such as Ambattur, Nungambakkam, Sowcarpet, Egmore, in Chennai region and also Nampally, Secunderabad, Medhipatnam etc. in Hyderabad region) indicates that the landscape consists of a single square urban patch or it is maximally compact (i.e., almost square) in contrast with the higher values in 1991 and 1989 (NLSI ≈ 1, specifying maximally disaggregated urban patches with complex shapes.

- Clumpiness: This metric indicates the aggregation and disaggregation for adjacent urban patches. Figures 11 and 12 show the values closer to 0 for the regions corresponding to circles 25-35, in NE direction (Manali new town, Ennore and SW direction includes Irungattukottai, Kondavakkam) of Chennai and the regions corresponding to circles 23-31, in NE, SE and SW directions (Keesara Mandal, Rampally, Manneguda, Shankarpally) in Hyderabad, highlighting less compact growth or maximal disaggregation. In 2012 and 2014 values, approaching +1 in core city areas (circles 1-15) of all directions indicate of very complex growth with all maximally aggregated patches forming large urban monotype patch.

Table 9: Year wise Shannon's entropy values for the two cities

CHENNAI					HYDERABAD				
Year/Direction	**NE**	**NW**	**SE**	**SW**	**Year/Direction**	**NE**	**NW**	**SE**	**SW**
1991	0.052	0.041	0.078	0.048	1989	0.029	0.046	0.081	0.055
2000	0.116	0.108	0.107	0.118	1999	0.034	0.052	0.106	0.096
2012	0.423	0.468	0.416	0.473	2009	0.249	0.326	0.354	0.321
2013	0.444	0.396	0.409	0.442	2014	0.352	0.422	0.444	0.355
Threshold limit = log 37 = 1.568					Threshold limit = log 33 = 1.518				

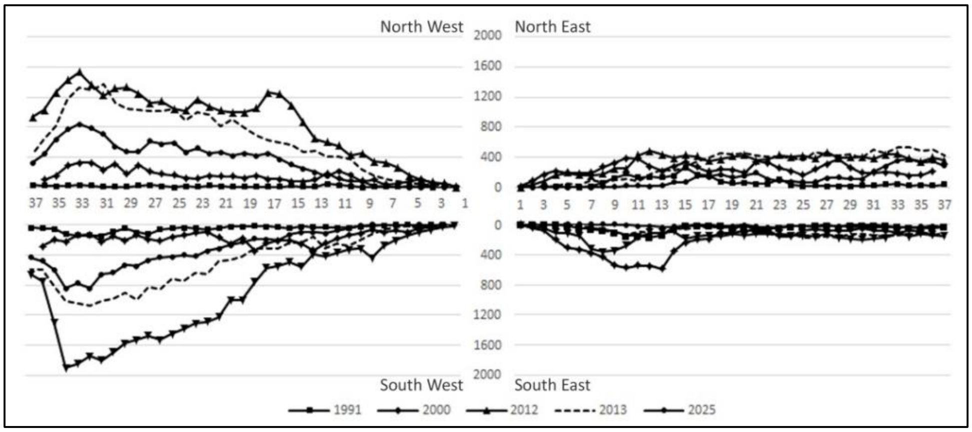

Figure 7: Number of patch metrics for Chennai

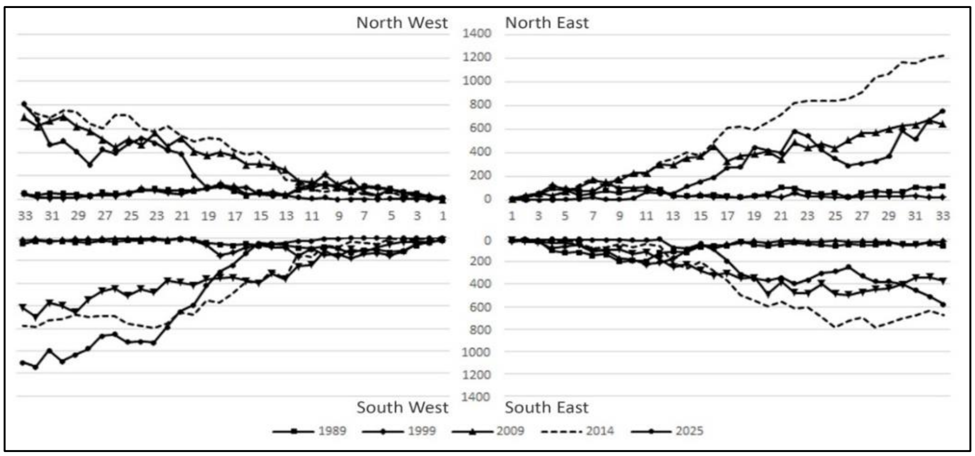

Figure 8: Number of patch metrics for Hyderabad

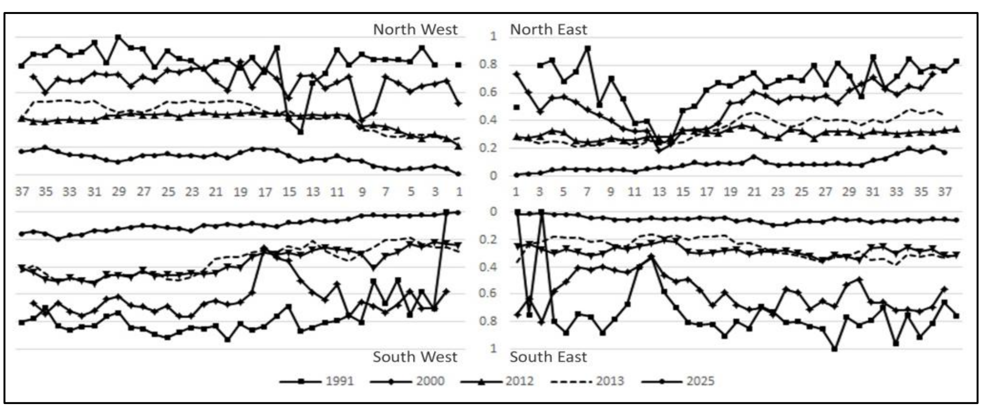

Figure 9: NLSI metrics for Chennai

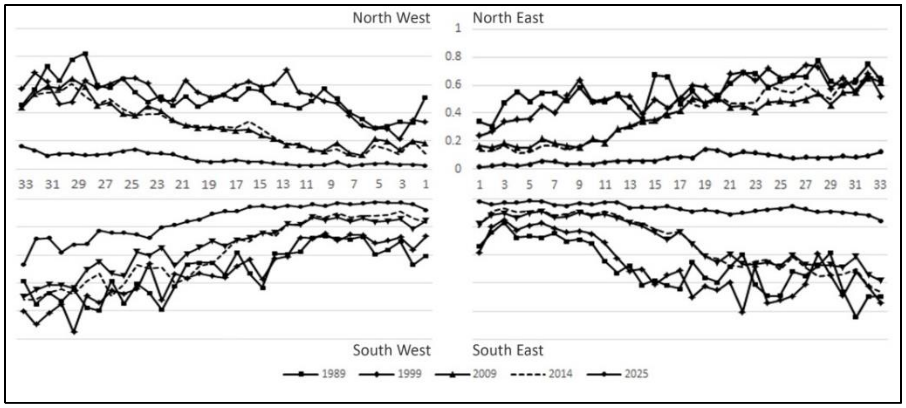

Figure 10: NLSI metrics for Hyderabad

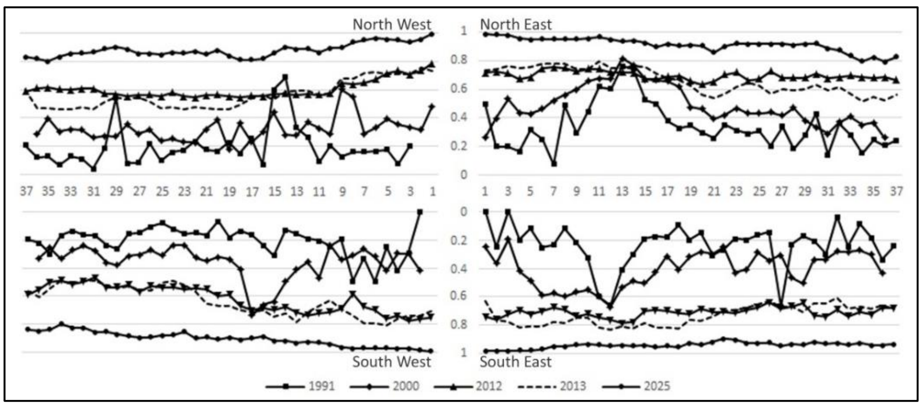

Figure 11: Clumpiness metrics for Chennai

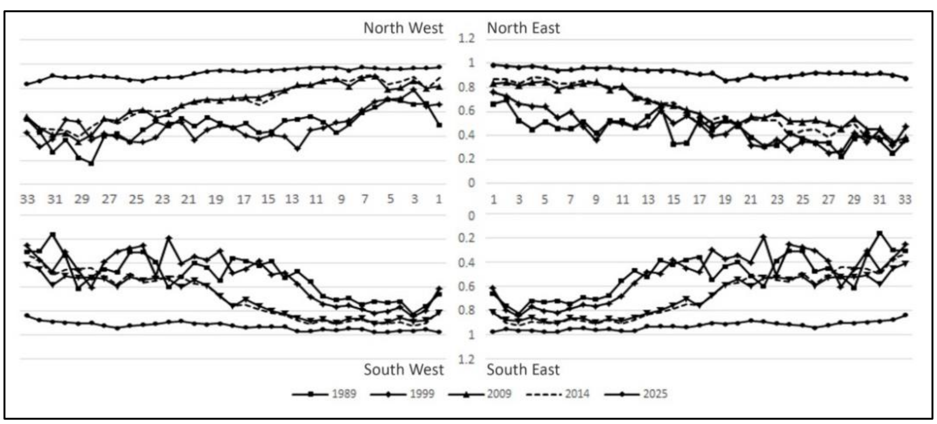

Figure 12: Clumpiness metrics for Hyderabad

- Interspersion and juxtaposition index (IJI): This metric show how well an urban patch is associated or interspersed with other adjacent patch types. Lower values as observed (figures 13 and 14) in 1990's indicates an urban patch is associated only with one other adjacent patch type. This phenomenon does not hold well at the outskirts since urban patch is equally adjacent to all other patch types (i.e., maximally interspersed and juxtaposed to other patch types) showing sprawl in these areas.

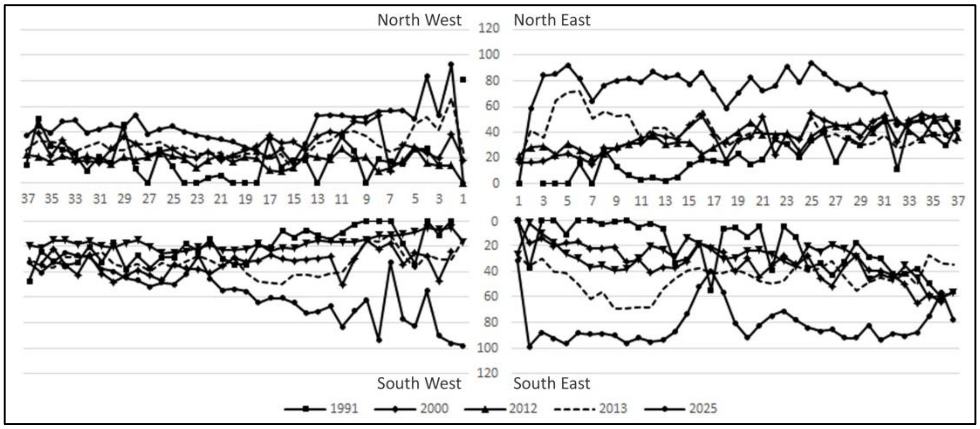

Figure 13: Interspersion and juxtaposition metrics for Chennai

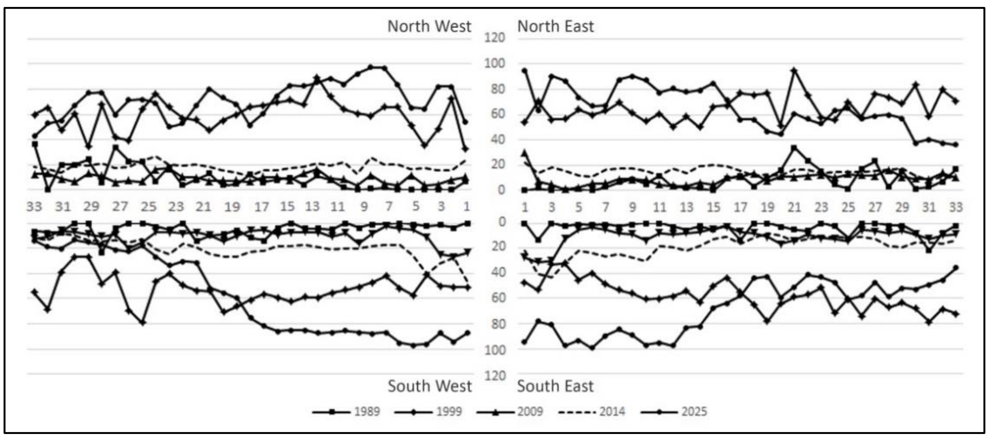

Figure 14: Interspersion and juxtaposition metrics for Hyderabad

Urban growth modelling: Land uses in 2025 were predicted considering various agents (amenities, road and railway network) and constraints (protected areas, drainage lines and slope) for Chennai and Hyderabad regions to visualize and understand the likely urban growth i. Pair wise comparison between two factors were done to obtain weights for these factors using AHP. Consistency ratio of 0.05 and 0.07 were achieved for Chennai and Hyderabad respectively, which is considered satisfactory to continue with further analysis. Land use changes for the year 2013 for Chennai region and year 2014 for Hyderabad region were simulated. This helped in validation for comparing simulated land use with the actual land use based on the classification of respective remote sensing data. Satisfactory kappa values with greater accuracy achieved, indicate of higher agreement between the actual and predicted land uses (table 10).

Prediction for the year 2025 was performed using Markovian transition estimator tool considering (i) constraint of CDP wherein water bodies, forest areas, catchment areas and coastal regulation areas (only in Chennai region) as no development areas. and (ii) without considering constraint of CDP. Table 11 lists percentage changes in land use categories, especially two fold increase in built-up areas with the decrease in vegetation and other categories. Two scenarios i.e. with CDP and without CDP showed similar statistics, but it is very essential to note that with the constraint of implementation of CDP, urban growth would be at the outskirts or at the periphery of the city boundary. However, in absence of CDP, distressing trend of large scale land use changes in areas within the CMDA boundary such as Korathur and Cholavaram lake bed, Redhills catchment area, Perungalathur forest area, Sholinganallur wetland area etc. which will either be encroached or completely occupied by built-up category (figure 15). A similar trend is observed in Hyderabad with violations in CDP, vulnerable ecologically sensitive areas such as Musi river bed (Malakpet), Mir Alam and Madeena guda lake bed, Kanchan bagh, Alwal wetland area and Janakinagar wetland gets changed into built-up categories (figure 16).

Zone and gradient wise spatial metrics were computed with 2025 predicted images to understand the spatial patterns of urban growth and sprawl. Figures 9 - 16 depict the metric wise spatial patterns of urbanization. Number of patches and patch density in the core city area (circles 1-9, Chennai and circles 1-12, Hyderabad) in all directions showed almost zero values implies that the entire landscape is completely dominated and saturated by only one single urban patch. For both the regions, in all directions (except Hyderabad, SE, circles 23-35) NLSI values were observed to be lesser than 0.2 indicating the urban patches are more compact, dense and has attained a standard shape. Clumpiness values almost reaching +1 as well as aggregation index values to 100, showed urban landscape maximally aggregated in both regions. Urban shape index values for 2025 are less compared to 2012/2013 for Chennai region and 2014 for Hyderabad region. This decreasing trend in urban landscape shape index further confirm of landscape attaining a standard or regular shape with the decrease in length of the edges. Largest urban patches were observed in circles 7-15, NE, SE (Kolathur and Vadapalani) and 7-11 SW (Poonamalle) of Chennai and circles 9-13 NW (Kukkatpally and Jeedimetla), 11-15, 23-29 SE (Secunderabad, Ghatkesar and Cherlapally IDA) and 9-11 SW (Manikonda and Hitech city) of Hyderabad. These metrics clearly indicate of intensified and concentrated urban growth in the core city and fragmented or dispersed growth in peri-urban regions.

Table 10: Validation statistics (Simulated and classified image)

City	Chennai	Hyderabad
$K_{Location}$	0.9058	0.8829
$K_{Standard}$	0.8229	0.8624
Overall Accuracy	92%	93.8%

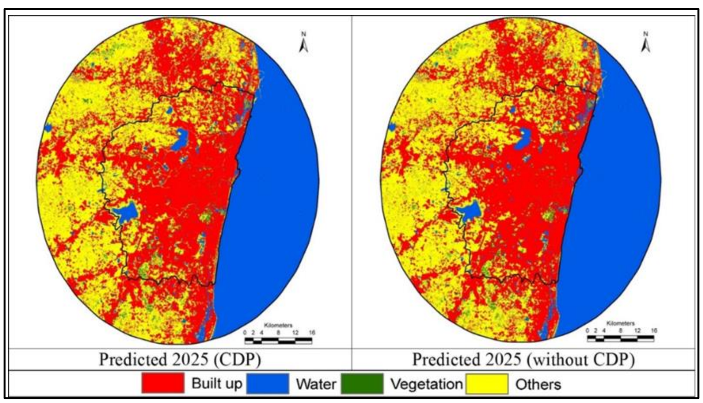

Figure 15: Predicted land use categories for the year 2025 – Chennai region

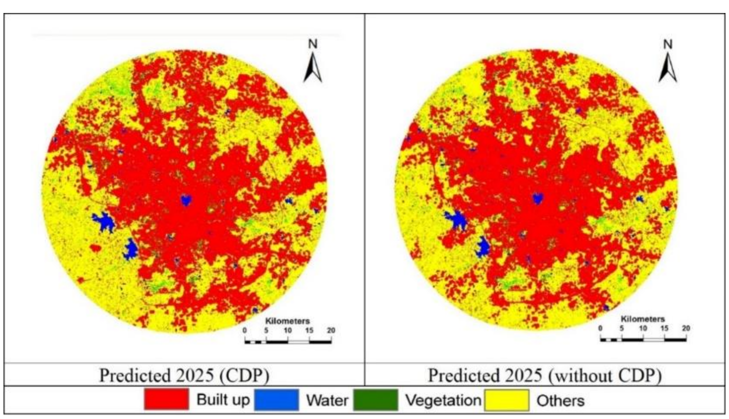

Figure 16: Predicted land use categories for the year 2025 – Hyderabad region

Table 11: Predicted land use statistics for the year 2025 for Chennai and Hyderabad regions

	Chennai region		Hyderabad region	
Categories / Year	**Predicted 2025 with CDP**	**Predicted 2025 without CDP**	**Predicted 2025 with CDP**	**Predicted 2025 without CDP**
	% land use		**% land use**	
Builtup	36.6	36.5	51.01	51.02
Vegetation	2.4	2.4	2.98	2.97
Water	27.9	27.8	1.98	1.98
Others	33.1	33.3	44.03	44.03

Conclusion and discussion

Poor environment, infrastructure and living conditions due to unplanned urbanization has been a major concern in metropolitan cities of India. Understanding spatio-temporal patterns of urban growth and its impacts on environment is possible with the availability of remote sensing data acquired through space borne sensors. In the current study, land cover dynamics during 1991-2013 and 1989-2014 were assessed through vegetation index. Chennai which had a lush green cover of around 70.47% in 1991 consistently declined accounting to about 50% in 2013. Land use dynamics analyses during four decades show a drastic increase of urban area by more than 20 times with the conversion of grazing, agricultural and open areas. Urban area was found to be spread over 77104 ha (2013) in Chennai region and 75768 ha (2014) in Hyderabad region. This tremendous growth may be clearly visualized in industry oriented land fragments like Ponneri, Avadi, Sriperumbudur in Chennai region and Malakpet, Madapur, Bollaram, Kukkatpally etc. in Hyderabad region. Higher overall accuracy values ranging from 86% - 97% (Chennai) and 87% - 94% (Hyderabad) proves the consistency of land use classifications. Shannon’s entropy values indicate of sprawl or dispersed growth in recent years. Spatial metrics were used considering the area, shape and contagion obtained through the moving window method to quantify the urban built up land density. The analysis also revealed that the process of densification at the city center (CBD: Central business district) with the initiation of the process of aggregations during 2010’s. Predication of urban growth in 2025 of complex urban landscape systems was done with integrated fuzzy-AHP, cellular automation and Markov chain techniques. The predicted spatial patterns of 2013 (Chennai) and 2014 (Hyderabad) were validated by comparing with the actual land use show conformity with higher accuracies and kappa statistics. The spatial analyses helped in visualizing and identification of urban growth regions and assessment of impacts on natural resources and agrarian lands. There has been a spurt in population and increased population density in the urban core; this would put lot of pressure on improving the accessibility of basic amenities to citizens both in Chennai and in Hyderabad. Social factor (S) and economy are two major factors that play a vital role in managing urban strata in a city and urban space. Social amenities as considered in the study in modelling the land use change are more concentrated in the city in Hyderabad, pushing growth around the region. Whereas in Chennai social amenities are present in both core city and outskirts in large number have fueled the growth and would be main factors that would allow growth in coming years. Chennai being a hub of industry and Hyderabad being a hub of information sector units would provide a huge push of economic growth near outskirts of the city and in the buffer zones thus all these factors showed a great influence in rampant urban sprawl and urbanization in both study regions.

The simulation and prediction of land uses with violations of CDP show of intensified urban growth within CMDA and HMDA boundary limits. Compared to this, with constraints of CDP implementation, indicate of fairly distributed built-up along highways such as Avadi, Triuchinapalli, Ponneri (NH- 4, 45 and 716 roads) in Chennai region and Kushaiguda, Safilguda, Uppal, Ghatkesar, Katedan, Serilingampally, Patancheru (NH – 5,7,9 and 202 roads) in Hyderabad region on the peripheries of metropolitan boundary zones. Urban areas are observed to be increased from 77104 ha (2013) to 151428 ha (2025) in Chennai and 75768 ha (2014) to 175009 ha (2025) in Hyderabad. These findings aid policy makers in provisioning basic amenities and adequate infrastructure in rapidly urbanizing landscapes. Decline of vegetation and wetlands in the landscape will lead to instance of frequent flooding, traffic congestions, higher level of pollutants, water scarcity, etc. which necessitates sustainable management of natural resources.

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References

Alberti, M. (2005). The effects of urban patterns on ecosystem function. International regional Science Review, 28 (2): 168-192.

Almeida, C.M., A.M.V. Monteiro, G. Camara, B.S. Soares-Filho, G.C. Cerqueira, C.L. Pennachin and M. Batty (2005). GIS and remote sensing as tools for the simulation of urban land-use change. Int. J. Remote Sens. 26 (4): 759–774.

Al-sharif, A.A. and B. Pradhan (2013). Monitoring and predicting land use change in Tripoli Metropolitan City using an integrated Markov chain and cellular automata models in GIS. Arabian Journal of Geosciences, 7 (10): 4291-4301.

Barnes, K.B., J.M. Morgan, M.C. Roberge and S. Lowe (2001). Sprawl development: Its patterns, consequences, and measurement. A white paper, Towson University.

Batty, M. (1998). Urban evolution on the desktop: Simulation with the use of extended cellular automata. Environment and Planning, 30: 1943-1967.

Batty, M. and Y. Xie (1997). Possible urban automata. Environment and Planning B, 24: 175-192.

Bharath, H.A., S. Bharath, S. Sreekantha, D.S. Durgappa and T.V. Ramachandra (2012). Spatial patterns of urbanization in Mysore: Emerging tier II city in Karnataka. Proceedings of NRSC UIM 2012, Hyderabad.

Bharath, H.A., S. Vinay and T.V. Ramachandra (2014). Landscape dynamics modelling through integrated Markov, fuzzy-AHP and cellular automata. in the proceeding of International Geoscience and Remote Sensing Symposium (IEEE IGARSS 2014), July 13th – July 19th 2014, Quebec City convention centre, Quebec, Canada.

Brueckner, J.K. and H. Kim (2003). Urban sprawl and the property tax. International Tax and Public Finance, 10: 5–23.

Census of India (2011). Government of India, http://censusindia.gov.in/

Chang, K.T. (2006). Introduction to geographic information systems. 4th edition, McGraw-Hill Higher Education publication.

Cheng, J. and I. Masser (2004). Understanding spatial and temporal processes of urban growth: Cellular automata modelling. Environment and Planning B: Planning and Design, 31: 167–194.

Deng, J.S., Ke Wang, Yang Hong and Jia G. Qi, (2009). Spatiotemporal dynamics and evolution of landuse change and landscape pattern in response to rapid urbanization. Landscape and Urban Planning, 92, 3–4: 187-198.

Duda, R.O., P.E. Hart and D.G. Stork (2000). Pattern classification (2nd edition). Wiley- Interscience Publication, ISBN 978-81-265-1116-7.

Dupont, V. (2005). Peri urban dynamics: Population, habitat and environment on the peripheries of large Indian metropolises - A review of concepts and general issues. French Research Institutes in India Publication.

Ewing, R., R. Pendall and D. Chen (2002). Measuring sprawl and its impacts. Washington, DC: Smart Growth America.

Furberg, D. and Y. Ban (2012). Satellite monitoring of urban sprawl and assessment of its potential environmental impact in the greater Toronto area between 1985 and 2005. Environmental Management, 50: 1068-1088.

He, C., N. Okada, Q. Zhang, P. Shi and J. Zhang (2006). Modeling urban expansion scenarios by coupling cellular automata model and system dynamic model in Beijing, China. Appl. Geogr. 26: 323–345.

Hepinstall-Cymerman, J., C. Stephan and L.R. Hutyra (2013). Urban growth patterns and growth management boundaries in the Central Puget Sound, Washington, 1986–2007. Urban Ecosystems, 16: 109–129.

Herold, M., H. Couclelis and K.C. Clarke (2005). The role of spatial metrics in the analysis and modeling of urban change. Computers, Environment, and Urban Systems, 29: 339–369.

Hossein, S.M. and H. Marco (2013). Spatiotemporal urbanization processes in the megacity of Mumbai, India: A Markov chains-cellular automata urban growth model. Applied Geography 40: 140-149

Hotton, D. (2001). Deer. In Maryland Game Program Annual Report 2000-2001. Annapolis, MD: Maryland Department of Natural Resources: 11-29.

Irwin, E. and N. Bockstael (2007). The evolution of urban sprawl: Evidence of spatial heterogeneity and increasing land fragmentation. Proceedings of the National Academy of Sciences of the USA, 104(52): 20672-20677.

Jat, M.K., P.K. Garg and D. Khare (2008). Monitoring and modelling of urban sprawl using remote sensing and GIS techniques. International Journal of Applied Earth Observation and Geoinformation, 10: 26-43.

Khwanruthai, B. and M. Yuji (2011). Site suitability evaluation for ecotourism using GIS and AHP: A case study of Surat Thani province, Thailand. Procedia Social and Behavioral Sciences 21: 269–278.

Kong, F. and N. Nakagoshi (2006). Spatial-temporal gradient analysis of urban green spaces in Jinan, China. Landscape and Urban Planning 78: 147–164.

Kowarik, I. (1990). Some responses of flora and vegetation to urbanization in central Europe. In: Sukopp, H., Hejny, S., Kowarik, I. (Eds.), Urban Ecology: Plants and Plant Communities in Urban Environments. SPB Academic Publishing B.V., The Hague, The Netherlands: 45–74.

Lau, K.H. and B.H. Kam (2005). A cellular automata model for urban land-use simulation. Environment and Planning B: Planning and Design 32: 247–263.

Li, X., Q. Yang and X. Liu (2008). Discovering and evaluating urban signatures for simulating compact development using cellular automata. Landsc. Urban Plann. 86: 177–186.

Li, Y., X. Zhu, X. Sun and F. Wang (2010). Landscape effects of environmental impact on bay-area wetlands under rapid urban expansion and development policy: A case study of Lianyungang, China. Landscape and Urban Planning 94(3): 218-227

Lillesand, T.M., R.W. Kiefer and J.W. Chipman (2012). Remote sensing and image interpretation. 6th edition, John Wiley and Sons publication.

Loibl, W. and T. Toetzer (2003). Modeling growth and densification processes in suburban regions-simulation of landscape transition with spatial agents. Environmental Modelling & Software, 18: 553–563

McCuen, R.H. and R.E. Beighley (2003). Seasonal flow frequency analysis. Journal of Hydrology, 279: 43–56.

McGarigal, K. and B. Marks (1995). Fragstats – Spatial pattern analysis program for quantifying landscape structure. Forest Science Department, Oregon State University.

Mukunda, D.B., N.B. Santosh, N.P. Sudhindra, R.B. Priti and S.R. Partha (2012). Modelling and analyzing the watershed dynamics using Cellular Automata (CA)–Markov model – A geo-information based approach. J. Earth Syst. Sci. 121: 1011–1024

O'Neill, R.V., J.R. Krummel, R.H. Gardner, G. Sugihara, B. Jackson, D.L. DeAngelis, B.T. Milne, M.G. Turner, B. Zygmunt, S.W. Christensen, V.H. Dale and R.L. Graham (1988). Indices of landscape pattern. Landscape Ecology 1: 153–162

Ottensmann, J.R. (1977). Urban Sprawl, Land Values and the Density of Development. Land Economics, 53 (4): 389-400.

Praveen, S., S. Kabiraj and T. Bina (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, no. 6: 126-132.

Pryor, R.J. (1968). Defining the rural-urban fringe. Social Forces, University of North Carolina Press, 47: 202–215.

Ramachandra, T.V., H.A. Bharath and D.S. Durgappa (2012). Insights to urban dynamics through landscape spatial pattern analysis. International Journal of Applied Earth Observation and Geoinformation 18: 329-343.

Ramachandra, T.V., H.A. Bharath and S. Vinay (2013). Land use land cover dynamics in a rapidly urbanising landscape. SCIT Journal, 13: 1-12.

Ramachandra, T.V. and U. Kumar (2009). Land surface temperature with land cover dynamics: Multi resolution, spatio-temporal data analysis of Greater Bangalore. International Journal of Geoinformatics, 5(3), 64-75.

Ramachandra, T.V. and U. Kumar (2010). Greater Bangalore: Emerging heat island. GIS for Development, 14(1): 86-104.

Ramachandra, T.V., H.A. Bharath and B. Barik (2014a). Urbanisation pattern of incipient mega region in India. Tema. Journal of Land Use, Mobility and Environment, 7(1): 83-100.

Ramachandra, T.V., H.A. Bharath and M.V. Sowmyashree (2014). Urban structure in Kolkata: Metrics and modeling through geo-informatics. Applied Geomatics, 6(4): 229-244.

Ramachandra, T.V., H.A. Bharath and M.V. Sowmyashree (2015). Monitoring urbanization and its implications in a mega city from space: Spatiotemporal patterns and its indicators. Journal of Environmental Management, 148, 67-91.

Saaty, T.L. (1980). The analytical hierarchy process: Planning, priority setting, resource allocation. McGraw-Hill publication, New York.

Sadhana, J., K. Divyani, R. Ram Mohan and B. Wietske (2011). Spatial metrics to analyze the impact of regional factors on pattern of urbanisation in Gurgaon, India. Journal of Indian Soc. Remote Sens., 39(2): 203–212.

Smart Cities - Mission Statement & Guidelines, 2015. Ministry of Urban Development, Government of India. http://smartcities.gov.in/ accessed on 07.04.2015

Stevens, D. and S. Dragicevic (2007). A GIS-based irregular cellular automata model of land-use change. Environment and Planning B: Planning and Design 34: 708–724.

Sukopp, H. (1998). Urban ecology—Scientific and practical aspects. In: Breuste, J., Feldmann, H., Uhlmann, O. (Eds.), Urban Ecology. Springer, Berlin, 3–16.

Taubenbock, H., M. Wegmann, A. Roth, H. Mehl and S. Dech (2009). Urbanization in India-Spatiotemporal analysis using remote sensing data. Computers, Environment and Urban Systems, Volume 33, Issue 3: 179–188.

United Nations (UN), (2012). Millennium development goals indicators, database.

Vishwanatha, Bhat, H.A. Bharath and T.V. Ramachandra (2015). Spatial patterns of urban growth with globalization in India's Silicon Valley. Proceedings of National Conference on Open Source GIS: Opportunities and Challenges, IIT (BHU), Varanasi. October 9-10, 2015.

Wagner, D.F. (1997). Cellular automata and geographic information systems. Environment and Planning B: Planning and Design 2: 219–234.

White, R. and G. Engelen (2000). High resolution modelling of the spatial dynamics of urban and regional systems. Comput. Environ. Urban Syst. 24: 383–400.

Whittaker, R.H. (1975). Communities and ecosystems. MacMillan, New York.

Wolfram, S. (2002). A new kind of science. Wolfram Media, Canada.

World Urban Prospects - Highlights, 2014 revision. Department of Economic and Social Affairs. United Nations, New York-2014.

Wu, J. (2006). Environmental amenities, urban sprawl, and community characteristics. Journal of Environmental Economics and Management, 52(2): 527-547.

Xian, G., M. Crane and J. Su (2007). An analysis of urban development and its environmental impact on the Tampa Bay watershed. Journal of Environmental Management 85(4): 965-976.

Yang, X. and C.P. Lo (2003). Modelling urban growth and landscape changes in the Atlanta metropolitan area. International Journal of Geographical Information Science, 17: 463–488.

Yuzer, M.A. (2004). Growth estimations in settlement planning using a Land Use Cellular Automata Model (LUCAM). Eur. Plann. Stud. 12 (4): 551–561.

Zhu, W. and M.M. Carreiro (1999). Chemoautotrophic nitrification in acidic forest soils along an urban-to-rural transect. Soil Biol. Biochem., 129: 1091–1100.