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SPATIAL EXPLICIT MODELING TO UNDERSTAND THE DYNAMICS OF LANDUSE SWITCH USING OPEN SOURCE SATELLITE DATA

S. Kalluvetty[a], S. Bandopadhyay[b]

[a] *Indian Institute of Remote Sensing (Indian Space Research Organisation), India*

[b] *Meteorology Department, Faculty of Environmental Engineering and Spatial Management, Poznan University of Life Sciences, Poland*

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Corresponding Author:
Subhajit Bandopadhyay
Meteorology Department, Poznan University of Life Sciences
Poznan; Poland
Email: subhajit.iirs@gmail.com

Abstract: *Restless global urbanization needs to monitor in order to design a stable and sustainable urban habitat. In this regard, remote sensing and GIS are considered as an efficient monitoring and decision-support tool in sustainable urban planning and practices. In this paper we accumulate the results of a research undertaken to measure the urban sprawl and land use dynamics of the Dehradun city, Uttarakhand using vast sixteen years data and spatially explicit cellular automata CA-Markov model. Furthermore, future scenario of the city and land use was also examined. To achieve the desired goal, sixteen years large temporal images of Landsat were used to analyze the spatial decoration of land use change in the study area. The outcome of this study was clearly reviled that there was a substantial change was take place in the Dehradun city and its surroundings in last sixteen years. Modeling proposed a clear trend of various land use classes' transformation in the area of urban built up expansions and urban encroachment whereas agricultural lands and forest covers are reduced at an alarming rate over the time. Dynamically increasing population of the city can be approximated by the predicted future scenarios. In order to promote a balance in between urban growth and environmental protection towards a sustainable urban habitat and environmental, local community involvement and capacity building program can be an efficient drive in this regard.*

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1. INTRODUCTION

Changing aspects of Landuse at the peri-urban areas is a complex and dynamic process that involves both natural and human systems (Xiao et al., 2006). Over recent decades the suburbs of the metropolitan area are designed by urban sprawl (Glaeser & Kahn, 2003). Urban sprawl is known as a multifarious concept that dealing with the expansion of auto-oriented, low-density development and has a considerable impact on the surrounding ecosystem (Yuan et al., 2005). It is characterized by the expansion of human population from a core urban area into previously rural and remote areas. The discussions about urban sprawl are often made partial by the view of metropolitan growth is inefficient and causes environmental degradation. But the other side of the issue says the beneficiaries of sprawl may be a silent majority who are not as politically active as center city boosters, environmentalists and the urban layman in voicing their views on the merits of the on-going decentralization of jobs and people taking place across cities.

In India, urban sprawl is in its zenith phase at the cost of farmland, forest, and other ecologically sensitive areas. Rapid urbanization in India is changing the dynamics between ecology, economy and the society (Bardhan et al., 2016). The exponential growth of urban population has clearly figured out by last few censuses results. The alarmingly diminishing forest coverage is upholding these findings. As like other states of India, cities of Uttarakhand is also experienced with population exploration evident by the census of India 2011 report illustrated in Figure 1.

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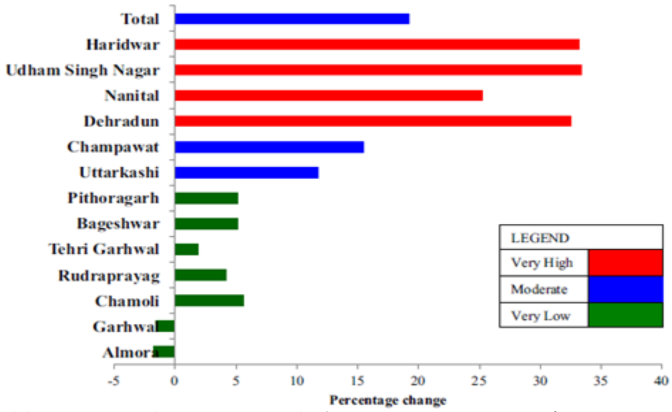

Figure 1. Uttarakhand population growth from 2001 to 2011 (Source: Census of India, 2011)

This report clearly suggests the tremendous increase in population in the districts of Dehradun, Udham Singh Nagar, and Nanital, while districts which are in hilly regions like Garhwal, Almora showing negative growth rate. This upward nature of population growth in Dehradun which is the capital city of the Uttarakhand state results in unplanned urbanization and changes in the land use patterns. In order to design a sustainable city profile through appropriate urban planning system the temporal land use transformation must be evaluated (Deep & Saklani, 2014). So as to figure out the increasing rate of urban sprawl an attempt has to be made to comprehend sprawl dynamics and to develop appropriate management strategies that could aid in the region's sustainable development.

In early days studies, cadastral maps (scale, usually 1: 4000) were utilized in mapping for land use/land cover and to investigate their changes (Jat et al., 2017). From twentieth century onwards the mapping of LULC was first replaced by aerial photographs, later on research was focused on multispectral satellite images. In recent past, implementation of mathematical techniques into satellite images have been utilized for the assessment of urban growth through preparation of LULC maps in this domain. But nearly all landscape models are spatially implicit in nature, since landscapes are fundamentally spatial entities where location is a prime factor. Spatial locations matters to the process which should be modeled. Spatial Explicit Model allows us to model the locations with answering all landscape-relevant questions and also providing precise relative location of each landscape category.

Several researches have already conducted to quantify the urban growth using various methods. Myint and Wang (2006) used post-classification change detection approach to identify the land use land cover changes in Norman, Oklahoma using Landsat multispectral scanned and thematic mapper (TM) images. An integration of Markov chain analysis and a cellular automata approach were employed to predict future land use land cover using multi-criteria decision-making and fuzzy parameter standardization approach. They compared projected results against the classified output of the same Landsat TM image. The study explained the usefulness of Markov and cellular modeling for urban landscape changes. They found that combination of Markov and a CA filter is reasonably accurate for projecting future land use land cover.

One of the important studies in this domain was done by Deep and Saklani (2014) showing the applicability of CA-Markov model which is effectively used to study the urban dynamics in rapidly growing cities using the commercial LISS-IV high-resolution data. Modeling suggested a clear trend of various land use transformation in the form of built up expansions. Islam & Ahmed (2012) carried the similar kind of research in Dhaka city, Bangladesh. They executed the Markov chain modeling for land use change prediction with the aid of GIS. Supervised classification image was given as the input for Markov chain and obtained accuracy less than 70% in the absence of a sufficient number of authentic, influencing variables. They observed that accuracy can be enhanced by increasing the influencing variables. Memarian et al. (2012) demonstrated the CA-Markov for Simulation of land use and land cover change using validation metrics, allocation disagreement, quantity

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disagreement and figure of merit in a 3D space. The results were poor for land use and land cover change due to uncertainties in the source data and the model calibration.

Nouri et al. (2014) predict the urban land use changes using the cellular automata technique. Outcome reviles that major expansions in urban areas were witnessed around western and eastern borders of the city, particularly close to the eastern border. But this study did not show the future trend of that particular city over the temporal scale. Another study was done by Aithal et al. (2013) in Bangalore city using the same technique. The results indicate that the future expansion of greater Bangalore will take place in the peri-urban landscapes. The current clumped urbanization at the city core will have little scope for further urban densification. This study was limited to less amount of datasets as they use only three years of datasets and predict the future of the Bangalore city for year 2020.

In this present research, we have used a large amount of freely available satellite datasets (Table 1) and predict the future urban growth of the Dehradun city with a higher level of accuracy which makes this research different from other existing studies. In this era of rapid urbanization where we need a strong quantification technique to understand the nature of the urbanization trend, Remote Sensing and GIS can be an effective tool for policy makers to design sustainable urban habitats (Deep & Saklani, 2014). The well-established CA-Markov model incorporated with RS-GIS platform can act as one of the planning support tools for analysis of temporal changes and spatial distribution with a higher level of competence and accuracy. Applied CA–Markov technique can also use for future prediction and trend analysis for a specific region (Park et al., 2010). The core idea behind this model is that model transits the one-pixel transition probability with respect to neighboring pixels (Pontius & Malanson, 2005). Markov chain modeling proved to be an effective approach for calculating change probabilities, but the adopted procedure followed in this model that the transition probabilities might not change over time. In other words, Markov Chain analysis predicts the future land use pattern only on the basis of the known land use patterns of the past. This is a limitation of the method in terms of simulating urban growth since new influences on the urban structure cannot be evaluated (Sun et al., 2007).

The objective of this study is to prepare an urban sprawl model for the growth of Dehradun city using available satellite data set and validate the model by comparing predicted result and obtained result. Finally, predict the year wise growth of urban sprawl of Dehradun city at near future. The remainder part of this paper as follows: the second section of this study presents related literature to urban sprawl assessment and modeling. The section 3 deals with datasets and methodology adopted followed by the description of the study area in section 4. The final section 5 discusses the findings and conclusion with recommendations followed by the future scope of this study.

2. DATA AND METHODS

2.1. Study area

The twin cities of Dehradun and Mussoorie are located in Dehradun district of Uttarakhand state, India (Figure 2). Dehradun is the capital and it is situated at the North-West corner of the state. The district is bounded by Uttarkashi district on the north, Tehri Garhwal and Pauri Garhwal districts on the east and Saharnpur district (Uttar Pradesh) on the south. Its western boundary adjoins Sirmour district of Himachal Pradesh separated by Rivers Tons and the Yamuna. The geographical coordinates of the study area are extended from 30°13’44.60” N to 30° 25’23’61” N latitudes and 77° 53’29.63”E to 78°09’06.81”E longitudes having an area of about 349.3495 sq /km with an average altitude of 640 m above MSL.

Dehradun manifests its position as an important city in the most fertile region of Doon valley between rivers Ganga and Yamuna. It is, in fact, the most developed city in the Shivalik foothills of the great Himalayas and gateway to the hilly areas of Uttarakhand. The study area is cosmopolitan in nature, characterized by forest, river and agriculture along with city agglomeration. Major rivers through the study area are Asan River in the

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west, Song River in the east, Rispana River and Bindal Rao through the center. The forest is mainly located on the northern side of the study area. It is a part of the Shivalik range of Himalaya.

The district has within its limits lofty peaks of the Outer Himalayas as well as the Dun Valley with climatic conditions nearly similar to those in the plains. Here, temperature depends on the elevation. The climate of the district, in general, is temperate. In the hilly regions, the summer is pleasant but in the Doon Valley, the heat is often intense. The temperature drops below freezing point not only at high altitudes but also even at places like Dehradun during the winters, when the higher peaks are under snow. The summer starts by March and lasts up to mid of June when the monsoon sets in.

Generally, the month of May and early part of June is hottest with mean temperatures shooting up to 36.20°C at Dehradun and 24.80° C at Mussoorie. The maximum temperature rises to over 42°C at Dehradun while at Mussoorie it doesn't exceed 32°C. Winter starts from November and continues up to February. The highest maximum temperature recorded at Dehradun was 43.9°C on June 4, 1902, and that at Mussoorie was 34.4°C, on May 24th, 1949. The mean daily maximum temperature during winter is 19.1°C at Dehradun and 10.2°C at Mussoorie. The mean daily minimum temperature in January is 6.10°C at Dehradun and 2.50°C at Mussoorie. In Mussoorie the temperature drops to about -60°C to -70°C when snowfall occurs. The lowest minimum temperature at Dehradun during winter was - 1.10°C, on February 1st, 1905 and January 1945 while at Mussoorie it was -6.70°C, on February 10th 1950. Monsoon starts by the mid of June and lasts up to September.

The district receives an average annual rainfall of 2,073.3 mm. Most of the rainfall is received during the period from June to September, July and August being the wettest months. The region around Raipur gets the maximum rainfall, while the southern part receives the least rainfall in the district. About 87% of the annual rainfall is received during the period June to September.

2.2. Population, agriculture and other activities

According to the 2011 census, Dehradun district is the second most populous district in the state having a population of 1,696,694 after Haridwar. The urban agglomeration has experienced a high growth rate of a population which has become almost double in one decade from 447,808 in 2001 to 714,223 in 2011 (Census of India, 2011). Agriculture fields are also present in outer parts of the city. Major Kharif crop in this region is paddy. In addition to that maize, mandus, Jhngora, Kulath, Arhar and Sugarcane are also cultivated during that period. On the other hand, wheat is the principal Rabi crop. Maize, mustard are the other Rabi crops. It should be noted that a chunk of land in this region is owned by the government. So it highly influences the dynamics of the urban sprawl.

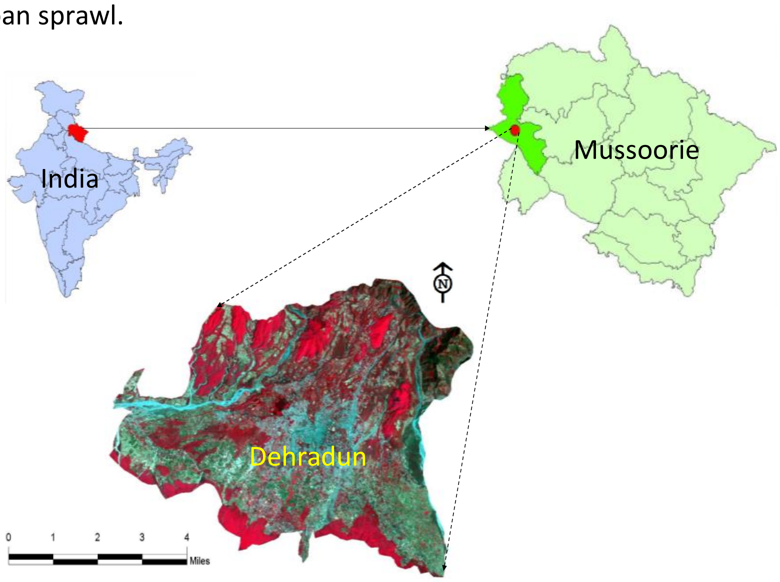

Figure 2. Location map of study area: Landsat 7 ETM+ image of Dehradun Mussoorie region.

It is home to numerous state and central government institutions. It is the most vital service center, which meets the trade and commerce requirement of its hinterland. Major activates of Dehradun are education, commercial, defence, and tourism. These are also driving factors of the local economy. Administrative area of Mussoorie Dehradun Development Authority (MDDA) boundary was chosen as the study area for this analysis.

2.3. Datasets

Landsat 7 with the multispectral sensor of Enhanced Thematic Mapper Plus or ETM+ and Landsat 8 with the multispectral sensor of Operational Land Imager (OLI) images were used for the study. Landsat 7 is having 8 bands with a spatial resolution of 30m for bands 1 to 5, 7, and 15 m for the panchromatic band 1 and 60 m for the thermal band 6. It is available from 1999 and after 2003 May 31 there are noises in the acquired data due to the failure of Scan Line Corrector (SLC). Landsat 7 was used for LULC classification in this study. On the other hand, Landsat 8 was launched on February 11, 2013, and is having 9 bands with a 15m resolution for panchromatic band 1 and 30 m for the other bands. It was used for the LULC classification for the year 2013-2014 in this work. Following Table 1 shows the details of the datasets used.

Table 1. Description of Satellite Data Used

Sl. No.	Satellite and Sensor	Path No	Row No	Date of Satellite Pass
1	LANDSAT 7 ETM+	146	039	22 October 1999
2	LANDSAT 7 ETM+	146	039	25 November 2000
3	LANDSAT 7 ETM+	146	039	11 October 2001
4	LANDSAT 7 ETM+	146	039	30 October 2002
5	LANDSAT 7 ETM+	146	039	01 October 2003
6	LANDSAT 7 ETM+	146	039	19 October 2004
7	LANDSAT 7 ETM+	146	039	06 October 2005
8	LANDSAT 7 ETM+	146	039	25 October 2006
9	LANDSAT 7 ETM+	146	039	12 October 2007
10	LANDSAT 7 ETM+	146	039	30 October 2008
11	LANDSAT 7 ETM+	146	039	18 November 2009
12	LANDSAT 7 ETM+	146	039	20 October 2010
13	LANDSAT 7 ETM+	146	039	08 NOvember 2011
14	LANDSAT 7 ETM+	146	039	25 October 2012
15	LANDSAT 8 OLI	146	039	18 September 2013
16	LANDSAT 8 OLI	146	039	16 May 2014

2.4. Tools used

To achieve the goal of this research three main image processing and GIS software had been used. For data preparation, classification, analysis were executed using Erdas Imagine 2013, whereas data conversion, reclassification, and mapping were performed in ArcGIS 10.1. CA-Markov analysis was the major phase in this project which had been done through TerrSet (formerly IDRISI Taiga) developed by Clark Labs at Clark University, USA. The satellite data corresponding to the present study area (LANDSAT, 1999 to 2014) in the form of multiple bands was stacked to a single image using the 'layer stack' feature in Erdas Imagine. For Landsat 8 images, layer stack operation involves the participation of consecutive bands from 2 to 7 and Landsat 7, consecutive bands from 1 to 7 except 6. In the case of LANDSAT data for the years 2003 to 2012, an additional step, focal analysis has to be carried out using the same software to remove a prevalent error in the image that arises due to the absence of scan line corrector in the sensor.

The stacked image and the respective PAN image of the study area are subsets to highlight the area of interest. Since the layer stacked image and PAN image are of different resolutions, they are subject to resolution merge in order to achieve a unified resolution of 15m. The resulting image can be referred to as the target image. Maximum likelihood approach based Parametric Supervised classification was carried out with 70 training sets for each class on the target images, followed by an accuracy assessment. The supervised classification meant for preparation of Land Use/Land Cover based on five different classes, namely, (i) Forest, (ii) Settlements, (iii) Agriculture, (iv) Water body and riverbed, (v) Open Land. If the resulting accuracy was satisfactory, then classified map was prepared.

Making use of the CA-Markov algorithm, predicted maps for the years 2013 and 2014 were prepared. Prediction was done by considering different temporal data for the time period between inputs images are 1 to 7 years. The actual classified map and the predicted map of these two years are compared and checked the prediction accuracy. Proving the validation successful, the future trend was predicted using the model accurately. Year wise future trend is predicted till 2020 by the same method. The detailed of research framework is illustrated in Figure 3.

2.5. Markov chain model

Markov model has been extensively used in ecological modeling (Brown et al., 2000; Muller & Middleton, 1994). Markov model takes into account past states to predict how a particular variable changes was done over time. The applicability of Markov model in land-use change modeling is promising because of its capability to quantify not only the states of alteration between land-use types but also the rate of conversion among the land-use types (Sang et al., 2011). A homogenous Markov model for predicting land-use change can be represented mathematically as equation 1:

$$L_{(t+1)} = P_{ij} * L_{(t)} \quad \text{......} \quad (1)$$

and $\begin{bmatrix} P_{11} & P_{12} & \dots P_{n} \\ P_{21} & P_{22} & \dots P_{n} \\ P_{n1} & P_{n2} & \dots P_{nn} \end{bmatrix}$ Where, $L_{(t+1)}$ and $L_{(t)}$ are the land-use status at time t+1 and t respectively.

{ $0 \le P_{ij} < 1$ and $\sum_{j=1}^{m} P_{ij} = 1$, $(i, j = 1, 2, \cdots, m)$ } is the transition probability matrix in a state.

2.6. CA-Markov model

Markov model combines with cellular automata (CA), is used to predict land cover change over time (Sang et al., 2011). It adds into Markov model not only spatial contiguity but also the probable spatial transitions occurring in a particular area over time. In CA-Markov module, the basic land cover image is given as reference image. In addition to that Markov transition area, file which is the output from Markov chain and output land cover projection are required for simulation. A number of cellular automata iterations, CA filter type is the important process parameter which has to be selected based on image and output requirement.

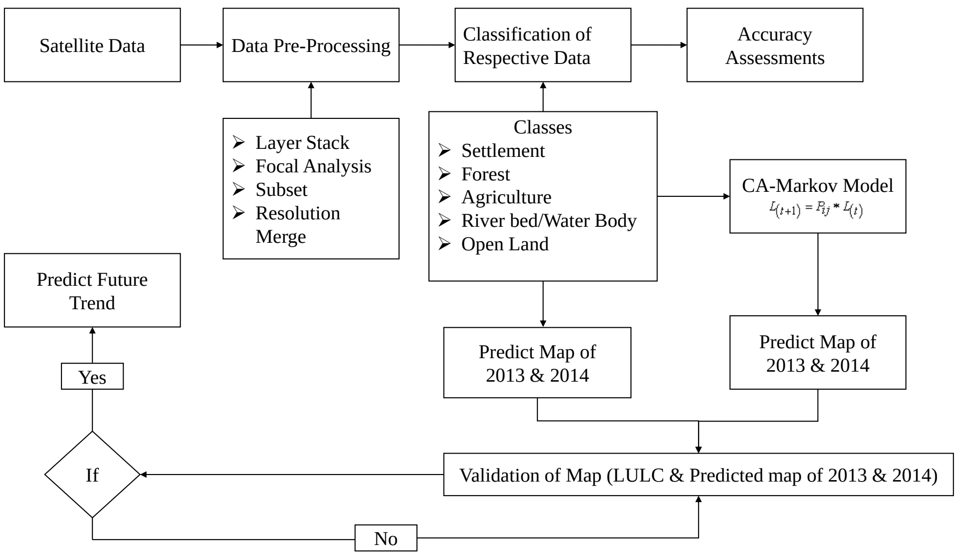

Figure 3. Framework of the study

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3. RESULTS AND DISCUSSION

3.1. Temporal LULC change interpretation

The LULC percentage and the area coverage of each land category were derived from the satellite images. Classification of the image was done by supervised classification. The Study area was classified into five classes as stated before. The results are illustrated in Table 2. It is be observed that there is a sharp rise in the area of the settlement over time. The percentage area of the settlement in 1999 was 8.16% and it has risen to 20.27% in 15 years and remarkable changes are noted in agriculture where the percentage area dropped from 28% to 13.03%. It is also evident from the Table 2 and Figure 4 that the 4.41% deforestation was also taking place in the study area which is might be converted to built-up areas. So from the given table and figure it can strongly state that urban sprawl was already processed in the study area over the time.

Table 2. Changes in LULC in between 1999-2014

LULC Classes	1999		2014	
	Area (Km²)	Area (%)	Area (Km²)	Area (%)
Open Land	120	34.80	145	41.14
Forest	100	28.36	84	23.95
Settlement	29	8.16	71	20.27
Agriculture	91	27.86	46	13.03
River Bed/Water Body	5	1.53	6	1.60
Total	351	100	351	100

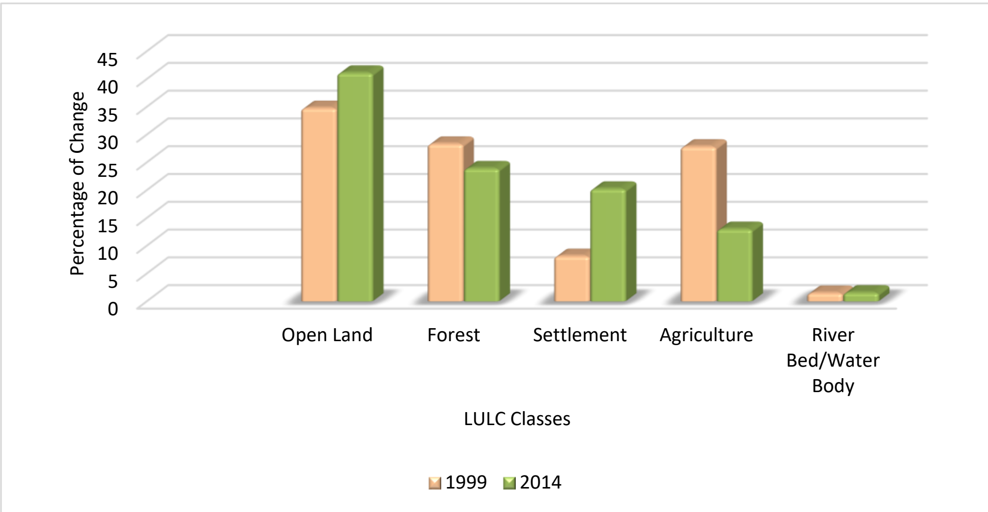

Figure 4. LULC Changes in between 1999- 2014

3.2. LULC classification of 2013 and 2014

Parametric supervised classification technique was considered to understand the LULC of the study area in the year of 2013 and 2014 (see Figure 5). For the change analysis LULC classification (Figure 5A) for 2013 has been done with an accuracy of 80.0% and the overall kappa statistics is 0.7561. 2014 LULC classification (Figure 5B) has been done with an accuracy of 90% with overall kappa statistics 0.8678.

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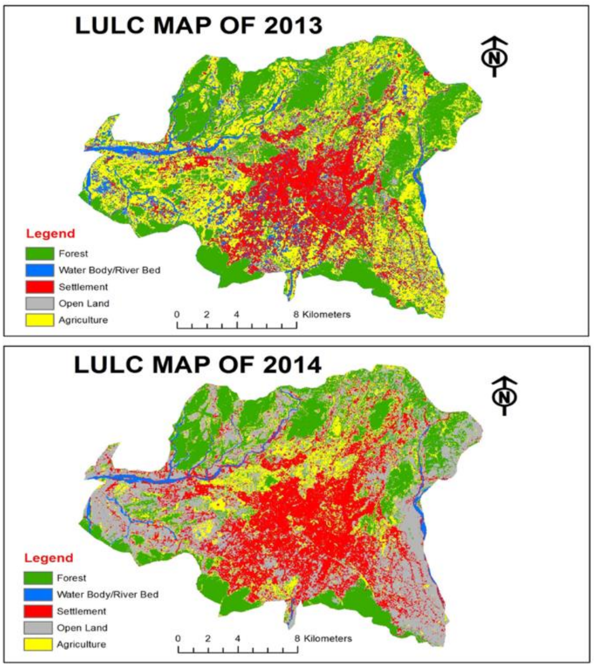

Figure 5. (A) LULC map of 2013 (B) LULC map of 2014.

3.3. Validation testing between projected and reference LULC

We tested the output LULC maps of the year 2013 and 2014 and validate the classified maps with the existing LULC maps of the study area. The validation of the predicted trend is carried out by estimating the kappa statistics of the comparison between projected and reference LULC map for the years 2013 and 2014. The kappa statistic was calculated for all the prediction maps. The prediction with the input images with time gap of one year to seven years. Table 3 shows the validation result using the Kappa values.

Table 3. Validation Table

Time Interval (year)	2013 Kappa Statistics	2014 Kappa Statistics
1	0.6008	0.6003
2	0.6528	0.6910
3	0.6762	0.7028
4	0.5975	0.7249
5	0.6908	0.7275
6	0.6563	0.6169
7	0.6375	0.6521

3.4. Comparative analysis of actual LULC map and predicted maps

In the first case of predicted LULC map of 2013 of the study area, the prediction has been done on the basis of a one-year temporal gap. LULC map of 2011 and LULC map of 2012 has been taken as input. It is clearly shown in the following (see Figure 6 (Ai, Aii, Aiii)) that open land and settlement class has been increased at a major portion. However, there was very little change in agriculture and forest class.

In the second case with the temporal change at a gap of two years, there is a marked increase in settlements (see Figure 6 (Bi, Bii, Biii)). In this case, LULC map of 2009 and LULC map of 2011 has been taken as input. It was also showing considerable changes in the agricultural area that has been decreased in 2013 output. In the third case, change analysis was made on the basis three years gap. For which LULC map of 2007 and LULC map of 2010 have been taken as inputs. There was a marked reduction of agricultural land observed in the predicted LULC map of 2013 (see Figure 6 (Ci, Cii, Ciii)). The results are showing rapid changes with increased open land and settlement areas.

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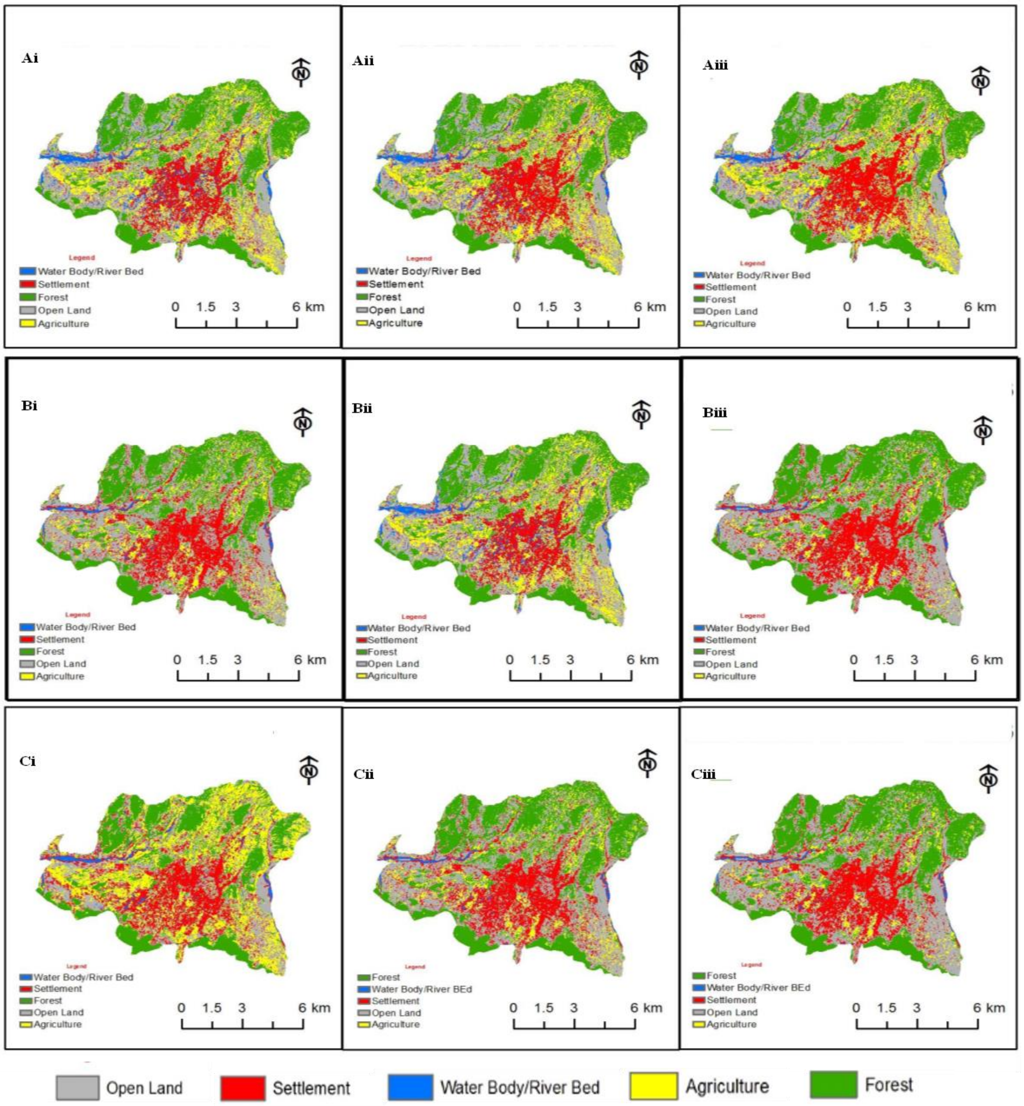

Figure 6. (Ai) LULC Map of 2011 (Aii) LULC Map of 2012 (Aiii) Predicted Map of 2013; (Bi) LULC Map of 2009 (Bii) LULC Map of 2011 (Biii) Predicted Map of 2013; (Ci) LULC Map of 2007 (Cii) LULC Map of 2010 (Ciii) Predicted Map of 2013

In the fourth case change analysis has been done on the basis of a gap of four years that was from 2005 to 2009 and from 2009 to 2013 (See Figure 7 (Ai, Aii, Aiii). In this case, LULC map of 2005 and 2009 has been taken as input for the prediction of LULC of the year 2013. It is very clear from the following figure that settlement class has been increased by a big amount of percentage. However, there is a marked reduction in agricultural fields. Some of the agriculture lands have been converted into an open area. In the fifth case, change analysis has been done on the basis of a gap of five years (See Figure 7 (Bi, Bii, Biii). In this case, LULC map of the year 2003 and 2008 has been taken as input for the prediction of the year 2013. It has been observed that there was a clear change in terms of increase for class settlements and surprisingly agriculture land was also increased by area.

In the sixth case, change analysis has been done on the basis of a gap of six years that is from the year 1999 to 2005 and from 2005 to 2013 (See Figure 7 (Ci, Cii, Ciii). As it is clear that LULC map of the year 1999 and 2005 has been taken as input for the prediction of LULC of the year 2013. This change was also representing a remarkable upsurge in settlement class. There was an increase of settlements by area. However, a noticeable decrease has been observed in class open lands. In the seventh case, change analysis has been done on the basis of a gap of seven years that is from the year 1999 to 2006 and from the year 2006 to 2013 (See Figure 7 (Di, Dii, Diii)). For this change analysis, LULC map of the year 1999 and 2006 has been taken as

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input. In this case, there was also an upward trend by area in settlement class. After the prediction of LULC map of the year 2013, LULC map of 2014 has been taken under consideration.

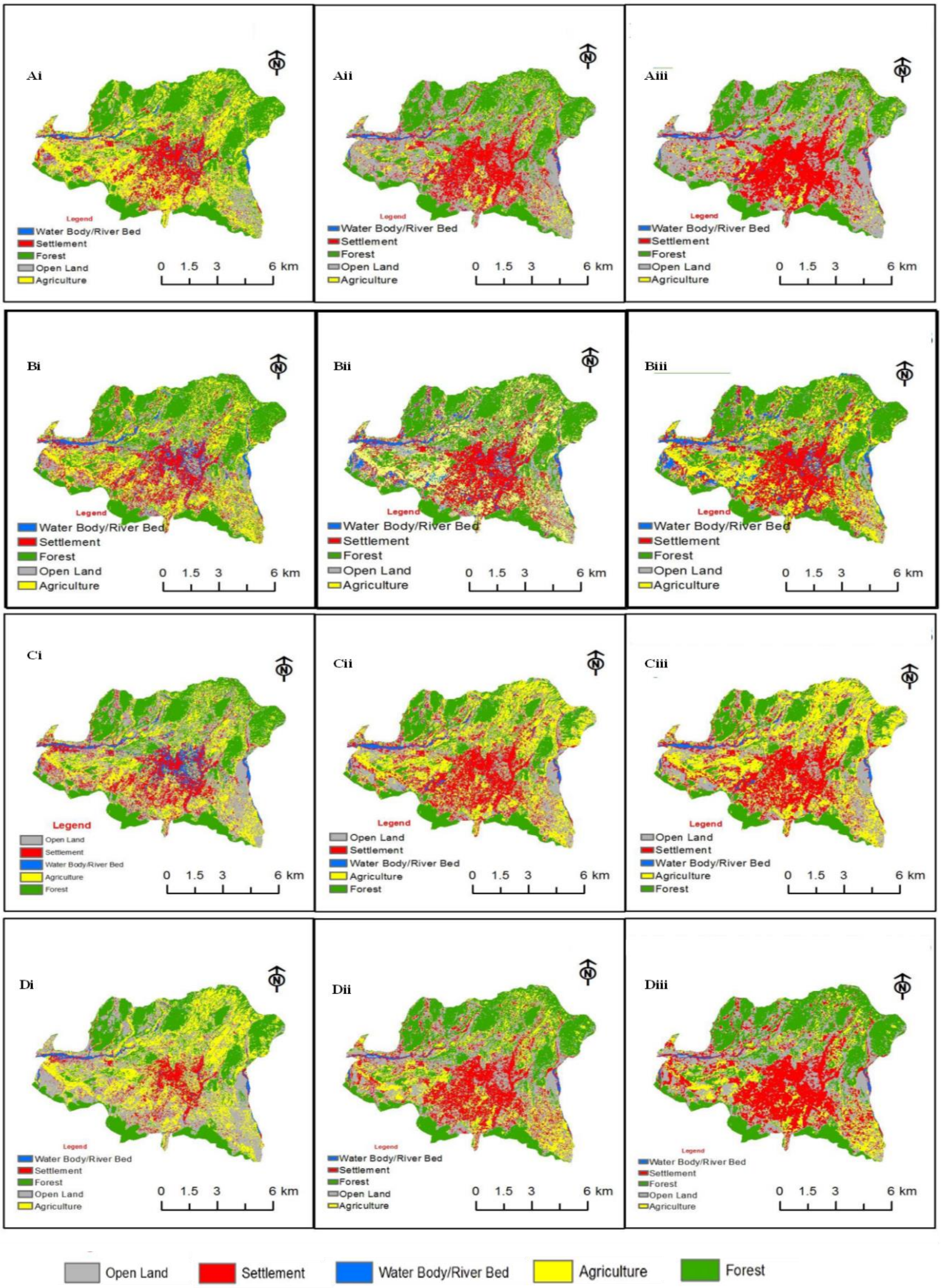

Figure 7. (Ai) LULC Map of 2005 (Aii) LULC Map of 2009 (Aiii) Predicted Map of 2013; (Bi) LULC Map of 2003 (Bii) LULC Map of 2008 (Biii) Predicted Map of 2013; (Ci) LULC Map of 2001 (Cii) LULC Map of 2007 (Ciii) Predicted Map of 2013; (Di) LULC Map of 1999 (Dii) LULC Map of 2006 (Diii) Predicted Map of 2013

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In the first case, a change analysis for the prediction of LULC of the year 2014 has been made on the basis of a gap of one year (See Figure 8 (Ai, Aii, Aiii)). For this analysis LULC map of 2012 and LULC map of 2013 has been taken as input for the prediction of LULC of the year 2014. A reduction has been noticed in open area class. However settlement class is showing a little increase by percentage. In the second case, a change analysis has been done on the basis of a gap of two years (See Figure 8 (Bi, Bii, Biii)). For this case, LULC map of 2010 and LULC map of 2012 has been taken as input for the prediction of LULC of the year 2014. The corresponding change for different classes has been given the following images. In the third case, a change analysis has been done on the basis of a gap of three years (See Figure 8 (Ci, Cii, Ciii)). For this change analysis, LULC map of 2008 and LULC map of 2011 has been taken as input for the prediction of LULC of the year 2014. In this case, open land has been increased by a big amount of percentage.

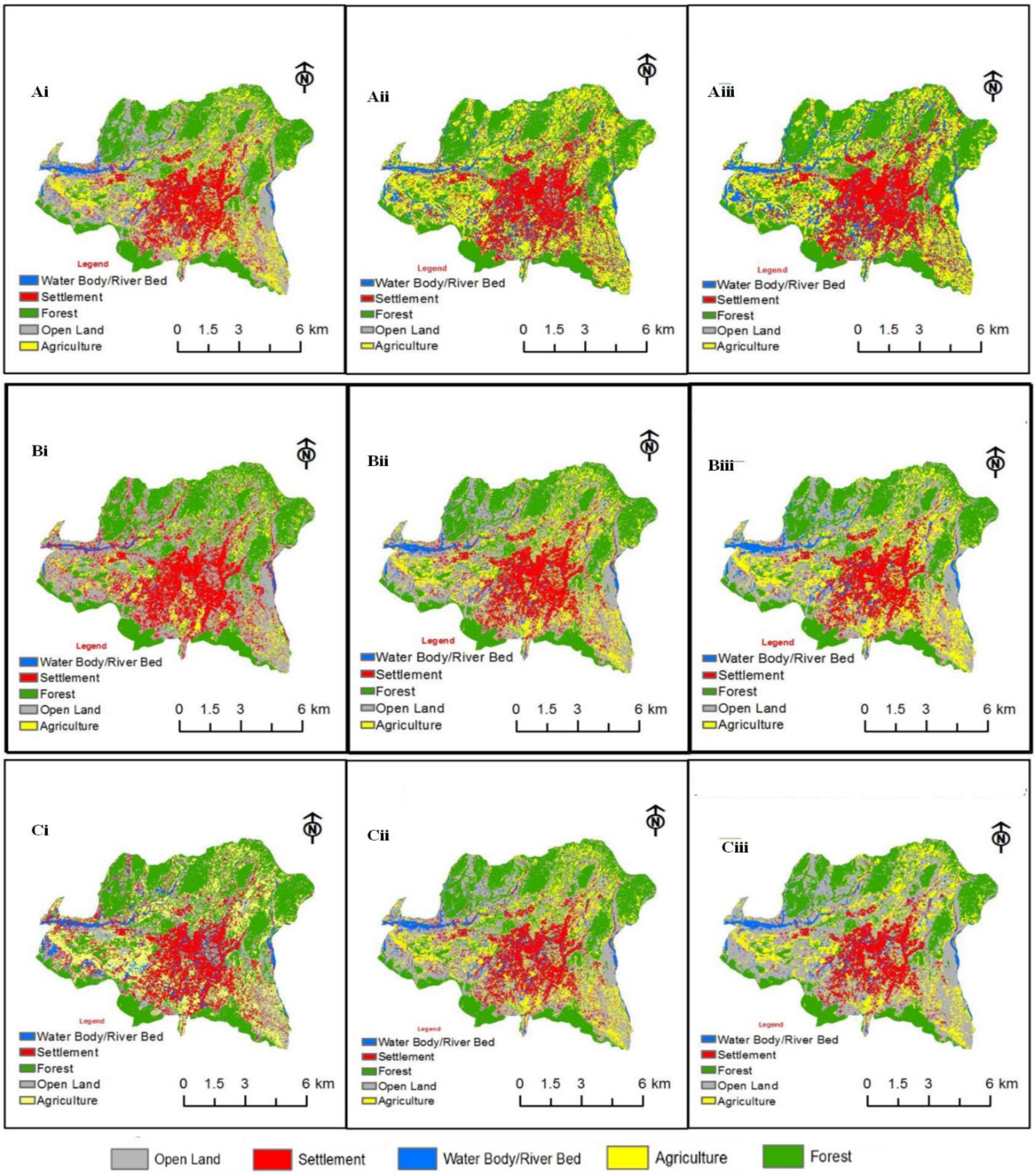

Figure 8. (Ai) LULC Map of 2012 (Aii) LULC Map of 2013 (Aiii) Predicted Map of 2014; (Bi) LULC Map of 2010 (Bii) LULC Map of 2012 (Biii) Predicted Map of 2014; (Ci) LULC Map of 2008 (Cii) LULC Map of 2011 (Ciii) Predicted Map of 2014

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In the fourth case, a change analysis has been done on the basis of a gap of four years (see Figure 9 (Ai, Aii, Aiii)). In this case for the LULC prediction of the year 2014, LULC maps of the year 2006 and 2010 has been taken as input. Agriculture class was showing a remarkable change. Also, there was an increase in settlement classes as usual. In the fifth case, change analysis has been done on the basis of a gap of five years (see Figure 9 (Bi, Bii, Biii)). For this analysis LULC map of 2004 and LULC map of 2009 have been taken as input for the prediction of LULC change of the year 2014. Both inputs are showing a big difference in each class. In 2009, open land is larger than the LULC of 2004. In the year 2004, agriculture area was large but in the year 2009 it has been decreased much. Also, there was an increment of settlement has found in 2009 than the year 2004. Based on these two inputs LULC of 2014 has been predicted which is showing an abrupt increase in settlement class.

In the sixth case change analysis has been done on the basis of a gap of six years (see Figure 9 (Ci, Cii, Ciii)). For this analysis, LULC of the year 2002 and LULC of the year 2008 has been taken as input. As it is clear from the figure that in the year 2002 there was a big agricultural land while it was decreased in the year 2008. Also, a settlement has also been increased during these years. Based on these two inputs, LULC map of 2014 has been predicted which was also showing an increment of settlement class by area. In the seventh case change analysis has been done on the basis of a gap of seven years (see Figure 9 (Di, Dii, Diii)). For this analysis, LULC of the year 2000 and LULC of the year 2007 has been taken as input and predict the LULC map of 2014. It was again observed that like the previous. Agricultural land was decreased over the time whereas settlement has been increased along with the reducing forest areas.

3.5. Predicted future maps

By using CA-MARKOV model the visual validation with respect to actual and predicted maps by using the Kappa statistics with one year gap are showing better results. The CA-Markov chain derived predicted future maps are illustrated in Figure 10. In this research using the above model predicted map for future changes in the proposed area with five year gap for year 2013 showing 0.6908 Kappa statistics and for year 2014 is 0.7275. For third year gap are showing 0.6762 for year 2013 and for year 2014 is 0.7028. The agricultural area is gradually decreased in between these year gaps. The urbanization and climatic variability would be the probable factor for the future changes.

This research establishes the application of remote sensing and GIS in mapping of urban sprawl and changes in land use system. Dynamically increasing population of the city can be approximated by the predicted future scenarios. The predictions for future land use or land cover changes on the basis of a CA-Markov model strongly propose a continuous rise in urban settlement built up and a subsequent decrease in agriculture, forests covers. The outcome of one of the study done by Jat et al. (2008) only focuses on the quantification of the urban form (impervious area) using Shannon's entropy model and also shows the urban growth but in spatial implicit manner. Whereas this study primly dedicated to represent the urban sprawl with accuracy assessment using cellular automata model which will help the decision makers to formulate the future plan.

Another study done by Taubenböck et al. (2012) monitor the urbanization rate over 27 cities but no mathematical model was done to show how the cities are changing in its structure. Our results concentrated on Dehradun city and proved that the outlook of the city is changing over fifteen years (1999-2014) in its spatio-temporal manner. Study done by Yin et al. (2011) showing the urban expansion and land use/land cover changes using normal maximum likelihood supervised classification algorithm on four Landsat images over the time of 1979–2009. No statistical modelling was implemented in this study to predict the changes over the time. This is important to do the statistical modelling like CA-Markov when we are dealing with large scale temporal images to consider the accuracy of the outcomes. Studies done by Bagan and Yamagata (2012) combined remote sensing and socio-economic data to quantitatively analyze urban growth using square grid cells method considering only three years intervals whereas we consider seven years interval and predict the future urban growth which is highly necessary for city planners from sustainable and correct planning perspective.

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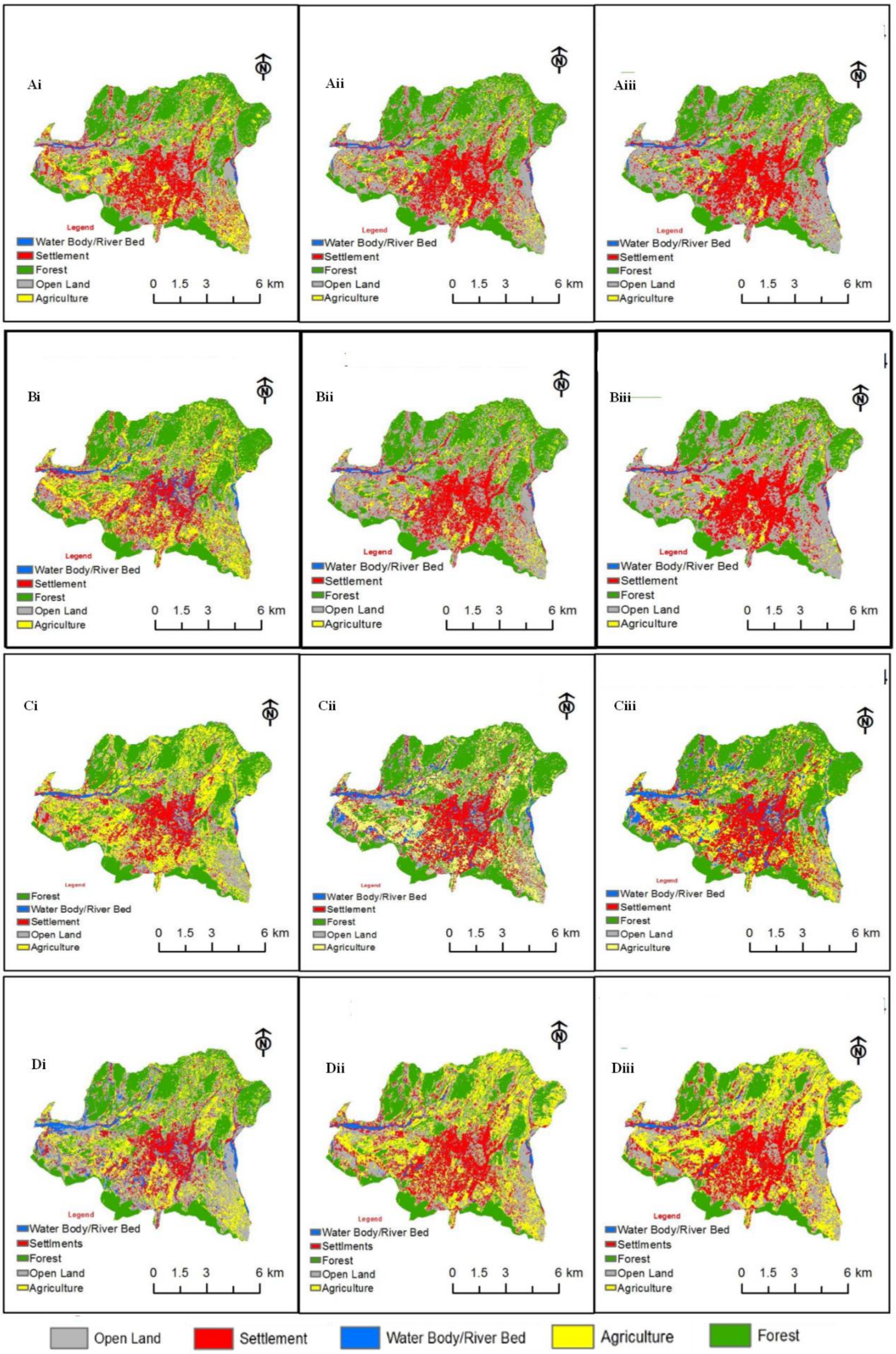

Figure 9. (Ai) LULC Map of 2006 (Aii) LULC Map of 2010 (Aiii) Predicted Map of 2014; (Bi) LULC Map of 2004 (Bii) LULC Map of 2009 (Biii) Predicted Map of 2014; (Ci) LULC Map of 2002 (Cii) LULC Map of 2008 (Ciii) Predicted Map of 2014;(Di) LULC Map of 2000 (Dii) LULC Map of 2007 (Diii) Predicted Map of 2014

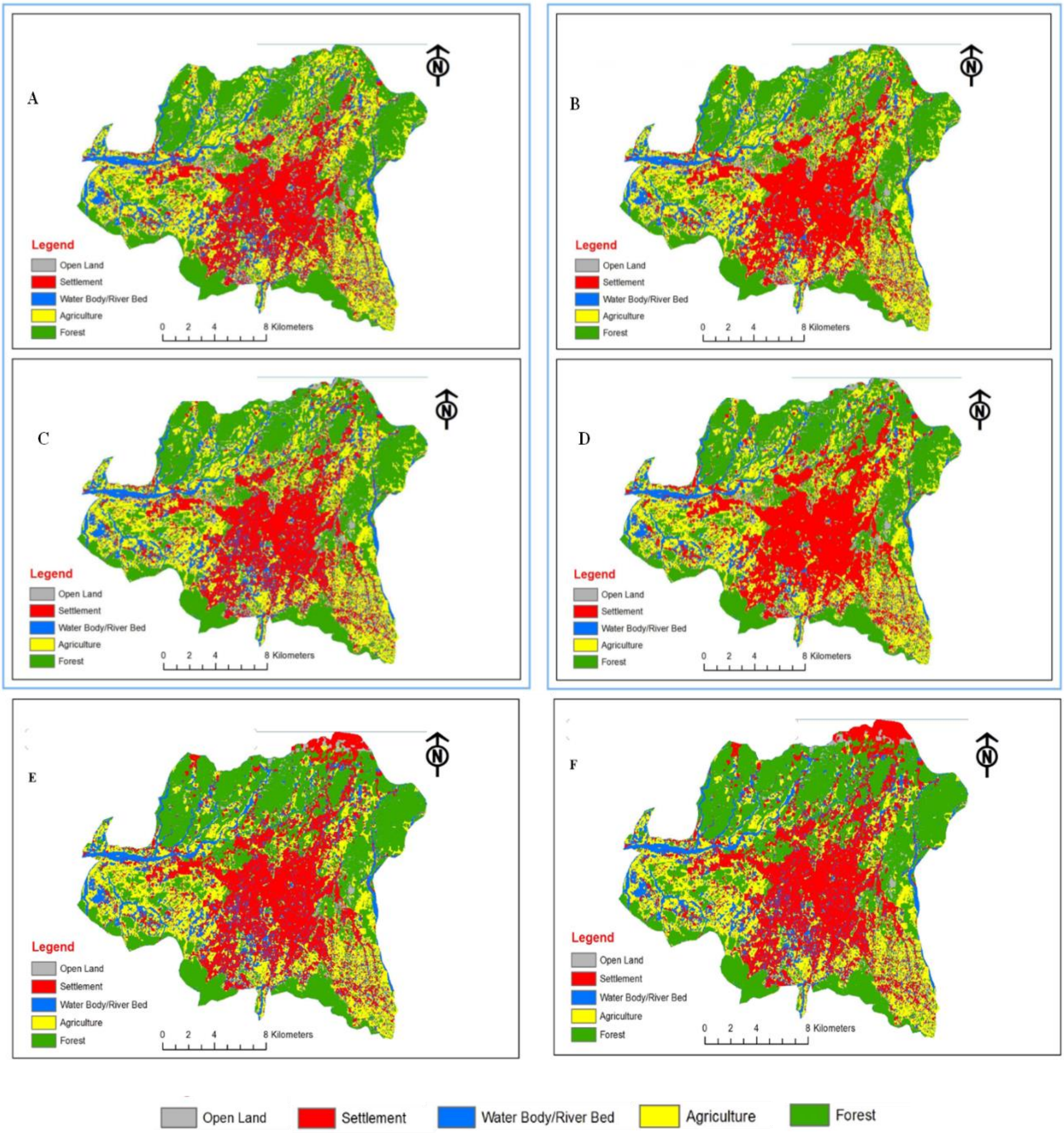

Figure 10. (A) Predicted Map of 2015 (B) Predicted Map of 2016 (C) Predicted Map of 2017 (D) Predicted Map of 2018 (E) Predicted Map of 2019 (F) Predicted Map of 2020

4. CONCLUSION

The Robustness of this study represents the reality of the Dehradun city which is defined by the accelerate rate of urban expansion with decreasing forest and croplands. The increasing rate of open lands supports the massive deforestation within the study area. The significant Kappa values of LULC classification for each of the 7 years interval between 2013 and 2014 make the prediction more accurate. Finally this study predicts next 6 years (2015-2020) LULC as well as the urban expansion which has never done by any other long term spatio-temporal studies in this domain. This sort of prediction presented in this study using CA Markov model can help to project sustainable urban systems. So, the mapping of urban sprawl using geospatial technology and mathematical model can be a device of decision support system (DSS) for policy makers to design urban expansion plans with an approach of sustainable city development.

In order to predict the future land use changes we need to study the important role of human activities and its impact on the environment. Besides the ecosystem and its functions with related to biodiversity, land use changes are the major contribution to the rapid destruction of agriculture and forest areas. Sometimes the transformation of land cover and fast urbanization leads to decrease the daily diurnal rage which ultimately punching with local level climate change (Bandopadhyay, 2016). Moreover, to minimize all this processes, it requires the involvement of the local community and capacity building programs, local governments (Bandopadhyay, 2017) regarding how to protect the environment for the future and move towards a sustainable urban habitat in a balanced approach.

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