

Agent Based Modelling Urban Dynamics of Bhopal, India

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ABSTRACT

Urbanization involves the transformation of traditional agrarian economy to urban economies dominated by industries and other commercial activities. Our study focuses on the urbanization process in Bhopal (India), a prominent Tier I city, during the last four decades and the visualisation of future growth in 2018 and 2022 with an understanding of urban morphology dynamics through spatial analysis of time-series (1977-2014) remote sensing data with spatial metrics, density gradients and Markov - Cellular automata. Zone-wise urban density gradients recorded between 1977 and 2014 aided in understanding the urban morphology with intense urbanization at core regions and sprawl at outskirts in NW and SE regions. Our study shows an increase of built up ranges by 162% (from 1977 to 1992), by 111% (from 1992 to 2000), by 150% (from 2000 to 2010) and by 49% (from 2010 to 2014). CA-Markov based urban growth modelling indicates urban changes of 50% (2018) and 121% (2022), while agent based modelling (ABM) indicates urban changes of 57% (2018) and 243% (2022) with increasing urban population as compared to 2014. ABM simulations captured reality more effectively and provided the flexibility to vary quantities and characteristics based on proximity of various amenities generating probability surface influenced by various agents, indicating urban development. Simulation of urban growth based on ABM can help planning infrastructure and basic amenities and support the sustainable management of natural resources.

1. INTRODUCTION

Urbanisation is a form of paved surface growth in response to technological, economic, social, and political forces and to the physical geography of an area [1], [2]. The increase in human population coupled with enhanced economic activities often leads to further development of town and urban agglomerations, and agrarian dominant regions evolve to industrially dominant regions. This has given impetus to the spread of the city towards their outskirts or urban sprawl [3]. Sprawl often takes place in the urban fringe, resulting in radial development of urban areas, or along major transport infrastructure, resulting in the elongated development of urban forms [4], which has been investigated in the developed countries [5], [8] and in developing countries such as China [9], [10] and India

[11], [12], [13], [14], [15], [16], [17]. Ciscel (2001) examined sprawl visualising and quantifying three major components for the cause: the jobs, business and housing and government infrastructure capital costs [18]. Urban sprawl was also captured indirectly through socio-economic indicators such as population growth, employment opportunity, number of commercial establishments, etc. [19]. Nevertheless, these techniques cannot effectively identify the impacts of urban sprawl in a spatial context. In this context, the availability of spatial data at regular intervals through space-borne remote sensors are helpful in effectively inventorying, mapping and monitoring land use changes [20], [21]. Galster et al. (2001) have quantified sprawl earlier using parameters such as density, continuity, concentration, clustering, centrality, nuclearity, proximity and mixed uses [22]. Tsai (2005)

employed four quantitative variables (i.e. metropolitan size, activity intensity, distribution degree and clustering extent) to differentiate compactness from sprawl [23]. Others employed multidimensional indicators to measure compactness within specific neighbourhoods or cities [24], [25], [26]. Computation of landscape metrics with the multi-resolution remote sensing data helps quantifying the spatial pattern of land use patches in geographical area to understand the patterns of variations in peri-urban regions [1]. However, these approaches still lack spatially explicit urban expansions in the past with the related urban planning policies and predict possible expansion scenarios in the future [27]. Attempts linking land use changes and transportation to predict urbanisation have been done through cellular automata (CA) modelling, agent based modelling (ABM), etc. In India, several studies approached urbanisation and urban growth in relation to transportation, energy, land use, climate, etc. and many studies have not addressed the problem of urban sprawl. Recent researches have asserted that urban systems are complex systems, while acknowledging the self-organisation in urban systems [28], [29], [30], [31]. Capturing urban systems as discrete models gained further momentum with the popularity of the cellular automata (CA) based techniques [33]. Yakoub (2005) has adopted a change detection approach to evaluate, detect, and estimate the areas of land use change in parts of the Delta area in Egypt [32]. Further, Courage et al. (2009) and Ramachandra et al. (2013) used Markov chain for generating transition probability matrices based on the understanding of past land use changes and could easily establish the developments in the region based on current land use with CA and Markov provided vital insights to the understanding of spatio-temporal patterns of urbanisation [3], [34]. There have been many other methods that use various techniques to model the land use changes [35]. However, these approaches do not take into account agent's interaction in the urban space for modelling the likely growth. This study aims to understand the spatio-temporal patterns of urbanisation in Bhopal city with a buffer of 10 km and to predict likely future urban growth based agent's interactions with land use change process and current rate of transitions.

2. STUDY AREA

Bhopal, also known as the City of Lakes, is the capital of the Indian state of Madhya Pradesh and the administrative headquarters of Bhopal district and it is the 17th largest city in India. Bhopal has an average elevation of 1400 ft, with climate ranging from 27°C to 40°C. It has an annual rainfall of 1140 mm on average. The annual growth of Madhya Pradesh is one of the highest in the country as the state Gross Domestic Product is of 11.68% in the 2014-2015. It is located in the central part of India and lies between the latitude 23°07' to 23°54' N, longitude 77°12' to 77°40' E (Fig. 1).

Bhopal Municipal Corporation is the urban civic body that is responsible for the development needs of the city and Bhopal urban development authority oversees the urban needs. The municipal corporation of Bhopal covers 285.88 km² and is divided into 85 wards. Bhopal city population is of 2.3 million (Census of India, 2011) and including 10 km buffer, the population reaches 2.9 million. Figure 2 depicts the growth in population of Bhopal along with the population density (person/km²).

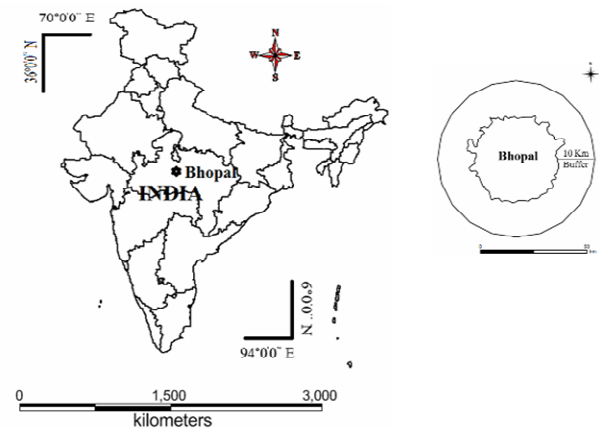


Fig. 1. Study area-Bhopal city with buffer.

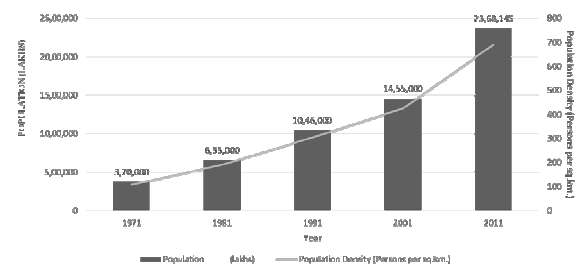


Fig. 2. Growth in population of Bhopal city along with the population density (person/km²).

3. DATA AND METHODS

The time series spatial data acquired from Landsat Series Multispectral sensor (57.5 m), thematic mapper (28.5 m), Enhanced thematic mapper sensor and Aster data for the period were downloaded from the public domain [36]. Table 1 summarises the data acquired for analysis.

Table 1. Data used for LULC analysis.

Data	Year	Purpose
Landsat Series MSS (57.5 m)	1977	Land use dynamics analysis
Landsat Series TM (28.5 m)	1992, 2000	
Landsat Series ETM+ (28.5 m)	2010	
Landsat 8 (28.5 m)	2014	
ASTER (30 m)	2011	Digital Elevation Model
Survey of India (SOI) toposheets of 1:50000 and 1:250000 scales		To Generate boundary and Base layer maps.
Pre-calibrated GPS		Ground control points, attribute data

3.1. Data analysis

The analysis was a 5 step process as shown in Figure 3, including the following:

a). *Pre-processing*. The remote sensing data obtained (Table 1) were geo-referenced, rectified and cropped pertaining to the study area. Geo-registration of remote sensing data (Landsat data) has been done using ground control points collected from the field using pre-calibrated GPS (Global Positioning System) and also from known points (such as road intersections, etc.) collected from geo-referenced topographic maps published by the Survey of India. The Landsat satellite 1977 image have a spatial resolution of 57.5 m × 57.5 m (nominal resolution) were resampled to 28.5 m comparable to the 1992–2014 data which are 28.5 m × 28.5 m (nominal resolution) using the nearest-neighbourhood resampling techniques.

b). *Land use analysis*. Land use categories were classified using supervised classifier based on Gaussian Maximum likelihood (GML) algorithm [37]. Remote sensing data are processed using signatures from training sites to quantify the land-use of Bhopal city broadly into four classes – built-up, vegetation, water bodies and others (detailed in Table 2).

Table 2. Land use classification categories adopted.

Land use class	Land uses included in the class
Urban	Residential area, industrial area, and all paved surfaces and mixed pixels having built up area
Water bodies	Tanks, lakes, reservoirs
Vegetation	Forest, cropland, nurseries
Others	Rocks, quarry pits, open ground at building sites, kaccha roads

False colour composite of remote sensing data (bands – green, red and NIR), was generated to visualise the heterogeneous patches in the landscape. The signatures were generated as polygons from heterogeneous patches and the attribute information corresponding to these polygons were obtained from the field using pre-calibrated Global Positioning System (GPS) and Google Earth [38]. Among the training data, 60% is used for classification using GML and the balance is used for validation of classified information /accuracy assessment.

c). *Zone-wise gradient analysis*. The study region consisting of the city boundary and 10 km buffer is divided considering the Central pixel (Central Business District) into 4 zones based on directions as Northeast (NE), Southwest (SW), Northwest (NW), and Southeast (SE). This has been done as most of the definitions of a city or its growth are defined based on directions. The growth of the urban areas was assessed in each zone through the computation of temporal urban density for different periods.

d). *Gradient analysis - division of zones into concentric circles*. Each zone was divided into concentric circles of incrementing radius of 1 km radius from the centre of the city, and this analysis helped in visualising the process of changes at local levels with the agents responsible for changes.

e). *Characterising sprawl using landscape metrics*. Landscape metrics provide quantitative description of the composition and configuration of urban landscape.

Table 3. Select metrics for urban growth patterns analyses (metrics prioritised as per Ramachandra et al., 2012a, 2014).

Indicator	Formula
Number of patches (Built-up) (NP)	$NP = n_i$ Range: $NP \geq 1$ $TE = \sum_{k=1}^m e_{ik}$
Total edge (TE)	Range: $TE \geq 0$, without limit $nLSI = \frac{e_i - \min e_i}{\max e_i - \min e_i}$
Normalised landscape shape Index (NLSI)	Range: 0 to 1 $Given G_i = \frac{g_{ij}}{(\sum_{k=1}^m e_{ik}) - \min e_i}$
Clumpiness Index (Clumpy)	$CLUMPYG_i = \left[\frac{G_i - P_i}{P_i} \text{ for } G_i < 5, \text{ else } \right]$ $\frac{G_i - P_i}{1 - P_i}$ Range: Clumpiness ranges from -1 to 1

Empirical studies on urbanisation and urban sprawl have demonstrated the usefulness of metrics to understand the spatial patterns of urban sprawl. Four spatial metrics chosen [1], [17] based on complexity, fragmentation, patchiness, and dominance in terms of structure, function and to characterize urban dynamics were computed zone-wise for each circle using classified land use data at the landscape level with the help of FRAGSTATS [39]. The metrics including the patch area (Largest Patch Index), number of urban patches, edge/border (total edge (TE)), and shape (Normalize Landscape Shape Index (NLSI)), epoch/contagion/dispersion, Clumpiness were computed for each region for understanding the process of change at local levels.

3.2. Modelling urban dynamics using Markov-cellular automata

Markov chain. Markov chain is based on a random phenomenon with the past changes (which affects the future through the present). The “time” can be discrete (i.e. the integers), continuous (i.e. the real numbers), or, more generally, a totally ordered set.

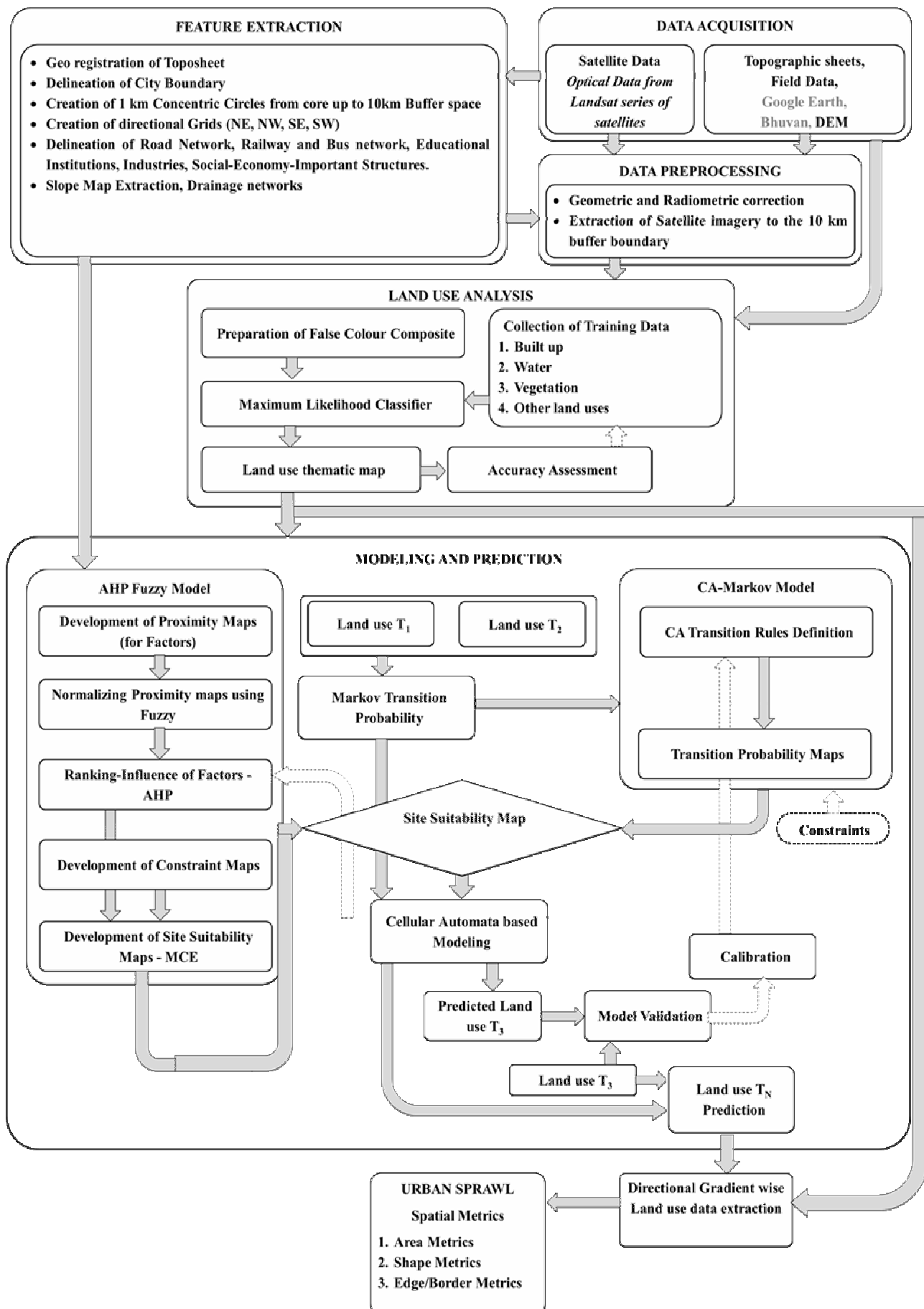


Fig. 3. Procedure adopted for analysis.

The basic assumption in the model is that the state at some point in the future ($t+1$) can be determined as a function of the current state (t). Space is assumed as discrete and changes as a stochastic process [40] mainly based on probabilities.

Mathematically, it is formulated as:

$$X(t+1) = f(X(t)) \quad (1)$$

where: t – time.

A stochastic process $\{X_t\}$ satisfies the Markovian property if:

$$P(X_{t+1}=j | X_0=k_0, X_1=k_1, \dots, X_{t-1}=k_{t-1}, X_t=i) = P(X_{t+1}=j | X_t=i) \quad (2)$$

For all $t = 0, 1, 2, \dots$ and for every possible state.

A stochastic process $\{X_t, t = 0, 1, 2, \dots\}$ is a finite-state Markov chain if it has the following properties:

- a finite number of states;
- stationary transition properties, p_{ij} ;
- a set of initial probabilities, $P(X_0=i)$, for all states i .

The main variables are LULC data, Markov transition (generated using Markov model), a transition suitability image (includes each class suitability images) developed by comparing the suitable sites and constraints for urban class and for other classes the Markov conditional probability images, based on the probability of each class occurrence in each pixel according to past experiences, used as suitability images. A contiguity filter is used for generating a spatially explicit contiguity weighting factor to change the state of cells based on its neighbourhoods.

Cellular Automata (CA). CA are spatially explicit, dynamic, discrete space and time systems [41]. A cellular automaton system consists of a regular grid of cells, each of which can be in one of a finite number of k possible states, updated synchronously in discrete time steps according to a local, identical interaction rule [28]. The state of a cell is determined by the previous states of a surrounding neighbourhood of cells and is spatially explicit [42]. The main components of CA are “cells”, “states”, and “neighbourhood and transition rules”. It is called discrete dynamic system which means the state of each cell at time $t+1$ is determined by the state of its neighbouring cells at time t , leading to transition rules.

CA induces spatial allocation, location of change into the model and Markov chains predict changes in the properties of land quantitatively, based on historical patterns, which are basic inputs to CA [43]. Global research affirms that MC-CA efficiently simulates urban growth patterns [44], [45], [46].

Validation. These models are typically calibrated using training data (i.e. past land use maps) which are then compared with an actual land use map, and kappa index [47]. The calibrated model can be applied to the prediction of future urban spatial patterns [48].

3.2.1. Agent Based Modelling

Modelling future urban land-use scenarios has been done by integrating developmental factors using an agent-based model (ABM). The model was calibrated by simulating land use for 2014 and compared with the actual land uses and then a 4-year simulation was performed. The goals of this model are to predict future land-use development under existing spatial policies.

Characterising influence of each agent using Fuzzy. Fuzzy logic is integrated into modelling methods in order to resolve representation of values in a derived complex environment [49]. Fuzzy rules expressed for each of the variable consist of a set of fuzzy expressions allowing for the evaluation of specific attributes considering distances as a measure with simultaneous application of several rules is allowed and with varying membership degrees [50]. Finally, distance of influence is measured and provides input to weighing process such as analytical hierarchical process based on influence of distance with high membership degrees. In this study agents with different degree of membership and representation function were utilised to derive the influence of distance characteristics which eventually become an input to explain their importance and influence in urban developments. Weights of influence derived from Analytical Hierarchical Process (AHP). This approach helps in multi criteria decision-making (MSDM). The AHP is one of the most commonly MCDM technique incorporated into GIS-based suitability procedures [51], [52], [53]. Further, these weights are used to generate Markov transition probabilities and in turn these probabilities are used in the prediction of urban growth using Cellular Automata.

3.3. Results

Land use analysis. Classified land uses during 1977, 1992, 2000, 2010 and 2014 are shown in Figure 4. Analysis of the temporal remote sensing data reveals an increase in built up area of 262% (from 1977 to 1992), 211% (from 1992 to 2000), 250% (from 2000 to 2010) and 149% (from 2010 to 2014). Similarly, the extent of other category (including the cultivation lands, barren lands, open lands, etc.) has drastically increased from 5% in 1977 to 65% in 2010 showing 300% growth during the last four decades with 70% decline of vegetation cover. LU analyses (Table 4) reveal that urbanization has led to the loss of arable land, decline

in natural vegetation cover as well as habitat destruction. Accuracy assessment and kappa statistics were calculated, overall accuracy ranged from 85% to 95% and kappa values ranged from 0.84 to 0.94.

Table 4. Land use of Bhopal during 1977 to 2014.

Year	Urban (%)	Vegetation (%)	Water (%)	Others (%)
1977	0.35	92.04	2.15	5.45
1992	0.93	66.52	2.38	30.17
2000	1.96	37.25	2.14	58.65
2010	4.90	28.02	1.82	65.26
2014	7.31	21.77	2.09	68.83

3.3.1. Density gradient analysis

The study area was divided into concentric incrementing circles of 1 km radius (with respect to centroid or Central Business District) in each zone. The urban density computed for each gradient of respective zones for the period 1977 to 2014 is given in Figure 6. This highlights the radial pattern of urbanization with the concentrated growth closer to the central business district and minimal growth in 1977. Bhopal grew

intensely in the NW and SE zones in 1977-1992 due to the industrialization in the region. The industrial layouts came up in SE and housing colonies in NW and NE and urban sprawl was noticed in other parts of Bhopal. This phenomenon intensified with the development of industrial sectors in SE and NW after 2000. The analysis showed that Bhopal grew radially from 1973 to 2014 indicating that the urbanisation has intensified from the city centre and reached the periphery of Bhopal. The annual growth of Madhya Pradesh is one of the highest in the country as Gross Domestic Product is of 11.68% in the 2014-2015.

After the reorganization in 1956 and designating Bhopal as the capital of Madhya Pradesh state, planners looked at building new Bhopal city away from the so called city centre, which remained planned until late 1990s, wherein industrialization took over developing the Bhopal Metropolitan Region that encompasses regions of Rajgarh, Raisen and Vidisha. Bhopal city enjoys the development of towns that are known as market towns established in late '90s named Berasia, Vidisha, Raisen, Sehore, Budhni, Itarsi. The fact is that planners have visualized good connectivity with road infrastructure but have failed to provide regional connectivity to the national mainstream, due to which we see huge developments in these regions in terms of sprawl.

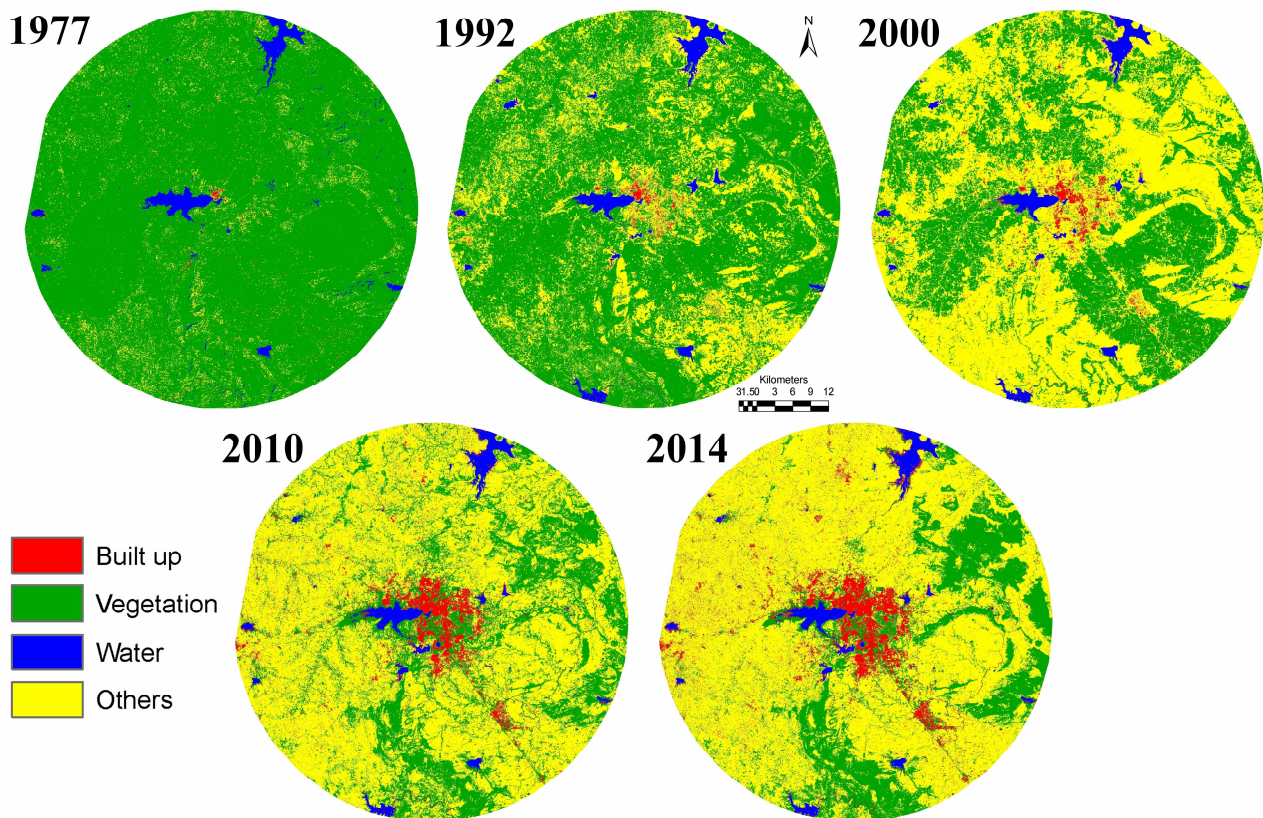


Fig. 4. Land use changes from 1977-2014.

Prior to industrial advent in Bhopal, city had few planned industrial colonies such as BHEL in the newly planned city regions, and connected the old city.

With the advent of industries in 1990s Bhopal started expansion towards northeast specifically towards Vidisha. This pattern changed in late '90s and with

industrial colonies in southern regions Bhopal expanded and sprawled towards southeast near Mandideep and Shobhapur, which has continued over the next decade with sprawl around the airport, railway

cantonment. Though planners had visualized the growth of Bhopal, the huge rampant urban sprawl was not understood.

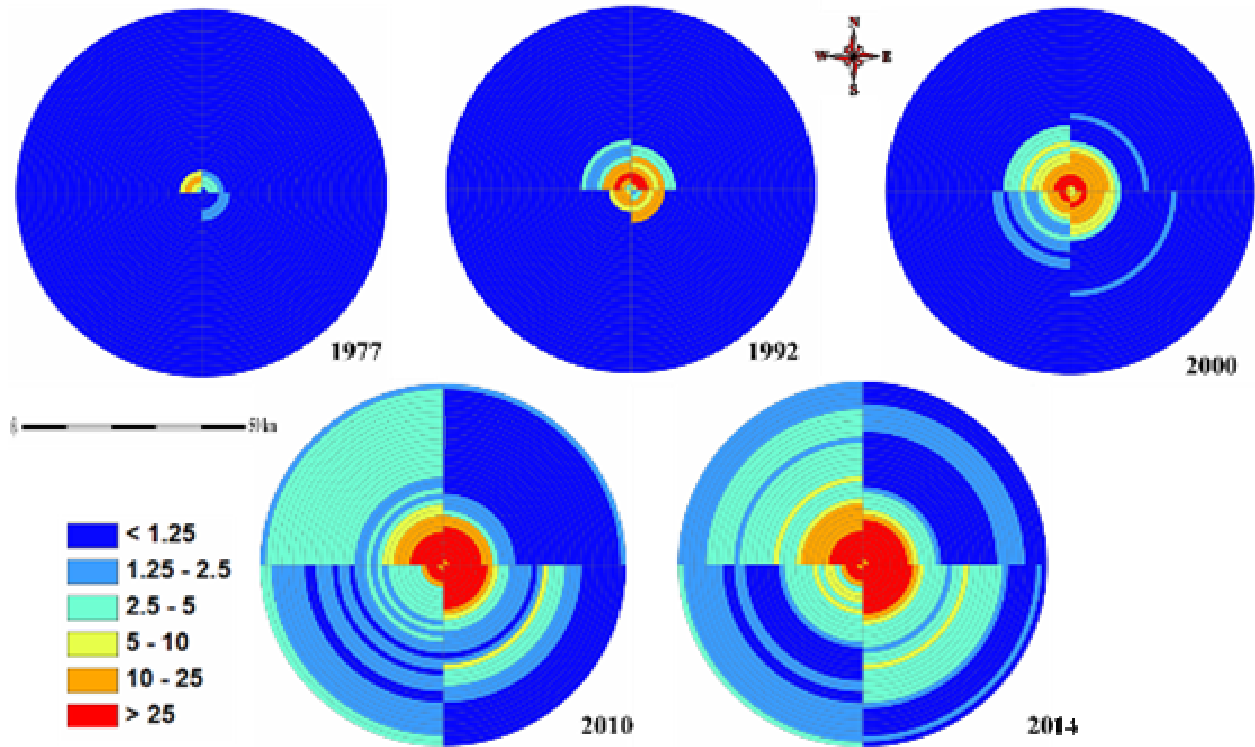


Fig. 5. Gradient analysis of Bhopal Built-up density circle (urban area/ total area) - and zone wise.

3.3.2. Spatial patterns of urbanisation

Spatial patterns of urban growth were analysed zone wise for each circle of 1 km radius considering temporal land use information using five landscape level metrics which are discussed below:

a). *Number of patches (NP)*. Figure 6 illustrates the temporal dynamics of number of patches. In the year 1977 the inner circles close to CBD (1-7) have patches close to 1, indicating the fact that these regions are in the state of clumped growth, which is common in NE, SE and SW directions. In the NW direction, the core is fragmented showing that these regions are dominated by all classes. In all directions, there are fragmented buffer regions with number of patches ranging from 10 to 40 except southwest, which experienced higher fragmentation in 1977. But in 2010 and 2014, the buffer regions have become more fragmented, with patches ranging from 280 to 518, showing that the regions are under the pressure of urban sprawl and fragments of urban area have increased, which in turn has led to the dominance of urban in the region. All directions show fragmented growth, with higher fragmentation ~500-800 fragments in northwest region in the buffer zone.

b). *Total Edge (TE)*. During 1977, the edges were smaller, as the urban patch was rare and concentrated in landscape, but post 2000 and in 2014 there are larger edges, which indicate that the urban area is continuous. This phenomenon is true in the city boundary, but the buffer region patches are yet fragmented and non-continuous. In 2014, TE steadily increased in the outer circle showing further fragmentations in all directions with the highest fragments in NW zone indicating that these regions are dominated by all classes. Southwest zone had minimal fragmentation but a concentrated growth with less number of edges.

c). *Normalized Landscape Shape Index (NLSI)*. Results depict fragmented landscape post 2000 and in 2014, the landscape is highly fragmented in the buffer region. In 1977, the lower value of NLSI in all three directions except NW, with regular shape (Circle, Square) in the inner circle near to CBD (1-7). NW direction close to city centre (1-7) shows fragments ensuring core is dominated by all classes. In 2014, the NLSI shows almost similar value for the core area (1-7) in all the direction indicating the fact that these regions are on the verge of forming a single urban patch and northeast is the direction that is severely affected by

urbanisation indicating irregular shape at the centre. In the SW direction (circle 7 and 8) having 0 value of NLSI shows single maximally aggregated patch completely dominated by water cover. The result also assures fragmented growth in 2014 near the CBD as compared to

1977 indicating irregular shape at the centre. NLSI demarcates that the urban area is almost clumped in all direction and all gradients especially in NW and SE direction. It shows a small degree of fragmentation in the buffer regions in SW direction.

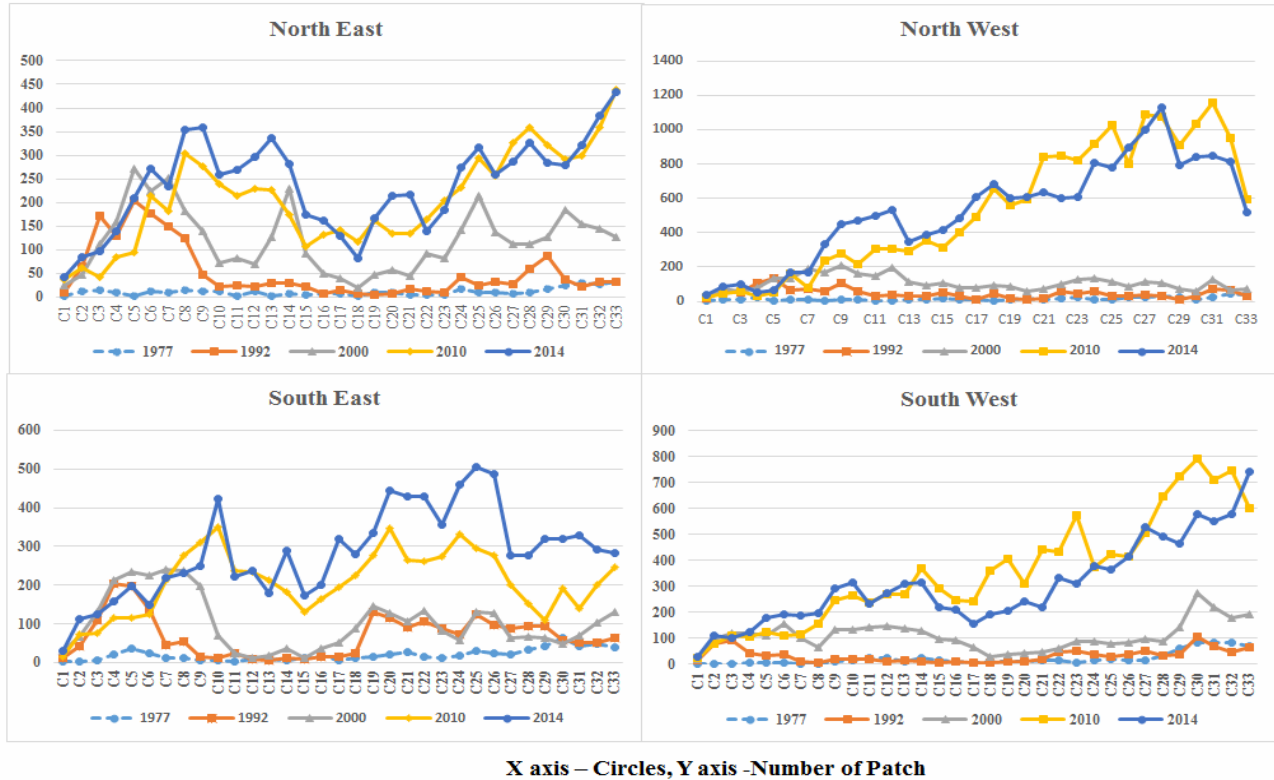


Fig. 6. Analysis of number of patches in the study region.

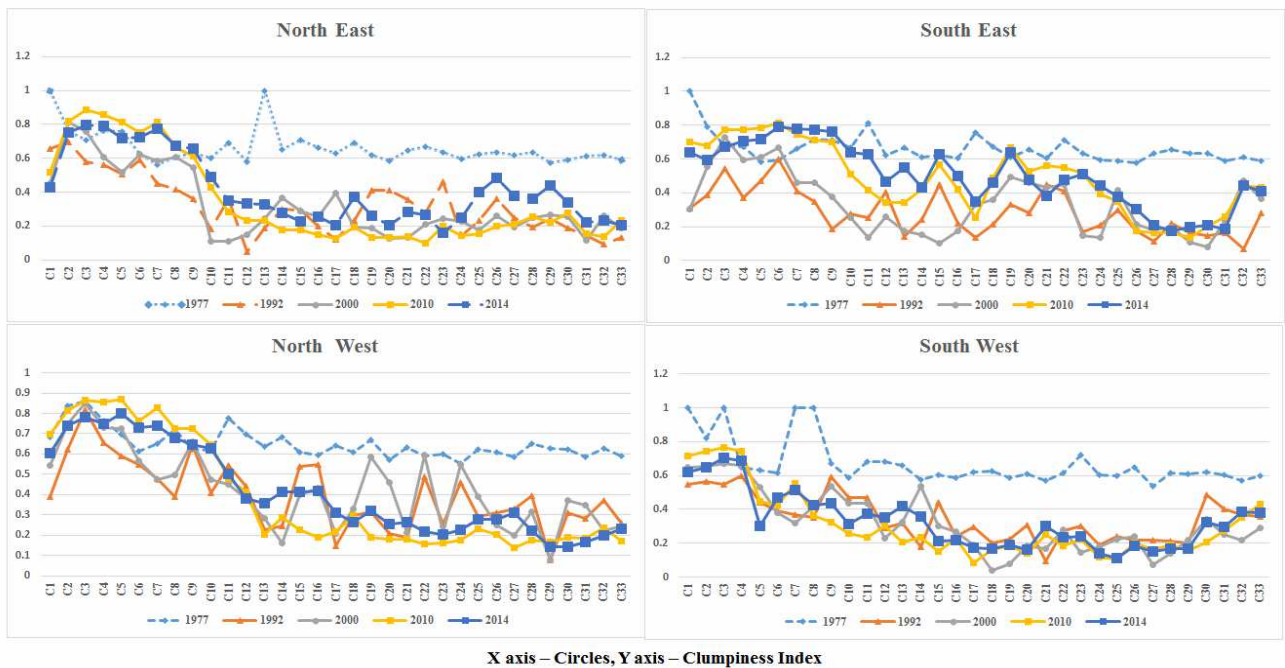


Fig. 7. Analysis of Clumpiness in the study region.

The core area is in the process of becoming maximally uniform shape (such as square, circle etc.) in all directions.

d). *Clumpiness index (CLUMPY)* represents the similar trend of compact growth at the centre of the city which gradually decreases towards the outer rings

indicating the urban agglomeration in the centre and phenomena of sprawl at the outskirts in 2014. Figure 7 with the Clumpy values of 1 at core areas (in 1977) indicates a clumped growth in all direction except for Northwest. In 2010, the value of clumpy index gradually decreased in the inner circle (1-7) showing that the CBD is under the pressure of urbanization with more aggregated growth in SE. NW in 2010 has lowest value of clumpy showing higher fragmentation in the buffer region. The buffer region has become more fragmented in northwest direction by 2014 followed by southeast, which shows that the regions are under the pressure of urban sprawl and fragments of urban area have increased which in turn has led to dominance of urban in the region. The analysis of spatial patterns using landscape metrics highlights compact growth with intense urbanisation in 2010. Central areas have a high level of spatial accumulation and corresponding land uses, such as in the CBD, while peripheral areas have lower levels of accumulation. Unplanned concentrated growth or intensified developmental activities in a region has significant influences on natural resources (disappearance of open spaces – parks), enhanced pollution levels and also changes in the local climate.

3.3.3. CA Modelling (validation and prediction)

Land use (LU) transitions were calculated to predict land use for the year 2014, using Markov chain based on LU of 2000 and 2010. CA hexagonal filter (5×5) was used to generate spatially explicit contiguity weight age factor to change the state of the cell based on neighbourhoods. Predicted land uses of 2014 were compared with actual land uses of 2014 classified based on remote sensing data with field data. Results reveal that predicted and actual land uses are in conformity with kappa value of 0.83 and overall accuracy being 86% (Table 5). With the knowledge of 2000, 2010 and 2014, LU is predicted for 2018 and 2022 (Fig. 8). This prediction was done considering water bodies as constraint and assumed to remain constant over all time frames. Table 6 tabulates predicted land use statistics of Bhopal city for the year 2018 and 2022.

The main concentration will be mainly in the vicinity of NH12 and proposed outer ring road. Predicted land use also indicates densification of urban utilities

near the Raja-Bhoj airport and surroundings, and a further exuberant increase in the urban paved surface growth due to industrial areas in southeast and northwest. The results also indicated the growth of suburban towns such as Vidhyanagar, Mandideep, Avadhpuri, Shobhapur, Obaidullganj, Bharkeda, Jharkheda, Toomda and Thuna Kalan (Fig. 9) with urban intensification at the core area. The predicted urban area is expected to increase by 50% in 2018 and 121% by 2022 as compared to 2014. This highlights the need for appropriate infrastructure and basic amenities to cope up with the visualized growth and minimize drudgery to the common public. Since the model does not consider the factors(s)/agents of growth, it may be noted that few regions especially the core and regions in Obaidullganj and Shobhapur that are major regions of today's growth have not shown urbanisation, mainly due to neighbourhood effect. Regions on the south and east that have new developments in today's context have been omitted since previous maps that were used for training and prediction had no reference of today's growth. Overall, CA-Markov underestimated the land use for 2014, which can be avoided using drivers of urban growth through Agent Based model. Factors that express influence and weights were obtained through fuzzy – AHP, which were used in ABM. Validation was performed showing kappa of 0.93 and overall accuracy of 93.5%. Figure 10 shows examples of selected factor(s) considered for ABM. Figure 11 shows the results of Fuzzy – AHP based agent based urban model for 2014, 2018 and 2022 and land use details are tabulated in Table 5 (for 2014) and 7 (for 2018 and 2022). ABM based prediction for built-up was comparable to the actual values (agreement greater than 99%). ABM could also bring out the major regions of growth such as Toomda and Sehore that are recently under the influence of urbanisation. Clearly ABM brought out region specific growth with different agents. It can be noted that infrastructure, i.e. road and rail, are good in Bhopal and we could understand the urban development happening in these corridors along with industrial areas. Roads, basic amenities such as schools, hospital and job locations were the main factors that were influencing urban growth in these regions. It may be essential to plan these basic amenities before planning further developments towards Indore, Sehore, and Obaidullganj.

Table 5. Comparison of predicted land use (2014) with actual land use of 2014.

Class year	Built-up area (%)	Vegetation (%)	Water (%)	Others (%)
2014 classified	7.31	21.77	2.09	68.83
2014 predicted (CA Markov)	5.71	33.93	1.73	58.63
2014 predicted (ABM)	7.02	18.84	2.12	71.98

Overall accuracy = 0.82 K location = 0.84 K standard = 0.73 (CA-Markov).
Overall accuracy = 0.935, K location = 0.93 K standard = 0.91 (ABM).

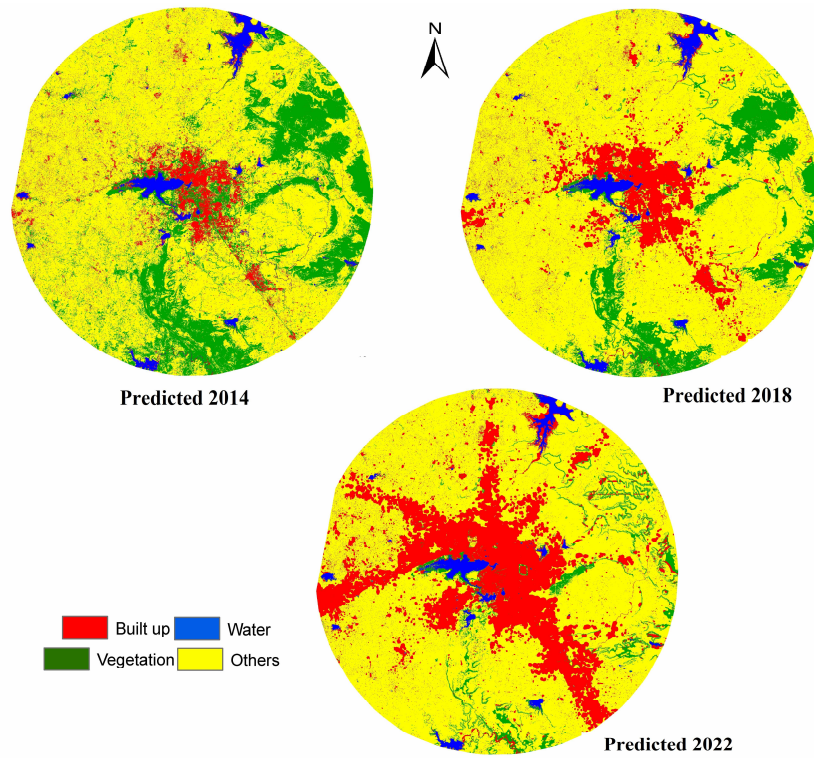


Fig. 8. Predicted growth of Bhopal using CA-Markov.

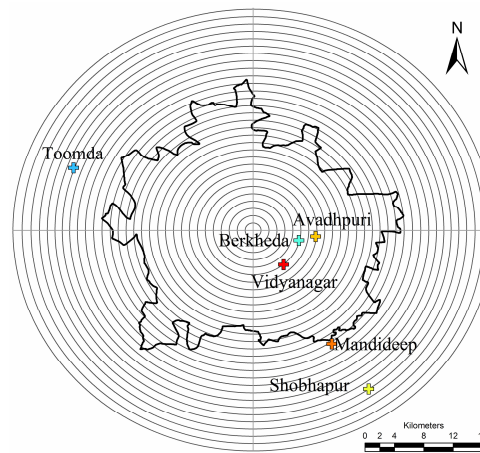


Fig. 9. Probable urban growth locations.

Table 6. Predicted Land use statistics of Bhopal using CA-Markov.

Class year	Built-up area (%)	Vegetation (%)	Water (%)	Others (%)
2018 Predicted	10.94	24.11	2.35	62.60
2022 Predicted	16.14	28.03	2.52	53.31

Table 7. Predicted Land use statistics of Bhopal using Agent based model.

Class year	Built-up area (%)	Vegetation (%)	Water (%)	Others (%)
2018 Predicted	11.51	11.1	2.41	74.99
2022 Predicted	25.09	4.71	2.12	69.09

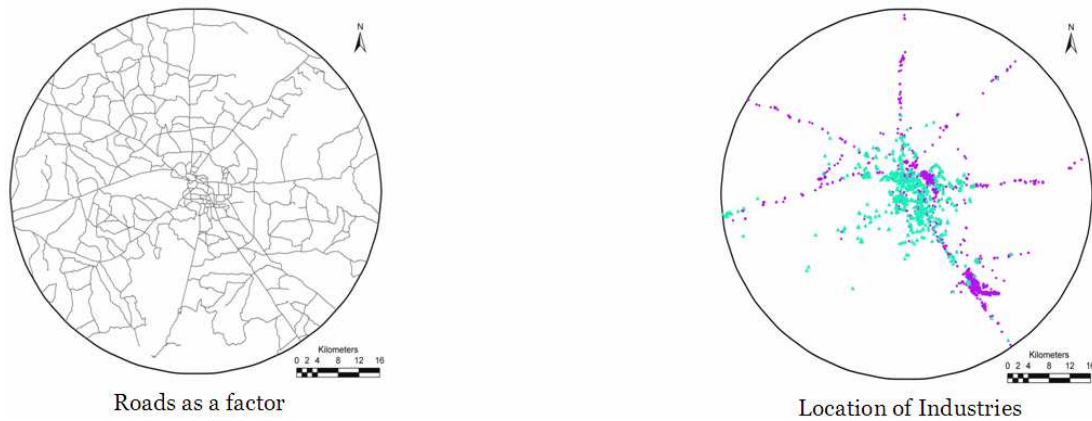


Fig. 10. Example of factor(s) considered for the analysis.

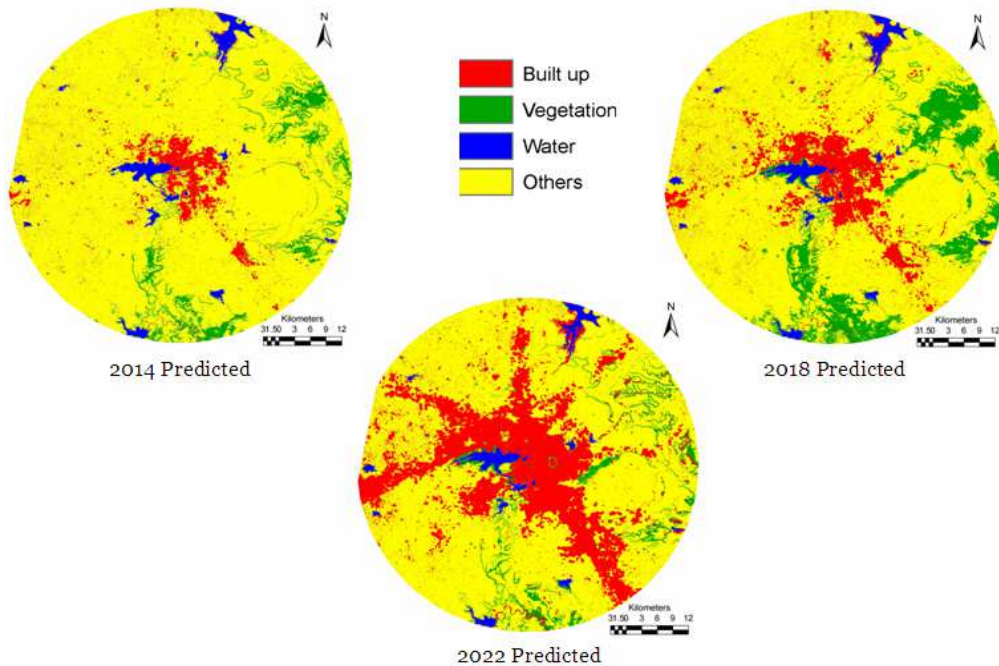


Fig. 11. Modelling urban growth considering agents (ABM).

4. CONCLUSION

Urban sprawl is posing challenges to sustainable development with key concerns of effective resource utilization, allocation of natural resources and infrastructure initiatives. The escalating urban growth in the study region has prompted concerns over the degradation of our living and environmental conditions. The study has attempted to understand LULC changes, the extent of urban expansion and urban sprawl in Bhopal city, quantified by defining important metrics (complexity, patchiness, density and contagion /dispersion) and modelling the same for future prediction. Remote sensing and GIS techniques were used to demonstrate their application for the monitoring and modelling of dynamic phenomena, like urbanisation. A cellular automaton was used to simulate growth in Bhopal and surrounding area as a prototype for further regional applications with modest computational resources. The results demonstrate that the urban extent primarily consists of residential and

commercial use that is assumed to have a linear relationship with population distribution. Thus, by incorporating urban extent, population distribution can be estimated by the model in an indirect way. Different location conditions, such as road networks, business centre, urban centre, etc., were considered with various weights (transition probability) based on their relative significance. These properties provide a significant potential for modelling growth and changes under different conditions. Future urban extent, predicted for 2018 and 2022 are useful for visualizing and exploring potential development, as well as for assessing the impacts on agricultural lands. The results from the prediction of LULC indicate that the built-up in this area will increase by approximately 120-225% (based on CA-Markov) and 240-245% (based on ABM) from 2014 to 2022. ABM based prediction for built-up (in 2014) was comparable to the actual values (agreement greater than 99%). ABM could also bring out the major regions of growth such as Toomda and Sehore that are in the influence of urbanisation recently. These results

will aid planners with prior visualization of growth for effective policy intervention. Despite the strengths of helping spatial and temporal decisions, CA-Markov has considerable limitations. The main drawback of the model CA-Markov is overcome with the consideration of current drivers or agents of changes through ABM for future transition probabilities. Physical urban growth in the region will undoubtedly continue, but it is required that city planners and developers of Bhopal take a note of the situation and plan to ensure sustenance of natural resources. Land development policy in these cities has been highly inconsistent in recent years, since population growth and land development rates are impossible to synchronize. This also poses another great challenge in capturing the dynamics in contrast with other cities across the globe. ABM approach is capable of estimating probable sites for urban planning which synchronize with real scenario [54], [55]. Agent based simulations can capture reality more effectively as it provides us the flexibility to vary quantities and characteristics based on proximity of various amenities generating probability surface influenced by various agents, indicating urban development. The results of ABM clearly indicated the growth in places that were under the influence of growth of these agents considered. Thus we conclude that agent based modelling was helpful and appropriate in developing future scenarios and that application of ABMs would help understanding the changing factors and dynamics to visualize the likely growth to provide basic amenities, infrastructure, etc.

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