The Egyptian Journal of Remote Sensing and Space Sciences 20 (2017) 223–241

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The Egyptian Journal of Remote Sensing and Space Sciences

journal homepage: www.sciencedirect.com

Research Paper

Application of geo-spatial techniques and cellular automata for modelling urban growth of a heterogeneous urban fringe

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ARTICLE INFO

Article history:
Received 19 March 2016
Revised 18 January 2017
Accepted 5 February 2017
Available online 22 February 2017

Keywords:
Urban growth model
Urban dynamics
SLEUTH
Cellular automaton
GIS
Remote sensing

ABSTRACT

Urban growth monitoring and assessment are essential for the sustainable natural resources planning & optimum utilization and reducing the risk of problems arising from unplanned urban growth like pollution, urban heat island and ecological disturbances. Cellular Automata (CA) based modelling techniques have become popular in recent past for simulating the urban growth. Present study is aimed to evaluate the performance of the CA based SLEUTH model in simulating the urban growth of a complex and relatively more heterogeneous urban area, Ajmer city of Rajasthan (India) which is quite different as compared to areas where SLEUTH has been tested in developed countries. Seven multispectral satellite imageries spanning over 21 years have been processed and used for SLEUTH parameterisation. Results of urban growth predicted by SLEUTH has been compared with other methods of land use/land cover extraction. The study has been proved to be successful in giving significant insight into issues contributing uncertainties in forecasting of urban growth of heterogeneous urban areas.

1. Introduction

Economic development and population growth have triggered rapid changes to earth land use/land cover as a result of urbanization & industrialization in last two centuries and there is every indication that the pace of these changes will accelerate in the future. Urban growth is the expansion of city area with respect to the increase in number and size of the settlement. Urban expansion chiefly depends upon the human desires for their betterment, need of better livelihood, facilities and employment (Brueckner and Helsley, 2011). Unplanned growth is one of the major factors responsible for many problems like urban heat islands, pollution, climate change, over-exploitation of natural resources and inadequate infrastructure facilities leading to unsustainable developmental situation. Understanding of urban dynamics is difficult for more heterogeneous urban areas as compared to relatively less heterogeneous urban areas. Heterogeneity is associated with different form of development, land use planning, constructions using different type of building & roofing materials, size of built-up units, cultural issues, human behavioural differences and their distribution. Urban areas are comparatively more heterogeneous in developing countries and their assessment, monitoring and prediction is difficult (Sakieh et al., 2015). The lack of knowledge of urban dynamics in developing countries attributed to, poor land use planning, pathetic resource allocation, wretched policy making, and despicable budget allocation (Xian et al., 2005).

In early days, cadastral maps (scale, usually 1: 4000) were utilized in mapping land use/land cover and to detect their changes. From the 20th century onwards land use mapping was replaced by preparation of land use/land cover maps using aerial photographs, which have later replaced by multispectral satellite images. In recent past different type of digital image processing and other mathematical techniques have been utilized for the assessment of urban growth through preparation of land use/ land cover maps using different type of remote sensing data products. Spectral methods, pixel to pixel classification of satellite imageries using supervised classification was in patronage, though, supervised classification has its limitation of overlapping or very similar signatures of different land use classes. For the enhancement of digital image quality, various methods have been used like image differencing, image rationing, differencing of NDVI images and the combined effect of both (photo & digital) type of image products offered better visibility and feature extraction. However, no single image enhancement technique is sufficient for mapping all

Peer review under responsibility of National Authority for Remote Sensing and Space Sciences.

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http://dx.doi.org/10.1016/j.ejrs.2017.02.002
1110-9823/

the land use classes and for correct assessment of urban growth (Prakash and Gupta, 1998). Also, spectral information based methods lacked in capturing urban structures of concrete, asphalt and various kind of roof top materials. Rather doing pixel to pixel image analysis, texture based classification methods and spectral-structural image differencing methods improved the accuracy of urban change analysis (Zhang et al., 2002; El-Asmar et al., 2013). Many land use/ land cover change detection methods were also developed for monitoring landscape change and urban growth in recent past. Efforts have also made to extract correct land use/ land cover and urban growth through analysis of data from different sources in GIS. Level of uncertainties in the results from available methods of land use extraction depends on a variety of issues like resolution of data, radiometric quality of data, level of heterogeneity at a particular place and local climatic characteristics. Therefore, correct mapping (with good accuracy) and land use/ land cover extraction from remote sensing images using different digital image processing methods is still a challenge for complex and heterogeneous areas like urban fringes in developing countries (Jat et al., 2008).

In recent past, new methods of urban growth assessment and prediction have been reported in the literature which include landscape metrics, knowledge based expert systems, agent based modelling, Cellular Automata based algorithms, artificial intelligence and machine learning based techniques. Use of landscape metrics like Number of patches (NP), the Mean patch size (MPS), the Landscape shape index (LSI), Shannon's Diversity index (SHDI), the Mean patch fractal dimension (MPFD) and the Total edge contrast index (TECI) have been used to understand urban growth phenomenon in many studies (Bhatta et al., 2010; Jat et al., 2008; Petit and Lambin, 2001). Landscape metrics are algorithms that quantify specific spatial characteristics of patches, classes of patches, or entire landscape (Butt et al., 2015; Gustafson, 1998; McGarigal & Marks, 1995; Rawat et al., 2013). However, landscape metrics are lacking in quantification of urban growth and its prediction.

In recent past, various models have been reported in the literature which have been used for assessment and prediction of urban growth like statistical models, GIS-based models, cellular automata-based models, agent-based models, rule based models, artificial intelligence based modelling and hybrid models. Few models have been used for the monitoring and assessment of growth and some of them used for growth predictions (Batty, 2001; Verburg et al., 2004; Silva and Wu, 2012).

Spatial Interaction models takes into account the human environment interactions in the form of growth influencing variables. But due to subjective weighting process, fragmented growth cannot be estimated through such models (Fang et al., 2005). Linear or Logistic regression based models are an enhanced approach in spatial modelling which examines the relationships between urban land uses and independent variables. Weighted regression tackle urban dynamics by calculating regression coefficient of spatial weights. Such models lack in calculating fragmented and heterogeneous urban growth due to its dependability on spatial weights. Also, linear and logistic regressions do not offer high modelling capabilities and they fail to capture non-linearity in spatial growth (Hu and Lo, 2007). For enhancing the performance of logistic regression model another model came into existence for example rule based model. As, logistic model rely on the empirical data like other models so, there were no scope of reflecting new growth policies into the scenario. Moreover, rule based models provide higher accuracy as compared to logistic regression modelling. However, implementing complex land use change behaviour in the form of rules did not imply its suitability for heterogeneous urban areas (Thapa and Murayama, 2010). Another modelling techniques is Agent based modelling, which have been used for modelling and prediction of urban growth. It follows a framework in which simulation of urban dynamics is done by the interaction among mobile agents. Also, growth influencing variables like land prices, traffic problem, and landscape attractiveness were included into the framework. In spite of the less computational complexity, initial conditions and interaction rules of agents lead to high uncertainties in the growth simulation results (Matthews et al., 2007). Another technique i.e., Fractal Based Modelling was developed to consider spatio-temporal patterns of urban change. But, due to differences in fractal dimension measurements of the same object using different techniques and sharing the same fractal dimension for different morphological characteristics of objects may not offer reliable results (Weng, 2001; Wu et al., 2009; Dimitrios, 2012). Also, it has limited capability to include the spatial heterogeneity in the modelling process (Triantakonstantis et al., 2013). In recent years, artificial intelligence techniques based urban growth modelling approach have been reported in the literature. Artificial neural network (ANN) was used for the forecasting of urban growth in few studies. Despite the fact of including spatial heterogeneity into the model, it lacked in modelling accuracy due to its tendency to overfit the data (Li and Yeh, 2002). Moreover, ANNs are unable to explicitly identify the contribution of each variable and it encompasses black-box behaviour which limits understanding of urban evolution, and noise tolerance, especially for small sample sizes (Guan et al., 2005). Cellular Automata (CA) based techniques and methods are another widely used approaches for urban growth assessment and forecasting (Candau, 2000).

The Cellular Automata (CA) based SLEUTH model (Silva and Clarke, 2002; Dietzel and Clarke, 2006; Onsted and Clarke, 2012) has been used extensively for the simulation and modelling of urban growth, especially in developed countries. The very first reported application of SLEUTH model was for San Francisco Bay area (Clarke and Gaydos, 1998) and later SLEUTH has been used for the assessment and prediction of urban growth for many other urban areas in different countries most of the developed one. The SLEUTH was tested for different areas with different constraints and growth scenarios for understanding the behaviour and complexity of urban growth phenomenon (Al-shalabi et al., 2013; Herold et al., 2003; Jantz et al., 2004; Oguz et al., 2007). In previous studies, it has been noticed that SLEUTH model is computationally inefficient, sensitive to spatial scale and not able to capture the fragmented urban growth (Silva and Clarke, 2002).

In recent past, improvements have been done in SLEUTH model for making it computationally efficient and for improving accuracy (Chaudhuri and Clarke, 2013). Parallel raster processing (pSLEUTH) has been proposed in SLEUTH for reducing the time constraint in the calibration of model by incorporating decomposition algorithms like QTB (Guan and Clarke, 2010). Efforts have been made to integrated GIS and artificial intelligence (AI) techniques like ANN with cellular automata for minimizing the complexity of transition rules by providing linking among automatic transient neurons and parameter values generated automatically, which was rather difficult in traditional model (Guan et al., 2005; Li and Yeh, 2002; Pijanowski et al., 2002). Additionally, for testing the suitability of the model at fine resolution, SLEUTH model was calibrated for multi-resolution satellite images. Model is very sensitive to the resolution of input land use land cover maps generally prepared from satellite data. Model has performed better in growth simulation with fine resolution data, however, at finer resolutions, it becomes computationally inefficient (Dietzel and Clarke, 2007). Resolution of the input data should be decided based on the average size of housing unit, which is very different from place to place. Form of the development is also very different in different parts of the world. The SLEUTH model has been implemented and found to be satisfactory in simulating the urban growth for the urban areas of developed countries which are less heterogeneous, well planned and having relatively larger size of average unit of built form (Candau, 2000; Clarke et al., 1996; Clarke and Gaydos, 1998; Dietzel and Clarke, 2007; Silva and Clarke, 2002; Syphard et al., 2007). So far, very few studies have been reported about urban growth simulation for relatively more heterogeneous urban areas and smaller unit size developments, which is very common in developing countries. Also, performance of SLEUTH in simulating the urban growth using different resolution of input data and effect of resolution on accuracy of model results have not been discussed well.

Urban area in developing countries including India are relatively more heterogeneous in absence of proper land use planning, infrastructure development and lack of funding. Proper growth assessment and prediction can help policy planners in optimum land use planning, resource & fund allocation and optimum utilization of natural resources. In Indian context, few studies of urban growth assessment and monitoring using comparison of classified remote sensing images, landscape metrics have been reported (Jat et al., 2008). Very few modelling efforts have been done to simulate the urban growth in Indian conditions such as, for Pune city and Hyderabad cities of India (Gandhi and Suresh, 2012; KantaKumar et al., 2011). The performance and sensitivity of SLEUTH model results against different input parameters including different resolution of satellite data has not been discussed well for heterogeneous urban developments. Therefore, an effort has been made to in the present study to investigate the SLEUTH model's performance in modelling and prediction of heterogeneous urban growth of an urban fringe, which happened due to different socio-economic, neighbourhood, climatic, cultural and human behavioural factors, as compared to prevailing urbanization factors in developed countries, where SLEUTH has been extensively tested and used. Further, an effort has been made to examine the sensitivity of SLEUTH to the spatial resolution of input variables and scale, which has not been discussed and examined well.

2. Materials and method

2.1. Study area

Ajmer city and surrounds has been selected for the present study which is situated in central part of Rajasthan State of India. Ajmer one of the important city having great historical and cultural importance. This is one of the few cities in India which have been selected to develop as smart cities by the Govt. of India. Location of the study area has been shown in Fig. 1. The study area is located between 26°20′N to 26°35′N latitudes and 74°33′E to 74°45′E longitudes. Ajmer is the 5th largest city of the Rajasthan State. Ajmer is situated in the articulation of two valleys, one formed by the Taragarh and Madar Hills and the other by the Madar Hill and Bhutia Dungar. Ajmer has a hot and semi-arid climate with over 55 cm (25.4 in) of rainfall every year, but most of the rain occurs in the Monsoon months (i.e. between June and September). Temperatures remain relatively high throughout the year, with the summer months of April to early July having an average daily temperature of about 30 °C (86 °F). Ajmer has witnessed an exponential urban growth in recent past being a cultural and educational hub in the State. Thousands of peoples also visit Ajmer throughout the year for prayers to religious places.

2.2. Input data

For the present study, satellite data, Survey of India toposheet (SOI), Ajmer district map, contour map and other secondary information has been used. Required data was collected from Government organizations, private companies and available online resources. Seven multispectral satellite images spanning over last 21 years (from 1989 to 2009) have been classified and used for SLEUTH model parameterization (Figs. 2a, 2b). Survey of India toposheet (1:25,000 scale) and a city plan map of Ajmer have been used for digitizing excluded area. An AutoCAD map of year 2002 prepared from aerial survey has been used for digitizing roads layer. A high resolution satellite image of year 2015 obtained from GeoEye satellite has been used for the accuracy assessment of simulated results.

2.3. Image processing

Standard image processing methods like image pre-processing, geo-referencing, signature selection, refining, generation of error matrix, classification and accuracy assessment have been used for the preparation of land use land cover maps for different years.

2.3.1. Image pre-processing

Satellite data was acquired from various sources in the form of multispectral data. First of all False Colour Composite (FCC) images have been prepared through layer stacking. Then the satellite images were georeferenced with UTM projection (43 Zone) and WGS 1984 ellipsoid parameters. Images used in the study area have been selected corresponding to similar illumination conditions which means acquired approximately in same month and at same time to have similar radiometric characteristics. No atmospheric or radiometric corrections have been applied to the images during pre-processing stage. The study area have been defined surrounding to the Ajmer Fringe. FCC's of different years have been shown in Figs. 2a and 2b.

2.3.2. Image classification

Satellite images have been classified to obtain land use land cover maps for the parameterisation of urban growth model. Seven land use/land cover classes have been identified based on the study of reference data of the study area i.e., open land, barren land, rocks, water body, river_bed, vegetation and settlement. First of all images (FCC) have been studied in detail with the help of spectral and spatial profiles to have an idea about Seperability of different targeted land use/land cover classes. Unsupervised classification was carried out using Iterative Self-organising Data Analysis Technique algorithm (ISODATA) again to understand seperability of selected land use/land cover classes and possible areas of misclassification. Misclassification can be imputed to the heterogeneity of land use classes and also spectral confusion between various land use classes (Bruzzone and Prieto, 2001; Islam et al., 2017). Further, supervised classification method has been used to classify the images. Suitable signatures have been selected for different targeted land use/land cover classes for training of classification algorithm in ERDAS Imagine software. Signatures have been examined and refined subsequently to the satisfaction. Further, error matrices have been generated to ascertain misclassification in selected signatures. The maximum likelihood classifier (MLC) has been used for the classification of the images (Maselli et al., 1994). Further, accuracy assessment has been done to determine the percentage accuracy of classification by comparing randomly selected pixels and comparing land use/land cover of such pixels with reference data. The accuracy percentage of classified outputs have been discussed in Table 1. Classified images i.e., land use land cover maps of different years have been shown in Figs. 3a and 3b.

Due to similar reflectance characteristics among land use/land cover classes such as, between vegetation & rocks, between rocks & barren land and rocks & settlement some misclassification have been observed in the classified outputs.

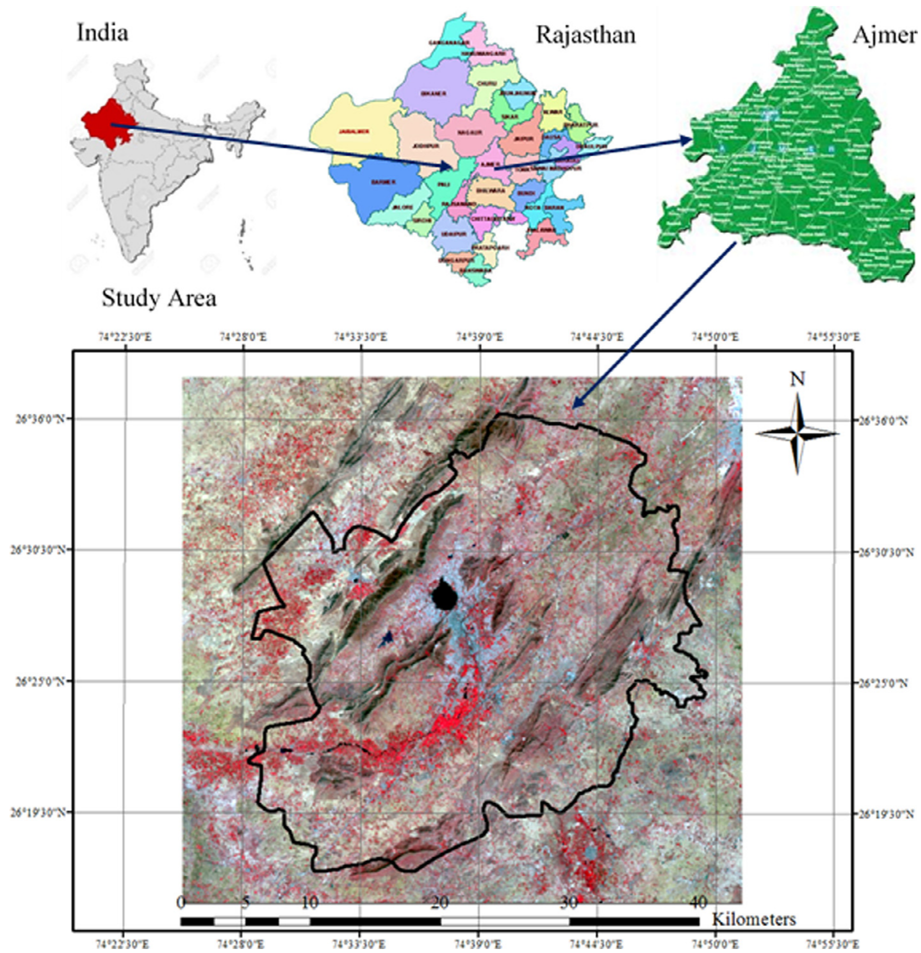

Fig. 1. Study Area.

2.4. Methodology

SLEUTH model has been implemented for the assessment and prediction of urban dynamics using different resolution satellite data obtained from different sources. First of all, the spatio-temporal data has been pre-processed using standard image processing and geo-spatial techniques. Urban growth assessed using CA based SLEUTH model involves first model parameterization, calibration and urban growth prediction, subsequently. Detailed methodology has been presented in Fig. 4. The detailed methodology has been explained in three sections; model parameterization, calibration and growth prediction.

2.4.1. SLEUTH model

SLEUTH is a cellular automata based urban growth model which comprises of two modules; Clarke Urban growth Model (UGM) and Land cover Deltatron Model (LCD). The UGM is used to simulate the urban growth of an area and LCD is used to simulate land use change and land transitions. The LCD is tightly coupled with the urban code but UGM can run independently. SLEUTH is an acronym for; Slope Land use Exclusion Urbanization Transportation Hillshade (Clarke & Gaydos, 1998; Silva and Clarke, 2002).

The model basically works based on five growth coefficients (diffusion, spread, breed, slope resistant and road gravity) for determining four types of growth rules; spontaneous growth, new spreading growth, edge growth and road influenced growth. Other level of growth rules i.e. self-modifying growth rules have instigated by an unusually high or low growth rate (Clarke et al., 1996). It have been incorporated into the SLEUTH model to produce S curve growth till the land is available to transform into urban areas. SLEUTH model runs in three phases i.e., test, calibration and prediction. Test phase runs to verify that the initial conditions and data set are complete and meets the desired conditions. It is very important to run test phase before calibrating the model unless it would be a waste of time if initial conditions or input data do not satisfy desired conditions. SLEUTH have two methods of model parameter estimation in the calibration phase i.e., brute force calibration method and genetic algorithm. Brute force algorithm works in three phases to derive optimum coefficient values. On the other hand, genetic algorithm involves searching of coefficient space in an adaptive manner.[1]

The calibration phase involves sequentially refining growth coefficient values from one phase to another phase (KantaKumar et al., 2011). At the end of each calibration phase run the model produces values for each growth parameter in the form of least square regression metrics such as, Composite Score, Compare value, Population, Edges, Mean Cluster Size, Leesalee, Slope, Urban Clusters etc. Each metric symbolizes the goodness fit between actual and modelled growth. The coefficient ranges for each calibration phase are selected on the basis of these metrics values. Various approaches are used to derive coefficient space, such as sorting of metrics in descending order, by assigning weightage to the metrics in which higher weightage metrics used to decide coefficient space (Dietzel and Clarke, 2007; Gandhi and Suresh, 2012;

[1] http://www.ncgia.ucsb.edu/projects/gig/Imp/implement.htm

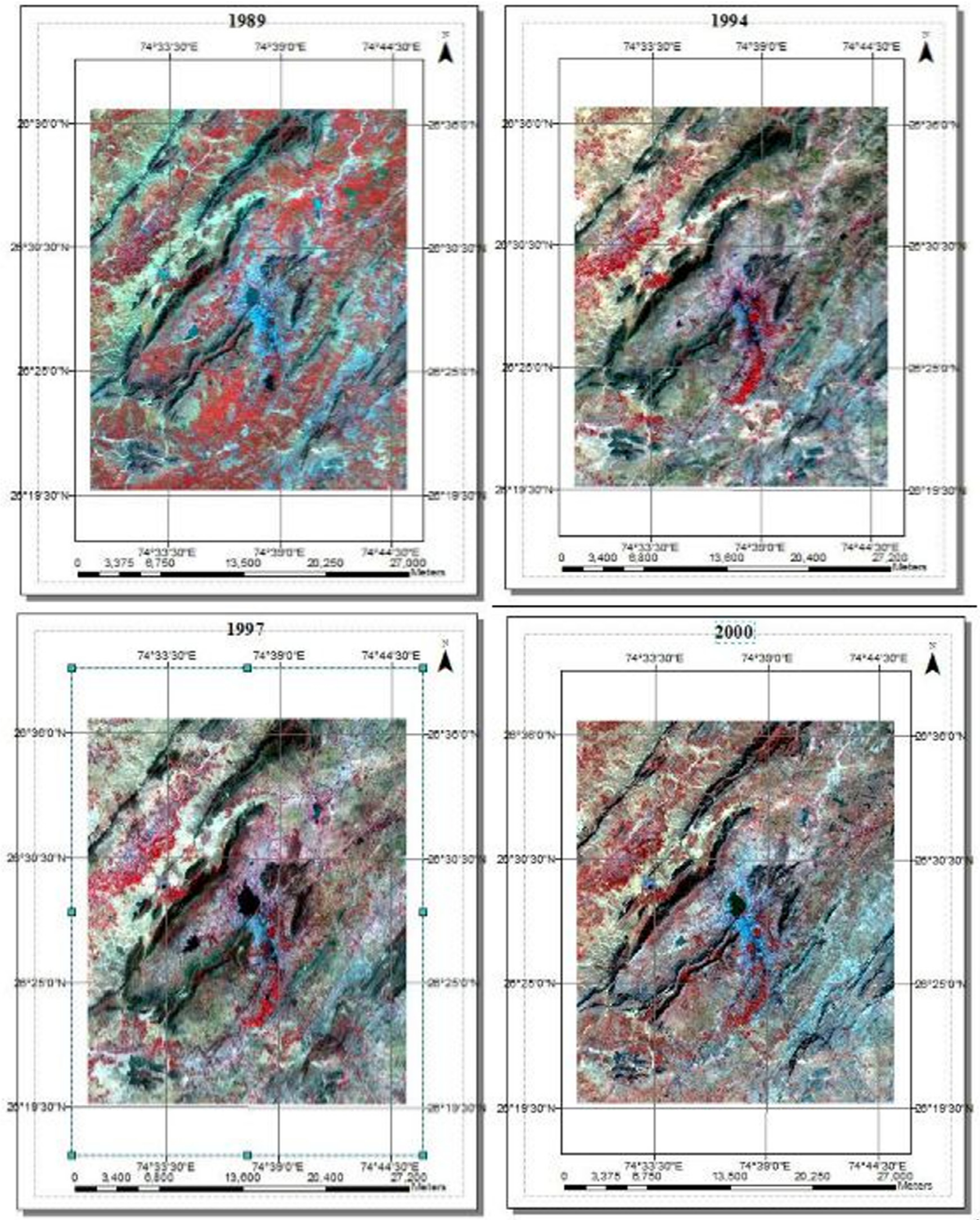

Fig. 2a. FCC of satellite Imageries.

KantaKumar et al., 2011). As recommended in previous studies that Leesallee metric has been used in the present study to decide the growth coefficient range for each phase of calibration run (Bhatta et al., 2010; Clarke, 2008). The refined values of growth coefficients from each calibration phase are then used for subsequent calibration runs. Further, values of growth coefficients obtained from final phase calibration will be used for growth prediction phase.

2.4.2. Parameterization of SLEUTH model

First of all, standard image processing techniques, such as image extraction, rectification, restoration, and classification have been used for the analysis of the satellite imageries, using the ERDAS imagine software. Study area extent was decided after examination of Ajmer fringe and surrounding. For parameterization of SLEUTH model different input files have been prepared from the classified satellite images and GIS database layers created through manual digitization. Seven multispectral satellite images of different years have been classified using standard digital image processing techniques like image classification using supervised method. The accuracy of classified outputs have been tested by comparing land use /land cover of selected random pixels in classified outputs with corresponding land use from reference data.

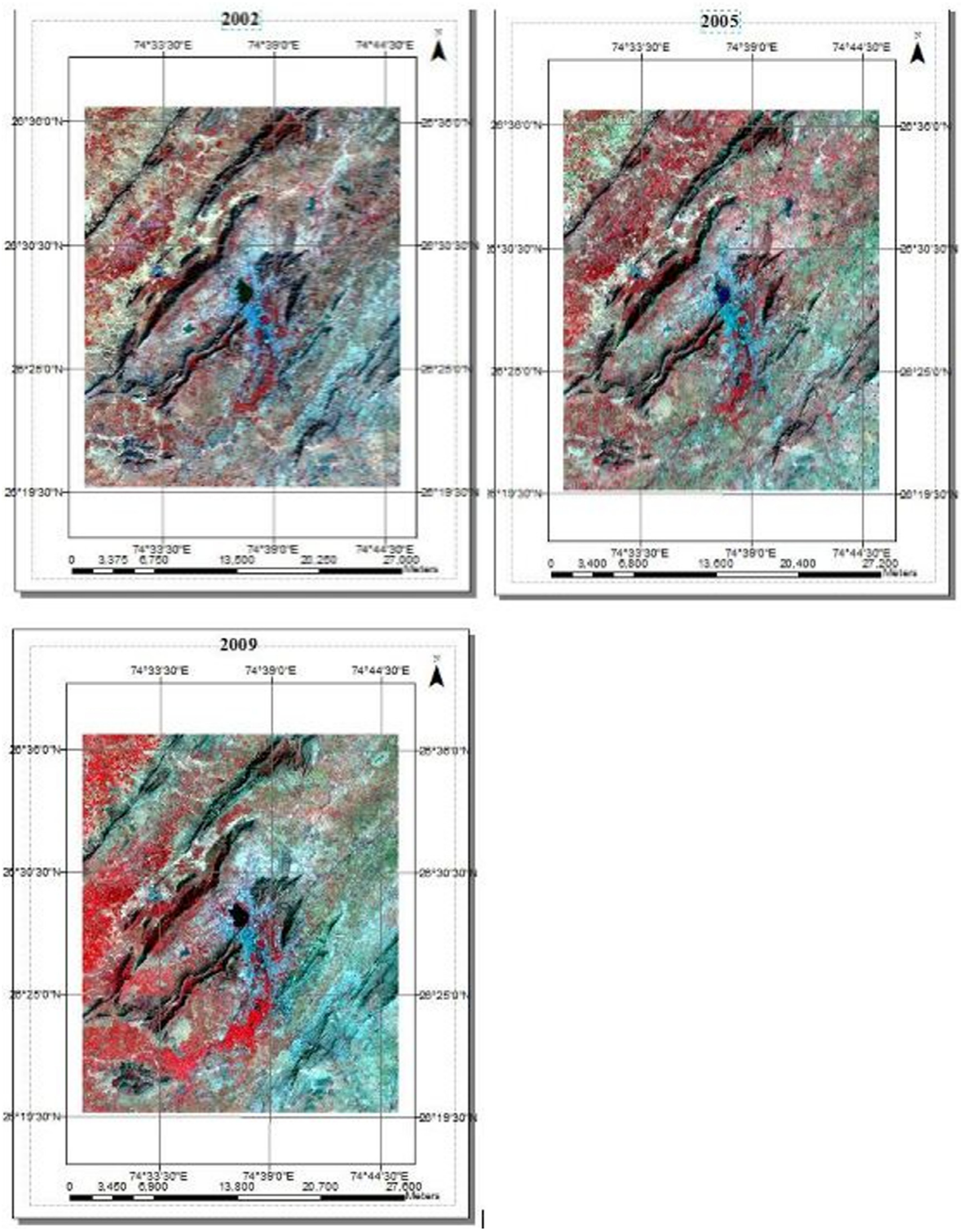

Fig. 2b. FCC of satellite Imageries.

Table 1
Kappa Coefficient and Accuracy Percentage of each Classified Satellite Image.

S.no	Satellite Image Year	Kappa coefficient	Accuracy Percentage
1	1989	0.77	80%
2	1994	0.80	82%
3	1997	0.79	81%
4	2000	0.78	79%
5	2002	0.85	86%
6	2005	0.84	86%
7	2009	0.88	89%

Stratified random sampling was used to generate test pixels. Accuracy assessment statistics in the form of percentage accuracy and kappa coefficient has been presented in Table 1. Classification accuracy has been found to be satisfactory as percentage accuracy ranges from 80% to 90% for all seven images. Kappa statistics found to be satisfactory with a range of 0.77 for year 1989 to 0.89 for year 2009. Accuracy of classification can be considered as satisfactory for such a heterogeneous urban fringe from the medium resolution satellite images. However, at few locations misclassification is clearly evident.

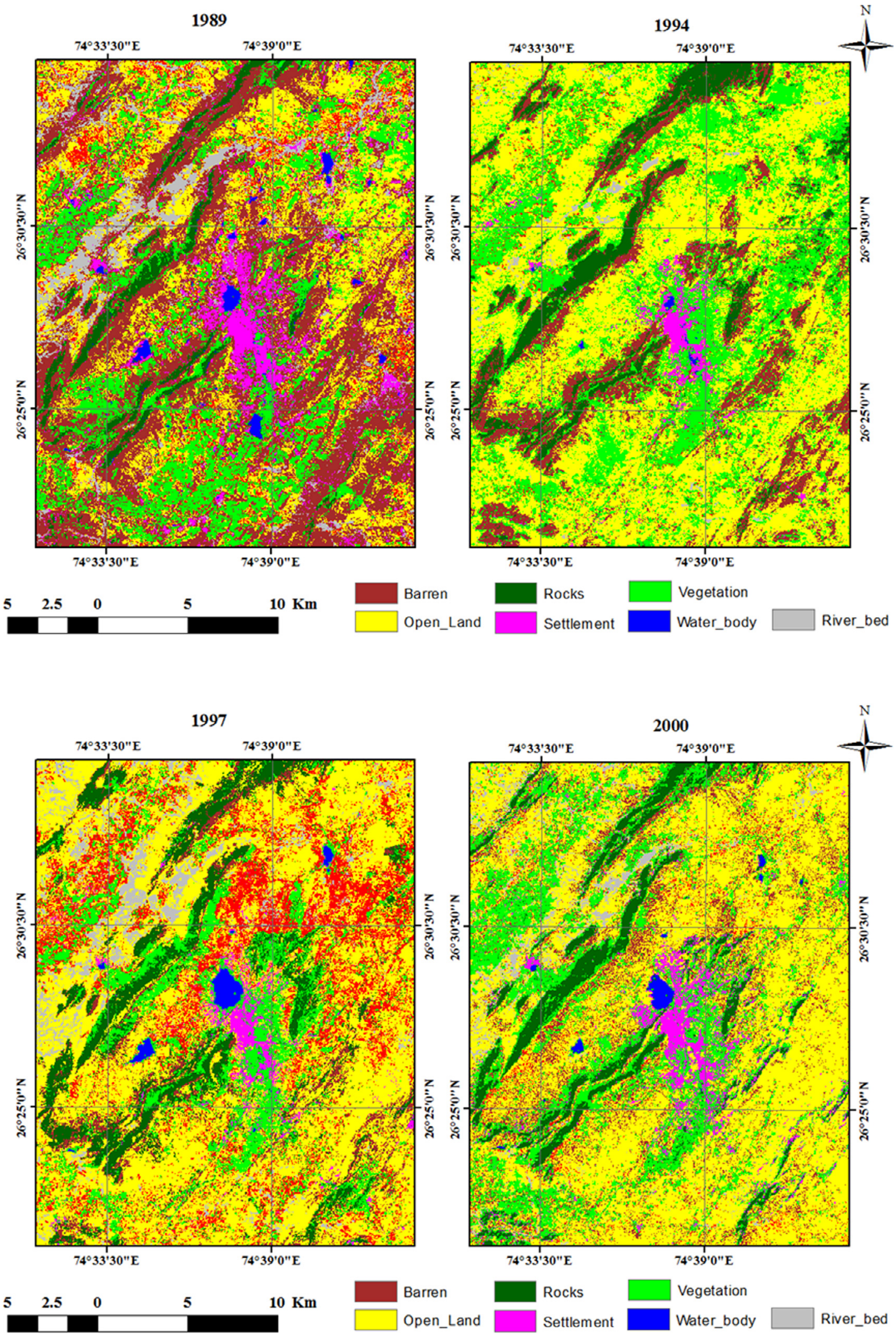

Fig. 3a. Classified Satellite Imageries.

For implementing SLEUTH model for the study area six type of input maps (slope, land use, exclusion map, urban map, transportation map and hillshade map) of different years are required. For initiating SLEUTH model at least four years of built-up maps, at least two years of transportation map, one exclusion map (which includes, protected land, water body, reserved forest etc.), one hillshade map (no role in SLEUTH processing, just for viewing topographical purposes) and two land use maps (if running Deltatron

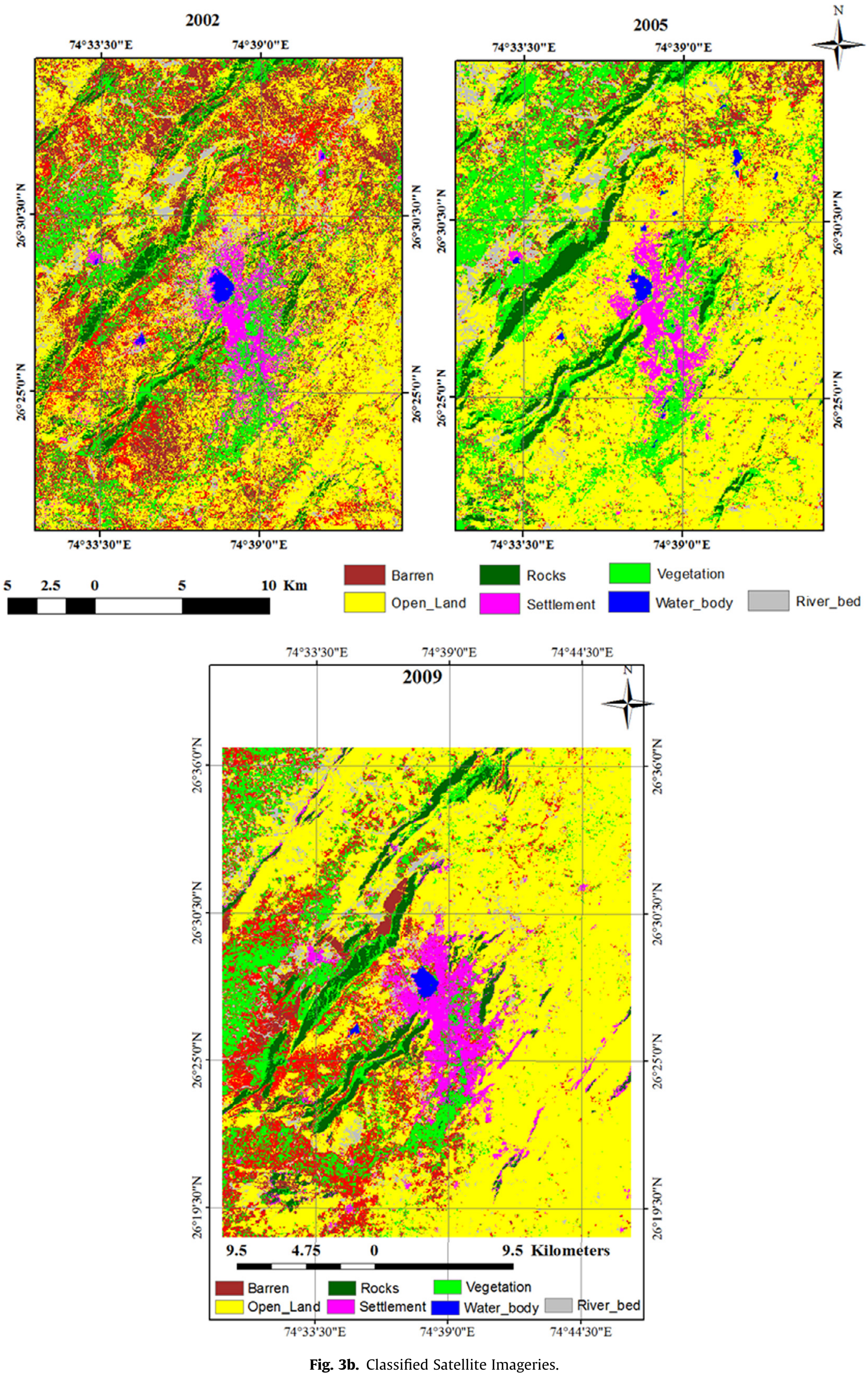

Fig. 3b. Classified Satellite Imageries.

model) are required. (Dietzel and Clarke, 2007; Herold et al., 2003; KantaKumar et al., 2011).

Urban built-up maps have been prepared by extracting built-up areas from classified images of seven years (Table 1). Two transportation maps have been prepared by digitizing roads from reference maps (SOI toposheet & AutoCAD map and satellite images) in ArcGIS. Exclusion maps have been prepared as a polygon map of reserved forests, protected land, other restricted areas and areas

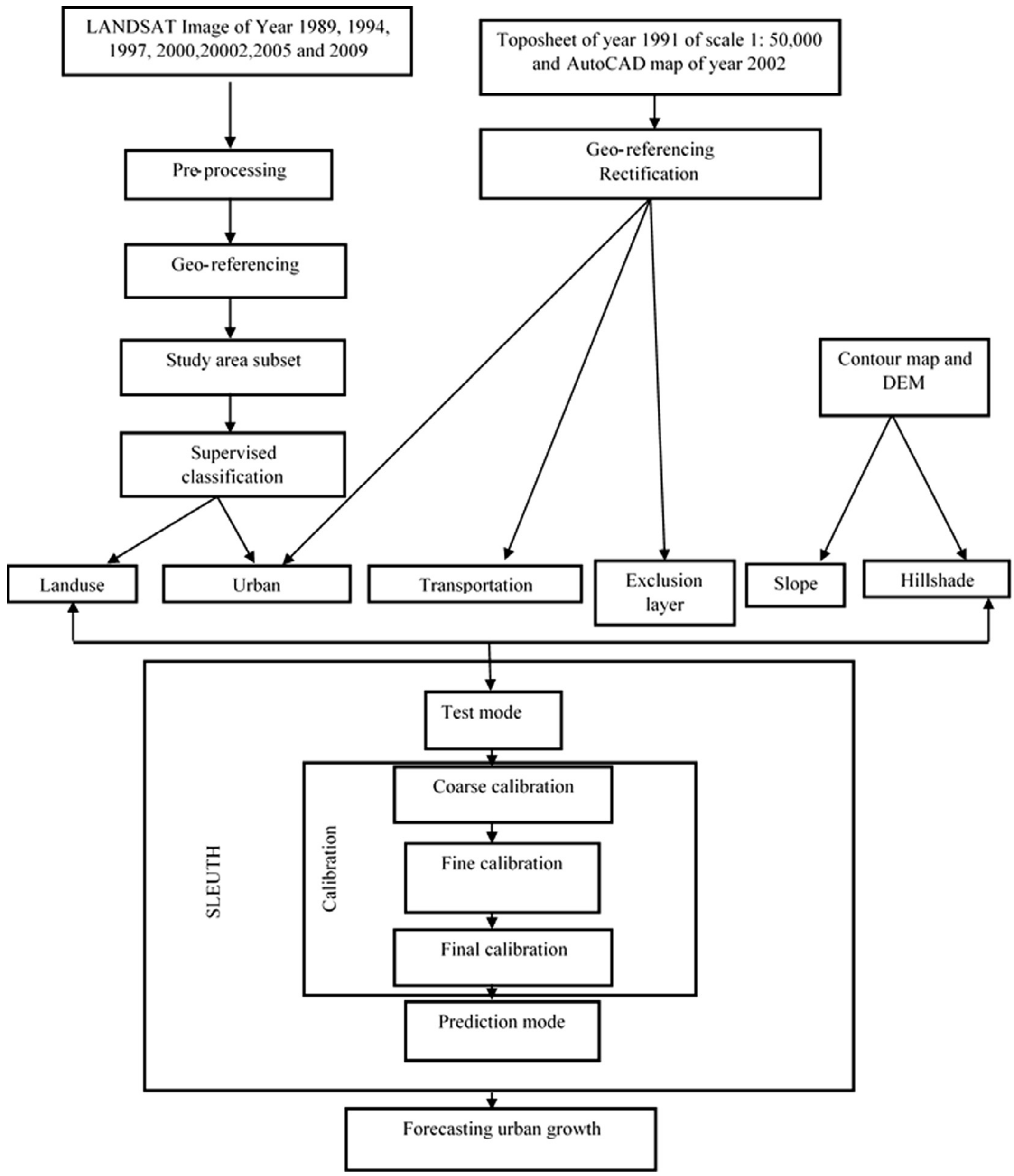

Fig. 4. Methodology flow chart.

having topographical slope more than 20%. Topographic slope (in percentage) and hillshade maps were prepared from Digital Elevation Model (DEM), which was prepared from a topographic map having contours at 1.0 m interval.

Further, all input data layers (slope, urban, transportation, hillshade and excluded maps) (Figs. 5a and 5b) have been resampled to same extent and radiometric resolution (8 bit). Three sets of input data has been prepared at 80 m spatial resolution for coarse calibration phase, 50.0 m for fine calibration phase and 25.0 m for final calibration phase spatial resolution for the three phases of model calibration.

2.4.3. SLEUTH calibration

Calibration is the one of important phase of urban growth simulation using SLEUTH (Dietzel and Clarke, 2006). Brute force parameter estimation algorithm has been used in the present study for the calibration of SLEUTH model. Details regarding calibration of cellular automata has been found in Barredo et al., 2003; Clarke et al., 1996 and Clarke and Gaydos, 1998. Calibration has been performed in three phases, coarse, fine and final. Coarse phase calibration has been performed using coarse resolution input dataset (slope, urban, transportation, hillshade and excluded maps considered here with 80 m spatial resolution), initial values of growth coefficients and selected number of Monte Carlo iterations (5). Then after, on the basis of computed statistical metrics, growth coefficient values were derived for the next phase calibration using 50 m spatial resolution input dataset and increased number of Monte Carlo iterations, as compared to coarse phase calibration (8). Again, for final phase of calibration, statistical metrics obtained from fine calibration phase were used to select value of growth coefficients. Final phase calibration was performed with finer resolution input data set (25 m spatial resolution) and increased number of Monte Carlo iterations (10). After final calibration, final refined values of growth coefficients have been obtained. Detailed calibration results have been discussed in subsequent sections.

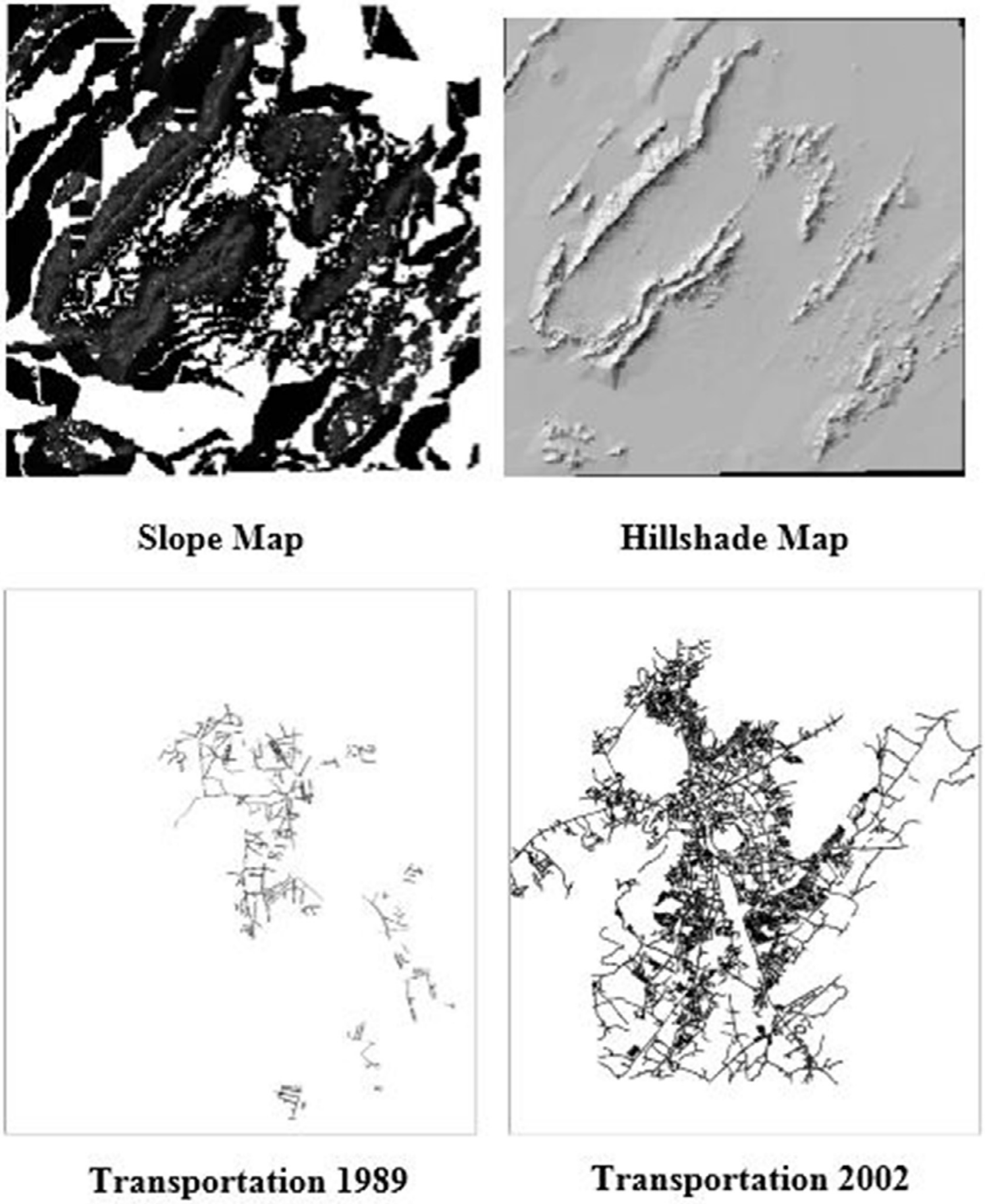

Fig. 5a. SLEUTH Input Data Layers.

2.4.4. SLEUTH prediction

Prediction phase of SLEUTH model includes running model in prediction phase on finer resolution dataset by setting the number of Monte Carlo iterations equal to or greater than 100 and by defining best fit growth coefficients obtained from final phase of calibration. It is a single run phase process produces prediction images and also statistical data files used for forecasting future urban growth. In the present study, SLEUTH model has been developed for year 2040 for the prediction of urban growth.

3. Results

Results of the urban growth modelling using SLEUTH model have been presented below. Parameterization and calibration of model has been discussed in previous sections. Model was implanted in three phases; test phase, calibration phase and prediction phase.

3.1. Test phase

The SLEUTH model was successfully run in test phase, which signify that desirable preliminary conditions of the model are achieved and model is ready for the calibration phase.

3.2. Calibration phase

The first phase of calibration i.e. coarse calibration was performed by taking full value of growth coefficient space (i.e. 100),

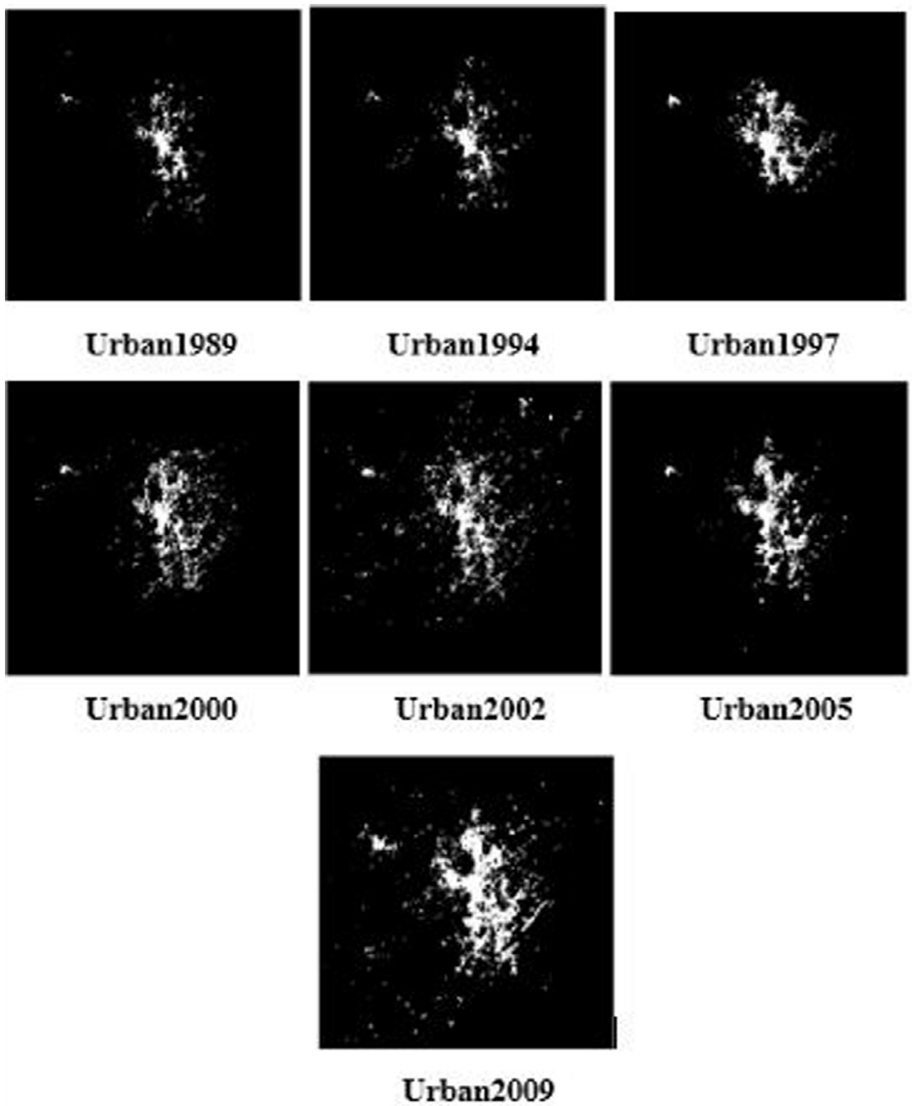

Fig. 5b. SLEUTH Input Data Layers.

iteration step of 25 and starting value of 0 with 5 Monte Carlo iterations. From coarse phase, growth coefficient values corresponding to top three values of Leesallee metrics (i.e. 0.36058, 0.35975 and 0.35968) were considered. The next, fine calibration was performed by utilizing the output of coarse calibration in which step values is taken as 1 for diffusive and breed coefficient, 10 for spread coefficient, 15 for slope coefficient, 20 for road gravity coefficient with 8 Monte Carlo iterations. Again top three values of Leesalee metrics (i.e. 0.45567, 0.45555 and 0.45369) were used for deciding coefficient values for final calibration with a step value of 1 for diffusive and breed coefficient, 5 for spread coefficient, 6 for slope coefficient and 7 for road gravity coefficient with 10 Monte Carlo iterations. This phase produced better Leesalee metrics (i.e. 0.54805, 0.54650 and 0.54556) as compared to previous phases. The best fit coefficient values i.e. 1 for diffusive coefficient, 53 for breed coefficient, 1 for spread coefficient, 32 for slope coefficient and 83 for road gravity coefficient were decided based on performed calibration. Details of optimum urban growth coefficients obtained from different phases have been presented in table Tables 2a–2c.

The comparison score of the modelled final urban area and the urbanization of the historical control years gives the comparison score of 0.80 which indicates that the prediction on the basis of refined modelled values of urban growth would be very much similar to what actually happened in reality. The final calibration value for urban edges is 0.83, which seems to confirm that there is much similarity between modelled urban edges and urban edges of control years. Also, urban area clustering value is 0.60 which indicates the comparison between modelled urban clustering and urban clustering of control years. Urban clustering comparison value is not very good (1.00 in the case of perfection) which reveals that the SLEUTH model is not very much efficient in capturing heterogeneous urban clusters of small sizes. As, in Indian scenario urban development is very heterogeneous and also of small unit size development, which are not captured by the model. The shape index is representing the similarity between shape characteristics of modelled urban growth and urban growth of control years. For Ajmer fringe, the Leesalee metrics, which is a shape index showing the comparison between shapes of modelled urban areas over urban areas of control years which has been found to be as 0.54, which is satisfactory for such a heterogeneous urban area. Therefore, a value of 0.54 can be considered as satisfactory (KantaKumar et al., 2011). These statistical metrics were computed to test the sensitivity of the SLEUTH model towards incorporating

Table 2a
Coefficient values from coarse calibration.

Leesalee	Diffusive	Bread	Spread	Slope	Road Gravity
0.36058	1	1	50	1	100
0.35974	1	1	50	25	50
0.35968	1	1	50	25	100
0.35560	1	1	50	75	100
0.34504	1	1	25	1	100
0.34490	1	1	25	1	25
0.34185	1	1	25	25	75

Table 2b
Coefficient values from fine calibration.

Leesalee	Diffusive	Bread	Spread	Slope	Road Gravity
0.45567	1	1	45	18	45
0.45555	1	1	45	18	85
0.45369	1	1	45	33	85
0.45071	1	1	35	3	85
0.45003	1	1	35	18	85
0.44593	1	1	35	33	85
0.44546	1	1	35	3	85
0.44429	1	1	35	48	85

Table 2c
Coefficient values obtained from final calibration.

Leesalee	Diffusive	Bread	Spread	Slope	Road Gravity
0.54805	1	1	44	26	68
0.54650	1	1	39	8	82
0.54556	1	1	39	14	33
0.54104	1	1	34	14	61
0.54095	1	1	34	14	40
0.54082	1	1	34	14	47
0.54054	1	1	34	14	82
0.54053	1	1	34	14	68

their local characteristics. So, from the above discussed metrics, it states that the model successfully replicates the historical urban growth.

3.3. Prediction phase

After successful calibration and validation corresponding to year 2002 and 2015, urban growth of Ajmer has been predicted for different years up to 2040. The prediction phase was run using 100 Monte Carlo iteration. Best fit values of growth coefficients obtained from calibration phase and used for the prediction phase are mentioned in Table 3. In present study, year 1989 has been taken as seed year for predicting the growth of Ajmer fringe considering restricted area i.e. protected reserved forests, steep slope regions, and water bodies like Ana Sagar and area around 3rd, 4th and 5th order streams.

SLEUTH has simulated urban growth through year 2009 (which has been shown in Fig. 6a) and predicted for the year 2040. The study reveals some variation in actual urban growth and modelled urban growth, it may be due to some misclassification occurred during classification of satellite images.

Model simulated for calibration period and predicted growth has been presented in Figs. 6a & 6b respectively. Significant urban growth has happened in Ajmer fringe during year 1990 to 2009 period and model satisfactorily simulated the same. The pale yellow colour in the Fig. 6b indicates the urban area in the seed year while light orange colour is showing less growth, green colour is showing medium growth and dark red colour is showing the highest probability of growing urban areas. The visual interpretation and comparison between actual urban growth (obtained from satellite images or reference maps) and model simulated urban growth for year 2002, 2005 2009 and 2015 of study area have been shown in Figs. 7a–7d. A red ring indicates differences in actual and model simulated urban growth. Such errors in simulated growth may be attributed to the relatively low accuracy of the land use/land cover maps used as input during the calibration phase, heterogeneity in construction material used in construction, smaller size of built-up units, lack of open spaces, improper land use planning and inadequate roads.

Table 3
Prediction best fit values.

Diffusive	Breed	Spread	Slope	Road Gravity
1	53	1	32	83

Since, land use/land cover maps have been prepared from the classification of medium resolution remote sensing images using maximum likelihood classifier (MLC). The MLC uses only spectral reflectance values for classification. Misclassification has been observed due to similar reflectance characteristics of few land use and land cover classes (like built-up areas and exposed rocky terrain, dry sand and barren land etc.) and heterogeneity in built-up areas due to different type of construction material & practices and lack of open spaces between built-up units.

Model simulated urban growth for the Ajmer fringe for year 2040 has been shown in the Fig. 8. By the year 2040 significant urban growth (more than 90 percent probability) will take place along the Jaipur road (NH8), area nearby highway and bypass roads (40 percent probability), (Fig. 8). As per the results, area around Ana Sagar Lake have 70 percent probability of getting developed in upcoming years as built-up density in the area is growing. Area nearby Foy Sagar have 80 percent probability of getting developed in upcoming years which might be due to the availability of developable relatively flat land. In recent past also, development of new housing colonies have been started in this area. Pushkar bypass road is also showing significant road influenced growth with 30 percent probability as new development will likely to take place in this area. Also, many new educational institutes and universities are coming up in this area. Madar area which is in North-East side of Ajmer will also project to grow significantly with 20 percent probability in near future. A huge road influenced urban growth has been projected by the year 2040 along with the Beawar road with 90 percent probability, which is in south of Ajmer. So, the study area will be developing at faster rate in upcoming years. Also, 20 percent chances of getting road influenced urban growth along the Nasirabad Road as predicted by the SLEUTH model. Area around Bisal Sagar will be grown with 80 percent probability by the year 2040 due to increased industrial activities. Areas nearby Khanpura Pond is also likely to get developed at smaller pace (with 40 percent probability) as many industrial activities are taking place at this region. The Pushkar region is one of the most important places in Ajmer fringe which is depicting higher growth (with more than 90 percent) in upcoming years. Pushkar region is a religious and popular place, commercialization is getting increased and also the urban density will increase in these areas.

SLEUTH generated various type of growth statistical measures for two years i.e., 2015 and year 2040 have been presented in Table 4. These are the measures which in turn determine the appropriateness of the used statistical analyses and these are obtained by statistical average log file produced after completing the prediction phase of the SLEUTH model run.

Results revealed that (Table 4), cumulative number of urban pixels by spontaneous growth ('sng') increases from 6.80 in year to 8.46 in year 2040, indicating the increase in new urban settlements in undeveloped areas. Cumulative organic growth pixels ('og') indicates relatively less development in existing developed

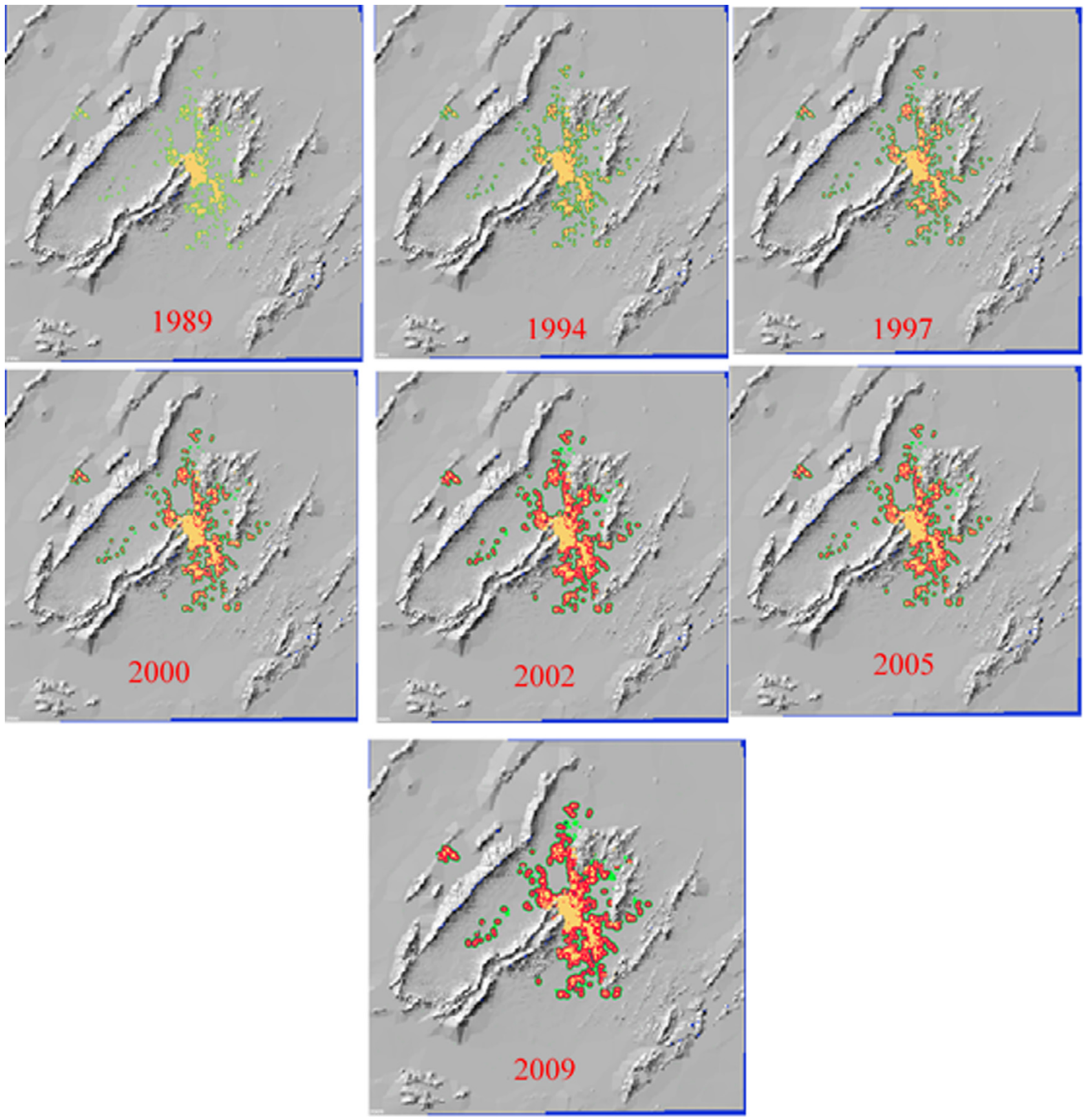

Fig. 6a. Simulated Urban growth from seed year to 2009.

urban settlements as compared to surrounding localities in year 2040. The rate of road influenced growth ('rt') is 2.64 in year 2015 to 1.58 in year 2040, which indicates that growth will slow down along the roads by the year 2040. This may be due to reason that scattered growth in outer areas may not be captured by the model due to coarse resolution of input data and simulation i.e., 25 m. Urban area within the selected extent around the Ajmer has been projected to increase from 52837.72 ha in year 2015 to 90261.58 in year 2040. Urban edges, which indicates rate of scattered growth or pixels represent urban areas with other land use classes, slightly reduced from 7531.75 in year 2015 to 7630.26 in year 2040. Such decrease in edges may be due to heterogeneous urban growth not captured by the model on account of coarse resolution. Also, increased urban clusters showing the growth of urban areas and radius of the urban enclosed circle ('rad') increases which definitely indicates the urban expansion of the study area. Urban growth in higher slope topographic areas in year 2040 remains almost same as in year 2015. Moreover, outward expansion of urban growth will also be there and new settlements will also be developed at large by year 2040, as indicated by the increase in diffusion coefficient. However, urban growth rate is declining in year 2040 as compared to year 2015 (refer Table 4) which may be attributed to vertical growth in built-up areas.

4. Discussion

Looking at the historical and cultural importance of the Ajmer City, Government of India has selected Ajmer as one of the city to be developed as smart city. Therefore, this city has become a significant area for urban growth studies. The results showed that, the urban growth is taking place rapidly in the north-east part of Ajmer. But, the road influenced urban growth will also take place along the highways like Beawar road, Jaipur Road and Nasirabad Road In addition, it is observed that the percentage growth rate which is represented in term of horizontal coverage decreasing through the year 2040 and the main reason can be the vertical growth in built-up activities like multi-storeyed housing. The SLEUTH model uses the information of past urban extent in predicting the future growth for urban areas, the third dimension development is not considered. This factor can be taken into account in land cover change predictions by SLEUTH model. There-

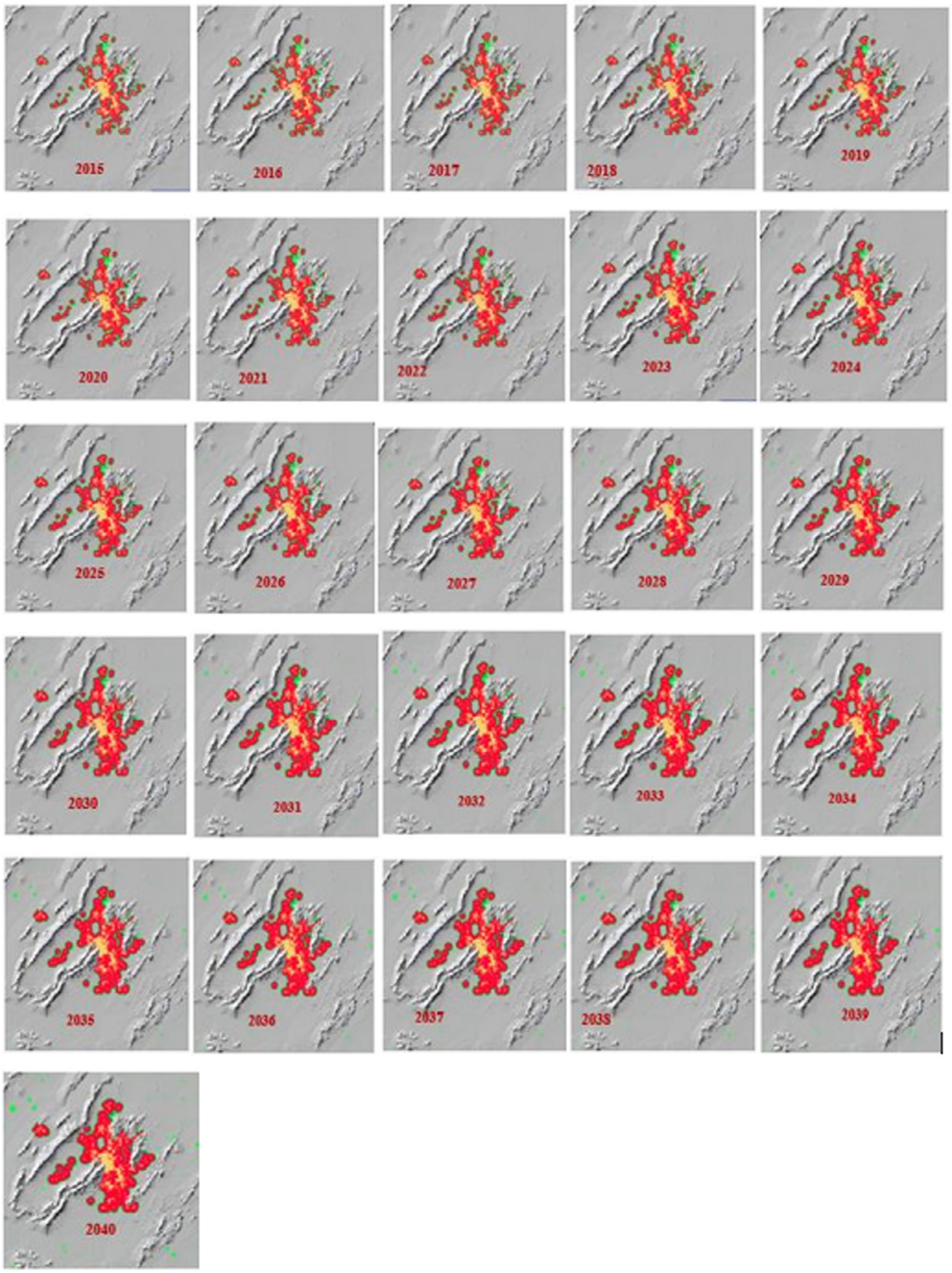

Fig. 6b. Predicted urban growth up to year 2040.

fore, the parameters used in the SLEUTH model may vary from one urban area to another since every urban retains its own properties.

Main outcomes of the study can be categorized into two groups which are technological and application. Study has demonstrated the utility of GIS, remote sensing and the cellular automaton based modelling for urban growth assessment and prediction.

SLEUTH is capable in handling the land use restriction along drains, rivers etc., in simulating the growth. By manipulating SLEUTH input data layers, self-modification rules, and growth control coefficients, SLEUTH can be used to generate different land use planning scenarios. Moreover, these outcomes would be useful for urban planning, land use policy planning, resources budgeting and resource allocation for the urban areas.

Performance of the CA based SLEUTH model has been found to be satisfactory in simulating the urban growth of Ajmer fringe. However, scattered urban growth in the form of smaller size built-up units seems to be underestimated by the model due to coarse resolution of input data used in calibration phase and while predicting the growth. In addition, model is computationally inefficient at finer resolution and requires longer computational time to complete even a single phase of calibration.

Average size of built-up units in Ajmer particularly housing units is less, that the spatial resolution of input data considered during the three phases of calibration i.e., 80 m, 50 m and 25 m leading to mixed pixels of built-up and non-built-up areas. Also, urban development is very heterogeneous in terms of different

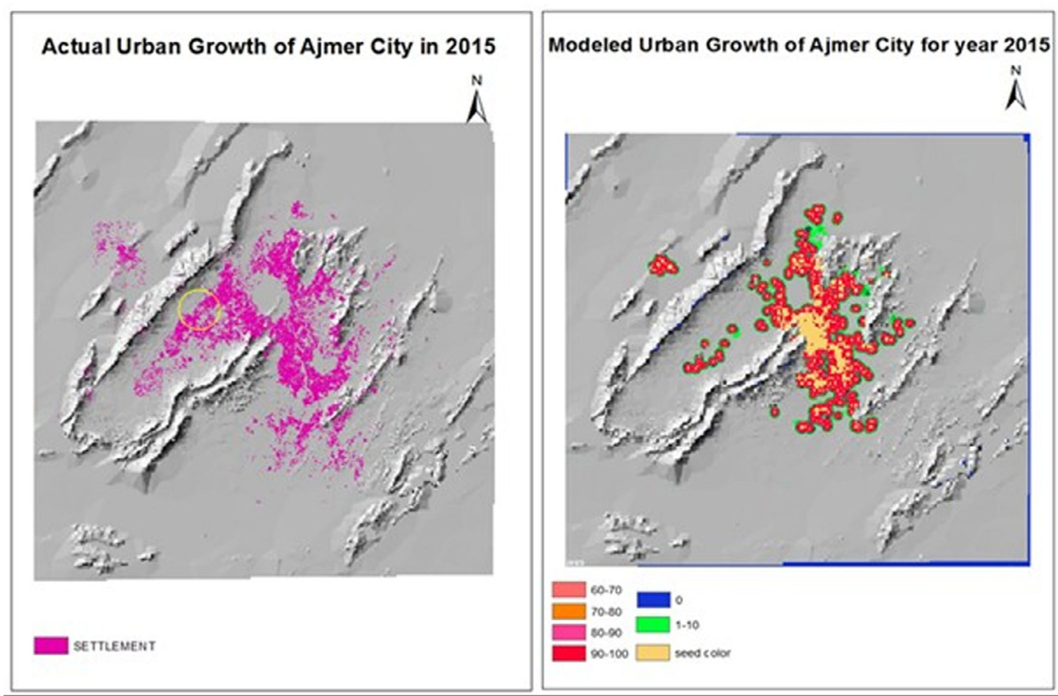

Fig. 7a. Modelled and actual urban growth for year 2015.

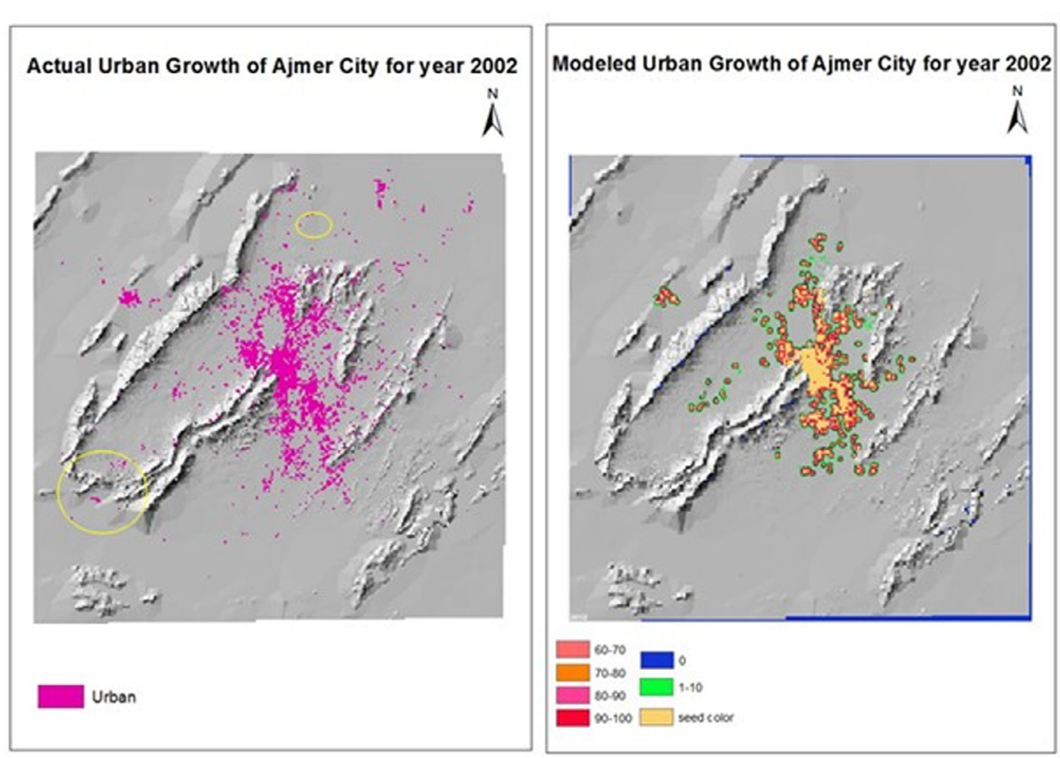

Fig. 7b. Modelled and actual urban growth for year 2002.

type of construction, lack of planning and inadequate infrastructure like roads. Therefore, smaller built-up units may have not detected by the SLEUTH, especially in newly developed areas, where urban growth is scattered (Figs. 7a–7d). Also, some fragmented construction are of very small sizes which has not been detected by the model as shown in Figs. 7a–7d. Densely developed areas have been well detected by the model because of less problems of mixed pixels i.e., built-up/non-built-up. Coarse spatial resolution have been adopted for the input data sets to avoid computational complexities and longer processing time as suggested by the various researchers (Candau, 2000; Dietzel and Clarke, 2007; KantaKumar et al., 2011; Silva and Clarke, 2002).

Still, urban growth simulation and prediction is challenging because of dynamic nature of urbanization process. Urbanization is a function of different explanatory variables such as, neighbourhood, proximity, demographic, socio-economic, institutional,

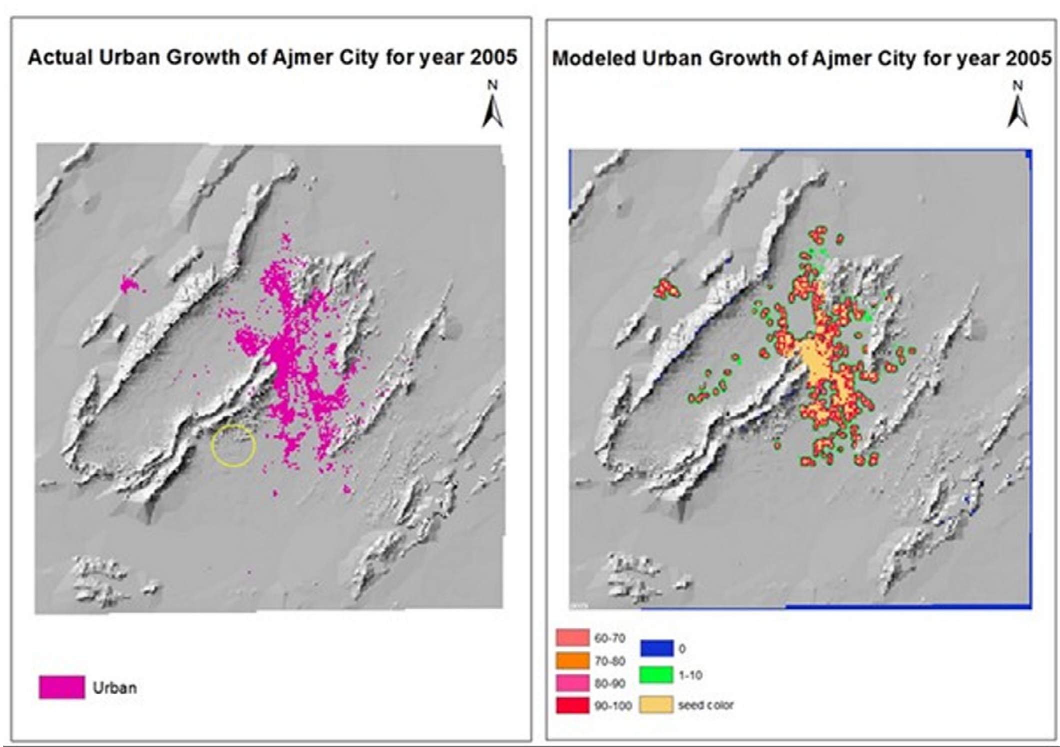

Fig. 7c. Modelled and actual urban growth for year 2005.

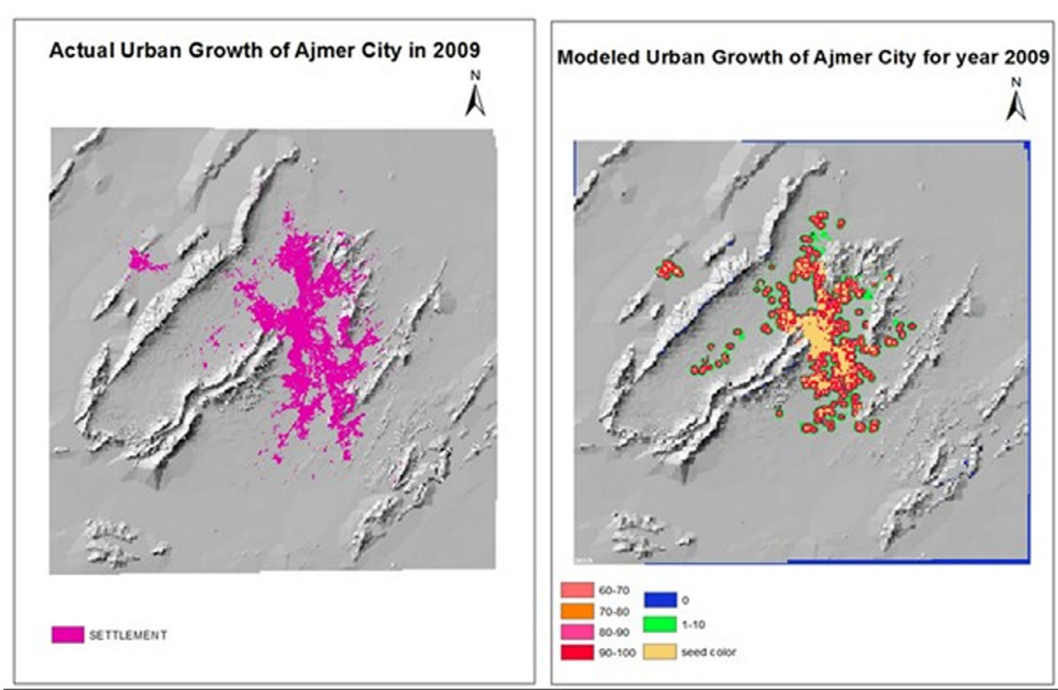

Fig. 7d. Modelled and actual urban growth for year 2009.

Suitability, Bio-physical and restrictive variables. *Neighbourhood* variables like a person would be more interested in constructing his/her house on the basis of neighbouring conditions like near residential areas, city centre etc. *Proximity*, distance to market, distance to road, distance to hospitals, distance to railways, distance to highways, distance to schools etc. are the factors which everyone consider. *Demographic*, according to statistics of population demand is estimated and included as driving factor into the model. *Socio-economic variables*, decision of development may be based on some socio-economic factors like, land cost, time to travel, opportunity cost, Tradition, Status, Education etc. *Institutional variable*, may comprise the decision taken by managerial authorities of or relating to the construction nearby already established industries and institutions. *Suitability***,** land suitability factor for building houses, agriculture etc. *Economic variables*, land tenure, farm size, income may be the important factors to be considered.

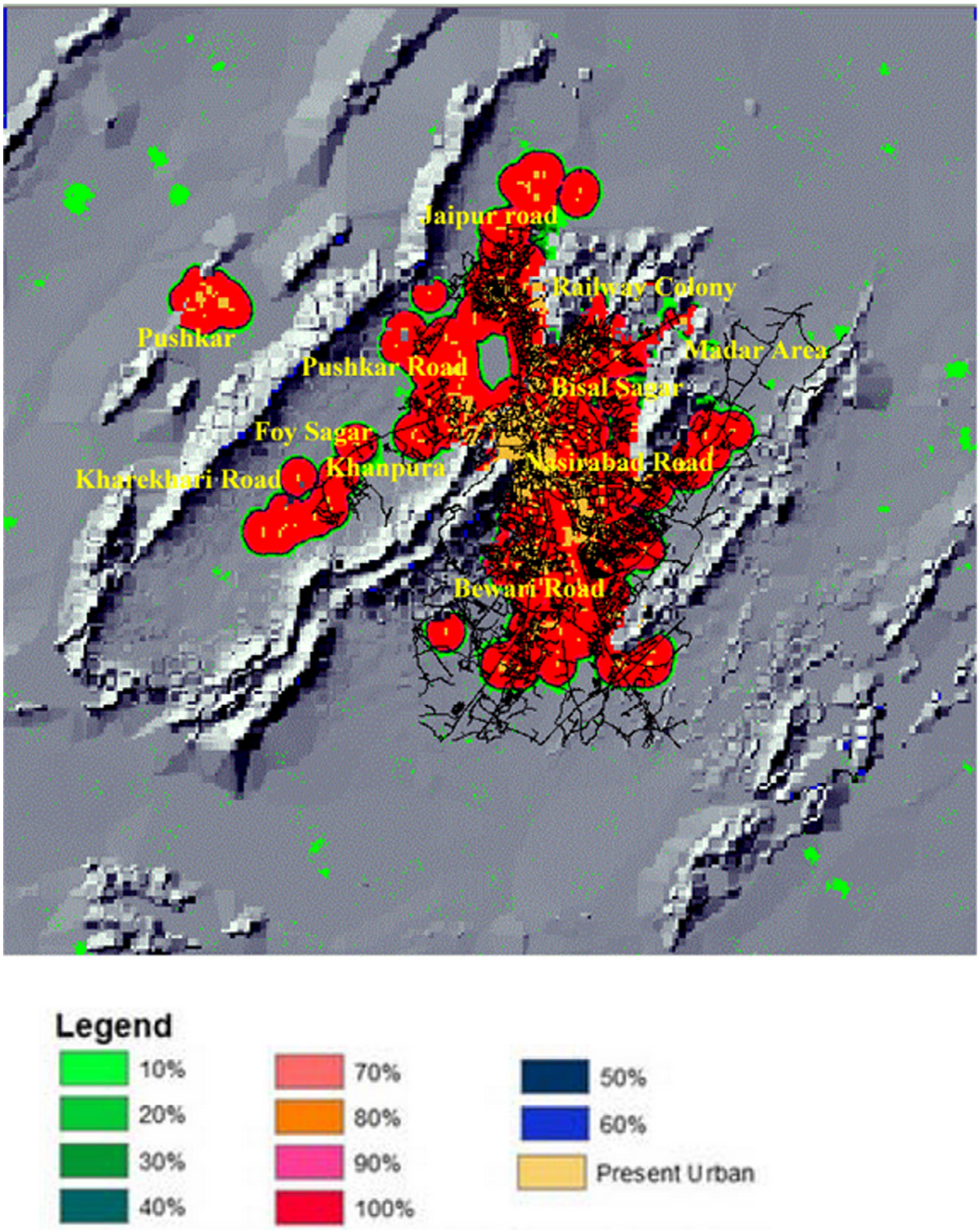

Fig. 8. Urban growth of the study area for year 2040.

*Climatic drivers***,** climatic variability, life zones are the factors which one consider while building their houses. *Bio-Physical drivers***,** Topography, Elevation, Slopes, Soil types, Altitude are the variables which are considered while making decision of or relating to construction (especially in disaster prone areas.) and *Restriction variables*, may comprise prohibited area for development such as, reserved forest, green belt, historical places, airport side area etc. The model behaviour would be different for different surroundings, geographical settings and practices. Also, calibration would be different as explanatory variables would be different for different regions. Therefore, understanding influence of such factors on urban growth is still a challenge due to their dynamic nature. The SLEUTH model has been widely tested for developed countries but very few studies have been made in developing countries like scenario where housing unit size are very small and fragmented. Also, different type of urban development in developing countries having different socio-economic, cultural and human behavioural characteristics instigate the urban growth modelling in developing country KantaKumar et al. (2011). Moreover, temporal variations in urban growth controlling factors makes it further complex. Incorporating vertical growth into model simulations is still an issue of research. SLEUTH is computationally inefficient in simulating the urban growth at finer resolution. Therefore, urban growth simulation is still very challenging especially for the heterogeneous urban areas. Uncertainties in model results can be reduced by improving accuracy of input datasets prepared from classified satellite data.

Table 4
Comparison of growth statistical Measures.

Statistical Measures	Definition of Abbreviations	2015	2040
sng	Cumulative number of urbanized pixels by spontaneous neighbourhood growth.	6.80	8.46
og	Cumulative number of urbanized pixels by organic growth.	1588.23	1405.05
rt	Cumulative number of urbanized pixels by road influenced growth.	2.64	1.58
area	Total number of urban pixels	52837.72	90261.58
edges	Number of urban to non- urban pixel edges	7531.36	6730.26
clusters	Number of urban pixel clusters	477.60	549.38
rad	The radius of cluster which encloses the urban area	129.69	169.50
slope	Slope coefficient	2.31	2.13
diffusion	Diffusion coefficient	1.28	1.64
spread	Spread coefficient	67.97	87.17
breed	Breed coefficient	1.28	1.64
Road gravity	Road gravity coefficient	86.30	90.76
Percent urban	Percent of urbanized pixels divided by the number of pixels available for urbanization	15.63	20.12
Growth rate	Urban growth rate	2.64	1.58
Growth pixels	Number of growth pixels each year	1597.77	1415.35

5. Conclusion

Economic development and population growth have triggered rapid changes to land use/land cover, as a result of urbanization & industrialization. Urban growth assessment and prediction are essential components of urban development and planning, which helps in better land use planning and sustainable use of resources. In developing countries like India, urban growth assessment and modelling is not common which leads to heterogeneous and unplanned urban growth. SLEUTH model has been tested and its performance was examined for the modelling of heterogeneous growth, which is quite different from the developed countries where SLEUTH was tested extensively. Model performance has been found to be satisfactory. However, few issues have been identified related to the sensitivity of the SLEUTH with respect to spatial resolution of input variables and scale. Model results further indicates that SLEUTH is not able to capture small unit size development i.e., in the form of fragmented growth in outer areas, which is very common in developing countries. Study have also concluded that further model sensitivity need to be studied to various model constants to capture small size fragmented growth. Moreover, fragmented urban growth has been underestimated by the model, which may be attributed to the coarse resolution adopted during the calibration and prediction phases, smaller average size of built-up units (less than the resolution) and errors in input data due to misclassification of satellite images because of heterogeneity in the form of development and construction material.

Conflicts of interest

No conflicts of interest to disclose.

Acknowledgement

We are highly indebted to Ministry of Human Resource Development (MHRD), Govt. of India for providing financial assistance. Also, we gratefully acknowledge Professor Keith C. Clarke, University of California Santa-Barbara and Lakshmi KantaKumar N, Institute of Environment Education and Research, Bharati Vidyapeeth University, Pune (India) for providing necessary help.

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