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Geo-visualization of landscape dynamics in the proposed mega industrial corridor

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Abstract Urbanization is associated with large-scale irreversible landscape changes in response to the demands of burgeoning population, etc. Lack of basic amenities, job, and infrastructures in rural areas often drives migration towards the urbanizing landscapes. Urbanization is resource centric, which involves, large-scale transformation of the landscape with the irreversible impacts on the regional ecology, hydrology, and environment, which is evident from large-scale land cover changes leading to deforestation, encroachment of lakes/water bodies, forest, and farmlands, conversion of agriculture landscapes, etc. damaging the environs. Visualization of urban growth based on the past spatial patterns would help in evolving appropriate policy framework towards the design of sustainable cites for the prudent management of natural resources. Current communication attempts to understand the landscape dynamics along the proposed Mumbai–Pune industrial corridor (with 10 km buffer) through (i) rule-based/non agent-based models (non-ABM) and (ii) agent-based models (ABM) with the evaluation of relative performance of ABM and non-ABM methods. Comparative assessment of the model performance through accuracy assessment and Kappa (relatively significant at $p < 0.05$) indicates the superior performance of the agent-based model approaches due to its interaction with factors and constraints that allow urban growth in the region. Non-ABM model predicted the growth of 49.69% by 2027 with the decline of vegetation to 9.63%. Compared to this, agent-based model predicted growth in urban landscape to 47.12% and the decline of vegetation to 11.10%. The current research was formulated based on the recommendations of the deliberation between academia and stakeholder industries that are likely to be benefitted by the implementation of the industrial corridor. The research outcome also helps local planning authorities in advance visualization of urban dynamics to design sustainable urban regions with the provision of appropriate infrastructure and basic amenities.

Keywords Urbanization · Landscape dynamics · Remote sensing · Modelling · Visualization

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Introduction

Urbanization is a dynamic and irreversible process involving changes in land use land cover [LULC] leading to the conversion of rural area into urban area. Burgeoning population with impetus to the industrialization, political, cultural, and other socio-economic factors act as catalysts of urbanization. Unplanned urbanization leads to the rapid landscape changes and urban sprawl with the increasing social, economic, and environmental problems (Ramachandra et al. 2012a, b; Yang et al. 2017). Landscape changes involving large-scale land cover changes would have devastating effect on the vegetation, quality and quantity of surface and subsurface water resources (Vinay et al. 2013), air quality, and climatic factors (Grimm et al. 2008, 2015).

The Government of India under the flagship Make-in-India program has planned five industrial corridor projects spread across India, with strategic focus on inclusive development to provide an impetus to industrialization and planned urbanization. In each of these corridors, manufacturing is a key economic driver with a goal to increase the manufacturing sector contributions 15 to 25% by 2025 in the nation's Gross Domestic Product (GDP). Also, smart industrial cities are proposed along these corridors to integrate mobility with land uses (Department of Industrial Policy and Promotion and Government of India 2007). These industrial corridors connect major cities with the coastal cities for accessibility of locally available resources and mobility of global resources. The industries are strategically located along these corridors with the improved infrastructure and would increase job opportunities at local level, while improving the travel and transport efficiency, and reduction in transit time (DIPP 2007). The industrial corridor initiative is expected to attract the regional and international investors with PPP (public private partnership), and create competitiveness among industries across and between regions/nations. This would also reduce cargo freight time, removing the barriers of employment, encouraging trade, tourism, economy, and cooperation and at the same time, cutting down cost of GHG (greenhouse gas) footprint. Globally, industrial corridors have been established with the strategy of connecting major cities and industries (De and Iyengar 2014).

Globally, there are numerous examples of industrial/economic/infrastructure/trade corridors connecting CBDs to improve the socio-economic level of the local, regional, or national such as Trans-European Transport Networks (TEN-T) (Trans-European Transport Network 2018); Rhine-Alpine Corridor (Blue Banana) (European Commission n.d.); U.S.-Canadian-Mexican trade corridor; Trans-Kalahari Corridor connecting Walvis Bay (east coast) to and Maputo (west coast); SIJORI Growth Triangle (Milne 1993; Smith 1997) connecting Singapore, Indonesia, and Malaysia, and Eastern Economic Corridor Thailand (Georg et al. 2016). The policy decisions that are likely to alter land cover in the region include industrial corridors (Department of Industrial Policy and Promotion and Government of India 2007) and Bharatmala Pariyojana (Government of India 2018), an umbrella program under the Ministry of Road, Transport and Highway (Ministry of Road Tranport and Highways and Government of India 2017). These programs focus on increasing efficiency of movement of cargo, passengers bridging critical infrastructure gaps through effective interventions such as economic corridor, infrastructure corridor, industrial corridor, up-gradation of highways, and increase in boarder and international connectivity, coastal, and port connectivity. These developments of connecting cities will have negative impacts such as urban sprawl while planned interventions would support the region's smart growth with the scope for sustainable development. The transportation network would induce the proportional social, economic, and environmental impacts such as loss of open spaces, forests, and water bodies, with increasing paved surfaces (McGrane 2016; Miller and Hutchins 2017; Ramachandra et al. 2014), fluctuating housing costs and expenditures over time (Ewing and Hamidi 2013). The corridors and its implications across time and space are less studied, as compared to studies made at city levels, despite being prime mover of the nation's development.

The conventional approach to understand the landscape dynamics across industrial corridors is time consuming. However, the availability of multi-resolution (spatial, spectral, and temporal) remote sensing data with advances in GIS (Geographic Information System) technologies has proved reliable and economical for understanding landscape dynamics (Ji et al. 2001; Ramachandra et al. 2012a, b; Ramachandra and Bharath 2012). Different modelling techniques using rule-based, agent-based models such as CA, CA-Markov, Geomod, Land Change Modeler, SLEUTH, SLUCE, Dynamica, Dyna-CLUES, ANN, Multi Regression, AHP, and CAPRI-Spat have been widely used for geo-visualization of landscape dynamics (Bharath et al. 2013, 2015, 2016; Brown et al. 2008; Guan et al. 2005; Jain et al. 2017; Jokar Arsanjani et al. 2012; Macal and North 2008; Mena et al. 2011;

Mohammady et al. 2014; Siddayao et al. 2014; Taubenböck et al. 2009, 2012; Wassenaar et al. 2007).

Urbanization is very dynamic and complex process involving multiple agents with diverse behaviors under changing spatial and temporal scales. Cellular Automata Markov Chain integrated model, a rule-based model wherein multiple rules are used in order to simulate the future scenario through historical data sets, is proved to be one of the best modelling technique for urban growth simulation. Cellular Automata is used to predict the state of the cell based on the previous state of the cells within a neighborhood, using a set of transition rules. Markov is used to provide probabilistic transition events. Although CA-Markov gives promising results, it fails to achieve accurate results due to non-accounting of agents—urban driving forces (He et al. 2013). Agent-based modelling (ABM) uses causal factors or agents that influence a particular process through interaction of the driving forces in the region of influences and defines the growth through neighborhood interaction of the drivers and the base modelling criteria. This communication is based on the ABM technique that generates the drivers of urban growth interaction through using fuzziness in the data sets and using Analytical Hierarchical Process (AHP) to account of its weight-based interactions through CA-Markov process (Bharath et al. 2013). ABM method is effective in simulating the real change based on agents. ABMs weigh/rank the growth factors and constraints as reflected by the real world scenarios to develop site suitability maps in order to model the land use. The site suitability maps provide the transitional areas describing where the particular land use has the probability to change or retain its state. The site suitability maps are combined with the CA-Markov in order to simulate and predict the land use dynamics. The modelling based on ABM has emerged as a promising approach for understanding the complex urban processes. Integration of fuzzy rules and Analytical Hierarchical Process (AHP) with ABM aid in defining the influence of the agents in urban simulation.

The agent gradually transfers from a non-member to a member. This gradual transfer happens through a function called as membership function that is used to characterize various sets of agents that interact with a particular urban land use. These agent's interaction is treated as a fuzzy rule to define somewhat influential to least influential and a precise numerical. This involved building a fuzzy network to extract fuzzy rules through an expert system. The fuzzy sets of inputs through fuzzy rules are combined to represent the agent's strength, which is then combined with AHP to define the site suitability with interaction of the current land use to weigh characteristics of diverse opinions in a complex environment. This is a two-step process involving the assessment of effectiveness and alternatives. AHP has been a commonly used MCE technique for suitability of landscape through pair wise analysis (Chen et al. 2010;). Integration of artificial intelligence with MCD technique improves efficiency of modelling real world situation and for understanding spatial patterns of urbanization. This output is then used in CA-MARKOV for modelling as discussed earlier.

The objective of this study is to assess landscape dynamics in Mumbai–Pune expressway industrial corridor connecting Mumbai and Pune Cities and understand the spatial contextual improvisation of modelling techniques using agent-based models.

Study area

Mumbai–Pune expressway (MPEW) also known as Yashwantrao Chavan expressway is a 6-lane expressway for a distance of 94 between Shil Phata, Navi Mumbai and Dehu Road, Pune. MPEW is the first six-lane highway built in India with Public Private Partnership Model connecting Mumbai, the business capital of India, and Pune, cultural capital and education hub of Maharashtra in the year 2000 (Mumbai-Pune Expressway, India 2018). The expressway has five interchanges and six tunnels covering an approximate length of 5.6 km. MPEW was planned to (i) reduce the traffic congestion along the national highway 4 connecting Mumbai and Pune, (ii) reduce accidents and mortality, (iii) increase business and trade potential, and (iv) reduce transit time of resources, etc. In the current study, we consider MPEW and major connecting between MPEW and City centers, i.e., about distance of 135 km with a buffer zone of 10 km on either sides to understand the role of industrial corridors on land use changes in the region. The study region (Fig. 1) consists of Mumbai–Pune expressway (MPEW) between 18° 25′ N to 19° 10′ N and 72° 46′ E to 73° 56′ E with 5 km buffer on either side of the expressway (region of 3022 km^2) passing through the districts of Mumbai, Thane, Raigarh, and Pune.

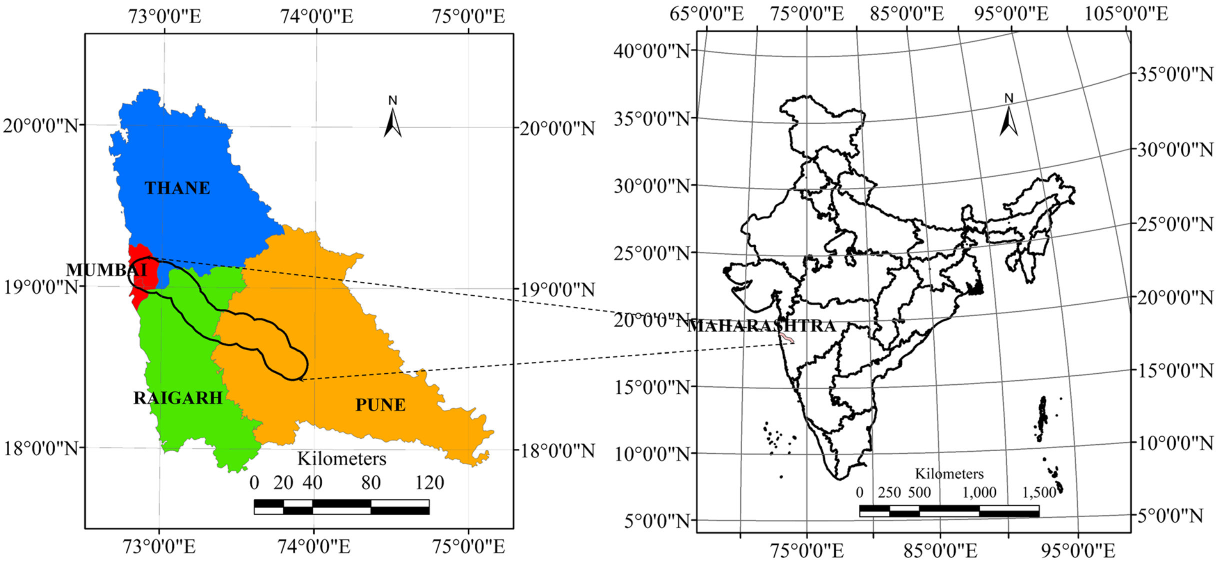


Fig. 1 Study area—Mumbai–Pune expressway (MPEW)

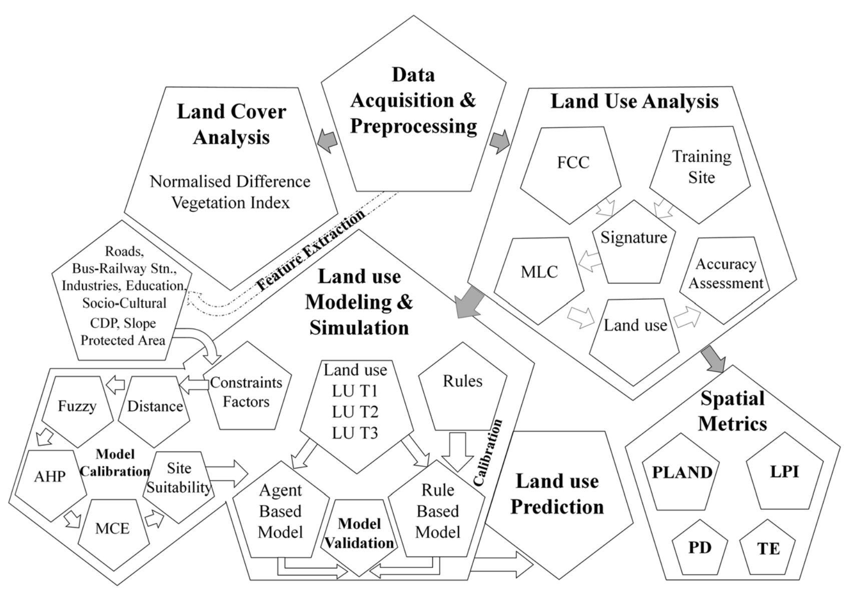
Data and method

Figure 2 elucidates the method opted for understanding landscape dynamics along the industrial corridors. The process involved (i) data acquisition and data preprocessing, (ii) land cover assessment, (ii) land use assessment through supervised classifier using GMLC (Gaussian Maximum Likelihood Classifier), (iv) spatial pattern analyses at micro levels through spatial metrics, and (v) modelling and prediction of future landscape transitions using rule and agent-based models.

Data acquisition and preprocessing

The process of data acquisition involves collection of primary and secondary data. Primary data includes collection of remote sensing data and field data. Remote sensing (RS) data for the period 1997–2015 were

Fig. 2 Method for landscape dynamics analyses



downloaded from USGS (United States Geological Survey 2015a, b; http://landsat.usgs.gov). Table 1 tabulates various data sets acquired for analysis. GPS-based field surveys were done in order to supplement land use analysis for 2009 and 2015. Secondary data collection involves collection of ancillary data such a French Institute Puducherry (http://www.ifpindia.org) vegetation maps (Pascal 1982) and the Survey of India topographic maps (Survey of India n.d.; http://surveyofindia.gov.in) supplemented with the virtual spatial data such as Google earth (Google 2016; http://earth.google.com) and Bhuvan (National Remote Sensing Centre 2016; http://bhuvan.nrsc.gov.in). The secondary data provides additional input to the field data for data preprocessing and classification. Data preprocessing involved radiometric and geometric corrections of remote sensing data.

Land cover

Land cover refers to physical cover of the earth surface that essentially indicates the spatial extent of vegetation present on the land surface. Land cover assessment is carried out to estimate overall vegetation cover as against non-vegetation. Vegetation cover included forests, current sown crops, grasslands, and all other forms of vegetation in the area. Normalized Difference Vegetation Index (NDVI) (Burrough 1986; Lillesand et al. 2004), a widely used index (Hatfield and Prueger 2010; Agapiou et al. 2012; Ramachandra et al. 2013), was used to quantify vegetation cover along the corridor. Temporal vegetation dynamics was assessed by computing NDVI across time.

Land use

Land use relates to human activity/economic activity on piece of land under consideration (Ramachandra and Bharath 2012). This analysis provides various uses of land as urban, agriculture, forest, plantation, etc., specified as per USGS classification system and National Remote Sensing Centre, India (Table 2). The land use analyses using multi spectral remote sensing data (Ramachandra and Bharath 2012) involved (i) generation of False Color Composite (FCC) of RS data (bands–green, red, and NIR); this composite image helps in locating heterogeneous patches in the landscape; (ii) selection of training polygons by covering 15% of the study area (polygons are uniformly distributed over the entire study area); (iii) loading these training polygons co-ordinates into pre-calibrated GPS; (vi) collection of the corresponding attribute data (land use types) for these polygons from the field; (iv) supplementing this information with virtual earth data (Google earth/Bhuvan); and (v) 60% of the training data has been used for classification based on Gaussian Maximum Likelihood algorithm, while the balance is used for validation or accuracy assessment. The land use analysis was done using a supervised classification technique based on Gaussian maximum likelihood algorithm with training data and this technique is proved to be one of the best probabilistic land use classification algorithm (Bharath et al. 2014a, b; Jensen 1996; Lillesand et al. 2004; Ramachandra et al. 2013, 2016, 2017; Sabin 1997). Mean and covariance matrix are computed using estimate of maximum likelihood estimator. Accuracy assessment to evaluate the performance of classifiers was done with the help of field data by testing the statistical significance of a difference, computation of kappa coefficients, and proportion of correctly allocated cases (Ramachandra and Bharath 2012). Recent remote sensing data (2015) was classified using the collected training samples. Statistical assessment of classifier performance based on the performance of spectral classification considering reference pixels is done which include computation of kappa (κ) statistics and overall (producer's and user's) accuracies.

Table 1 Satellite data used in the analysis

Data	Year	Spatial resolution
Landsat 8 – Operational Land Imager	2015	30 m
Landsat 8 – Operational Land Imager	2009	30 m
Landsat 5 - Thematic Mapper	2003	30 m
Landsat 7 - Enhanced Thematic Mapper Plus	1997	30 m

Table 2 Land use categories

Class	Features
Water	River, reservoir, check dams, streams, lakes, ponds, ocean, estuary, etc.
Vegetation	Forest, avenue trees, parks, gardens, current sown (agriculture), mangroves, macrophytes, etc.
Built up	Buildings, roads, industries, layouts, concrete and paved surfaces, etc.
Others	Open lands, current fallow (agriculture), quarries, etc.

For earlier time data, training polygon along with attribute details was compiled from the historical published topographic maps, vegetation maps, revenue maps, etc.

Spatial patterns of urbanization through landscape metrics at micro levels

Landscape metrics aid in capturing inherent spatial structure of landscape pattern and biophysical characteristics of spatial change dynamics. Landscape metrics such as patch size and patch shape have been used widely to convey meaningful information on biophysically changed phenomena associated with patch fragmentation at a large scale (McGarial and Marks 1995; Ramachandra et al. 2012a, b; Bharath and Ramachandra 2016). Heterogeneity-based indices have evolved to quantify the spatial structures and organization within the landscape. Quantification of spatial patterns of urbanization has been done by combining landscape metrics with linear gradient analysis, which helps in capturing the spatial variation of land use patterns along a predefined direction. Thus, landscape metrics are important indicators of the growth patterns, neighborhood effect at a temporal scale, and help in understanding the spatial patterns of urban dynamics at micro level (zones) along the corridor with insights to the landscape configuration and interaction between urban and neighboring land uses. MPEW with buffer region (5 km on either side of MPEW) was divided into zones of 25 km width (Fig. 3) between Mumbai to Pune. These zonal gradients provide the information of neighborhood changes at local levels. Spatial metrics were computed for each zone to understand the spatial patterns of urban dynamics based on composition, configuration pattern, and spread at local levels (Bharath and Ramachandra 2016; Gkyer 2013; McGarial and Marks 1995; Ramachandra et al. 2012a, b). Spatial metrics prioritized based on earlier studies (Bharath and Ramachandra 2016; Ramachandra et al. 2012a, b) were considered and are listed in Table 3.

Land use modelling and prediction

Land use change models are inherent to uncertainties due to limited knowledge of the complexity of urban system. In the current work, uncertainty is addressed through calibration by performing sensitivity analysis, wherein the model is run with different parameter values and the results are validated. Prioritized parameters were considered for modelling. The validation of the model is done by measuring the accuracy and kappa of the simulated result against known observations. The agent-based models reduce the approximations based on fuzzy rules generated.

Land use modelling, simulation, and prediction of likely changes were done through the rule-based and agent-based modelling techniques. Rule-based models use set of rules and conditions to predict future landscapes. Cellular Automata combined with Markov chains were used in the current study to predict landscape dynamics (Adhikari and Southworth 2012; Ramachandta et al. 2013; Sang et al. 2011). Markov Chains explains the conversion of land use from one state to the other through transition probabilities based on two-time period land use, i.e., historical and current state of land use. Cellular Automata (CA) is a spatial modelling technique that considers local interaction between neighboring cells and transition rules. A kernel of 5×5 is used to define the neighborhood rules with defined transition cell probabilities and current state of each cell. Coupling CA-Markov chains considers the transition probabilities obtained from the Markov Process which is used as input to CA to model the spatial dynamics, i.e., state of pixel is thus calculated as summed effect of each transitional potential, interaction with its neighbors, and the transition rules. In the current work, transition probability areas were evaluated for the year 2009 and 2015, which were compared with actual land uses for assessment of prediction accuracy and then land uses for the year 2021 and 2027 respectively were predicted.

Agent-based models (Arsanjani et al. 2013; Bharath et al. 2016, 2018; Gilbert 2008) evaluate and account various factors and constraints of growth to derive site suitability maps which are used with CA-Markov to predict future landscape. Google Earth, City Development Plans (Pune Municipal Corporation 2012; UDRI 2014) French Institute Maps were used to digitize features such as airports, city centers, bus stops, railway stations, educational institutions, industries, socio-cultural structures, roads, parks, protected areas, and water bodies, respectively. Digital elevation model (DEM) from SRTM (United States Geological Survey. 2015a) was used to derive slope. Distance maps were developed for all the factors/agents aiding as catalyst in urban growth, namely, all point features and road network. Distance maps were overlaid on built-up area to understand the magnitude and influence of each of the features on built-up areas. Based on the range and behavior of the feature, distances were normalized (0 to 255) through fuzzy techniques. Analytical Hierarchical

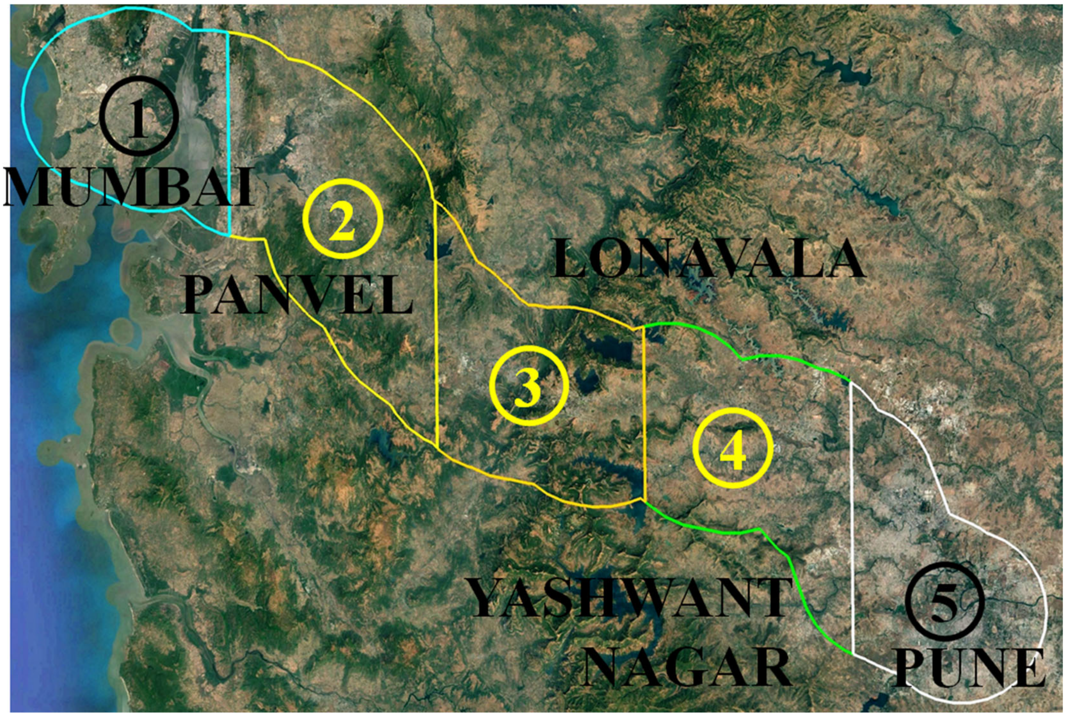


Fig. 3 Zonal approach for understanding sprawl at local levels

Process was used to prioritize and weigh each of the feature using pairwise comparison for built up, others, and vegetation land uses. Slope map, protected areas were used as constraints for urban development and were classified using Boolean algebra, i.e., 0 and 1.0 representing no change and 1 represents areas where is land us can change. Fuzzy maps, constraints, and weightages obtained for each factor were used to create site suitability maps using multi criteria evaluation. Then, Markov Chains used to derive transition probability between two time data. These transition probabilities and site suitability maps are used in conjunction with CA to derive future urban growth based on suitability. Kappa and confusion matrix-based accuracy assessment was done to assess the relative performance of the techniques (Bharath et al. 2014a, b; Ramachandra et al. 2013, 2017).

Table 3 Spatial metrics

Metrics	Equation	Range
Patch density (PD)	f (sample area) = (Patch Number/Area) × 1000000	PD > 0, without limit
Largest Patch Index (LPI)	$\mathrm{LPI} = \frac{\max_{i=1}^{n}(A_{ij})}{A} \times 100$ A_{ij} = area of patch i belonging to class j A = Total Landscape Area	$0 \le \mathrm{LPI} \le 100$
Total Edge (TE)	$\mathrm{TE} = \sum_{k=1}^{m} e_{ik}$ e_{ik} = total length of edge in landscape involving patch type k	TE ≥ 0, without limit. TE = 0 when there is no class edge.
Percentage of Landscape (PLAND)	$\mathrm{PLAND} = \left(\frac{\sum_{i=1}^{n} Aij}{A}\right) \times 100$ A_{ij} = Area of Patch i belonging to class j. A = Total Landscape Area	$0 \le \mathrm{PLAND} \le 100$

Results and discussion

Land cover analysis for the MPEW between 1997 and 2003 given in Fig. 4 illustrates that the vegetation cover has decreased from 40.55 to 23.99% (Table 4). Vegetation cover along the corridor has reduced by ~ 10%, i.e., from 33.9 to 23.99% during 2009 to 2015.

Land uses during 1997 to 2015 are depicted in Fig. 5 and category wise, land uses are listed in Table 5. Land use classification accuracy was more than 90% with kappa of 0.8 (Table 5). Temporal land use dynamics showed that the urban areas have increased from 3.66% (1997) to 19.81% (2015). Rampant urbanization in Mumbai was observed since 2003, whereas in Pune during the post 2009. Development in the outskirts of Mumbai, Pune, and other cities such as Lonavala is attributed to the improved connectivity through the MPEW.

Category-wise land use transitions are listed in Table 6. Across the study area, large-scale transition was observed from vegetation landscape to others. During 2009 and 2015, about 20% of the land of vegetation landscape has changed to others. Similarly, large-scale landscape transitions were observed from others to built-up category (nearly 14.8%) during 2009 and 2015.

Table 4 Land cover dynamics along the Mumbai–Pune corridor

Year	Vegetation (%)	Non-vegetation (%)
1997	40.55	59.56
2003	36.42	63.69
2009	33.9	65.7
2015	23.99	76.09

Spatial patterns of urbanization at micro levels using spatial metrics

Spatial patterns of urbanization are assessed through the prioritized spatial metrics (Ramachandra et al. 2012a, b) in each zone along the industrial corridor and are depicted in Fig. 6. PLAND shows increase from 0.3 to over 1% in zone 1 (Mumbai) and increase from 0.29 to over 1.58% in zone 5 (Pune) during 1997 and 2015 indicating an increase

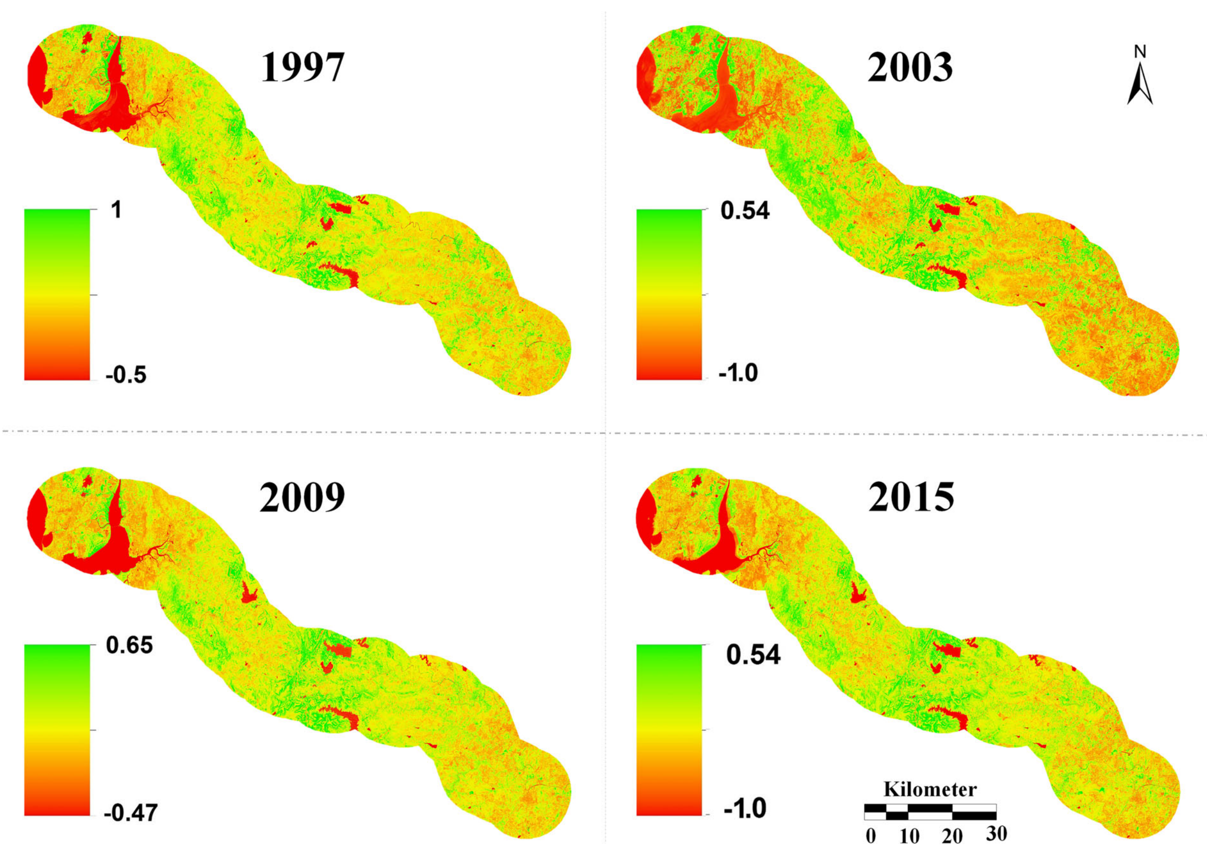


Fig. 4 Land cover (NDVI) – Mumbai–Pune express corridor and buffer

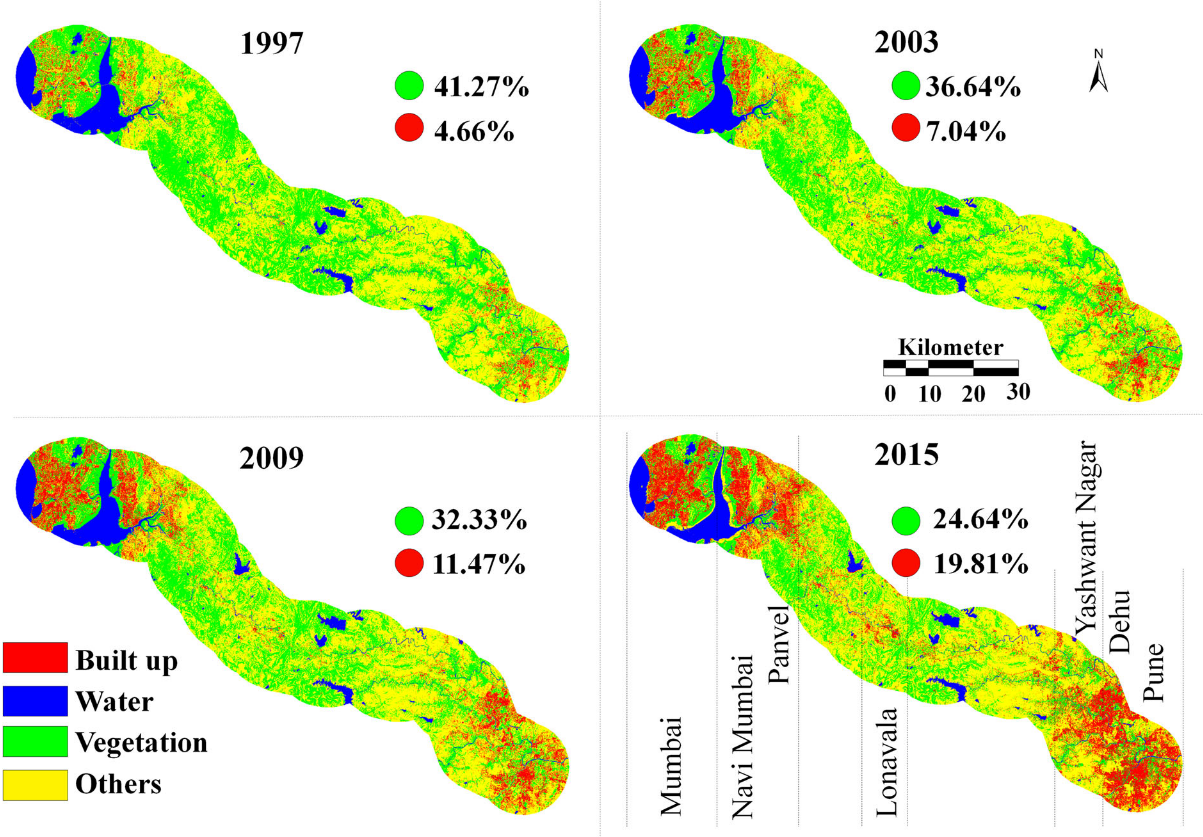


Fig. 5 Land use dynamics

in percent landscape at outskirt regions (zones 2, 3, and 4), which also highlight of sprawl with the significant urban expansions. PD shows increasing urban patches in the fringes of Pune and Mumbai and peri-urban areas in other zones, whereas the city centers showed decreasing PD indicating compact growth or concentrated growth. LPI showed increasing trend across all zones; Mumbai and Pune showed LPI closer to 1 indicating dominance of urban patch. The length of total edge for Mumbai increased till 2009 and declined by 2015 indicating that the entire area transforming to a single patch. The rest of all patches shows temporal increment in total area of urban class. Spatial metric analysis showed compact growth in

Table 5 Land use statistics and accuracy assessment

Year	Land use area (%)				Classification accuracy	
	Water	Forest	Urban	Others	Overall accuracy (%)	Kappa
1997	7.30	41.27	3.66	47.77	92	0.8
2003	7.12	36.64	7.04	49.21	91	0.8
2009	7.77	32.33	11.47	48.42	90	0.81
2015	7.06	24.64	19.81	48.5	91	0.85

Table 6 Land use transition matrix

	Transition year	Water	Vegetation	Built up	Others
Water	1997–2003	93.2%	0.0%	0.6%	6.3%
	2003–2009	98.1%	0.0%	0.2%	1.7%
	2009–2015	100.0%	0.0%	0.0%	0.0%
Vegetation	1997–2003	0.1%	88.8%	0.6%	10.5%
	2003–2009	0.7%	88.0%	1.2%	10.1%
	2009–2015	0.0%	76.5%	3.6%	20.0%
Built up	1997–2003	0.0%	0.0%	100.0%	0.0%
	2003–2009	0.0%	0.0%	100.0%	0.0%
	2009–2015	0.0%	0.0%	100.0%	0.0%
Others	1997–2003	0.6%	0.0%	6.5%	93.0%
	2003–2009	1.9%	0.0%	8.1%	90.1%
	2009–2015	0.0%	0.0%	14.8%	85.2%

Mumbai and Pune, whereas fringes and other areas indicated sprawl.

Modelling landscape dynamics through rule-based models

Urban growth models aided the simulation of probable future situations. Models need to be based on a robust modelling strategy considering the high level of complexity of urban environments. Modelling of likely land use changes has been done through both non-ABM (CA-Markov Chains) and ABM techniques. Cellular Automata (CA) was used to obtain a spatial context and distribution map. CA aided in simulating and predicting land use changes based on the transitional rules depending on the state of cell changes according to

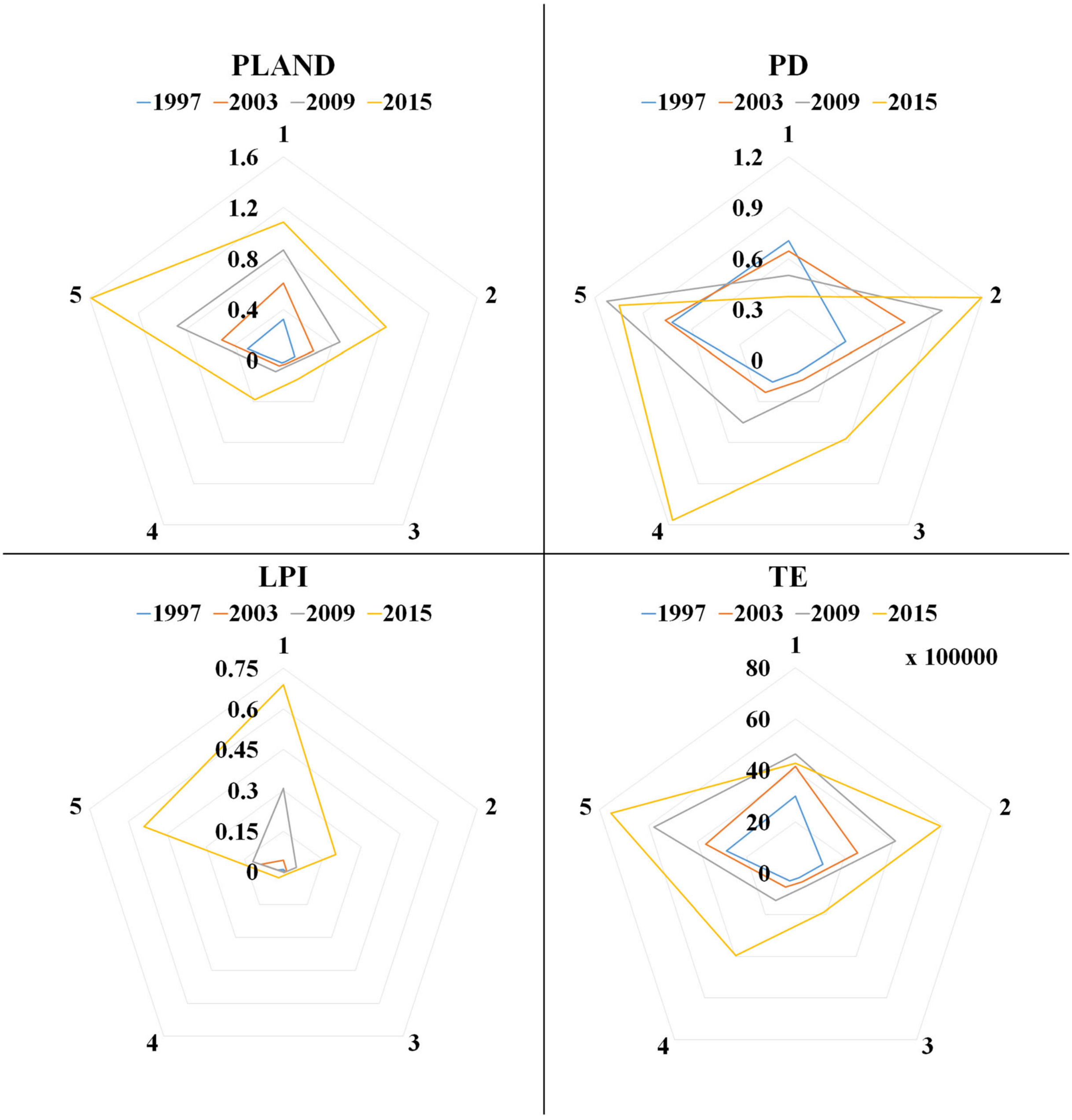


Fig. 6 Zone wise (along the industrial corridor) spatial statistics

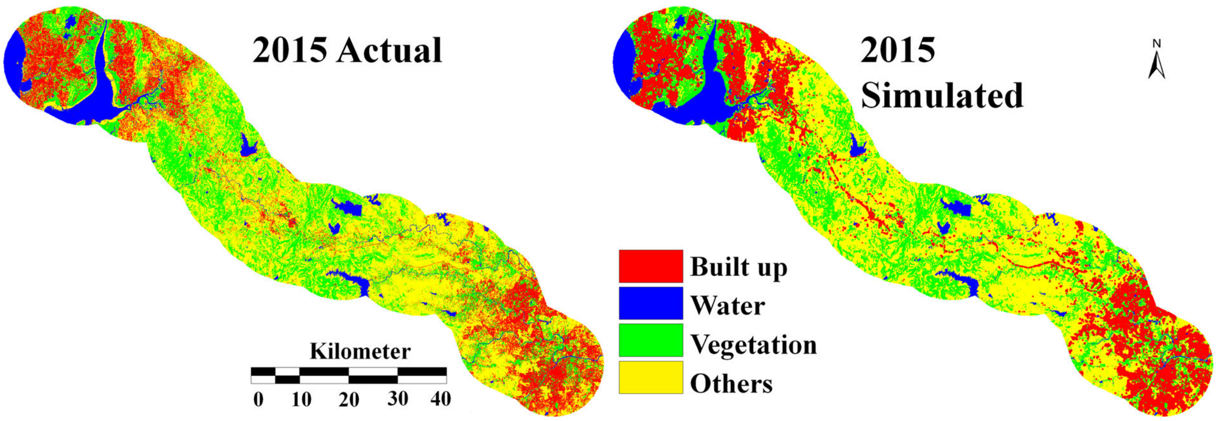


Fig. 7 Validation of rule-based model

the neighborhood cells and the previous state of the current cell with the local and regional interactions. CA transition rule based on land use transition is governed by maximum probability transition and will follow the constraint of cell transition that happens only once to a particular land use, which will never be changed further during simulation.

The land use change patterns follow the Markovain random process properties with various constrains that include average transfer state of land use structure stable and different land use classes may transform to other land use class given certain condition (such as non-transition of urban class to water or vice versa). Thus, Markov was used for deriving the land use change probability map for the study region. CA-Markov Chains model was calibrated for rules such as (i) vegetation changing to urban, (ii) vegetation changing to others category, (iii) others changing to urban, (iv) urban areas remaining intact, and (v) water bodies remaining intact. Land use of known year (t3) was predicted considering the past land uses (t1 and t2). The variables are calibrated for kappa and overall accuracy. Land use data for the year 2003 and 2009 was used to calibrate the model and simulate land use 2015 (Fig. 7). Validation showed that the calibrated model had an accuracy of 94% with Kappa of 0.85.

Agent-based model

Fuzzy Logic, Boolean Algebra, Analytical Hierarchical Process (AHP), and Multi Criteria Evaluation (MCE) were used along with Cellular Automata and Markov Chains in agent-based model. Several factors such as roads, industries, railways, bus stops, educational institution, and socio-cultural places having positive impact on urban growth were digitized using virtual Google Earth data (Fig. 8). Distance maps were prepared for each of these factors and urban bodies were overlaid on each of the distance maps to estimate the range and type of influence. Influence range of various features area is

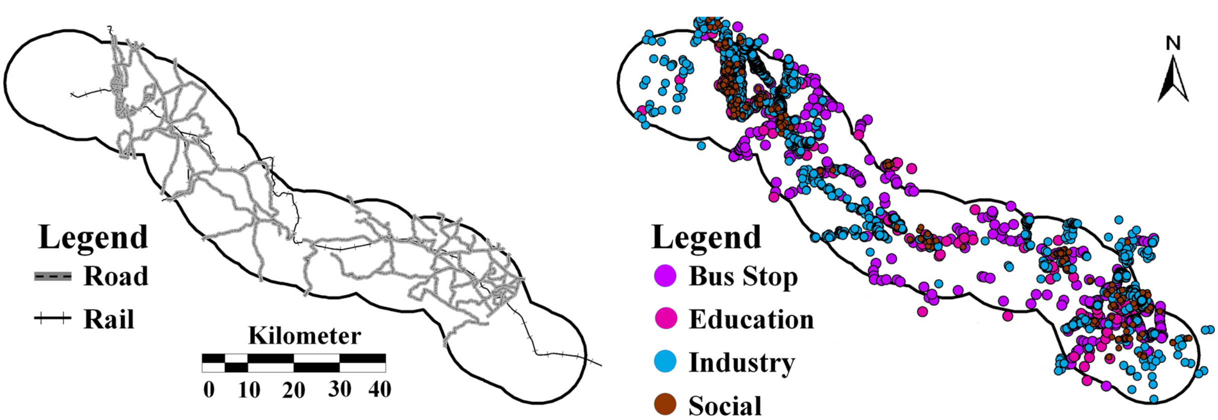


Fig. 8 Agents of land use changes

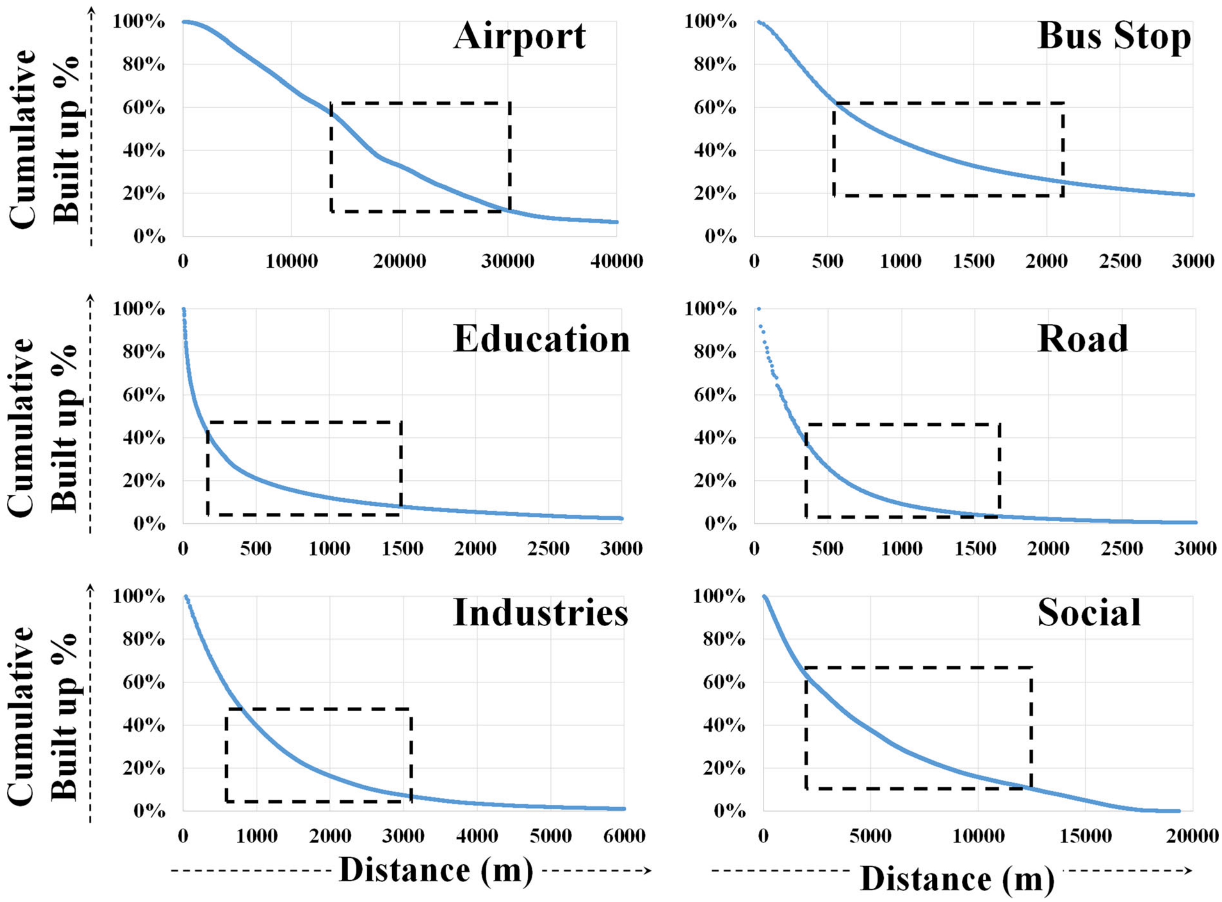


Fig. 9 Zone of influence (*X*-axis, distance; *Y*-axis, cumulative built-up percentage)

given in Fig. 9. All the growth factors had a declining influence with distance on built-up areas whereas for other land use classes, has increasing influence with distance. Airports had highest influence up to 12,000 m that stated declining up to 30,000 m after which it has almost no influence on urban area. Similarly, bus stop/ railway stations had highest influence up to 750 m which gradually reduced to 2000 m; educational institutions influence was high up to 500 m with gradual reduction to 1500 m. Roads had influence range of 500 to 1500 m, industries 800 to 3500 m. Based on the range of influence, distance maps were normalized between 0 and 255 using fuzzy (Monotonically decreasing function for Built-up and Monotonically increasing function for others and vegetation class). These normalized spatial data sets were used to understand their influence on the landscape dynamics. Pair wise comparison was carried out (i.e., by comparing one driver over other drivers), to understand influence of a driver towards land use changes. Table 7 lists weightage of contributing factors of urbanization. AHP using pair wise comparison method indicated that road network had highest influence, i.e., 0.309 followed by Industries and Bus

Table 7 Weightage of various contributing factors

Factor	Built up
Road network	*0.309*
Industries	*0.199*
Bus station and railway stations	*0.199*
Educational	*0.156*
City centers	0.072
Airports	0.036
Social (police station, community halls, etc.)	0.029
Consistency ratio	0.07

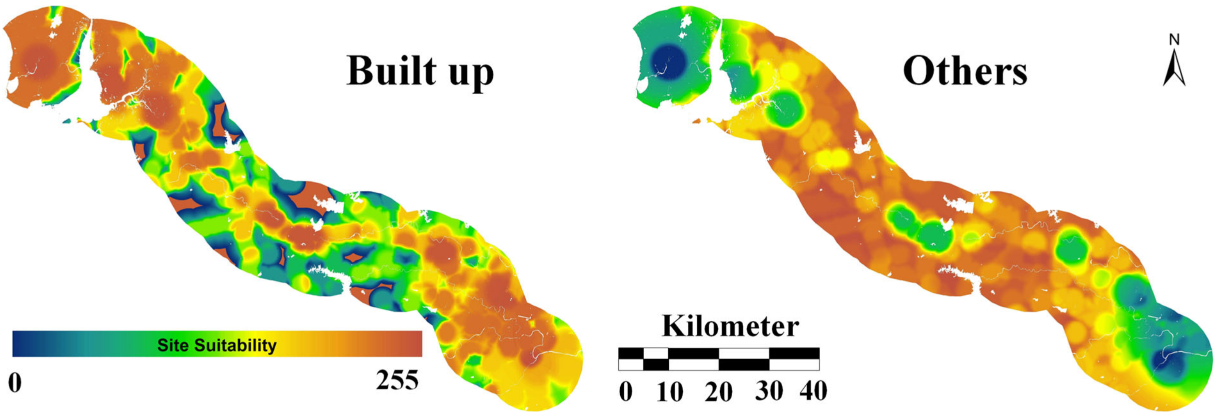


Fig. 10 Site suitability

Stop with weight of 0.199, and educational institutes had influence of 0.156 on built-up areas (Table 7). Consistence ratio (measure of inconsistencies) of 0.07 was achieved indicating that the weights obtained are precise and can be further used for the next process (MCE).

Site suitability maps were prepared using MCE (Fig. 10) for built-up, vegetation, and other land use classes. Site suitability of built-up shows high suitability towards CBD (central business district), fringes, and at close proximity along the MPEW. Other landscape shows high site suitability away from city and the highway, while high slope areas are less preferred for urban growth. Land use simulation for the year 2015 (Fig. 11) showed better persistency with accuracy of 96.5% and Kappa of 0.9.

Land use predictions

Rule-based model (Fig. 12) projected urban growth along the expressway indicating an increase of urban area from 19.81% (2015) to 33.7% (2021) and 49.7% (in 2027) with decline in vegetation to 9.63%. Agent-based model (Fig. 13) predicted urban growth increase from 19.81% (2015) to 32.16% (2021) and 47.12% (2027) with decline in vegetation to 11.10%. Comparative assessment of the model performance through accuracy assessment and Kappa (relatively significant at $p < 0.05$) indicates the superior performance of the agent-based model approaches.

Urban growth in Mumbai and Pune regions would reach saturation by 2021 and the growth would spill to the peri-urban regions along the expressway. The regions to the SE Mumbai that is the Navi Mumbai and Rasayani regions are experiencing high urban growth in 2021 and 2027 according the prediction and these regions are undoubtedly influenced by the metropolitan city of Mumbai. Similar situation towards the NW of Pune as they are facing an urban sprawl during 2015 and 2021 leading to a more compact growth by 2027. Urban growth along the

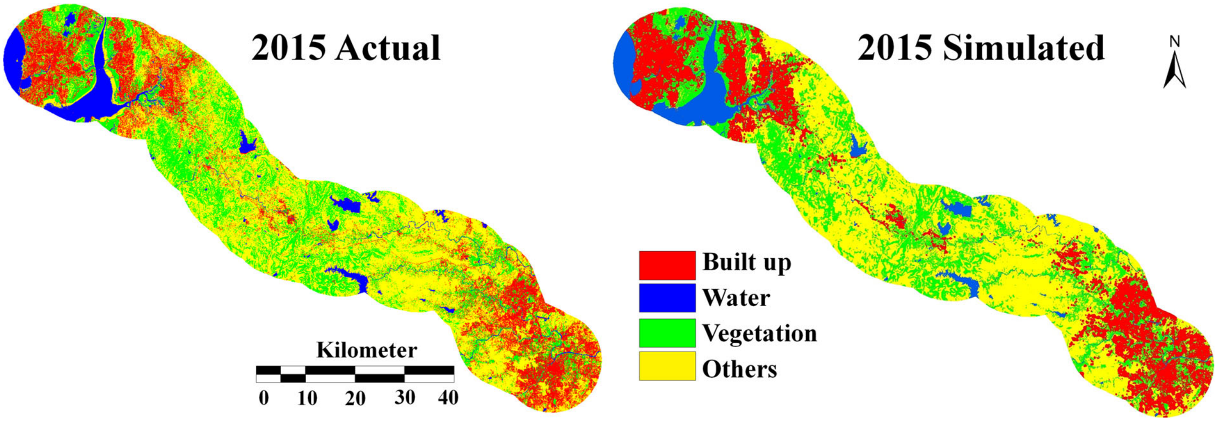


Fig. 11 Validation of agent-based model

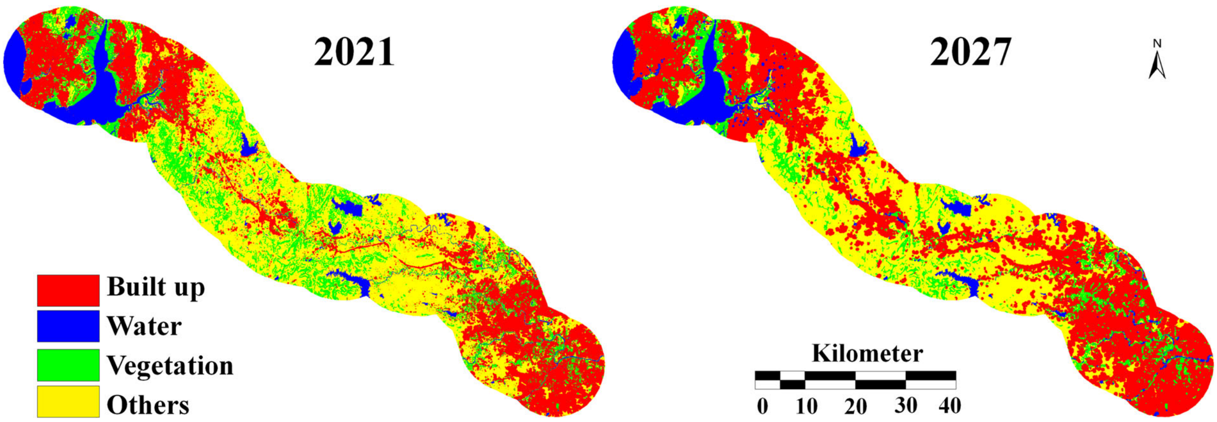


Fig. 12 Land use prediction CA–Model (non-ABM)

Mumbai–Pune express highway also shows the influence of industrial and transportation corridors in the urban expansion. Lonavala region is experiencing high urban sprawl due to the influence of the expressway.

Non-ABM method did predict the growth, but it overestimated the growth in the city and well-known urban regions that are dense already due to the exclusion of the growth rules based on new planned regions and tasks (Maes 1995). Consideration of rules and features as agents (Wooldridge and Jennings 1995) with the location specific inputs avoid overestimation of urban growth in the region. Navi Mumbai outskirts for example was over estimated by non-ABM-based methods; this was corrected using agent growth poles as it can be seen that their also exists other category near the outskirts as it is reserved for non-development (non-paved). This compares the improvement over modelling using ABM. However, the main issues in these techniques are dependency on user-based data and a requirement of strong suitable database of all agents as described by De Smith et al. (2007). This cannot be used in real-time modelling, as there is uncertainty in the agent behaviors. This can however be overcome by integrating with the real-time urban data observatory that can provide real-time agent behavior required for modelling.

The study reveals the role of industrial corridors in land use transitions and future natural resource utilization. The study highlights that the land use dynamics due to the industrial corridors would not just concentrate at urban centers but would establish growth beyond, along the corridors, industrial pockets, etc. Visualizing the future land use trends allows regional planners and managers towards the provision of appropriate infrastructure and basic amenities, while ensuring sustainability through prudent management of natural resources.

Conclusion

Industrial corridors in developing countries aid in creating better infrastructure with the enhanced potential of

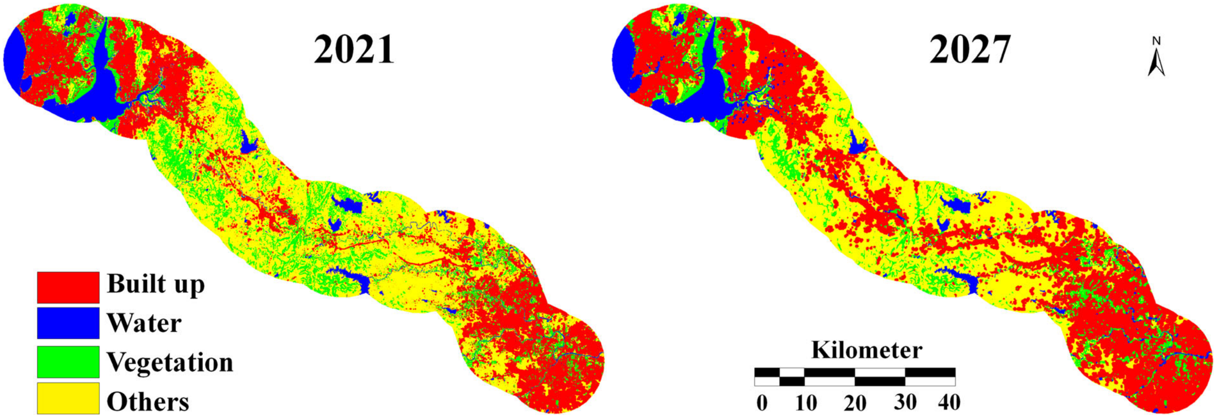


Fig. 13 Land use prediction using ABM

the region, which aid in the development of a nation, with increased job opportunities. Land cover dynamics along the corridor show declining vegetation cover that can be associated with increasing land use conversion for the urban-industrial developments. Land use analysis showed accelerated urbanization being experienced by Mumbai, Navi Mumbai, Pune, and fringes. Built-up area has increased from 3.66% (1997) to 19.81% (2015) with growth concentrated towards CBD's and sprawl along the MPEW. This was explained by various landscape metrics, which showed that growth in Mumbai and Pune are becoming more of concentrated or aggregated due to infilling and ribbon development, whereas other areas show sprawl with increasing urban patches.

Land use change models are inherent to uncertainties due to limited knowledge of the complexity of urban system. In the current work, uncertainty due to the future values of the exogenous factors has been considered. Uncertainty issue is addressed through calibration by performing sensitivity analysis, wherein the model is run with different parameter values and the results are compared. Prioritized parameters were considered in agent-based model based on Fuzzy Logic, Boolean Algebra, Analytical Hierarchical Process, Multi Criteria Evaluation that were used along with Cellular Automata and Markov Chains. The agent-based models reduce the approximations based on fuzzy rules generated. The validation of the model is done by measuring the accuracy and kappa of the simulated result against known observations. Comparative assessment of the model performance through accuracy assessment and Kappa (relatively significant at $p < 0.05$) indicated the superior performance of the agent-based model approaches.

Land use modelling and simulation showed precise results in both rule- and agent-based models. Rule-based model had an accuracy close to 94% with Kappa of 0.85 as against agent-based model was precise evident from the higher accuracy of 96.5% and Kappa of 0.9. The rule-based model tends to have clustered development in and around the core city and existing built-up area whereas ABM shows developments across the study area. Rule-based model predicted that about 49.6% of entire landscape would be urbanized as against ABM predicting 47.12% of landscape being urbanized by 2027, protecting more of vegetation in the study area indicating better predictability of agent-based model as against rule-based model. However, in the case of non-availability of factors and constraints of growth, one can also use rule-based models, which also provide reasonably precise results.

This work illustrated the potential of agent-based models versus the non-agent based and its integration with land use to interact and develop the scenario. Agents are used as features in space with realistic form by considering various plans and process. These agents associated with temporal change have been used as network cell configuration integrating social, environmental condition of city network, etc. Lastly, this model has varied heterogeneous variables that can carefully model real system dynamics. This model can be improved by including the economic data and integration of real-time primary data collected by the governmental organizations.

The current research helped in understanding the landscape dynamics and visualized the future growth patterns based on historical land use trends as well as the inception of industrial corridors. The study highlights that the land use dynamics due to the industrial corridors would establish growth beyond urban centers, along the corridors, industrial pockets, etc. Understanding such likely growth and land use transitions aid in the regional planning towards the provision of appropriate infrastructure and basic amenities, while ensuring sustainability through prudent management of natural resources.

Further, the analysis dissected the land use to understand the urban growth pattern in the neighborhood. All gradients indicated a fragmented growth in the region pointing out that the urban growth had changed the characteristics of the entire landscape to fragmented further the analysis pointed out that if business as usual scenario is considered the landscape would become more fragmented destroying the entire landscape structure to urban landscape. The study also reveals the role of industrial corridors on landscape transition and future natural resource utilization. The study highlights that the land use dynamics due to the industrial corridors would not just concentrate at urban centers but would establish growth beyond such as along the corridors, industrial pockets, etc. Visualizing the future land use trends allows planners and managers to conserve environment by practicing sustainable local and regional level developments.

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