AN INTEGRATED APPROACH FOR NATURAL RESOURCES MONITORING USING GEO-INFORMATICS AND CA

Ankita Saxena
and
Mahesh Kumar Jat*

ABSTRACT

In last few decades, it was observed that land use land cover (LULC) changes are more extensive and occurring at faster pace to meet the developmental demands of ever increasing population. Such unplanned development and growth is leading to adverse impacts on natural resources like degradation of land resources, reduction in vegetation cover, loss of agricultural land, loss of forest, over-exploitation of water resources and environmental degradation. Correct assessment and monitoring of natural resources including land, water and vegetation are prerequisites for sustainable land use planning and optimum utilisation of other natural resources. Geo-spatial technologies like remote sensing, satellite based positioning and mapping, laser based data collection and Geographical Information System (GIS) are very effective in systematic data collection and monitoring of natural resources through LULC change detection. The current study presents integration of geo-spatial technologies and Cellular Automata (CA) - based mathematical modelling for monitoring of natural resources through assessment of LULC changes over a period. Multi-spectral satellite data for different years have been processed to extract historical LULC information and parameterisation of CA based LULC change detection model i.e., SLEUTH. Further, LULC changes and change in natural resources have been predicted for the year 2030 using calibrated model. The study has been found to be successful in demonstrating the use of geo-spatial technologies and SLEUTH in simulating the LULC changes and assessment of natural resources. The study reveals future changes in natural resources which can help planners and authorities to take proactive measures for their sustainable development.

Keywords: Geo-spatial, Land use/Land Cover Change, Natural Resources, Cellular Automata.

Introduction

Land Use Land Cover (LULC) and rural change especially in the developing world has been increased to satisfy the development demands in the last few decades. LULC change and rural development are important phenomen which transform naturally available land into some other forms in an unplanned and environment disrupting manner. Increased population and urban development lead to significant changes on earth's surface which causes environmental, ecological and socio-economic problems such as, degradation of land resource, reduction in vegetation cover, loss of agricultural land and forest, over-exploitation of water resources, environmental degradation, traffic congestion, air contamination and degradation of hydrological characteristics (Geist and Lambin, 2002). These issues are critical for sustainable environment. To mitigate adverse impacts of such unplanned LULC changes and degradation of natural resources, systematic data collection and LULC monitoring at different temporal is crucial. Further, natural resources data collection, inventorying and monitoring is very essential for their optimum planning, development and utilisation. Geomatics, in the current digital era, is the leading technology which observes earth's surface remotely through sensors, stores, processes and analyses land surfaces, temporarily, very effectively (Jat et al., 2008). Moreover, integration of geo-spatial technologies with modelling approaches may be helpful in giving LULC change on a continuous basis and also can predict future landscape

changes (Clarke et al., 2007; Saxena et al., 2016, Jat et al., 2017). Various modelling approaches have been developed like empirical statistical modelling in which a relationship is established between LULC change and its explanatory. However, such models may not be suitable for the regions outside the area for which such models are formulated. Stochastic modelling utilised transitional probabilities which is calculated statistically from a sample data to model land use change. Although, these are purely dependent on historical trend and may not be appropriate to include dynamism into the model. Optimisation based modelling techniques use linear and non-linear programming methods to model LULC change phenomenon and to monitor LULC change efficiently for small regions. However, complexity incurred while implemented for large scale applications (Lambin et al., 2000). Expert system and Artificial Neural Network (ANN)- based models are the product of computer technologies, developed to introduce dynamism and multiple explanatory variables in to the model. The Cellular Automata (CA)-based models were developed as a powerful tool in simulating LULC changes by introducing stochasticity, complexity and dynamism into the model (Clarke, 2008) and became very successful. Among various CA- based models, SLEUTH model was prominently applied for urban growth modelling and found very successful (Clarke and Gaydos, 1998; Jat et al., 2017). However, its applicability and performance for LULC change monitoring are still to be tested. The model incorporates socio-economic and bio-

physical factors which majorly are responsible for LULC change (Saxena et al., 2016). The model utilises five coefficients (i.e. diffusion, breed, spread, slope resistant and road gravity) which form four rules (diffusive, new spreading centre, edge and road influenced growth) to derive LULC change (Clarke and Gaydos 1998; Clarke, 2008). The CA is a cellular structure upon which mathematics is applied in the form of rules. LULC is spread over cellular structures and each cell represents a state, in terms of LULC classes. The rules are applied to each LULC pixel in multiple phases to determine LULC changes. Present study utilises multispectral satellite data to extract LULC information for different years, transportation networking, terrain information in terms of slope in percentage, exclusion layer to protect areas from urban development and historical urban information for different years for parameterisation of SLEUTH model. The study determines the changes that have occurred in natural resources including land over a period and how likely they are going to change in near future. Main objectives of the study are:

1. Extraction of temporal LULC information from remote sensing data.

2. Conceptualisation, calibration of SLEUTH model and assessment of changes in natural resources i.e., land, LULC, water through change detection process.

3. LULC and natural resource prediction (up to year 2030) using SLEUTH model.

Study Area

The Ajmer fringe i.e., study area, lies in the geographical graticule of 26°20'N to 26°35'N latitudes and 74°33'E to 74°45'E longitudes (Figure 1). Ajmer is the fifth largest city in Rajasthan and being a spiritual place, it is an attraction for tourists all around the world. Ajmer is one of the few cities selected for smart city proposal by the Government of India. Ajmer urban fringe has very heterogeneous LULC, topography and physiography. Urban growth is largely fragmented due to complex geographical surroundings. Unplanned development and rapid LULC changes have adversely affected the ecology, natural resources and environment of the area. Present study will be helpful to have an idea about present pattern of LULC changes and an estimation of further LULC change in near future, change direction and temporal changes in natural resource.

Methodology

The study used different types of data obtained from multiple sources like government and private organisations. Present study used different types of data and methods of geo-spatial techniques and cellular automata.

Input Data: Present study utilises seven years of multi-spectral Landsat satellite data (i.e. 1989, 1994, 1997, 2000, 2002, 2005 and 2009), an AutoCAD map for digitising transportation layer, topographic maps, town plan map for digitising exclusion layer, DEM of 1 meter spatial resolution for preparing slope and hillshade map. Salient details of input data listed in Table 1.
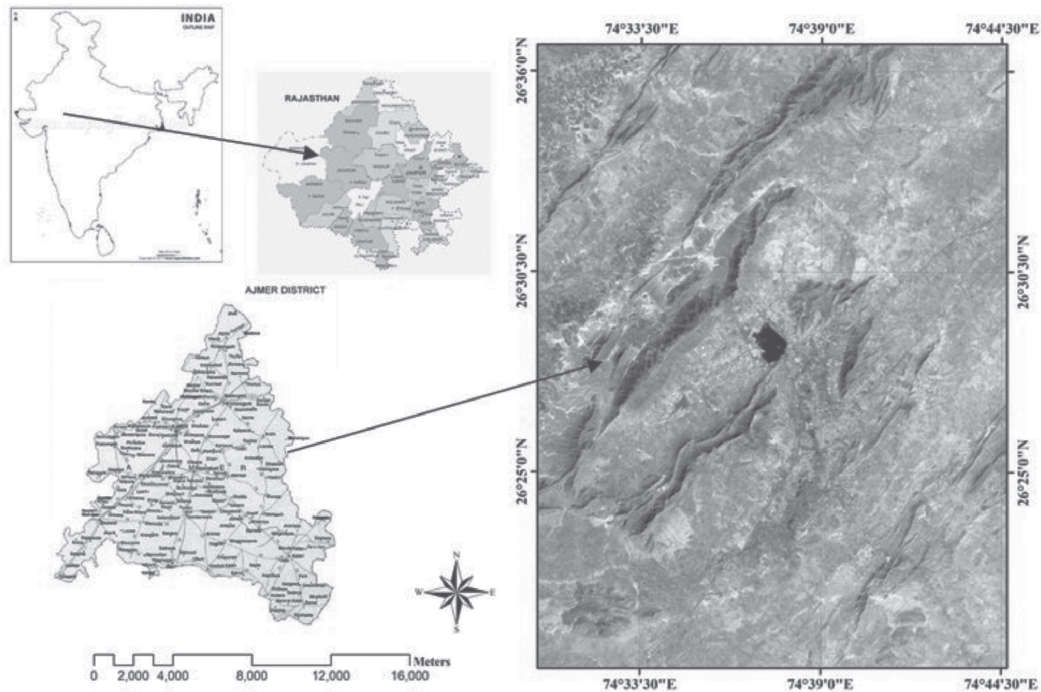
Figure 1: Study Area

Table 1: Salient Details of Input Data

S.No.	Input Data	Specifications
1	Satellite Imagery (1989, 1994, 1997, 2000, 2002, 2005 and 2009)	28.5 meter resolution
2	AutoCAD	1m Resolution
3	Referenced Images (Toposheet and Ajmer district plan map)	1:25,000 scale toposheet of year 1991, 1:1000000 scale Ajmer district map of year 2011
4	Contour Map	1m interval
5	Google Earth image	0.5m resolution (GeoEye Satellite)

This section includes a detailed discussion of methodology used in the current study. Satellite images were processed as a preliminary step to extract LULC information. Also, GIS database was prepared using ArcGIS for the parameterisation of SLEUTH model. Subsequently, SLEUTH model was calibrated and LULC change detection was performed to determine natural resource changes. Model was validated corresponding to reference data before

predicting the LULC changes in near future and changes in natural resources subsequently.

Image Processing and Analysis: Satellite imagery and other ancillary data were first georeferenced in UTM WGS-84 (zone 43N) coordinate and projection system. The satellite images were studied in terms of spectral profiles and digital numbers to have an idea about the number of separable targeted LULC classes. False Colour Composites (FCCs) for different years are presented in Figure 3. LULC information can be extracted from classification of satellite imagery. Present study utilised supervised classification method for the classification of satellite imagery.

Signatures were selected for the identified LULC classes (seven LULC classes i.e. barren, open, rocks, settlement, vegetation, river bed and water body were identified during image analysis). Selected signatures were evaluated to check their separability and whether selected signatures for a class actually belong to that class with the help of two methods i.e. histogram analysis and contingency matrices. After refinement of signatures, maximum likelihood classifier was used to classify the images of different years. Classified outputs were assessed for the classification accuracy in terms of accuracy percentage and kappa statistics (Table 2)

Table 2: Accuracy Percentage and Kappa Statistics

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

by comparing classified LULC information of randomly selected test pixels with their actual LULC class in reference data obtained from high resolution satellite imagery (GeoEye).

More than 80 per cent accuracy was achieved for the years except for the year 2000, in which classification accuracy was 79 per cent. Accuracy percentage and kappa statistics were found to be acceptable for such a medium resolution data. The classified outputs are shown in Figure 4.

GIS Database Creation: GIS layers like slope, LULC maps, exclusion layer, urban maps (1989, 1994, 1997, 2000, 2002, 2005 and 2009), transportation layers (1989 and 2002) and hillshade maps were prepared using different data and methods as discussed in earlier section for parameterisation of SLEUTH (Figure 5).

Parameterisation and Calibration of SLEUTH Model: SLEUTH model was first run in as a test phase to validate the input dataset and

prerequisite conditions. After successfully performing the test phase, the model was calibrated to refine the coefficient spaces and derive the best fit values for final prediction. The model calibration was done in three phases i.e. coarse, fine and final. Coarse phase was run for a full range of coefficients i.e. 0-100, with a step of 25 for all the coefficients. Fine phase of calibration was performed for a refined set of growth coefficients followed by final phase calibration which also utilised refined growth coefficient values in the previous stage. All the calibration phases were performed for same spatial resolution dataset i.e., 25 meter and same number

of Monte Carlo iterations i.e. 10. After successful model calibration, best fit growth coefficient values were derived on the basis of best fitness measure utilised into the model i.e. Optimal SLEUTH Metrics (OSM) which is a product of eight statistical metrics produced during model calibration. These model derived growth coefficient values, were utilised for final prediction of LULC change and extracting intermediate years LULC information. Performance of calibrated model was validated by comparing the simulated LULC from the SLEUTH and LULC information extracted from the reference data of year 2015 and 2016.
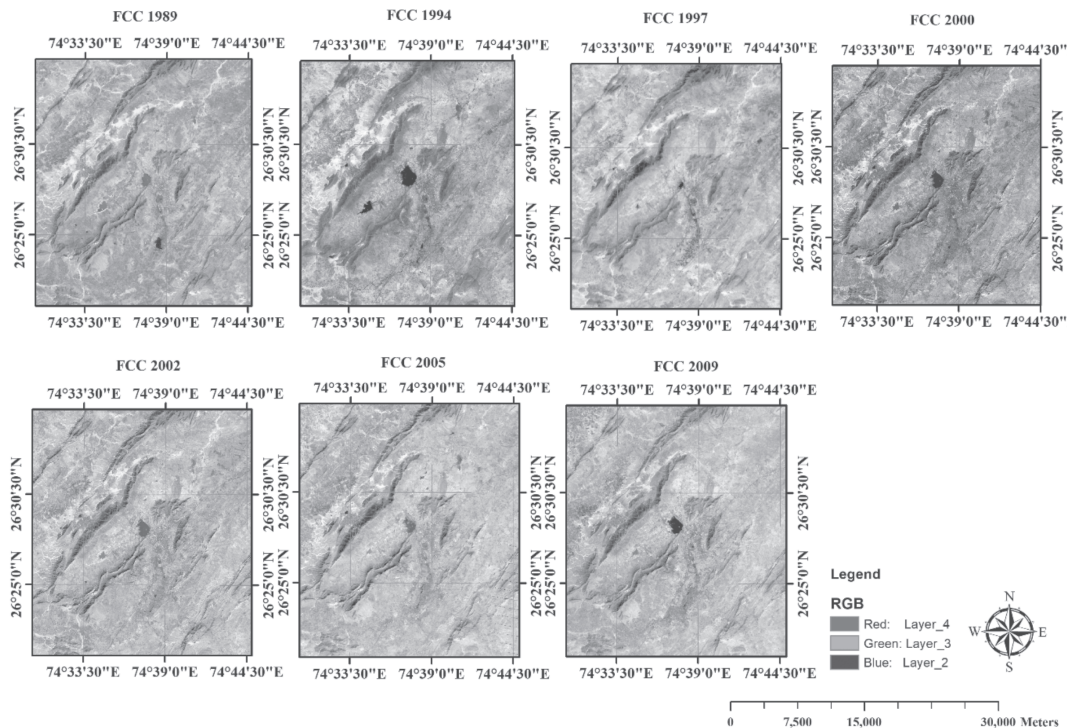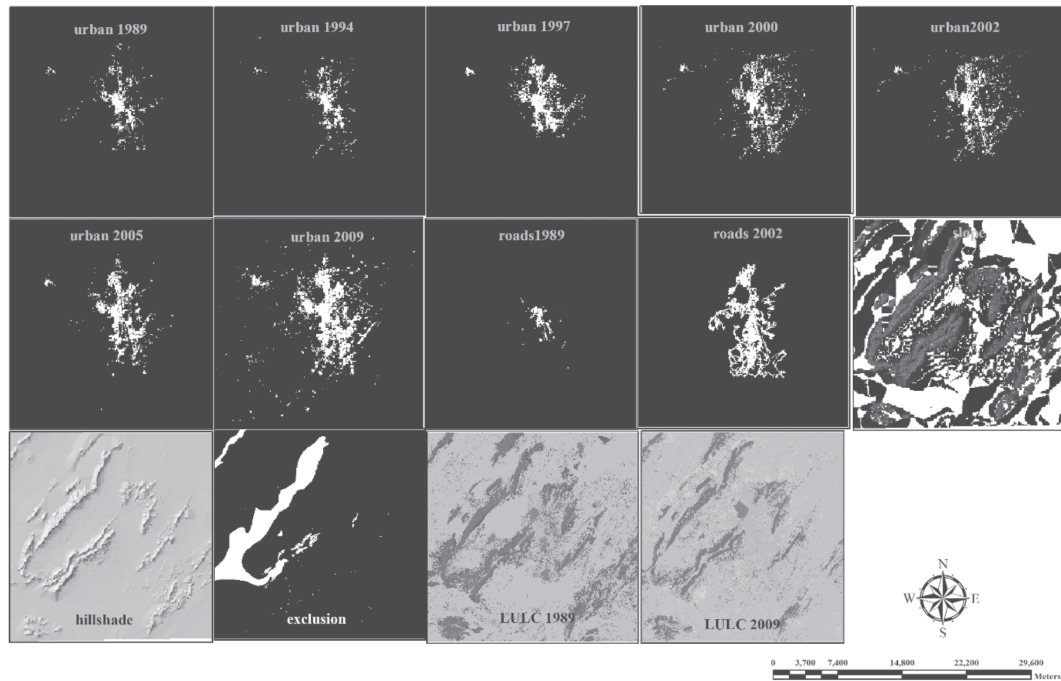

Figure 3: FCCs Prepared for Analysing Satellite Images
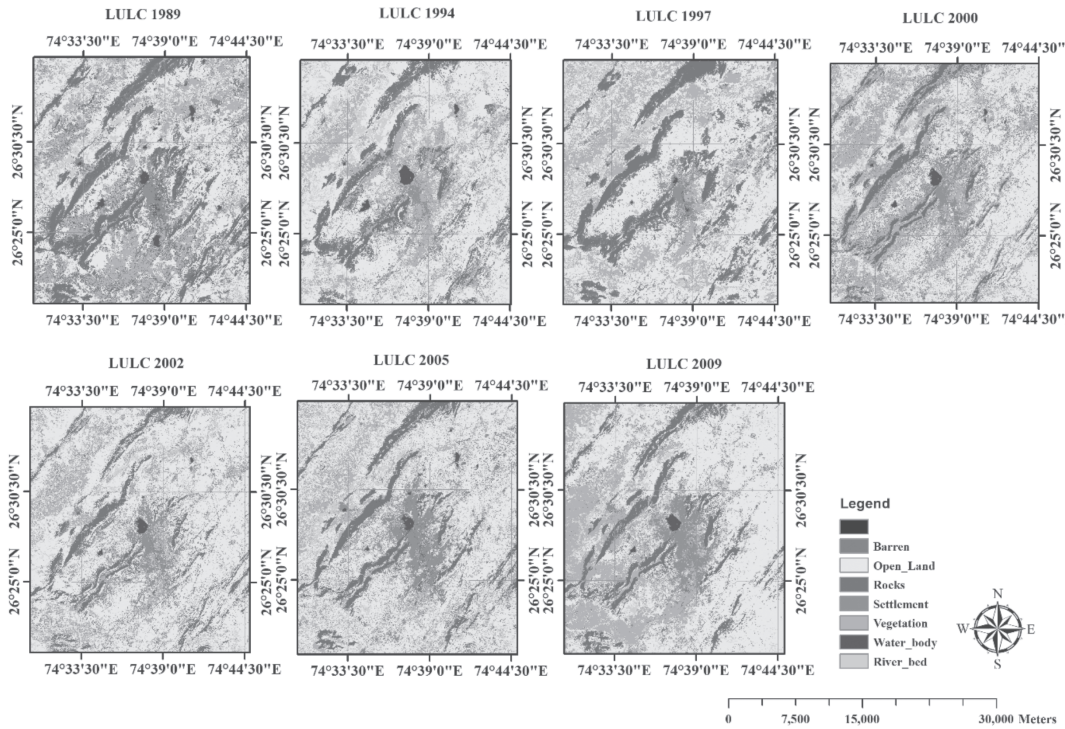
Figure 4: LULC Maps Prepared for year 1989, 1994, 1997, 2000, 2002, 2005 and 2009

Further, calibrated model was used to predict the LULC for the year 2030 and possible changes in natural resources are determined subsequently.

Figure 5: Input Dataset for LCD Model

Results

The model was calibrated in different phases to fit the model at its best and we observed model fitness as 0.020. Due to a non-homogeneous and disaggregated landscape, model fitness is low. However, LeeSallee which is a pattern index indicates better model fitting with a value of 0.35, indicating that model simulates the historical LULC satisfactorily and can be used for future LULC change predictions. The details of model calibration and resulting statistical measures and the best fil coefficient values are presented in Table 3.

Model first simulated LULC change for a specified temporal period (i.e. 1989- 2009) and further predicted for up to year 2030. The model simulation results were used to derive LULC change matrix as well which were given to/ from change among LULC classes from year 1989 to 2009 (Table 4).

The study reveals that vegetation has been reduced from 15758 ha in the year 1989 to 11939 ha in year 2009, waterbodies have also been reduced to 259 ha in the year 2009 from 543 ha in year 1989. The rocky terrain and dense vegetation LULC classes were reduced from 7665 ha in year 1989 to 4581 ha in year 2009. Lots of vegetative area was exploited to sustain the ever increasing population's demand of better livelihood and growth as clear from the LULC change matrix computed in the form of to/from Table 4. Also, open land was greatly reduced from
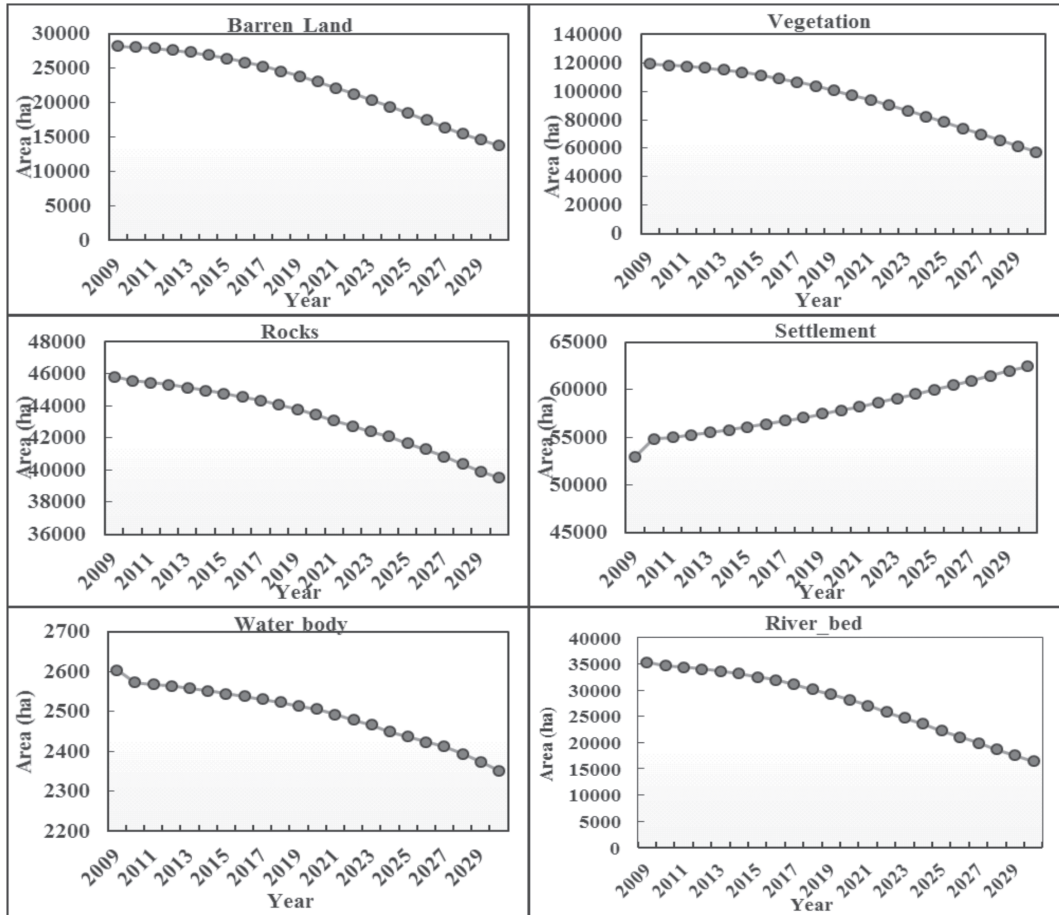
1989 to 2009 i.e. 54587 ha to 29346 ha (Table 4). The study indicates a large decline in natural resources like vegetation cover. Pervious areas have converted into impervious areas leading to hydrological and ecological changes in recent past which is not feasible for sustainable development. In addition, assuming the current scenario of LULC change, in near future also LULC change for up to year 2030 was forecasted. The study revealed major land transformation as built-up increased at a faster rate and waterbody, dense vegetation and rocks, open land and vegetation would be reduced greatly (Figure 6).

Table 3: Model Calibration Values and Refinement

Coefficient Values	Diffusion	Breed	Spread	Slope Resistant	Road Gravity	Best Lee Sallee	Best OSM	Computational Time (s)
Coarse Phase Calibration								
Start	0	0	0	0	0			
Step	25	25	25	25	25			
Stop	100	100	100	100	100	0.35	0.018	103527
Best Fit								
Value	25	50	50	50	50			
Fine Phase Calibration								
Start	1	5	5	5	5			
Step	5	10	10	10	10	0.35	0.018	103527
Stop	25	50	50	50	50			
Best Fit								
Value	25	45	45	35	45			
Final Phase Calibration								
Start	1	5	5	5	5			
Step	5	10	10	10	10	0.36	0.020	80804
Stop	21	45	45	35	45			
Best Fit								
Value	1	1	45	32	45			

Figure 6: Natural and Land Resources Change Prediction up to year 2030

Table 4: LULC Change Matrix Derived from SLEUTH Model

1989	Barren	Open land	Rocks	Settle-ment	Vege-tation	Water-body	River_bed	2009
Barren	539	2732	622	550	891	16	262	5612
Open land	1074	15133	460	1447	4059	58	1856	54587
Rocks	714	2165	3025	80	1020	8	153	7665
Settlement	14	486	43	1602	132	1	9	2287
Vegetation	359	8065	311	1032	5220	13	758	15758
Waterbody	8	124	47	108	114	112	30	543
River_bed	68	1041	73	9	503	1	399	2174
	2776	29346	4581	4328	11939	259	3527	
LULC classes in 1989								
LULC classes in 2009								

The simulation results were assessed for simulation accuracy of the model by selecting some random sample pixels from modelling outputs, compared with ground truth data and kappa statistics and accuracy percentage was calculated. An acceptable range of kappa and accuracy percentage was observed which is quite satisfactory for such real time applications of LULC change (Table 5). However, some errors in LULC change detection were found due to misclassification of images and medium resolution of spatial data. Some small size built-up patches were not captured well which are very common practices in the Indian scenario. Moreover, study simulated LULC maps for up to year 2030 which are helpful in analysing the

Table 5: Accuracy Assessment in Terms of Percentage and Kappa Statistics

Year	Accuracy Percentage (%)	Kappa Statistics
2016	83	0.52
2017	86	0.65

change in natural resources like dense forest and rocky terrain, land, vegetation and waterbody also, increased urban growth can be clearly seen (Figure 7).

Discussion and Conclusion

Present study observed large diminution in natural resources including open land and water in recent past which is definitely not feasible for sustainable development as pervious areas have been transformed into impervious areas which reduces groundwater recharge, deforestation causes impurities in groundwater and slows down the infiltration rate and badly influences eco-enviro system. Therefore, timely and accurate monitoring of LULC change is very important for sustainable LULC planning. Present study is helpful in analysing changes in LULC and natural resources quantitatively as well as visually which will be helpful in land use planning, resource management and budget allocation. The model was well calibrated and validated with an acceptable range of accuracy which is justifiable to forecast LULC change in future as well. The study revealed that natural resources including open land will be declining in near future also and these will gradually be transformed into settlement or built-up activities. The study is successfully implemented in the study area which is quantifying and giving simulated maps that will help the analyst to plan land and natural resources in such a manner that sustainable development goal can be achieved.
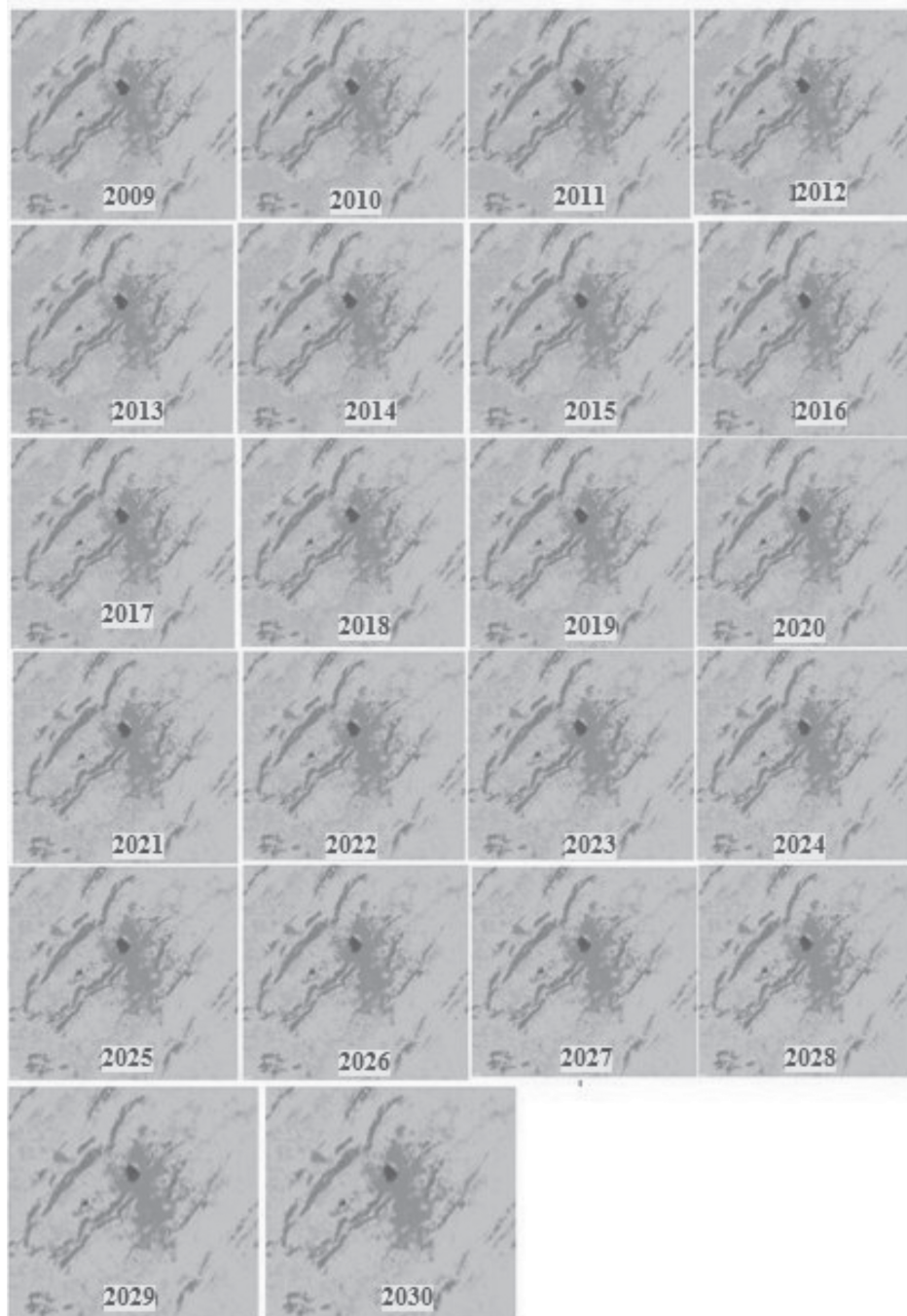
Figure 7: LULC Change Maps Predicted for up to Year 2030

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