

CHAPTER: V

CELLULAR AUTOMATA MODELLING: PREDICTING FUTURE GROWTH

5.1 Introduction

In recent decades, rapid urbanisation has led to many negative impacts on the environment, such as the loss and fragmentation agricultural lands and of natural areas that support wildlife. To avoid these impacts, anticipatory planning has to be considered (Moore, N. et al, 2012). Faced with these severe negative impacts, there is an urgent need for urban planners to develop predictive models of urban growth. These models not only provide an understanding of the urban growth process but also provide realisations of the numerous potential growth scenarios that an urban area may take in the future. This kind of information can be very helpful in regulating urban growth, and proper planning also can be done for the future urbanise areas (Routray, 1993, 2000).

Though the traditional urban modelling approaches are based on sound theories, they have major weaknesses such as poor handling of space-time dynamics, coarse representation of data and top-down approach, which finally fails to reproduce realistic simulations of urban systems. Most of these models perceive the city as static and attempt to simulate how land uses are located with respect to each other at a cross-section of time.

Urban growth models have been proposed to use the capabilities of a new generation of spatial analysis tools within the geospatial information systems (GIS) framework. They investigate urban regions using various multi-temporal data sets such as remote sensing images to detect changes over the time (Pijanowski, B.C, 1997, Wu, F, 1998, Batty, M., 1999, Brown, D.G, 2005, Dewan, A.M, 2009, Ozturk, D, 2015.).

A number of urban growth models have been proposed to use the capabilities of a new generation of spatial analysis tools within the geospatial information systems (GIS) framework.

It is well accepted that urban growth is a complex process (Batty, M, 1994, Verburg, P.H, 2004, Li, X., 2006) consisting of several interacting elements. Thus, to model this process several urban growth models have been presented such as Markov chain models (Wu, Q.et al, 2006) spatial logistic regression (Store, R.,2001) multi-criteria evaluation (Wu, Q.et al, 2006), cellular automata (CA) (Batty, M., 1994, Wu, F., 1998, JokarArsanjani, J., 2013, Liu, X., 2014) agent-based models (Verburg, P.H et al, 2004, Benenson, I., et. al 2004) and machine learning and artificial intelligence (AI) methods like artificial neural networks (ANN) (Pijanowski, B.C, 2002,Tayyebi, A.2011), support-vector machine (SVM) (Huang, B, 2009 Samardži'c-Petrovi'c, 2015), genetic algorithms (GA) (Tang, J.,2007) and data mining (Tayyebi, A.,2014). AI-based methods can capture existing nonlinearities and heterogeneities of the urban growth process. It is clear that superiority of methods depends on how to set the configuration parameters of the algorithms, the size of training and test sets, designing classifiers in two classes or multiclass, choice of datasets for training and validation and so on (Xu, R.2005, Dwarakish, G.S.,2016).

5.2 CA Model for Urban Growth

Towards the mid-1980s, Cellular Automata (CA) based urban growth models were proposed as an alternative to the traditional models as the CA-based models were inherently spatial, dynamic and have a natural affinity towards GIS and remote sensing data (Couclelis, 1997; Torrens, 2000, 2001). This incorporation of CA with GIS opens up a new view to advance urban modelling.

John von Neumann (von Neumann, 1966; Toffoli, 1987) and Stanislaw Ulam introduced Cellular Automata in the late 1940's. From the more practical point of view, it introduced in the late 1960's when John Horton Conway developed the *Game of Life* (Gardner, 1970; Dewdney, 1989; Dewdney, 1990).

CA's are *discrete dynamical systems* and often described as a counterpart to *partial differential equations*, which have the capability to describe *continuous* dynamical systems.

Ulam and Von Neumann originally conceived cellular automata (CA) in the 1940s to provide a framework for investigating the behaviour of complex systems (Torrens, 2000). The concept of self-organization, which is one of the main characteristics of complex systems, is central to CA-based modelling. Self-organization refers to the tendency of a system to spontaneously develop ordered patterns, often on a large scale from local decision-making processes (Torrens and Sullivan, 2001). Thus, CA is able to simulate processes such as urban growth where global or centralised order emerges because of local or decentralised rules

Cellular Automata (CA) based models were proposed as an alternative to traditional models due to the following reasons (Sullivan and Torrens, 2000a):

- Simplicity;
- Potential for dynamic spatial simulation;
- Capability of detailed or high-resolution modelling; and
- Affinity to Geographic Information Systems

Primarily CA draws interest for application is its ability to summarize the complexity in the form of simple rules and enables to draw down the future prospect with its self-learning approach irrespective of the other mathematical models.

The CA approach is also in line with bottom-up thinking and a decentralized understanding of processes (Torrens and O'Sullivan, 2001). It can simulate any physical system (Silva, 2005).

The model can encompass underlying direction which makes this model different is its ability to consider the suitability of the growth of the phenomenon, depending on the interaction of the pixels/cells with the surrounding, available land and the constraints /zoning of earmarked land use and the accessibility of the region physical and infrastructural.

Cellular Automata (CA) shows the potential of application in urban studies due to its ability to learn and simulate complex processes that not possible with mathematical models. CA model is composed of the cell, state, neighbourhood and transition rules.

The cell is supposed to change its state during the course of time, which primarily depends on its current state, Neighbourhood states, Transition rules.

The basis of CA is in four components:

1. **Cell:** A cell is the sub-unit of the lattice or the regular geometrical grid. A cell at any instant of time can be in only one state out of a given number of states. The states of all cells in a grid are updated during CA iterations. The basic element of a CA is the cell. A cell is a kind of a memory element and stores - to say it with easy words - states. In the simplest case, each cell can have the binary states 1 or 0.

Lattice A regular uniform and infinite 'lattice' or 'array' with discrete variables at each cell. Lattice space can have n dimensions, but two-dimensional CA is the most common in urban simulation. These cells are arranged in a spatial web - a lattice.

2. **State:** A state is a variable, which takes different values in each cell. It can be a property, a number or word (0 or 1, urban or non-urban). In the more complex simulation, the cells can have states that are more different.
3. **Neighbourhood:** In a lattice, there are normally the cells that are physically closest to the central cells, which influence the state of the central cell in the next step. Neighbourhood interactions is similar to pull and push factor for the suitability of the region.

The neighbourhood cells act as immediate areas of interest for the central cell, as the transition rules that decide the state of the central cell in next step are based on the neighbourhood values. The neighbourhood also includes the central cell itself. The neighbourhoods also can be extended from their 3x3 cells size to other larger odd numbered sizes (e.g. 5x5, 7x7, 9x9 and so on). Some of the widely used neighbourhoods are

- a. *von Neumann Neighborhood* includes four cells, the cell above and below, right and left from each cell are called the von Neumann neighbourhood of this cell. The radius of this definition is 1, as only the next layer is considered.

Von Neumann

Moore

Extended Moore

- b. *Moore Neighborhood*: the Moore neighbourhood is an enlargement of the von Neumann neighbourhood containing the diagonal cells too. In this case, the radius $r=1$
- c. *Extended Moore Neighborhood*: equivalent to the description of Moore neighbourhood above, but in this type neighbourhood reaches over the distance of the next adjacent cells. Hence the $r=2$ (or larger).

4. **Transitional rules:** These are a set of conditions or functions that define the state of change in each cell in response to its current state and that of its neighbours. The future state of cells is determined by the transitional rules in a discrete period.

State Transition Rules are

- The states of cell on an automaton change over time in discrete *timesteps*
- The state of each cell is modified in parallel at each time step according to the *state transition rules*
- These determine the new states of each of the cells in the next time step from the states of that cell's *neighbours*

Thus, an urban cellular automaton consists of a two-dimensional lattice of cells (Raster) that represents the urban landscape. Every cell in the lattice has a single value or state, which

corresponds to the land uses i.e. built up and non-built-up. Each cell changes its states in the time steps as a function of the states of its immediately adjacent neighbours, which updated at each iteration. The function, which is used to change the cell states between the time steps, is called as transition rule and gives a chance to infuse urban theory directly into the model. In the sequence of time (t, t+1, t+2...) which are treated as discrete, each cell in the CA lattice updates its state based on the transition rules. The general definition of mathematical notation is:

$$S_{t+1} = f(\{S_t\} \{I_{th}\})$$

Where;

$\{S_{t+1}\}$ is the state of the cell in the CA at time (t+1)

$\{S_t\}$ is the state of the cell in the CA at time (t)

$\{I_{th}\}$ refers to the neighbourhood,

$f()$ denotes the transition rules

t is the time steps in temporal space

h is the neighbourhood size

Hence, this capacity to integrate spatial and temporal dimensions makes CA appealing for the development of robust and reliable urban dynamics models.

Out of the two main approach for formulating transition rule viz. knowledge or perception was driven and data driven .the data-driven method approach is applied in this study which is statistical based and quantifiable. Whereas another method is perception based and large no of the informed respondent is required to formulate a rule for the model, which may suffer biases due to subject ignorance or inappropriate response, which can be a qualitative issue.

5.3 Limits and Strengths of CA

Conceptually and theoretically, CA for urban studies has some limitations and strengths with regard to the development of an urban dynamics framework. This section first discusses some of the limitations of CA and then expands on its strengths to model complex phenomena like urban growth.

The original framework of CA is not appropriate to support realistic urban dynamics (Wolfram, 1986). For instance, the overall original structure of CA is too simplistic and constrained to apply in real urban applications (Sipper, 1997). Similarly, it is not reasonable to apply the concept of an infinite space plane (two-dimensional) and uniform regular space to the city because cities are not infinite, regular, or uniform. Moreover, the notion of neighbourhood is too coarse and does not take external factors and distance-decay actions into consideration. Another criticism is that CA only assumes the bottom up approach, and accounts for local specificities that ultimately define the overall representation of the space. Generally, not all constituents of urban systems, however, exhibit bottom up behaviour like urban planning decisions, national policies, macro economy, and so on. These factors operate from top to bottom and serve to constrain the urban growth.

In the original CA, transition rules were universal and applied synchronically to all cells. In real urban growth processes, however, no single rule governs the behaviour of the entire system. To solve the rigid transitional rules, urban dynamics CA transition rules are formulated using Boolean statements, and probabilistic expressions such as {< IF >, < THEN >, < ELSE >}. The flexibility thus gained in these expressions simplifies the representation of more complex systems (Batty, 2000).

Turning to strength, the simulation of urban dynamics is an area of research where CA has been recently implemented. Here, CA represents a useful tool for understanding urban dynamics, improving theory, achieving realistic and operational urban models (White, 1998). White and Engelen (1993) have demonstrated that a cellular automata approach can lead to a better understanding of spatial patterns as well as representing realistic patterns. In the spatial modelling perspective, the strengths of CA lie in their capacity to perform dynamic spatial modelling over discrete and continuous Euclidean space. Similarly, CA has the ability to exhibit.

Explicit spatiotemporal dynamics. Several studies (For example Bivand and Lucas, 2000; Openshaw and Abrahart, 2000) have shown how CA models can be integrated with other

spatiotemporal models to improve the representation of urban features. Finally, the flexibility of transitional rules embedded into CA architecture favours an effective control over the dynamic patterns that are generated.

The role of CA is to discover, understand and explain how cities emerge and change (Couclelis, 1985; White and Engelen, 1994; Portugali, 2000; Ward *et al.*, 2000). The introduction of CA approaches in Geography may be traced back to the work of Hägerstrand (1968) who highlighted the major components of current CA architectures as discrete time and state, cell, neighborhood, uniform transitional rules and lattice. Investigation of Hägerstrand was limited by the capacity of the simulation (e.g., less than 200 cells), yet it was theoretically and conceptually well formulated. Tobler (1970) further developed a forecasting model based on urban growth. In fact, Tobler's study laid the theoretical and conceptual foundation of CA for future applications in Geography. In 1979, he published a paper formalising the concept of CA (Tobler, 1979) in which he opened the gates for geographers to use CA for urban planning applications, spatial modelling and simulation. However, the temporal dimension of Tobler's CA was considered weak because the simulated maps developed for each year were very different from the actual growth simulation (Wegener, 2000). Tobler's work was improved by Couclelis (1985, 1989, 1997), Batty and Longley (1986, 1994) and Batty and Xie (1994c, 1997), who enhanced the theoretical and methodological aspects of CA for analyzing and modelling complex urban dynamics. In the same spirit, Couclelis (1989) demonstrated the use of CA as a metaphor to study different varieties of urban dynamics. Couclelis claimed that although CA was not originally intended to produce realistic representations of urban dynamics, it could be reformulated and integrated with some spatial models to form better predictive models. White and Engelen (1993, 1994) went further to advocate that CA was capable of generating real patterns of urban land use change. Thus, it is during the last two decades that impetus on the use of CA models for urban growth simulation can be seen. The following section describes the uses of CA in the simulation of urban growth. In the Indian context, very few attempts have been made to develop CA-based

models for urban growth simulation. Jacob et al (2006) developed a CA model for simulating land use dynamics for degradation-prone areas in the State of Andhra Pradesh. In the published works of Maithani (2010), Singh (2003) and Sudhira(2004), CA models for urban growth simulation in Dehradun(Deep. S et al 2014) and Saharanpur planning areas, Shimla District and Mangalore city respectively have been developed. Pune Metropolitan area (Lakshmi et al, 2011),) Mumbai (Moghadam .S et al 2013) Hyderabad (Franco et al 2015) SILTARA industrial belt (Baghmar et al.2015)

Thus, not much work has reported on urban growth simulation using CA-based models in India. Nevertheless, the CA-based models can be quite useful in the Indian context, as the present day focus on the Indian Government is on infrastructure development in urban areas.

Cellular Automata model is applied to study the growth pattern of Hyderabad City an emerging megacity in South India. Considered as an urban growth simulation tool to measure the urban extent of Hyderabad City and to predict the structure of land use at a future time. (Sainu Farnsco et al: 2015)

Hossein Shafizadeh Moghadam and Marco Helbich conducted to examine past urban land use changes based on remote sensing data collected between 1973 and 2010. An integrated Markov Chains Cellular Automata urban growth model implemented to predict the city's expansion for the years 2020-2030. They concluded towards the highest urban growth rates in Mumbai.

Study by sheikh (Sheikh Mustak1 et al: 2015) attempted to study present and future scenarios of industrial growth through Multi-objective Land Allocation (MOLA) and Linear Regression. A suitable platform was designed to estimate by integrating physical, social, cultural factors and land acquisition policy future industrialization.

Sleuth model was applied for predicting urban growth of Pune city by 2030 (Lakshmi Kanta Kumar N, et al:2011) by considering the following variables, the Slope, Land use, Exclusion, Urban extension, Transportation and Hill shade - model (SLEUTH)

5.4 Methodology

The Markov-cellular automaton was applied in conjunction with the Multi-Layer Perceptron (MLP) neural network process, to show the futuristic growth of the urban realm of the Vadodara. The brief methodology followed was in three stages.

1. Identifying the statistically significant driving factors, looking to the multitude of the factors used in the several studies list of factors following parameters was found to have a scalable relationship in the expansion of the built-up of the VUDA region.
 - i. Distance to the Built-up
 - ii. Distance to the Existing road
 - iii. Distance to the CBD
 - iv. Distance to the Industrial area
 - v. Open land price
 - vi. Share of the service sector worker to total population
 - vii. Elevation
2. Learning and training stage of the neural network based analysis. The land use of the year 1990 and 2001 was used as the initial stage for training the neurones, calculating the transitions potential for which the year 1990 is referred as the base layer and land use of 2001 was a transition year, using which the land use for the year 2011 was generated. This predicted 2011 map was further validated with the derived land use map of the year 2011. The transition model was evaluated and ran for most of the time to calibrate the hidden neurone in Multi-Layer Perceptron (MLP) neural network training process, each time the training parameter was modulated for increasing accuracy rate within the RMS error of the 0.01 with 10000 iterations. In the present model out of the total, 1500 samples were randomly generated and 50% of samples were used to train and the 50% of samples were to be used as a test sample. The accuracy rate of the 82% for the built-up class was finalised for generating

the transition potential matrix. The transitions potential matrix for the year 1990 to 2001 was obtained as shown in the Table.

Table 5.1 Transitions probability matrix for the year 2011

Probability Matrix 2011						
Class	Builtup	Waterbody	Agriculture	Vegetation	Scrubland	Openland
Built-up	0.543	0.014	0.258	0.076	0.030	0.065
Waterbody	0.132	0.446	0.211	0.072	0.046	0.085
Agriculture	0.073	0.002	0.482	0.138	0.108	0.174
Vegetation	0.049	0.004	0.488	0.219	0.080	0.118
Scrubland	0.097	0.001	0.323	0.035	0.078	0.462
Open land	0.143	0.002	0.420	0.075	0.098	0.253

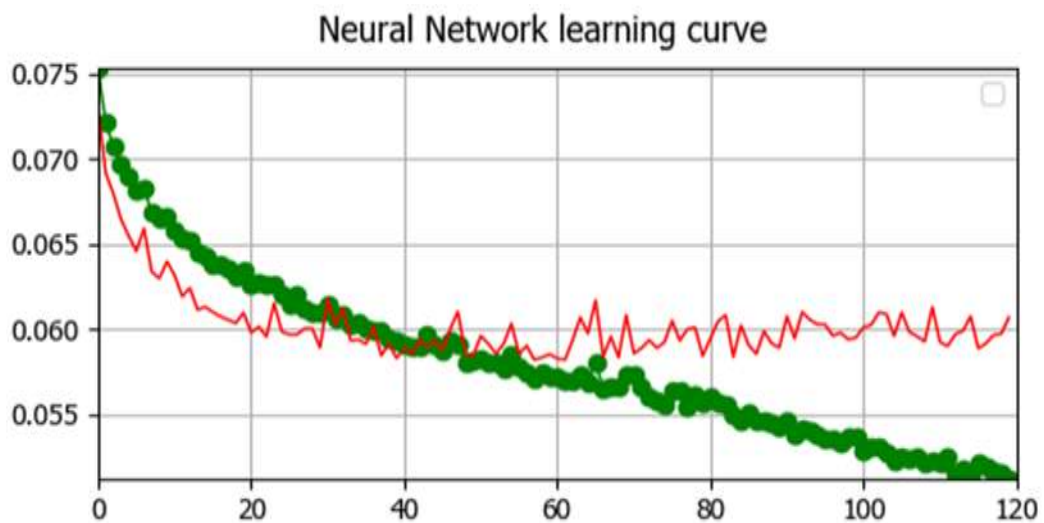


Figure 5.2 Neural Network Learning Curve

As the significance of the others category was very low in comparison to other class it was not considered for the prediction of the future development.

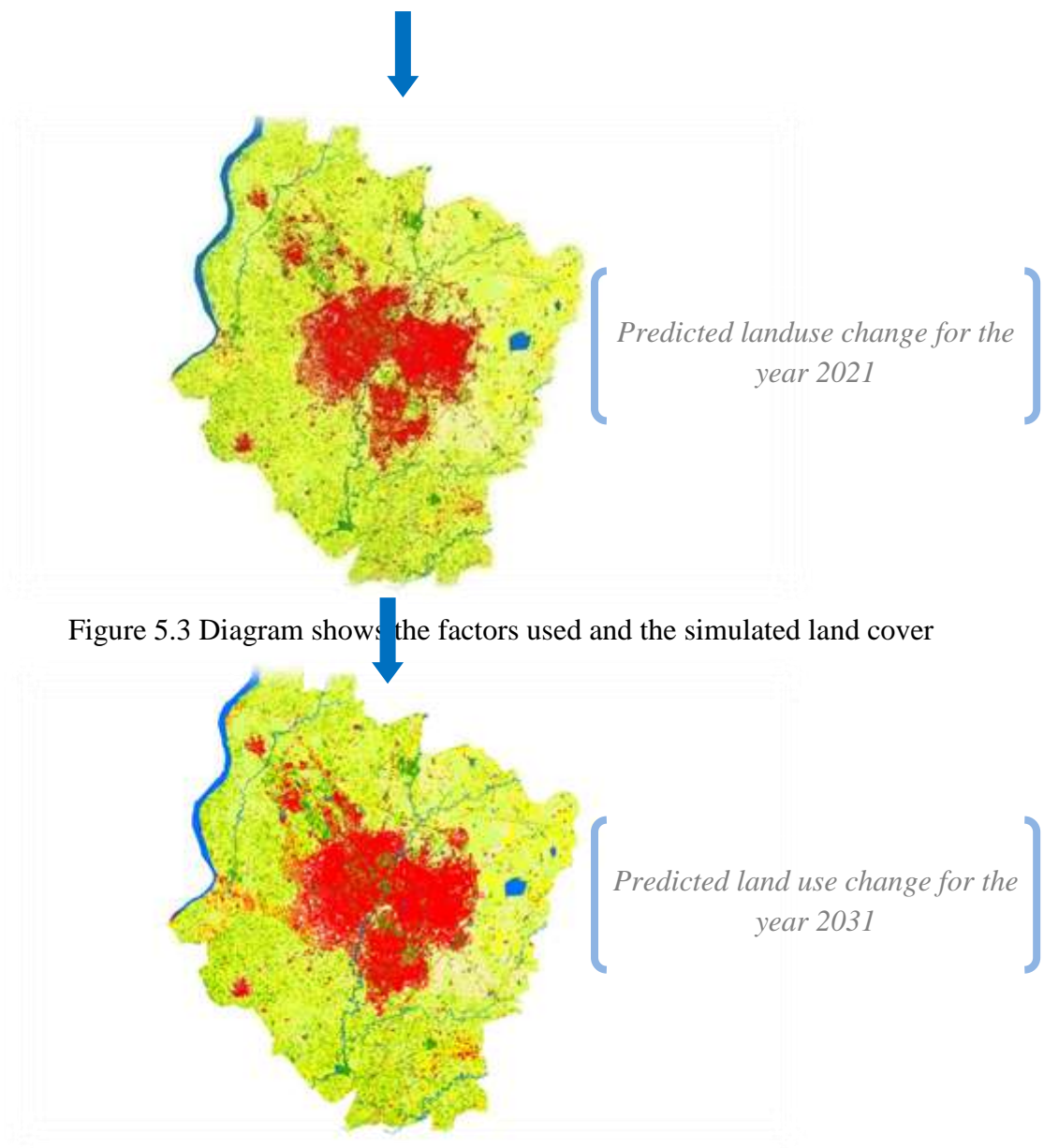
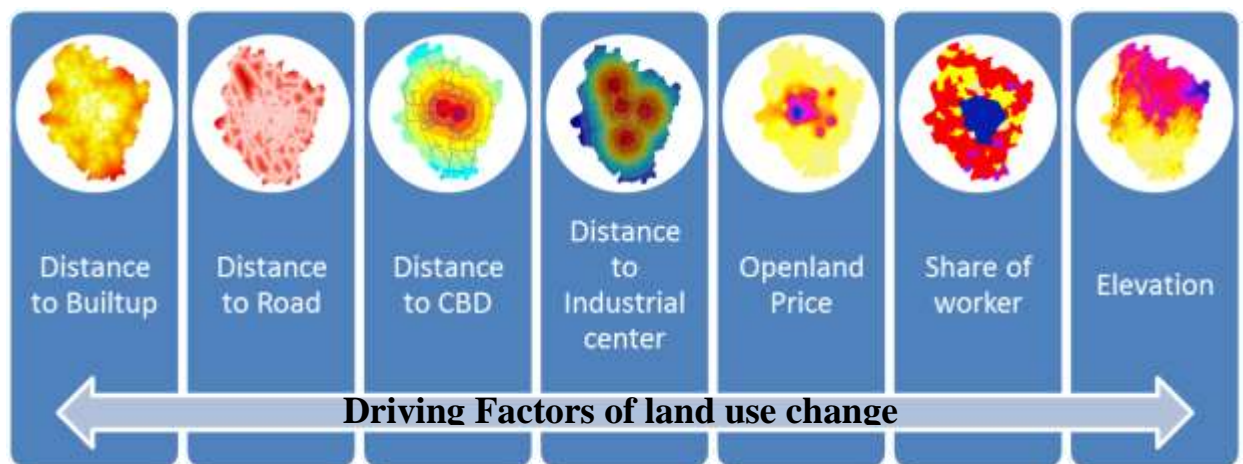


Table 5.2 Transitions probability matrix for the year 2021

Probability Matrix 2021						
Class	Builtup	Waterbody	Agriculture	Vegetation	Scrubland	Openland
Builtup	0.6053	0.0162	0.165	0.0618	0.0986	0.0532
Waterbody	0.0802	0.7251	0.1126	0.0476	0.0162	0.0183
Agriculture	0.0689	0.0057	0.4312	0.1344	0.2744	0.0853
Vegetation	0.0307	0.0079	0.4604	0.2742	0.1928	0.0341
Scrubland	0.0425	0.0049	0.3788	0.0826	0.3691	0.1222
Open land	0.0928	0.0059	0.2765	0.0739	0.321	0.2298

Table 5.3 Transitions probability matrix for the year 2031

Probability Matrix 2031						
Class	Builtup	Waterbody	Agriculture	Vegetation	Scrubland	Openland
Builtup	0.39	0.0238	0.2533	0.0893	0.1706	0.0729
Waterbody	0.1183	0.5283	0.1765	0.0704	0.0716	0.0349
Agriculture	0.0956	0.0107	0.3874	0.1283	0.2798	0.0983
Vegetation	0.0707	0.0122	0.4131	0.1578	0.2644	0.0818
Scrubland	0.0817	0.0096	0.3825	0.1159	0.2996	0.1107
Openland	0.113	0.0109	0.3544	0.1069	0.2917	0.1232

- Subsequently, the period of 2001 to 2011 was subjected to the evaluating the influence of the driver owing to the transition potential of the validated relationship owing to the changes. The transition potential is then subjected to the prediction of the futuristic growth of the built-up area. The prediction maps of the year 2021 and 2031 were thus generated based on the physical factor influencing the built form of the region as per the objective of the study area.

The area change, identified for the various land cover as summarised in the table 5.4 suggest that around 25 sq km of the area is going to be transformed into the built-up usage in the VUDA region by the year 2031. The expansion of the built-up cover will have its impact on the agriculture, scrubland and open land usage. It is worth mentioning that city rejoices two land cover class of open land and scrubland in the center owing to the Laxmi Vilas Palace, a site of heritage importance, also huge plots of the golf course and Navlakhi ground along the side of the Vishwamitry River, are continuously under the pressure of the transformation. Also, this site is the only one, which has thick vegetation cover of the

Vadodara city, and one can feel the temperature gradient while passing through this area. On the other hand, it is also observed the horizontal expanse has been seen all over the city periphery. The basic reason has been the establishment of the higher education hub, near Sayajipura and Waghodia Road in the east and northeast due to which rapid growth of this region is noticed post 2001, bounded by the national highway 8. Beyond this, the linear pattern of development is anticipated owing to large-scale conversion of land and residential plans are coming up. The change observed from the year 2011 as shown in the graph5.4

Table 5.4 Predicted area change from 2011- 2031

Landuse class	Actual Area 2011	Predicted Area (in Sq Km)		Area Change (in Sq Km)		% change during	
		2021	2031	2011- 2021	2021- 2031	2011- 2021	2011 - 2031
Built-up	91.0	102.1	127.0	11.1	24.9	12.2	39.6
Water body	9.5	9.3	8.7	-0.2	-0.5	-2.4	-8.0
Agriculture	257.9	252.9	240.1	-4.9	-12.8	-1.9	-6.9
Vegetation	89.3	88.0	86.5	-1.3	-1.5	-1.4	-3.1
Scrubland	182.9	180.0	175.2	-3.0	-4.8	-1.6	-4.3
Open land	75.1	73.4	68.1	-1.7	-5.3	-2.3	-9.3

The modelled change shows the increasing trend in the built-up land use in VUDA region owing to the existing infrastructure in the region. The 12.2% increase is anticipated in a decade following the year 2011. This transformation is claiming the loss of the open land and agricultural land in the vicinity of the existing built-up land cover. Assuming the cycle of the conversion to built-up , to be agricultural land left uncultivated to obtain non-agricultural status than cleared for scrubs and converted into open plots readily available for construction. The region has also witnessed the vertical growth as the number of multi-storey buildings has come up on the outskirts which house 5 to 7 floors along with the raising of the floor in the interior parts of the

city. The limitation of multispectral coarse resolution remote sensing fails to attempt this type of land cover identification, thus this study also lacks this dimension.

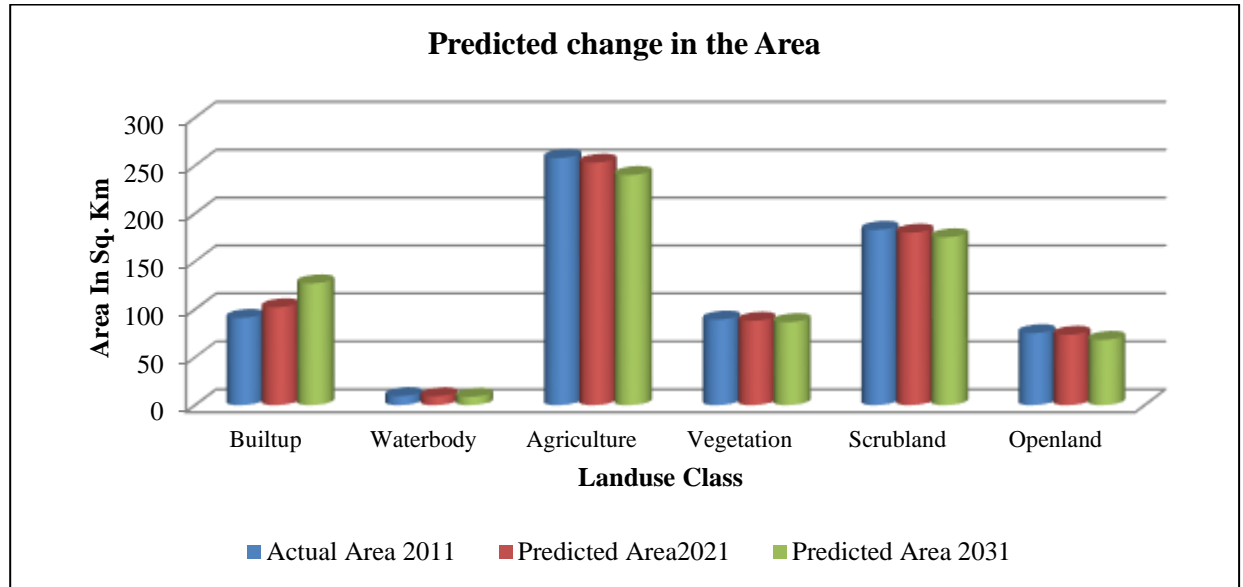


Figure 5.4 Predicted area change from 2011- 2031

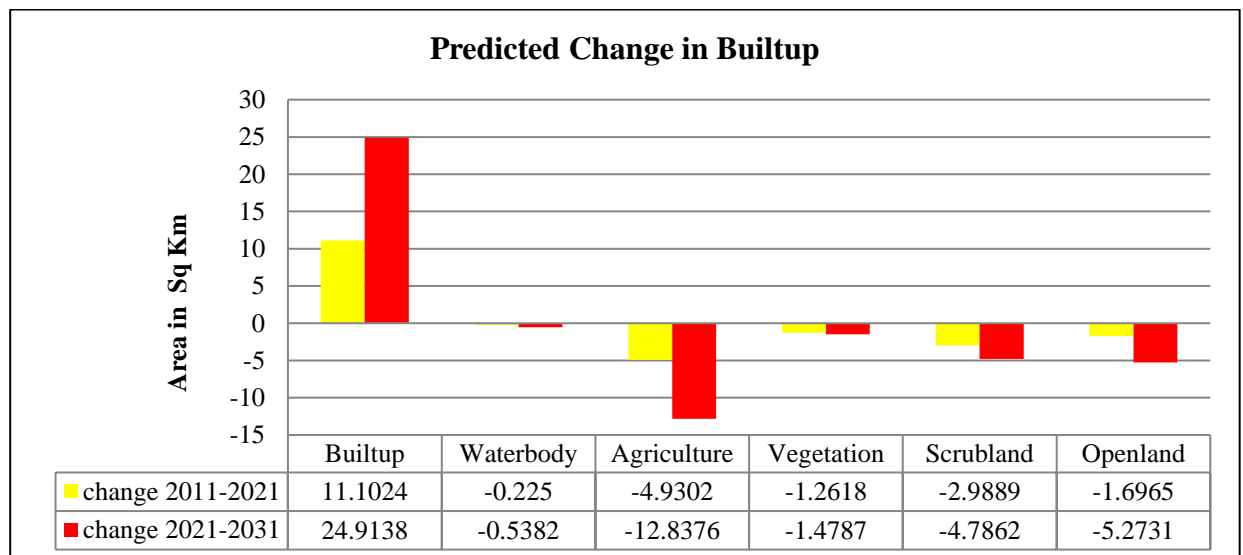


Figure 5.5 Predicted area change in builtup from 2011- 2031

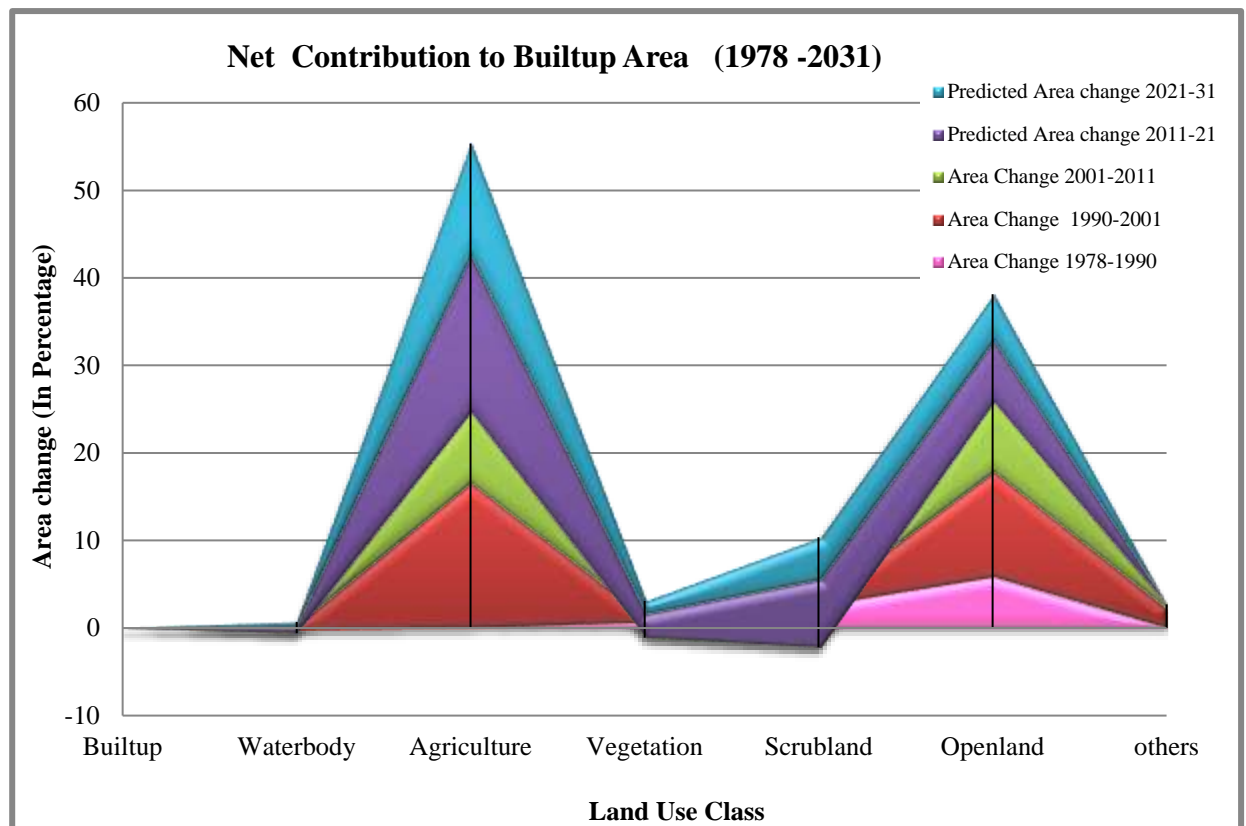


Figure 5.6 Net contribution to built-up area from 1978- 2031

The change modelled considering the physical parameter and the share of the worker it shows that the majority part of the agricultural area is transformed in the built-up and followed by the open land over past history and the prediction. Vegetation cover share remained more or less unharmed during the course of expansion of Vadodara urban region. As such that is the scanty and is bounded by the barriers due to which the transformation is not obtained.

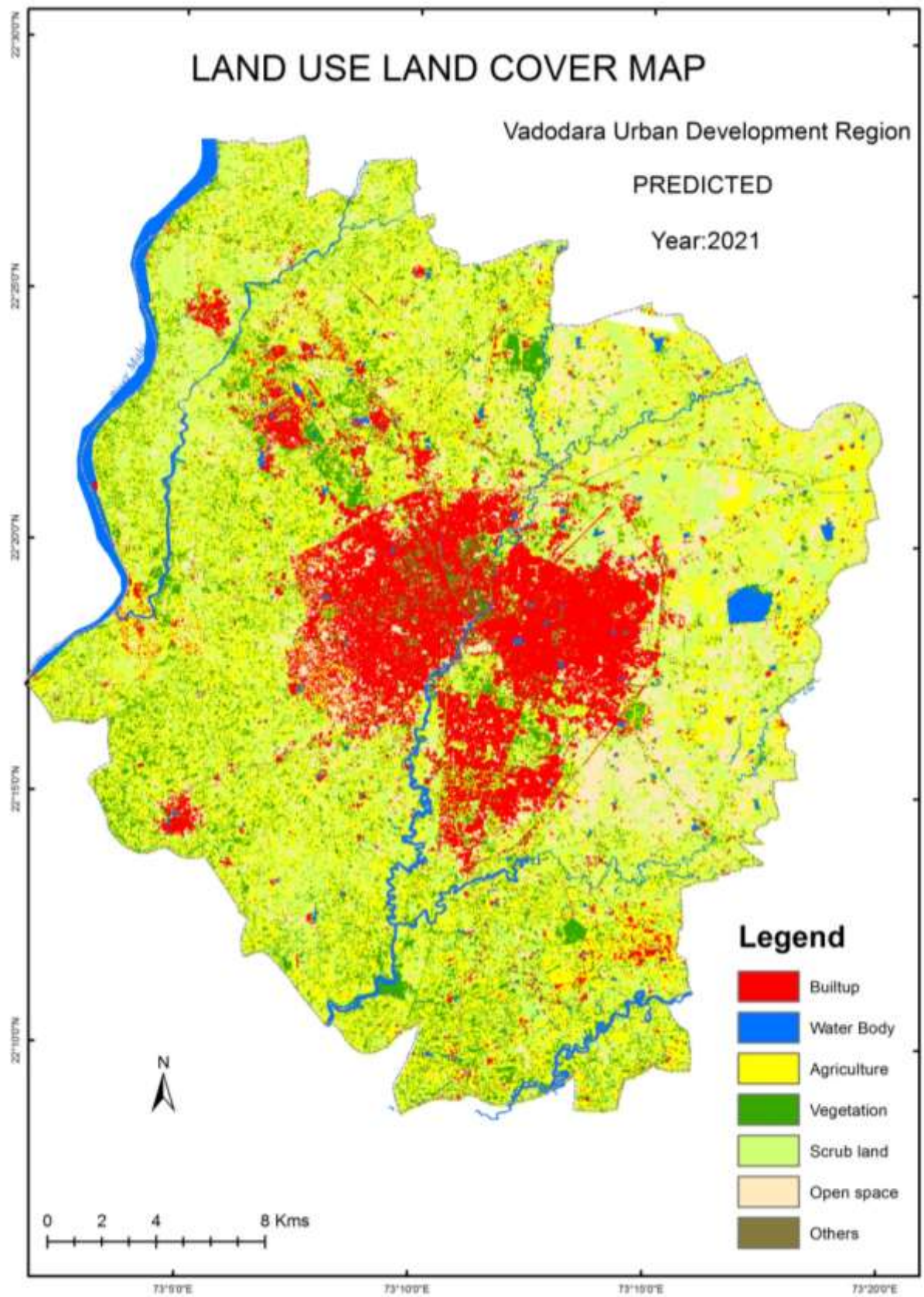


Figure 5.7 Land Use Land Cover Prediction map of 2021

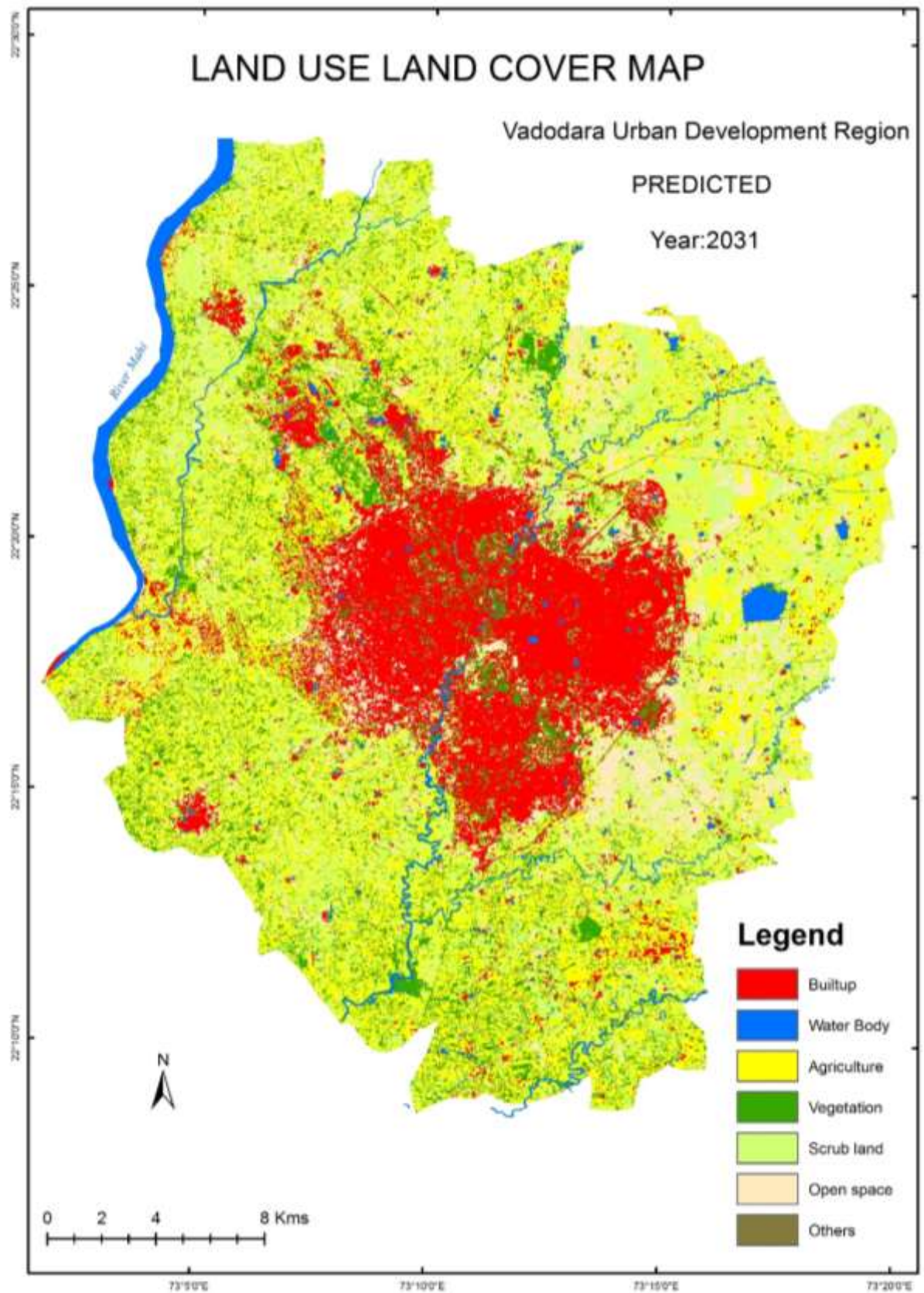


Figure 5.8 Land Use Land Cover Prediction map of 2031

Conclusion

In developing countries like India, there is an urgent need for sustainable urban development. The cities are growing with government catalyst schemes like JNNURM and PMAY that are promoting the urbanization by providing infrastructure and the housing demands. Thus planner is required to conceptualize the demand the resource available and the constraints to be forced to maintain the sustainability of the region along with the provision of the better life. CA-based models, which simulate urban growth realistically, can be used and operated as an urban planning tool to build projected growth scenarios and answer “what-if” questions. The CA models can be used as a planning tool for developing alternative scenarios and the urban planner can take more rational and scientific decisions by looking at the various scenarios generated, thus providing a scientific basis for implementing decisions.