

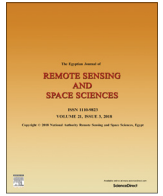
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Research Paper

Modelling urban dynamics in rapidly urbanising Indian cities

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ABSTRACT

Metropolitan cities in India are emerging as major economic hubs with an unprecedented land use changes and decline of environmental resources. Globalisation and consequent relaxations of Indian markets to global players has given impetus to rapid urbanisation process. Urbanisation being irreversible and rapid coupled with fast growth of population during the last century, contributed to serious ecological and environmental consequences. This necessitates monitoring and advance visualisation of spatial patterns of landscape dynamics for evolving appropriate management strategies towards sustainable development approaches. This study visualises the growth of Indian mega cities Delhi, Mumbai, Pune, Chennai and Coimbatore, through Cellular Automata Markov model considering the influence of agent (s) of urban growth through soft computing techniques. CA Markov model is considered to be one of most effective algorithm to visualise the growth of urban spatial structures. Prediction of growth using agent based modelling considering the spatial patterns of urbanisation during the past four decades has provided insights to the urban dynamics. The industrial, infrastructural, socio-economic factors significantly influence the urban growth compared to the biophysical factors. Visualisation of urban growth suggest agents driven growth in the cities and its surroundings with large land use transformations in urban corridors and upcoming Industrial and ear marked developmental zones. Integrating local agents of urban growth help in identifying specific regions of intense growth, likely challenges and provide opportunities for evolving appropriate management strategies towards sustainable cities during the 21st century.

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1. Introduction

Rapid urbanisation is a pivotal factor in altering the landscape structure affecting the ecology and environment during the last two decades (Sivaramakrishnan et al., 2005; MOUD, 2011; Ramachandra et al., 2012; Bharath et al., 2012; Ramachandra et al., 2014a). Urbanisation refers to a form of paved surface growth in response to increasing human activities with implications of economic, social, and political forces and to the physical geography of an area (Sudhira et al., 2007; Ramachandra et al., 2014a). The transformation of a landscape from rural to urban has a finite cycle with the regions evolving to form industrially dominant regions.

This would, further leads to rural push and spreading of city towards outskirts (Ramachandra et al., 2013). Dispersed urban growth in peri-urban regions is referred as urban sprawl. Sprawl takes place at the urban fringes in the form of radial development or development along the highways with the elongated urban development (Sudhira et al., 2003; Ramachandra et al., 2012). Regions under the influence of dispersed growth or sprawl are often devoid of basic infrastructure and amenities such as treated water supply, electricity, sanitation, etc. as planners were earlier unable to visualise these sporadic growth pockets. This has necessitated studies on urban sprawl across the globe (Batty et al., 1999; Torrens, 2000; Sudhira et al., 2004; Huang et al., 2007; Bhatta, 2009a,b, 2010; Ramachandra et al., 2012, 2015). Often these sprawled regions are left out in the population census and also in vision documents such as city developmental plans, etc. However, technological advancements in remote sensing technologies and Geoinformatics (Geographic Information system (GIS)) has overcome the limitations of data, skills, etc. (Adhvaryu, 2011; Bharath et al., 2014).

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Remote Sensing data acquired through space borne remote sensors enables a repetitive synaptic bird eye view of the landscape at low cost (Lillesand and Kiefer, 2005). Availability of multi-resolutions (spectral and temporal) spatial data at local, regional and global scales helps in land cover (LC), Land use (LU), land use land cover changes (LULCC) and surveillance of problematic sites (Campbell, 2002). Spatial data acquired remotely aids in the identification and assessment of land use patterns which is important for environmental management and decision making. Availability of these data at regular intervals have aided in advance simulation of urban growth for planning of infrastructure and basic amenities. Simulation of land use would provide an excellent feedback to plan and understand the real world scenarios and changes before implementing on ground (Zhang et al., 2011). Thus defined as a process of changing scenarios variables and observing the results to study the levels of abstraction in changing scenarios and change of events (Banks et al., 2004). Simulation also allows planners and city managers to study a problem at several different levels of abstraction. By this a planner can understand the complexity of the overall system (Santé et al., 2010). Early 90's urban simulation approaches were based on theories, and suffered from significant weaknesses due to lack of understanding of space–time dynamics. The integration of space, time, and attributes in modelling was further enhanced with the evolution of Cellular automata (CA) models (Allen, 1997; Batty et al., 1999; EPA, 2000; Alberti and Waddell, 2000). CA techniques are simple and easily integrated with raster GIS with adaptability to various urban growth situations. CA models represent complex patterns through the use of simple rules and considering its neighbouring properties since these models operate on basis of cell states, size, neighbourhood and transition rules (White and Engelen, 2000). CA modelling aids in addressing the spatial complexity with discrete time changes, evident from satisfactory simulations of spatial urban expansions (Clarke et al., 1997; Leao et al., 2004; Bharath et al., 2013; Ramachandra et al., 2013; Arsanjani et al., 2013). Advantages of CAs are based on site-specific rules that are predefined based on historical transitions represented by pixel based raster simulations in discrete time (Guan et al., 2011). CA based urban models usually pay more attention to simulating the process of urban development and defining the factors or rules driving the development (Batty, 2007). The CA model with powerful spatial computing can be used to simulate the spatial variation of the system effectively. CAs represent local raster-based simulation for modelling urban expansion for discrete time steps (Guan et al., 2011). Despite these appealing properties, CA models lack the ability to account for the actual amount of change. Therefore, coupling the MC and CA approaches (Eastman, 2009) provides a powerful modelling framework in which the shortcomings of each are eliminated. A The CA–Markov model absorbs the benefits from the time series and spatial predictions of the Markov and CA theory, and it can be used to carry out the Spatial–Temporal Pattern stimulation. The CA–Markov model also considers the land use changes' suitability and the effect of natural, societal and economic factors about land use changes. Different CA models have been developed to simulate urban growth and urban land use/cover change over time. The differences among various models exist in modifying the five basic elements of CA, i.e., the spatial tessellation of cells, states of cells, neighbourhood, transition rules, and time (White and Engelen, 2000; Liu, 2009). Among various others approached such as regression modelling have been effectively analysed and applied (Arsanjani et al., 2013).

1.1. Agent based modelling framework

Urban growth is mainly altering the land use changes according to human activities with complexity involving drivers that are influenced by human thinking and natural drivers (Le et al.,

2008). Land use change occurs from decisions made by individual drivers that are derived from various socio economic ecological setting. These changes are rather complex and needs understanding by approaches that are process oriented, pattern oriented or objects of change oriented (CO) associated to human and natural drivers. Considering these CO process would help in help in understanding micro to macro level process and in policy interventions affect the behaviour of the individuals that produce changes at micro-level (Lambin et al., 2003). These non-linear transformative processes are not captured using normal conventional models (Le et al., 2008). Land-use models that are statistically driven often ignore human drivers as transformation of land use factors (Veldkamp and Verburg, 2004). Agent based modelling has been recognised to be well suited to express the co-evolution of the human and landscape systems based on the interactions between human actors and their environment (Batty, 2001; Verburg et al., 2005). This essentially requires to understand the process of modelling requires integration of human drivers socio economic drivers and classic land use change models. The objects of change oriented models are therefore useful in integrating these drivers using real land use change altering forms through understanding the behaviours of various known entities that are influential in attracting the urban growth. These influential agents are termed as “Agents of change” (Castella and Verburg, 2007). The coupled human, socio–economic, environment system is described in the form of agents which have their specific roles in modelling land use change. Agents are described by several characteristics they are self-governing, interacting systems and behave with mutual effect to environment. Agents have been used to represent a wide variety of entities, including industries, cars, people, cells, social factors etc., (Parker et al., 2003; Robinson et al., 2007; Wooldridge, 2009). Thus, the agents can represent human behaviour more accurately than the conventional models (Fujita and Kashiwadani, 1989). Jokar et al. (2011) used a CA–Markov model to monitor land use changes and to predict future states. Further Arsanjani et al., in 2013 showcased employed a logistic regression based CA model integrating agents but could not attribute the behaviours of agents to illustrate human tendency of being fuzzy in nature. Artificial Neural Networks (ANN) was also employed by Tayyebi et al. (2011) to develop an agent based model but this could integrate human tendency but failed to exhibit the real complex behaviour of agents in urban systems. There has been an development of various Multi agent simulation based systems but these have not showcased the effectiveness of mapping policy, social, economic data with human behaviour and actions. Therefore, the primary objective of this study is to consider the behaviour and the preferences of humans, agents (which represents the examples of social, economic, policy decisions) and to model urban growth in five major metropolitan areas of India. This has been accomplished by integration of CA Markov with AHP (Analytical hierarchal process) and Fuzzy for providing multi criteria performance with the definitive spatial allocation of changes (Eastman, 2009, Jokar Arsanjani et al., 2013) and to integrate the behavioural contribution. Artificial intelligence based fuzzy analysis coupled with Analytical hierarchal process (AHP) that integrates agents is used in the current study to account for changes in the allocation pattern in rapidly urbanising five landscapes in India. Fuzzy and AHP were used to characterise the agent's behaviour and to compute the influence of agent(s) on land use and urban growth. and urban growth with spatio temporal observations of neighbourhood change was computed with CA–Markov based analysis. Thus integrating agents with conventional modelling system.

Fuzzy transition rules: Urbanisation process is complex involving multiple agents with diverse patterns of behaviour under changing spatial and temporal scales (Cheng and Masser, 2003), while mimicing the dynamic process of urbanisation. In recent

years the integration of Cellular Automata with artificial intelligence techniques (such as neural networks, etc.). Fuzzy logic gave better performance than statistical techniques (Yeh and Li, 2002; Guan and Clarke, 2005; Mandelas et al., 2007; Pradhan and Pirasteh, 2010; Janssen et al., 2010; Keshavarzi and Heidari, 2010). Fuzzy logic also integrates modelling human behaviour of thinking and model complex environments (Han et al., 2005). Fuzzy rules specifically are built upon a set of fuzzy expressions which evaluates every specific attribute of the function. Fuzzy rule can provide a better of modelling output that simulates the real world situation through different function and can have different membership degrees to the allocation pixels (Dubois et al., 2007). The final decision is reached with maximising the membership degree. Urban models have been developed (Mantelas et al., 2008) through a set of fuzzy rules to process the data and calculation of indices regarding urban pattern of development and these indices are used as rules in a Cellular Automata model to predict urban growth.

Analytical Hierarchical Process (AHP): AHP has been used (de Quadros et al., 2006; Elaalem et al., 2010; Elaalem, 2013) as multi-criteria decision making (MCD) techniques with fuzzy rules and indices to weigh characteristics of diverse opinions in a complex environment. This involves choosing the criteria to measure the agent's effectiveness in a landscape, specifying alternatives and assigning weights to the criteria of observation. AHP is commonly used MCD technique for suitability of landscape through pair wise analysis (Chang et al., 2008; Chen et al., 2010; Thapa and Murayama, 2008). Artificial intelligence integration with MCD techniques improves efficiency towards modelling real world situation for understanding spatial patterns of urbanisation. This study models the urban process through Cellular Automata with criteria and decisions from real world using different agents (of influences).

2. Study area

Study area considered for the analysis are Tier I cities as shown in Fig. 1. Mumbai is the commercial capital of India with hub of economic activities (GDP of 12.1 trillion) and the capital of the

Indian state of Maharashtra and (bounded by Arabian Sea towards the west). Mumbai has maximum population density of 4893 persons per square metre with the population crossing 12 million (2011 population census) and. Mumbai Metropolitan Region Development Authority (MMRDA) was setup on 1975 under the Mumbai Metropolitan Region Development Authority Act, which is responsible for the planning and development activities in the Mumbai region. With the formation of Greater Mumbai, Brihan Mumbai Municipal Corporation (BMC) is the town planning authority for Mumbai.

Delhi (FDI inflow: US\$ 20.1 billion, GDP: 9.6 trillion rupees.) with more than 16.75 million inhabitants in the territory and with nearly 22.2 million residents in the National Capital Region urban area is the eighth largest metropolis in the world by population. It borders the Indian states of Uttar Pradesh to the east and Haryana on the north, west and south and is situated on the banks of the River Yamuna. Delhi lies about 300 m above the sea level. National Capital Territory (NCT) of Delhi is spread over an area of 1484 sq. km and the Delhi metropolitan area lies within NCT. The NCT has three local municipal corporations: Municipal Corporation of Delhi (MCD), New Delhi Municipal Council (NDMC) and Delhi Cantonment Board.

Chennai, previously known as “Madras” is the capital city of the Indian state of Tamilnadu and the fourth metropolitan (GDP 3.8 trillion rupees) in India, with the population of 8 million (2011 population census) and population density of 2109 persons per sq.km. Chennai is the one among industrialised and economically developed cities in India. Major industries include automobile, software, textiles, and post the 1900's, information technology. Greater Chennai Corporation is responsible for the development of city, and GDP of Chennai is 3.8 trillion rupees.

Coimbatore lies on the banks of the river Noyyal in the rain shadow region of the Western Ghats is the second largest city in the state of Tamil Nadu, India, encompassing a total area of 246 sq. km. The rich black soil of the region has also contributed greatly to the agricultural industry especially in the successful growth of cotton that has served as a foundation for the establishment of textile industries in this region and is popularly known as the Manchester of South India (GDP: 3.2 billion rupees) due to the numerous textile mills and engineering industries built over the last 100 years. The population of Coimbatore is about 0.35 million (2011 population census). Coimbatore city is governed by Coimbatore City Municipal Corporation (CCMC).

Pune (GDP: 2.7 trillion rupees), earlier known as Poona is the cultural capital of Maharashtra and is also known as “Queen of Deccan”. The Pune Municipal Corporation covers an area of 243.84 sq. km. Population during 1901 to 2011 shows an increase by 347% and the current population is 9 million (Census 2011). Pune Municipal Corporation with forty-eight wards is the civic body that is responsible administration and infrastructure development of the city and it is known as the Pune Mahanagar Palika (PMP).

3. Data and method

Temporal remote sensing data of Landsat TM and ETM + downloaded from GLCF (<http://glcf.umd.edu/data> <http://www.usgs.gov>) were preprocessed to correct geometrical and radiometric integrity. Remote sensing data were supplemented with the Survey of India topographic maps (of 1:50,000 and 1:250,000 scale), which were used to generate base layers of the administrative boundary, drainage network, road network etc. Slope map was extracted using ASTER data (30 m) downloaded from USGS (www.usgs.gov). Ground control points (GCPs) and training data were collected using pre calibrated Global Positioning System (GPS) and virtual

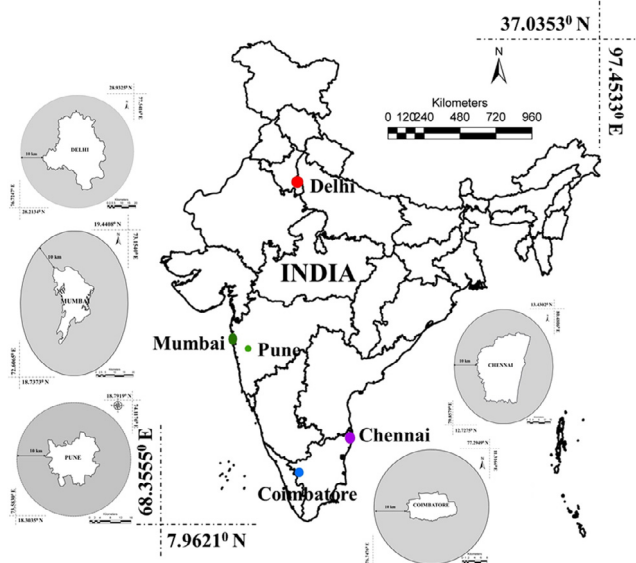


Fig. 1. Major cities considered for understanding urbanisation process and visualisation of urban growth are (i) Mumbai, (ii) Delhi, (iii) Chennai, (iv) Coimbatore and (v) Pune.

online spatial maps such as Bhuvan (<http://bhuvan.nrsc.gov.in>) and Google Earth (<http://earth.google.com>). GCPs were useful in geometric rectification of remote sensing data. Census data (1991, 2001 and 2011) was used to understand population dynamics.

Modelling of urbanisation and sprawl (procedure described in Fig. 2) involved: Data generation, Land use and land cover analysis and integrated model generation and validation.

Data creation: Data were obtained from survey of India topographic sheets. The sheets with scale 1:50,000 and 1:2,50,000 were scanned with high resolution. City administrative maps were obtained from respective metropolitan development authority database. Ground truth data of various locations within the study region were considered using hand held GPS. Places which were inaccessible and remote were surveyed with recent data of Google earth and Bhuvan. All these data sets corresponding to different study regions were geo-referenced and re-projected to common datum world geodetic system 1984 (WGS84) and respective Universal Transverse Mercator (UTM) zones to ensure uniformity in mapping. Hence region specific administrative boundary maps were obtained. Further, 10 km buffer were drawn from centroid of central business district (CBD) to better understand the urbanisation process beyond city administrative boundary.

Land use analysis: Satellite data for various time periods were geo-referenced (to WGS84 and respective UTM zones), geo-corrected, rectified and cropped pertaining to different study regions. To maintain similar resolution and for better comparison, satellite data were resampled to 30 m using nearest neighbourhood function. Land use analysis was performed to understand change in landscape pattern throughout the study regions temporally. It involved the following process – a) Generation of false color composite (FCC) image, b) Digitizing training polygons using FCC as base layer to distinguish heterogeneous features, c) Collection of training polygons using Google earth (<https://www.google.com/earth>) used as ancillary data for classification, d) Classification using Gaussian Maximum Likelihood (GML) classifier, based on probability and cost functions (Duda et al., 2000; Ramachandra et al., 2012). Land use with gradient analysis done earlier (Ramachandra et al., 2014a; Ramachandra et al., 2014b,c,d; Chandan et al., 2014) aided in understanding the behaviour of agents at local levels, which were used to model and predict urban growth. Historical land use details with transition probabilities were used to model and visualise urban growth in five major cities. Land use analysis was performed using geographical analysis support system (GRASS) open source software as four different categories as shown in Table 1.

Classification process is complete only when its accuracy is tested. Accuracy can be obtained by preparation of error matrix or confusion matrix. User accuracy, producer accuracy, overall accuracy and kappa statistics were calculated from error matrix. Overall accuracy considers only diagonal elements of reference map and classified map whereas kappa statistic takes off-diagonal elements also into account (Lillesand and Kiefer, 2005).

Integrated model generation and validation: Urbanizing agents and constraints were delineated in the form of points, lines and polygons using Google earth interface. Proximity maps were generated using minimum and maximum distance functions from each agent layers. Data values were normalized using fuzzy functions and the entire range were between 0 and 255, 0 indicating no changes and 255 indicating maximum probability of change in land use types. Analytical hierarchical process (AHP) was employed to estimate Principal Eigen vector and therefore priority maps were created. Classified land use maps for initial stages say, T_0 , T_1 and T_2 were considered along with slope and drainage layers analysed using DEM imagery were given as inputs to generate land use transitions from T_0 to T_1 and T_1 to T_2 . Markov chain analysis was used to calculate transition probability matrix based on two different time periods of classified images, where probability of each land use type changing to remaining other categories within the region considered is recorded after specific number of iterations. Cellular automation with Markov chain was used to predict future land use for a specified year. Model validation was done by generating kappa statistics for time period T_2 of both classified image versus simulated image.

Modelling using FUZZY AHP-CA: Integration of Fuzzy Logic, Analytical Hierarchical Process (AHP), Multi Criteria Evaluation (MCE), Markov chains and Cellular Automata (CA) were used to model and visualise the urban growth. Agents (roads, industries, educational institutions, bus stands, railway stations, metro, population, etc.) of urbanisation were normalized. Water bodies considered as constraints as they are identified as conservation regions (in CDP: city development plan). The fuzzy based analysis is used to normalize the contributing factors between 0 and 255, where 255 showing the maximum probability of change and 0 indicating no change, for different land uses. The model is a multiple input and based on fuzzy rules. Each agent that has been added for creating fuzziness represents each rule that contribute for determining the factors of urbanisation. With a N-Dimensional space, with n dimensions an image set A is then described using a Gaussian membership function as per Eq. (1)

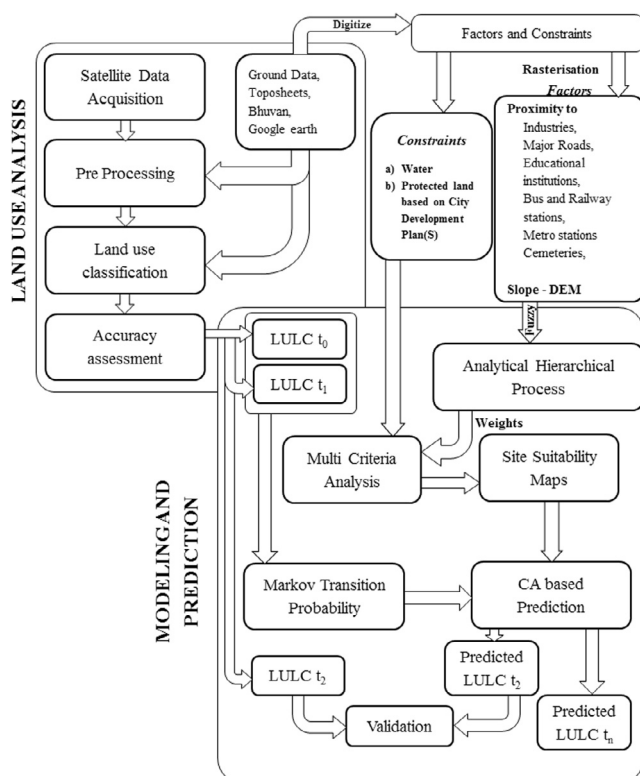


Fig. 2. Method for spatial data analysis, metrics and modelling.

Validation

Table 1

List of different categories used for land use analysis and corresponding features.

Category	Features involved
Built up	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.

$$\mu_d(x_n) = \exp\left(\frac{(x_n - v_n)^2}{2s_n^2}\right) \tag{1}$$

where v_d is a pixel location for the n^{th} agent and s_d is this agent's deviation.

Further these create fuzzy sets rules. For example, if E is a fuzzy set, an output of all inputs of S rules, fuzzy set $\mu_{e_j}(s)$ where s belongs to S with different decision of agents X and denoted as in Eq. (2)

$$\mu_E(X) = \oplus_1^S \mu_{E(s)} \tag{2}$$

Fuzzy sets are defuzzified to obtain values that represent the influence of agents. Fuzzy results provide us details of influence of each agents through the nodal values that are defuzzified based on rating that are based on perspective of modelling criteria based on gradients of influence. This is in the numerical form of influence is considered as an input to AHP. This essential indicates people's perception of thinking and ways that they can interact in urban growth. The values of agents were considered as input to AHP to determine the weights of driving factors using pair wise comparisons i^{th} weights as Eigen vectors. The weights analysed and calibrated through AHP is verified using measured consistency ratio (CR). CR below 0.1, the model is consistent and used for subsequent processes. These weights along with the factors of growth are combined along with use of constraints to obtain site suitability maps for different land uses using Eq. (3).

$$LC = \frac{1}{n} * \sum_{i=1}^n D_i * W_i \tag{3}$$

where LC is the linear combination of weights, n is the number of factors, D decision factor, W is the weight of the factor. Markov chain are used to determine the change probability between two historical datasets to derive the growth in the future scenarios based on different criteria's. The Markovian transition matrix indicates the probability of the particular land use being converted to other land uses on single time step. Cellular Automata based on the site suitability and the transition matrix is used to spatially predict the changes in land use based on current land use at every single time step, based on the neighbouring pixels. Fuzzy characterises the agents based on human behaviour and thinking with certain rules and analysis, AHP considers the numerical form of fuzzy behaviour to obtain the most and least influential agents for every point in the study region. These modules act to convey the agent based influence on the land use. CA-Markov is used to understand the spatial allocation of each cell based on rules and neighbourhood as to how each change and adapt in changing environs. This integration of agents to conventional modelling using CA Markov is understood using case studies of five cities of India. Validation of the simulated datasets were performed with classified datasets through kappa indices, as a measure of agreement. Once these data and agents are trained and validated, data is used to model and simulate for future trends (ten years) with definite time steps.

4. Results and discussion

Geo-visualisation of urbanisation of five tier I cities are depicted in Fig. 3–7 and results are as given in Tables 2–6. The cities on an average would grow by 1.5 to over 2 times the current state in next decade. Prediction reveals that built up area in these cities and surroundings, grows over 57% (Delhi), 27% (Mumbai), 45.8% (Chennai), 50% (Pune) and 37% (Coimbatore) respectively by 2025. The various drivers of growth for different cities are listed in Annexure 1. In all these cases, if CDP (City Development Plan) implemented in true spirit, which would help in regulating the unsustainable growth within the city though still some growth takes place in peri-urban regions. Prime agents of growth include the transportation network, industrialisation, educational sector, etc.

4.1. Validation and calibration of land use data

Validation and calibration of land use data: Land use was calibrated by predicting for year land use has already been calculated. If T0, T1 and T2 are three different years of known land use. T0 and T1 were used to calibrate and match the T3 image. Error was calculated using Kappa statistics (Pontius and Malanson, 2005) as a measure of agreement. Based on the accuracy agreement, the combination of T2 and T3 were used in already calibrated method, constraints and values of CA-Markov to predict for 2020, 2025 as per the case of temporal data availability. Validation of data for Delhi with optimal parameters was observed with value of kappa of 0.91 and similarly for Mumbai kappa obtained was 0.93, Chennai kappa value was 0.94, Pune kappa value was 0.89 and Coimbatore kappa value was 0.96. Future scenarios was compared to data obtained by developmental plans and other plans based on various sectorial growth. Models predicted growth showed a great coherence to these plans and specified growth areas.

4.2. Delhi

Spatial analysis and modelling reveals of same pattern of urban densification covering about 57% and 70% of the landscape by 2025 and 2035 respectively. Delhi is one among the fastest and largest growing global cities with huge expansion in both industrial and

Table 2
Predicted landscape dynamics of Delhi.

Year	Built up	Vegetation	Water	Others
2016	45.80	17.98	1.25	34.97
2025	57.37	8.77	1.18	32.68
2030	70.86	3.76	1.19	24.18

All units as percentage area.

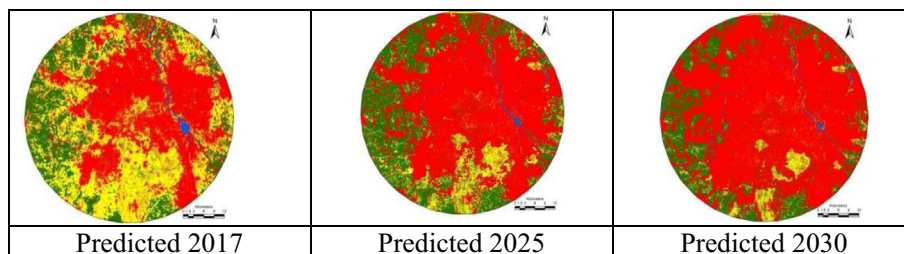


Fig. 3. Prediction land use of Delhi.

housing sectors. The neighbouring regions would also experience unprecedented growth with escalations in land values. This would lead to an increased outward expansion in almost all directions. Regions such as Ghaziabad, Noida, Bahadurgarh, Sonipat, Dadri, Modinagar, Bhagpur and Pataudi would experience urban growth/expansions in the next decade. Visualisation also highlights the need for an immediate policy intervention for regulating haphazard growth at outskirts

4.3. Mumbai

Being the business capital of India, Mumbai has been experiencing urbanisation with ever increasing urban footprint. During the past four decades (1973–2009), urbanisation has significantly modified the landscape structure of Mumbai city and its outskirts. The built-up area has significantly increased by 155% in past four decades, at the expense of non-forest land in the study region (Mumbai metropolitan area with 10 km buffer). Urban sprawl is seen toward the southwest and northeast sectors of the metropolitan area. This trend would continue considering that major driving force behind the urban growth and sprawl in Mumbai as per the analysis is setting up major industrial parks and corridors along with increase in the population density mainly for employment opportunities. It can be noted that major growth would happen in regions of Navi Mumbai region, Bhiwandi, Badlapur, Matheran. The developments majorly are in towards Raigad district with Rasayani and Khalapur would be next urban centre of development in current trends. Mumbai and Navi Mumbai would also see huge infilling growth and reach saturation of horizontal development considering resources. Considering the study region, the urban would cover about 31 percent of the total region though 44% is water. With Pune also gaining massive urban development the requirement of land mass for urban region would grow in Mumbai in coming years. Government of India declaring Navi Mumbai, Greater Mumbai, Thane, Kaylan as some of the cities that would translate as smart cities would also pressurise the development of Mumbai and its core with requirements of Basic services and amenities. Land use predicted is given in Fig. 4 and category wise land use percentage is listed in Table 3.

4.4. Chennai

Urban growth in 2026 predicted considering agents is given in Fig. 5 and category wise details are provided in Table 4. This shows an increase in built-up areas by two folds with decrease in vegetation. Significant changes can be seen in areas which falls within the CMDA boundary such as Korattur and Cholavaram lake bed,

Table 3
Predicted landscape dynamics of Mumbai.

Year	Built up	Vegetation	Water	Others
2020	25.83	9.09	44.52	20.56
2030	31.27	6.33	44.52	17.88

All units as percentage area.

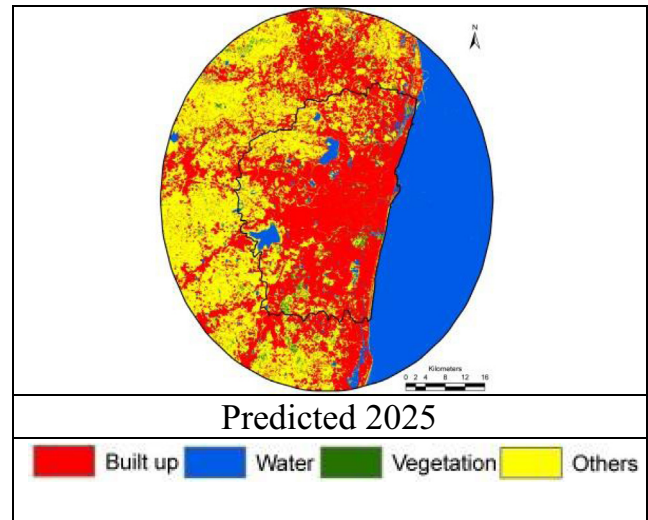


Fig. 5. Predicted landscape use of Chennai.

Table 4
Predicted landscape dynamics of Chennai.

Year	Built up	Vegetation	Water	Others
2026	45.80	17.98	1.25	34.97

All units as percentage area.

Redhills catchment area, forests at Perungalathur, wetland in Sholinganallur, etc. The regions closer to Chennai boundary lying in peri urban region (such as Kanchipuram, towards Pulicat, Kavaraipettai, Vellore and towards Krishnagiri) have also shown significant urban expansions by 2026.

4.5. Pune

Model (Fig. 6, Table 5) predicts that the Localities such as Mar-kal, Lonikand, Dattwade, Girinagar, Lavale, Pimpri, Chinchwad, Khadakwasla, Dhayari phata, Katruj, Yerwada, Pashan in and around Pune would experience a large scale land use change. These regions are the ones that are offering better lands for industrial growth in and around Pune and have been considered as sprawling areas with associated problems such as lack of basic amenities, etc. Pimpri Chinchwad was established in 1988 and developed to cater the requirement of industrial needs (Ramachandra et al., 2014a). Model shows that the region would experience an unprecedented urbanisation and built-up land use would dominate with 50% of the total land use in the study region. There would be higher pressure in the city boundaries since infilling would be very high and also towards regions connecting Mumbai show a huge spurt of urban.

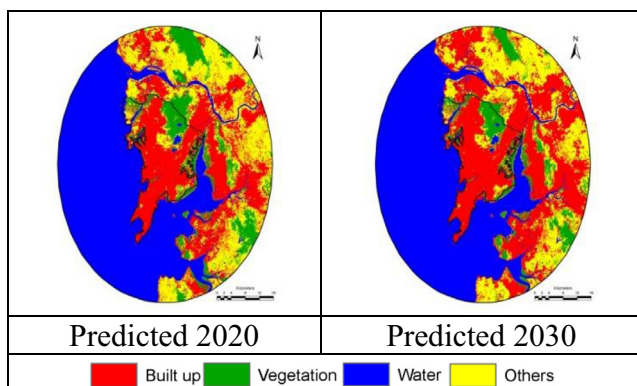


Fig. 4. Predicted land use of Mumbai.

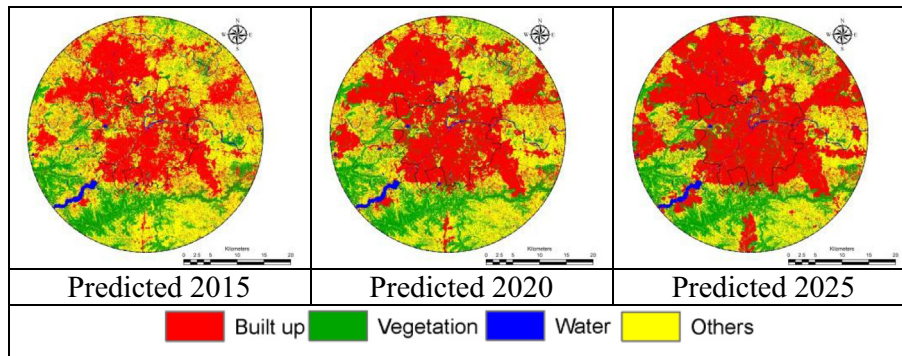


Fig. 6. Predicted land use of Pune.

Table 5
Predicted landscape dynamics of Pune.

Year	Built up	Water	Vegetation	Others
2015	37.78	1.75	16.37	44.11
2020	41.64	1.75	20.16	36.45
2025	50.02	1.75	20.16	28.06

All units as percentage area.

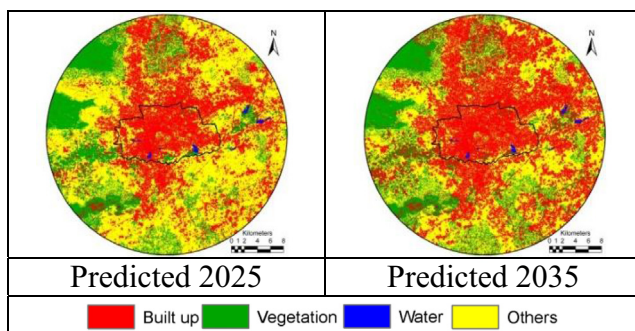


Fig. 7. Predicted land use of Coimbatore.

Table 6
Predicted landscape dynamics of Coimbatore.

Year	Built up	Water	Vegetation	Others
2025	32.64	0.29	17.14	49.94
2035	42.92	0.29	17.58	39.21

All units as percentage area.

4.6. Coimbatore

Coimbatore is facing an unprecedented urban growth with likely increase of about 42% by 2035 (Fig. 7 and tabulated in Table 6). Coimbatore would develop towards Salem, Suler, Tiruppur, Annur, Kanathur, etc.

5. Conclusion

Advance geo-visualisation of urban growth would aid in decision making towards sustainable cities with basic infrastructure and amenities. Temporal remote sensing data with GIS helps in

mapping and understanding of urban dynamics. Identification of regional factors that are most likely to influence a land-use changes has improved the accuracy of prediction. The predictions of land use/cover changes through CA-Markov model suggest a continual increase in urban settlements with a decline in local natural vegetation cover in all the regions considered for the analysis. Use of fuzzy decisions and Analytical Hierarchal Process in modelling has enabled incorporation of human decisions for addressing spatial problems. Fuzzy proved to be particularly effective for characterising decisions based on various spatial agents and land use spatial unit for each decade.

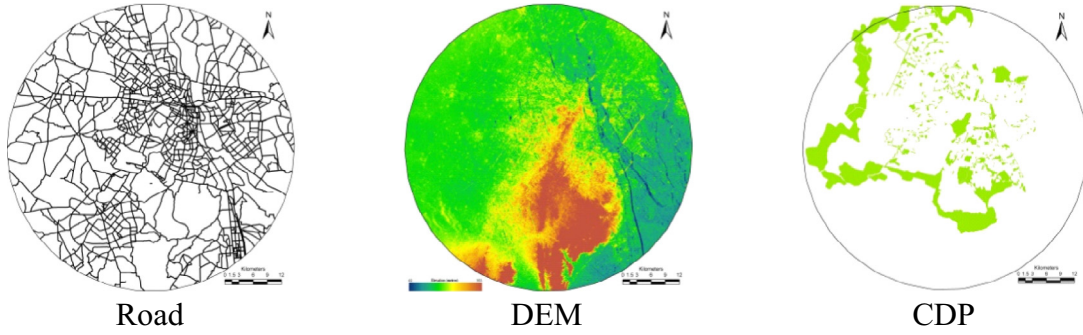
All cities grew during post 1990, from the city centre towards the outskirts. Model suggests that post 2010 the growth would be more likely infilling, suggesting a complete concretisation of core area and further would spread beyond its boundaries that necessities an immediate look at natural balances and planning in terms of provision of basic amenities to all stakeholders. Chennai and Mumbai floods are the warning bells to the city administrators for planned interventions to mitigate implications of urban growth. Further the recent episodes of urban floods in heart of Delhi depict the status of planning of these citing and again cited a warning bell for proper utilisation of spaces and balancing of other land use types are immediate necessity. Visualised output has consolidated various major probabilities of current scenarios. It has showcased development in the regions and suggests that in next ten years these would be the urban hubs. It could strongly bring out the fact that other natural resources are being depleted in terms of urban growth. Vegetation ratio to human population in major cities suggest a dismal figure that would bring in more infectious diseases along with health issues among human problem (Ramachandra et al., 2014a). These visualisations must be considered as an important need to build up policy decisions that would influence further growth of these regions. Visualisation of urban growth considering the agents helps in providing better decisions Analytical Hierarchal Process accounted the future urbanisation state of each city was weighed based on factors that is likely to influence the growth. The adopted technique being spatially and temporally interactive model helped in visualising spatial patterns of urbanisation with insights.

Acknowledgement

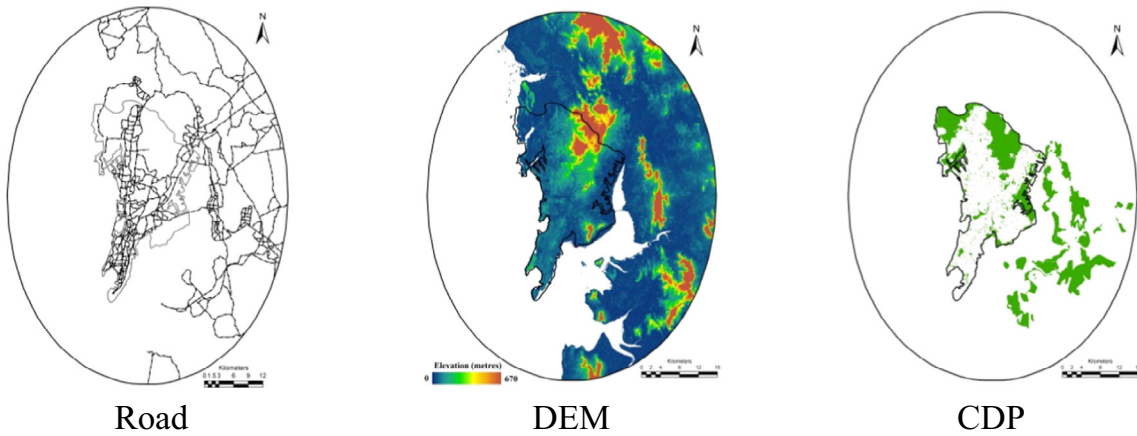
We are grateful to SERB, India, The Ministry of Science and Technology, Government of India, Centre for Ecological Science, Indian Institute of Science and Ranbir and Chitra Gupta School of Infrastructure Design and Management, Indian Institute of Technology Kharagpur for the financial and infrastructure support.

Appendix A.

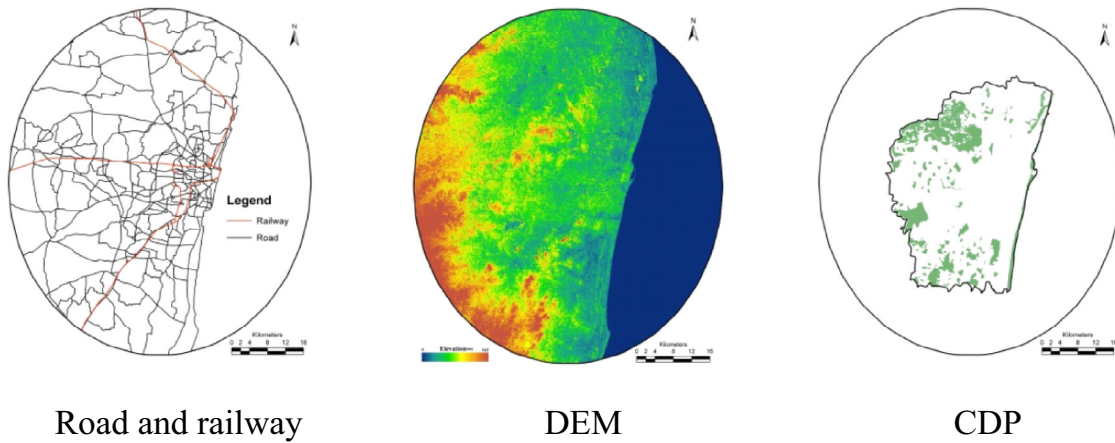
Annexure 1(a): Example of factors and constraints of growth for Delhi.



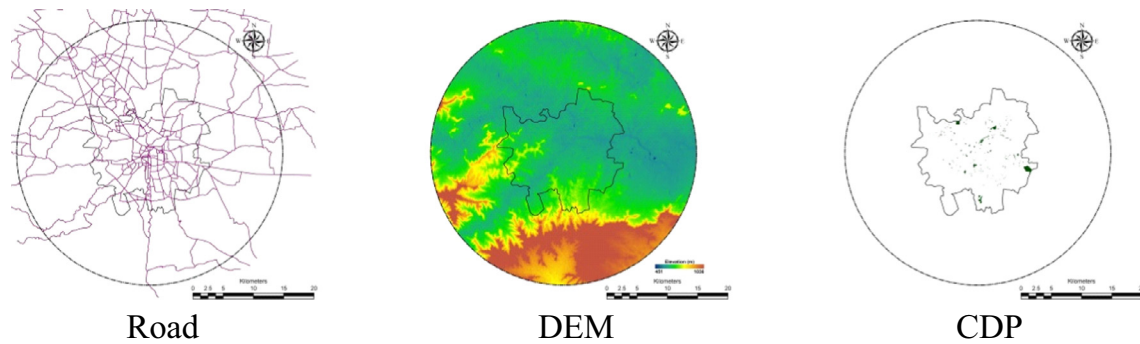
Annexure 1(b): Example of factors and constraints of growth for Mumbai.



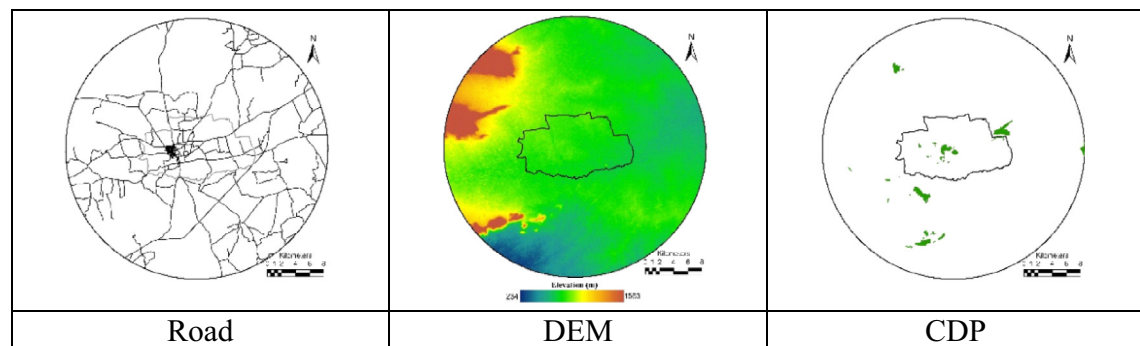
Annexure 1(c): Example of factors and constraints of growth for Chennai.



Annexure 1(d): Example of factors and constraints of growth for Pune.



Annexure 1(e): Example of factors and constraints of growth for Coimbatore.



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