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RESEARCH PAPER

Urban sprawl modeling using cellular automata

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KEYWORDS

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Abstract The population settlements in the fast-growing urban world need to be monitored in order to design a sustainable urban habitat. The remote sensing and GIS are considered as an effective monitoring and decision-support tool in urban planning. This study compiles the results of a study undertaken to measure the urban sprawl in Dehradun city, India through cellular automata CA-Markov model. CA-Markov model can effectively be used to study the urban dynamics in rapidly growing cities. Being an effective tool for encoding spatial structures, the information generated by it could be used to predict urban scenarios for sustainable growth. To achieve the goal, the temporal images of LISS IV were used to analyse the spatial pattern of land cover change in the area and the future growth was modeled by applying CA-Markov model. The results clearly suggest that major changes between the periods of 2004 and 2009 occurred in built up classes (about 27%) followed by agriculture (17.7%) and fallow land (10.2%). The projection as predicted using CA-Markov model suggested a value of kappa coefficient = 0.91 which indicates the validity of the model to predict future projections. Modeling suggested a clear trend of various land use classes' transformation in the area of urban built up expansions. It is concluded that RS and GIS can be an effective decision support tool for policy makers to design sustainable urban habitats.

1. Introduction

Urban sprawl is known as a multifarious concept dealing with the expansion of auto-oriented, low-density development and has a considerable impact on the surrounding ecosystem (Yuan et al., 2005). Urbanization is an inevitable process due to economic development and rapid population growth (Shalaby and Tateishi, 2007). Accurate and updated land cover change information is required to understand and assess the environmental consequences of such changes (Giri et al., 2005). The urbanization is a major concern of many world regions (Samat et al., 2011) which includes outward spreading of a city with poor planning. The unplanned urbanization has been creating problems like pollution, traffic, deforestation, and congestion of places. Land use changes at the peri-urban area is a complex and dynamic process that involves both natural and human systems (Xiao et al., 2006). Cellular automata are dynamic models that are discrete in time, space and state

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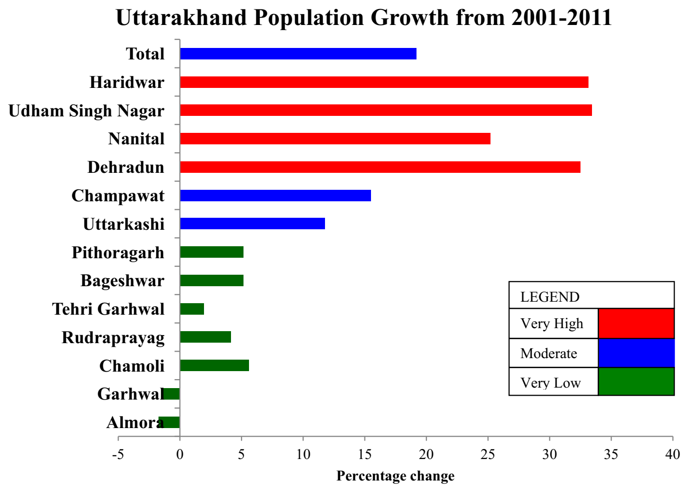


Figure 1 Uttarakhand population growth from 2001 to 2011. (Source: Census of India 2011).

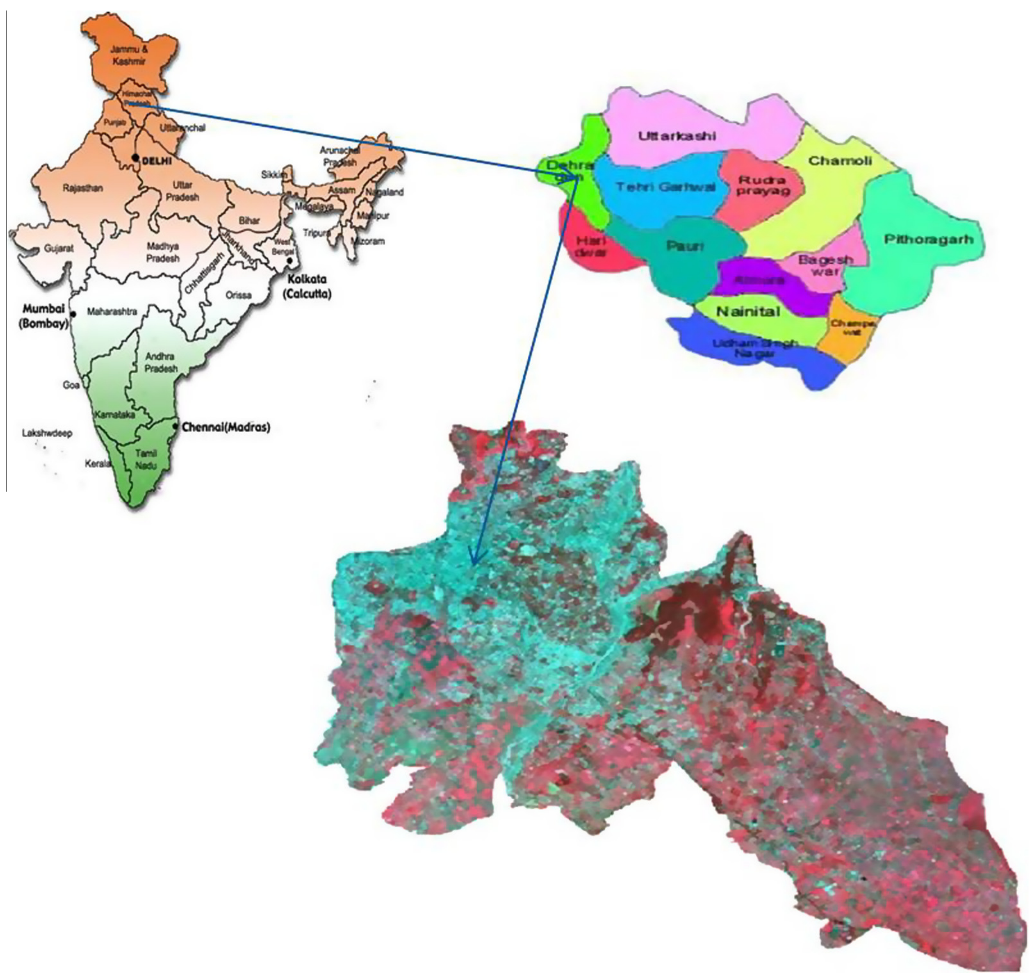


Figure 2 The location map of the study area.

(Balzter et al., 1998). A hybrid model consisting of logistic regression model, Markov chain and cellular automata (CA) was designed to improve the performance of the standard logistic regression model to simulate urban expansion (Jokar Arsanjani et al., 2013). Depending upon site-specific rules representing land use transitions CAs represent local raster-based simulation for modeling urban expansion for discrete time steps (Shafizadeh Moghadam and Helbich, 2013), (Guan et al., 2011). GIS can effectively be used to monitor and evaluate the dynamics changes of land use transformation

(Batty, 1997). The uncontrolled population growth and migration in urban areas have created the issues like of urban sprawl. However, population growth and urban sprawl are directly dependent on each other. In India level of urbanization increased from 27.81% in 2001 to 31.16% in 2011 (Census, 2011).

The economic reformation and industrialization of economy has transformed the rural areas into unplanned urbanizations. Urban expansion can be said as the transformation of the rural areas as cities and towns, but this urbanization is coming along with a cost. This cost can be easily seen as degradation of the environment, above all in the loss of farmlands and forest. In state like Uttarakhand the migration from rural hilly terrains and remote areas to urban centres is at an alarming rate during the last decade. The results of Census of India 2011 clearly suggest the tremendous increase in population in the districts of Dehradun, Udham Singh Nagar and Nanital while districts which are in hilly regions showing negative growth rate as shown in Fig. 1 which mainly forms the motivation of this study. The high population growth results in unplanned urbanization and changes in the land use patterns of the urban centres. In order to design an appropriate urban planning system the land use transformation must be evaluated.

An attempt is carried out in this study to map the status of land use and land cover of the Dehradun area using multi-temporal data of LISS IV, in order to detect the land consumption rate and the changes that have taken place particularly in their built-up area. This will also help in predicting the changes that might take place in the next few years using remotely sensed data. Satellite images and geospatial tools were used to quantify and analyse the spatiotemporal urban land use and land cover (LULC) changes during the study periods.

2. Study area and dataset

A sustainable development strategy can be designed by city developers and planners through measuring development trend and future land use patterns. The present study focuses on Dehradun City, Uttarakhand, India. Assessment of urban sprawl was measured in the city covering surrounding areas of cropland, forest, wastelands etc. Geographically the city is located in between 29°57′ and 31°27′50″ North latitudes and 77°34′27″ and 78°18′30″ East longitude (Fig. 2). The temporal data of IRS (Indian Remote Sensing Satellite) Linear Imaging Self Scanner (LISS-IV) which operates in three spectral bands in the Visible and Near Infrared Region (VNIR) with 5.8 m spatial resolution and has revisit of 5 days were used in this study. The data is provided by NRSC-ISRO Hyderabad, India.

3. Methodology

The acquired data of the Dehradun area were processed and analysed using remote sensing and GIS techniques to collect information on urban growth and environment monitoring (Fig. 3). In order to detect, quantify and analyse the changes, post classification change analyses were measured using ERDAS IMAGINE, Arc Map and CA-Markov in IDRISI Taiga. The LISS-IV data between the year 2004 and 2009 were collected along with the toposheet 53J/11. Pre-processing was done to remove the radiometric and geometric errors from the dataset so that further classification can be done. The LULC was generated using unsupervised classification of the years 2004 and 2009. The factors affecting the urban sprawl were considered which determined the CA-transition rules. The rules for this study are defined as Euclidean distance from

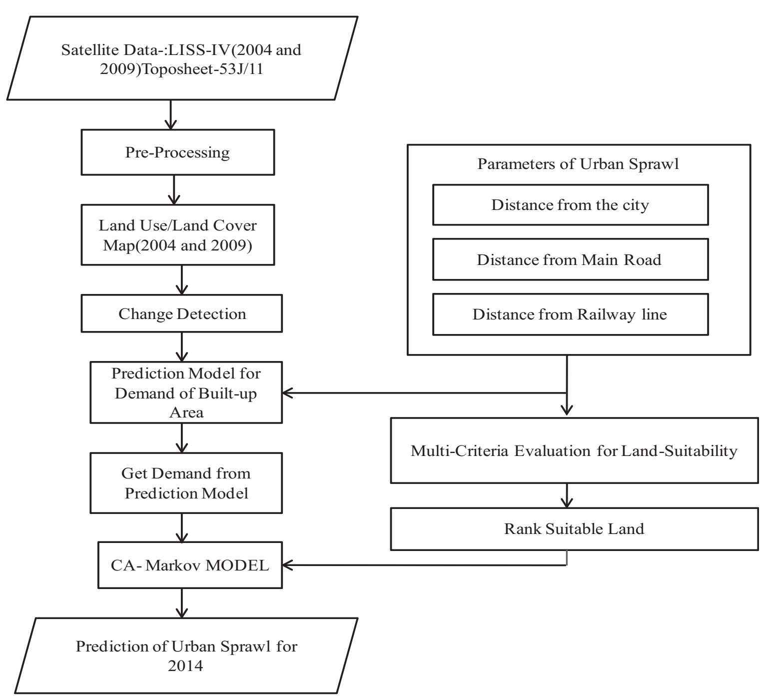
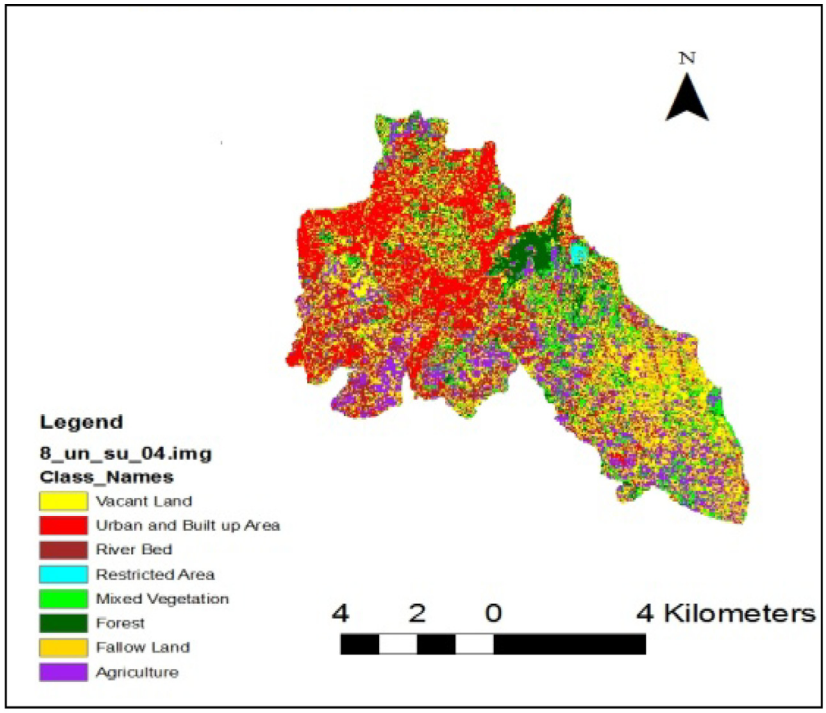
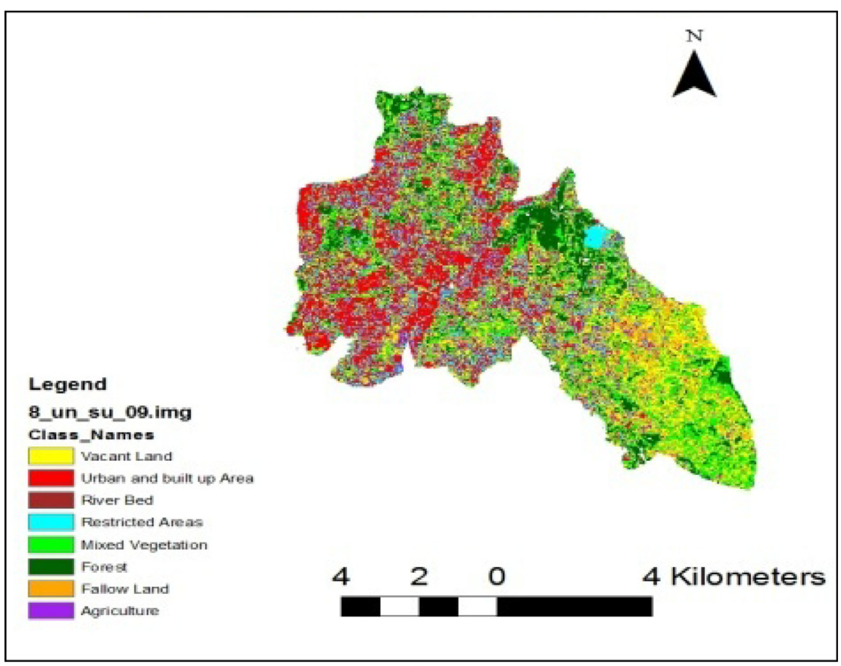


Figure 3 Schematic presentation of methodology adopted to conduct study.



A



B

Figure 4 Unsupervised classification A (2004) and B (2009).

the clock tower (CBD area), roads and railway line. The area closer to the CBD area has a higher probability of development, whereas areas farther away from main roads are less prone to development. The transition matrices were constructed from the change/no change matrices obtained in the change detection analysis and the modeling processes implemented using algorithms supplied with the Idrisi software. The model calculated the change between 2004 and 2009 and thus predicted the LULC 2009. Based on the predicted and generated LULC 2009 the model was validated. Finally using CA-Markov prediction of LULC 2014 was done, incorporating the above mentioned parameters.

4. Results and discussions

Classification algorithm is used to classify the data into separate classes. Unsupervised classification method employs

Table 1 Accuracy totals.

Class name	Reference total	Classified total	Number correct	Producer's Accuracy (%)	User's accuracy (%)
2004					
Forest	8	10	8	100.0	80.0
Mixed vegetation	11	13	10	81.82	76.92
Vacant land	12	15	11	97.67	73.33
Fallow land	13	17	12	76.92	70.58
Agriculture	25	16	14	56.0	87.5
River bed	5	7	5	100.0	71.42
Built up	19	15	15	78.95	100
Totals	93	93	75	80.64	80.64
2009					
Forest	11	12	11	100.0	91.67
Mixed vegetation	15	15	14	93.33	93.33
Vacant land	10	14	10	100.0	71.43
Fallow land	9	13	9	100.0	69.23
Agriculture	23	11	11	47.83	100.0
River bed	9	12	9	100.0	75.0
Built up	13	13	13	100.0	100
Totals	90	90	77	85.55	85.55

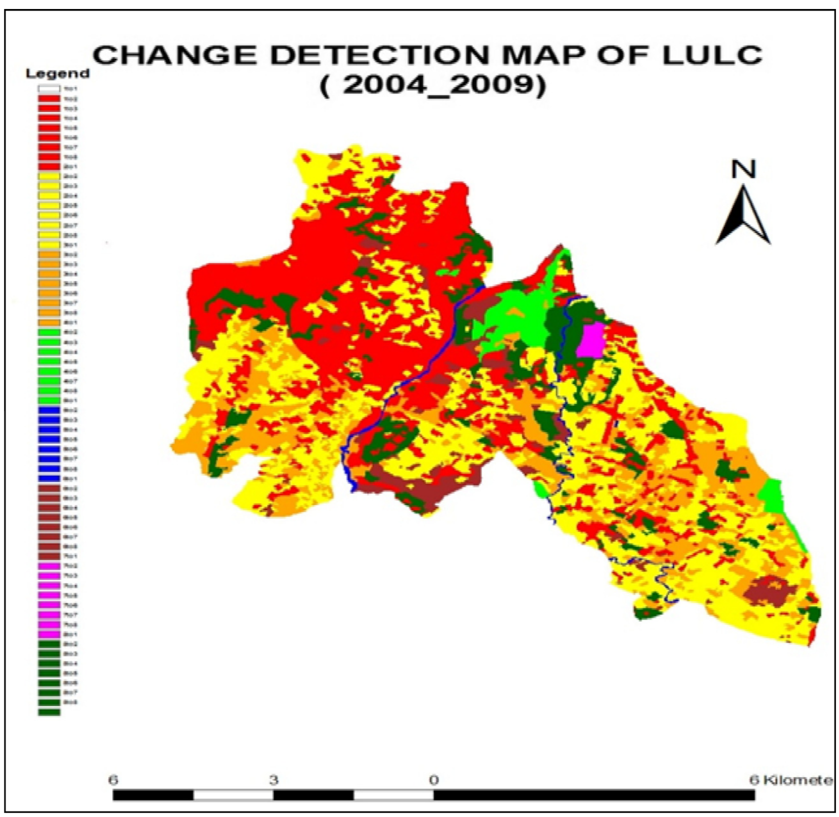


Figure 5 Map showing change detection.

the ISODATA method (Al-Ahmadi and Hames, 2009) and this is one of the most popular methods of unsupervised classification. Any other method of unsupervised classification will not make a difference, provided the same method is used for classifying all the satellite imagery. The unsupervised classification for two different years is presented for Dehradun city in Fig. 4.

It is clear from the visual interpretation that urban and built up has increased significantly during the period 2004–2009. The accuracy assessment was used to validate the classification and to check the similarity of our classification with the actual classification. The accuracy of a classification is usually done by comparing the classification with some reference data. The results of classification are described in

Table 2 The conversion matrix of land use and land cover change from 2004 to 2009 (percentage change).

Classification	Built up	Agriculture	Forest	Fallow land	River bed	Vacant land	Restricted area	Mixed vegetation	Row total
Built up	27.16	0	0	0	0	0	0	0	27.16
Agriculture	3.15	17.73	0	3.89	0	0.45	0	0.42	25.45
Forest	0.006	0	2.13	0.15	0	0.01	0	0.06	2.54
Fallow land	1.18	1.90	0	10.20	0	0.48	0	0.02	13.97
River bed	0.02	0	0	0	0.88	0	0	0	0.89
Vacant land	0	0	0	0	0	4.31	0	0	4.31
Restricted area	0	0	0	0	0	0	0.43	0	0.44
Mixed vegetation	1.01	0	0	0.43	0	0.24	0	6.20	7.96
Column total	32.45	19.73	2.13	14.77	0.88	5.56	0.43	6.78	82.69

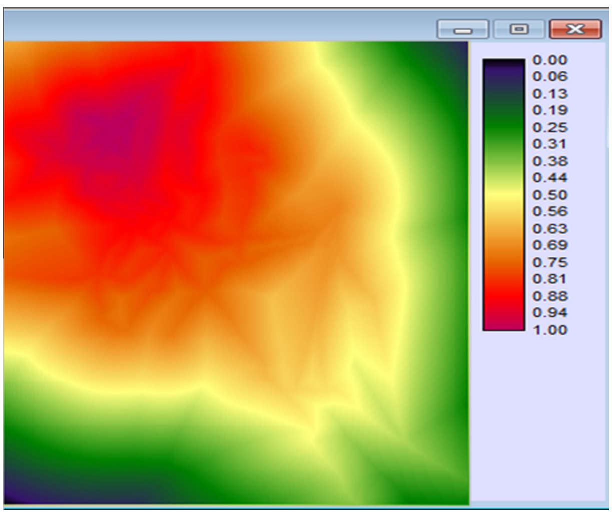


Figure 6 Suitability map for urban sprawl.

Table 3 Iterations and filter used.

Iteration	Filter	Max kappa
2,4,6,8,10,12	3 * 3	0.57
2,4,6,8,10,12	5 * 5	0.59
2,4,6,8,10,12	7 * 7	0.61
2,4,6,8,10,12	9 * 9	0.62
2,4,6,8,10,12	11 * 11	0.65
2,4,6,8,10,12	15 * 15	0.71
2,4,6,8,10,12	17 * 17	0.75

Table 1. The accuracy assessment should be conducted in order to measure the difference between user's classification and the reference data. The accuracy of classification was measured through Kappa statistics (Congalton, 1991) which was derived from the error matrices. The kappa coefficient for the years 2004 and 2009 was 0.8 and 0.9 with overall accuracy of 80.64% and 85.55% for 2004 and 2009, respectively.

4.1. Change detection and future growth projection

The change detection algorithms can be used effectively to detect the change in a particular area using temporal data sets. In this study land change modeler was used to calculate the change detection. It is the process of identifying differences in the state of an object or phenomenon by observing it at different times. Essentially, it involves the ability to quantify temporal effects using multi-temporal data sets. In post classification two multi-temporal images are classified separately and labelled with proper attribute values. Then, the area of change is extracted through direct comparison or subtraction after establishing the classification result. The post-classification approach provides "from–to" change information and the kind of landscape transformations that have occurred can be easily calculated and mapped (Yuan et al., 2005). It involves a prior independent classification of each image and then it is further over layered according to the themes. To minimize the problems of inconsistency, classification rules for each of the two images were the same and similar samples were collected and final map is shown in Fig. 5.

The percentage change for different classes of LULC is described in Table 2. The results clearly suggest that major changes between the periods of 2004 and 2009 occurred in built up classes (about 27%) followed by agriculture (17.7%), fallow land (10.2%), mixed vegetation (6.2%), vacant land (4.31%) and forest (2%). Result clearly suggested that new urban settlement and housing caused a significant impact on the land use pattern in the city during the period 2004 to 2009. In majority of cases the agriculture, vacant land and fallow land were occupied by new built-up land for housing and industrial/commercial activities. The high population growth and being capital of the state enormous human migration occurred during the last decade in the city which resulted in urban sprawl in the city.

The future projection of urban sprawl was measured through Markov's cellular automata model (CA). The ability to "spontaneously" give rise to global dynamics out of local interaction rules makes this CA system more attractive to predict the urban sprawl patterns for future (Batty et al., 1999; Blecic et al., 2004). In this CA system, the space was represented by a grid and time by uniform steps. The states of the system were finite (i.e., integer numbers). The CA system consisted of four elements—cells, states, neighbourhoods and rules. Cells are the smallest of spatial units. A neighbourhood represents the cells immediately adjacent to a certain cell. The next state of each cell was determined by the states of its neighbouring cells and Rules were used to define the states of the cells in the next time step. In Idrisi Kilimanjaro, cellular automata analysis is accomplished by the CA-Markov module, which uses the output of the Markov chain analysis and applies a contiguity filter to predict land use from time period two to a later time period. The Markov chain analysis describes the probability of land cover change from one period

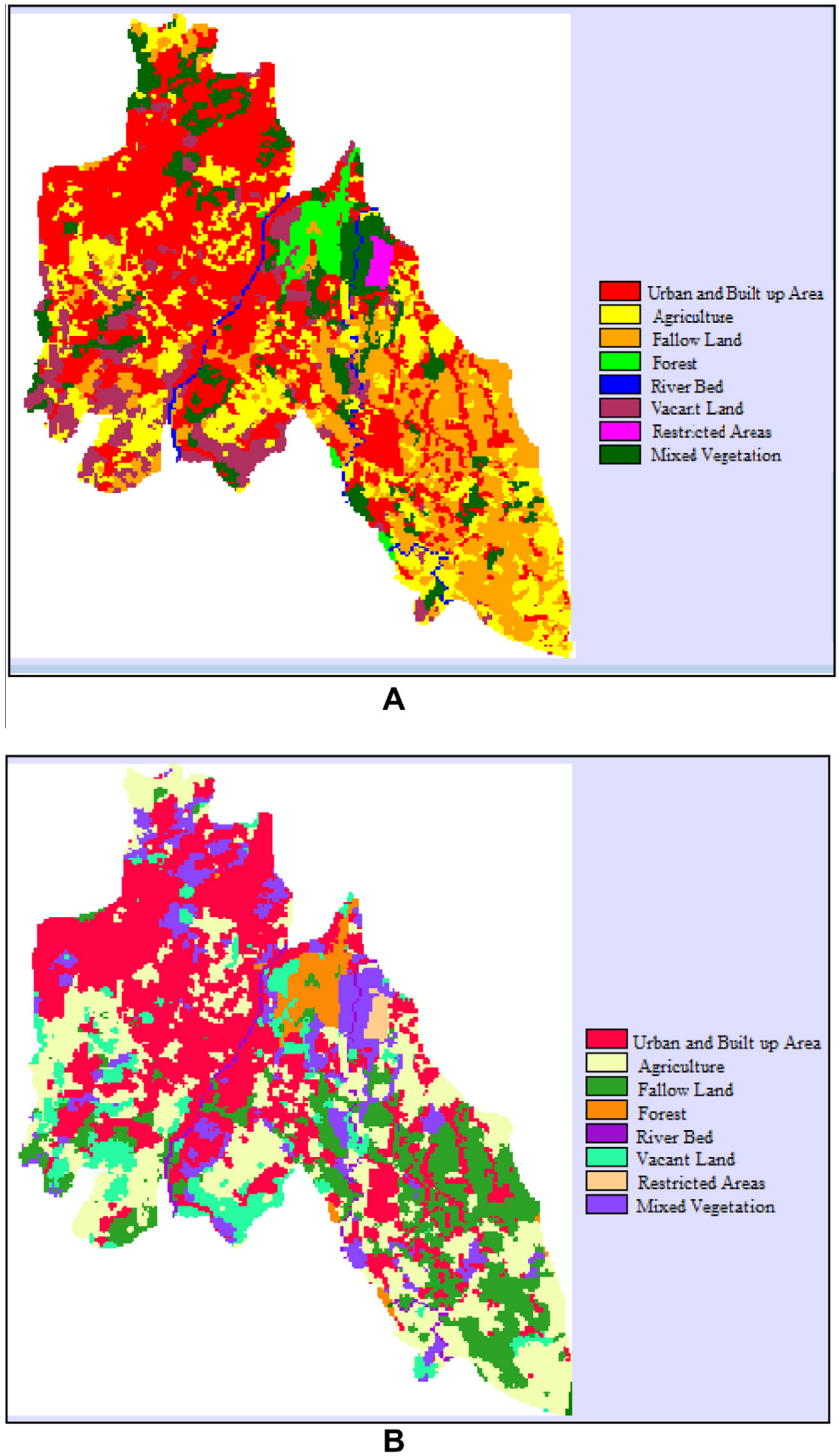


Figure 7 (A) Thematic (2009) and (B) predicted (2009).

to another by developing a transition probability matrix between two times (Araya and Cabral, 2010). CA-Markov alone cannot predict the sudden changes but adding other approaches like artificial neural network (ANN) or agent based modeling (ABM) can include any unanticipated change. A more detailed description of CA models for urban simulation can be found in the review by (Santé et al., 2010) (Rui and Ban, 2010). Suitability maps were prepared by setting transition rules from a land-use state to another state (Subedi et al., 2013) shown in Fig. 6.

The best results were obtained by using 12 iteration and 17 * 17 Neighbourhood (maximum kappa = 0.75) as shown in Table 3. Using the transformation matrix a map of all LULC classes was prepared for 2009 and was predicted for the same year. Results clearly suggest a close similarity between observed patterns and predicted patterns with a value

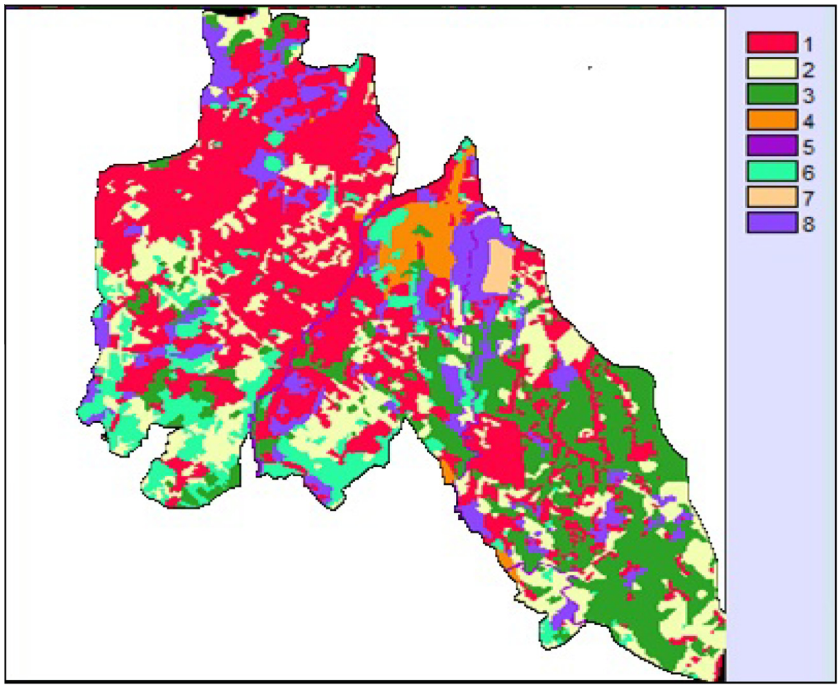


Figure 8 Predicted LULC for 2014 (code: 1, built up; 2, fallow land; 3, agriculture; 4, forest; 5, river bed; 6, vacant land; 7, restricted; 8, mixed vegetation.)

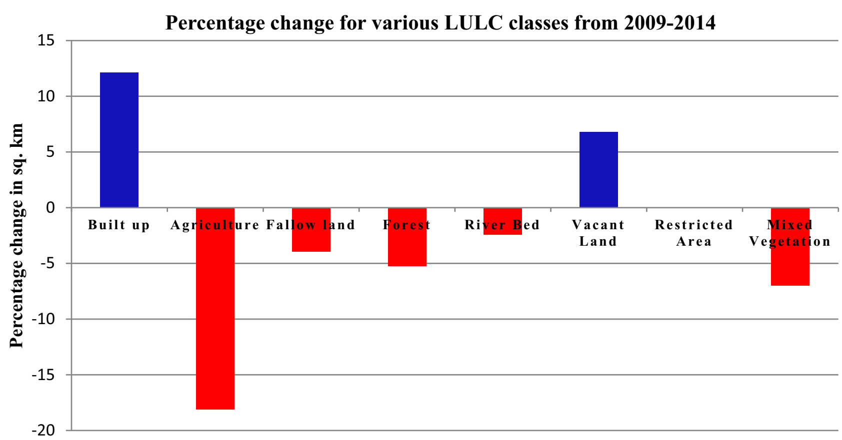


Figure 9 Percentage change for various LULC classes from 2009 to 2014.

of kappa coefficient = 0.91. The thematic and predicted images are shown in Fig. 7. This clearly validates the suitability of CA model for future projection assessment. By using the same parameters the projection for the year 2014 was measured and results are presented in Fig. 8. It is clear from the results that the major changes will be in agriculture land (18%) followed by mixed vegetation (7%) shown in Figs. 8 and 9. The built up will be around 12% higher than the projected level of 2009. This clearly suggested the conversion of agriculture and other LULC classes into urban built-up class.

However, the increase in vacant land clearly indicates that increasing proportion of real state lands in the city which in future is used for urban colonization and built up projects. The real estate has appeared as major economic activity in developing urban centres and a large area of urban agriculture land is being converted into vacant land for further built up activities.

5. Conclusion

This study demonstrates the application of remote sensing and GIS in mapping of urban sprawl and changes in urban land use system. Uttarakhand has immense potential for the development of tourism sector as the major driver of the state economy. The dynamic population of the city, which it will have in future, can be approximated using the predicted future scenario. Accordingly the tourism development planning can be done especially of infrastructure and its location. CA can incorporate spatial component. With simple rules it is easy and addresses dynamism; also increasing the computational efficiency. The model does not incorporate the socio-economic factors. Not only the proximity to existing land-use but also the geographic factors, constrain the land-use change. The identification of factors which are most likely to influence a land-use class would greatly contribute to accuracy of prediction. The predictions for future land use/cover changes on the basis of a CA-Markov model clearly suggest a continuous increase in urban settlement built up and a subsequent decrease in agriculture, forests and other natural vegetation covers. There is much more increase in the built-up area during the duration 2009–2014 as compared to 2004–2009. Especially the Urban built up and fallow land have shown more changes than the other classes which continue to change with nearly the same rate. The results clearly suggest that such kind of prediction using CA model can help to design sustainable urban transportation system. The mapping of urban sprawl using RS and GIS can be an instrument of decision support system for policy makers to design urban expansion plans with an approach of sustainable habitat development.

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