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PREDICTION OF LAND USE CHANGES BASED ON LAND CHANGE MODELER (LCM) USING REMOTE SENSING: A CASE STUDY OF MUZAFFARPUR (BIHAR), INDIA

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Abstract: Land use change models are tools to support the analysis of the causes and consequences of land use dynamics. Land use and land cover change (LUCC) has been recognized as an important driver of environmental change on all spatial and temporal scales. The primary objective of this paper is to predict and analyze the present and future growth of Muzaffarpur city and its surrounding, Bihar (India) using the Landsat satellite images of 1988 and 2010. These data are used for change prediction and for preparation of prediction map of year 2025 and 2035. IDRISI, Land Change Modeler (LCM) was used to analyze the land use and land cover changes between various classes during the period 1988-2008. Erdas Imagine software (ver-9.3) were also used to prepare land use/cover classification using image processing supervised classification method in a multi-temporal approach. The prediction of land use land cover change was done on neural network built-in module in the Selva version of IDRISI. The accuracy was obtained as 72.28% for all the conversion types.

Key words: remote sensing, land use change, land change modeler (LCM), satellite images, IDRISI.

Introduction

Land use term usually defined more strictly and refers to the way in which, and the purposes for which, humans employ the land and its resources (William 2000). Land cover refers to the habitat or vegetation type present, such as forest and agriculture area. Land-use and land-cover change (LUCC) also known as land change is a term for the human modification of Earth's terrestrial surface.

It is widely accepted that LULC have an important effect on both the functioning of the Earth's systems as a whole (Lambin et al. 2001) and the majority of ecosystems (Hansen et al. 2001; Millennium, 2005; Fischlin et al. 2007). This change is based on the purposes of need, which is not necessarily only making

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the change in land cover but also change in intensity and management (Verburg et al. 2000).

Land use and land cover change has been recognized as an important driver of environmental change on all spatial and temporal scales (Adepoju et al., 2006), as well as emerging as a key environmental issue and on a regional scale is one of the major research endeavors in global change studies. These changes encompass the greatest environmental concerns of human populations today, including climate change, biodiversity loss and the pollution of water, soils and air. Monitoring and mediating the negative consequences of LULC while sustaining the production of essential resources has therefore become a major priority of researchers and policymakers around the world.

In this context, it is much needed to estimate the land use changes over the time and predict the future scenario of Muzzafarpur. For this study, analysis is performed by a remote sensing based Land Change Modeler (LCM) method. Based on past trend (from 1988-2010) of land use changes, the future land use prediction map of Muzaffarpur city and in its surrounding for the year 2025 and 2035 have been generated. The result shows that some of the classes will change significantly. This kind of analytical study can be remarkable in sustainable development.

Study Area

The study area, a part of Muzaffarpur district (Bihar) India is lies between 26°14'55"N to 25°59'41"N latitudes and 85°11'15"E to 85°33'22"E longitudes and the total area is about 492.32 sq. km (Figure 1). It is situated on the banks of the perennial Burhi Gandak River, which flows from the Someshwar Hills of Himalayas. Muzaffarpur is one of the gateways to Nepal. It has an average elevation of 47 meters. This saucer shaped, low-centered town lies on the great Indo-Gangetic plains of Bihar, over Himalayan silt and sand brought by the glacier-fed and rain-fed meandering rivers of the Himalayas. The soil of the town is highly fertile, well drained and sandy, white coloured and very soft. The landscape is green all year round. The town is surrounded by the flood plain dotted with ponds and oxbow lakes, with sparkling sandy river banks and clean air and water. Numerous private fruit orchards and idyllic rivers are also nearby. The city has a water-table just 6 meters below ground level.

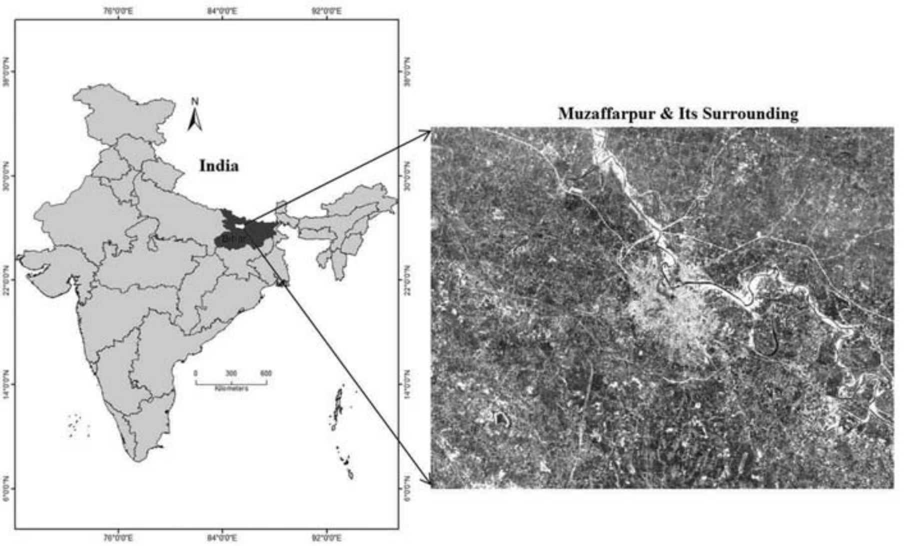

Figure 1. Geographical location of the study area as viewed on Landsat TM data of 2010.

Materials and method

The satellite images were sorted and classified for analysis and interpretation. Landsat images are among the widely used satellite remote sensing data and their spectral, spatial and temporal resolution made them useful input for mapping and planning projects (Sadidy et al., 2009). Landsat TM images of year 1988 and 2010 were employed as the source in this study to produce land use/cover categories respectively. The images are projected to WGS-1984 and UTM Zone-45N Coordinate System.

ERDAS Imagine (ver.-9.3) was used to perform land use/cover classification in a multi-temporal approach. To predict the future land use/cover of the study area, remote sensing based techniques have been used. Total 12 land use/cover categories have been identified for this study. Each image was separately classified using the supervised classification maximum likelihood algorithm in ERDAS Imagine. Eight separable land use/cover categories have been identified in this study such as agriculture land, vegetation, scrubs, fallow land, waste land, built up area, water bodies and river bed. Flow chart of methodology is shown in the figure 2.

Land Change Modeler for ecological sustainability is integrated software developed by IDRISI Selva for analyzing land cover changes. Land cover change model tools support the analysis of the land use changes. Use of such model also gives a better understanding of the functions of the land use systems and the support needed for planning and policy making. Such models can also predict the possible future change and use of the land cover under different scenario (Costanza & Ruth, 1998, Clark Labs, 2009, Ahmed and Ahmed, 2012).

By using this two land cover maps were analyzed that have identical legends. The change analysis panel provides a rapid assessment of quantitative change by graphing gains and losses by land cover categories. A second option, net change, shows the result of taking the earlier land cover areas, adding the gains and then subtracting the losses. The third option is to examine the contribution to changes experienced by single land cover (Clark Labs, 2009). The land cover change analysis was performed between the pairs of Landsat TM images of year 1988 and 2010. Accordingly the transitions and exchanges that took place between the various land use/cover categories during the years were obtained both in a map and graphical form. All the land cover categories were used in sq. km. unit. Transitions below 1 sq.km. were ignored. The cross classification found its most useful application in land cover change analysis where a cross tabulation or a cross correlation is done between two qualitative maps of two different dates that targets on the same features (Clark Labs, 2009). It is used to compare two classified images where the classification assigns the same unique and distinct identifier to each class on both the dates. The aim is to examine whether the areas fall into the same class on the two dates or a change to a new class has occurred.

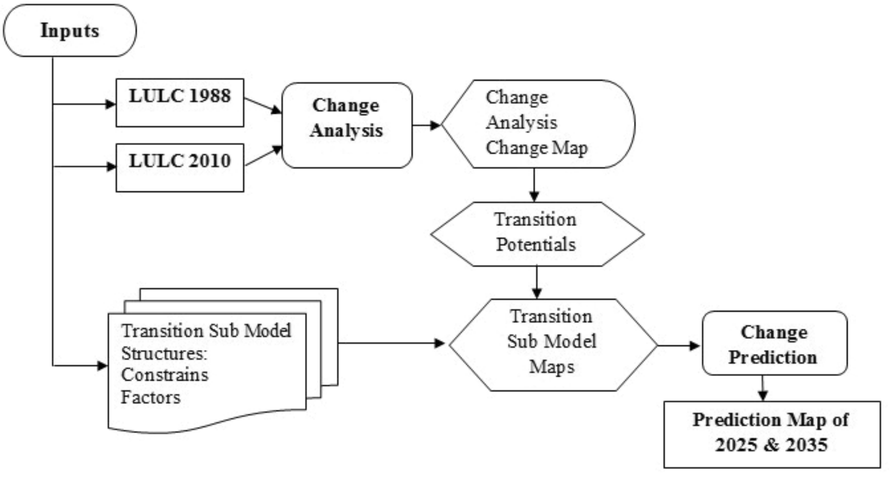

Figure 2. Methodology Flow Chart for LCM.

Results and discussion

Land use change analysis

From both the classified images of 1988 and 2010, the area of each land use categories were computed (Table 1; Figures 3 and 4) and compared statistically if there are differences between the images.

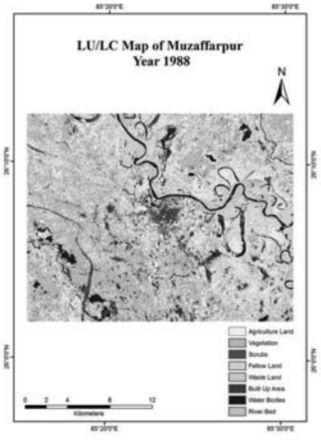

Figure 3. Land use/cover map of study area for 1988

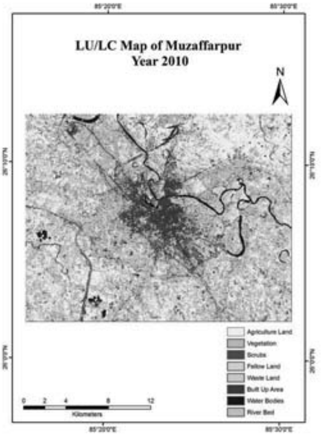

Figure 4. Land use/cover map of study area for 2010

From the table 1 it is clear that over the year there are significant changes in land use/cover categories especially for agriculture land and built up areas.

Table 1. Land use and land cover classification statistics between 1988 and 2010

LUCC Class	Year 1988 Area (in Sq. Km.)		Year 2010 Area (in Sq. Km.)		Changed Area	Changed Area (In %)
Agriculture land	137.485	27.85 %	154.229	31.33 %	16.743	12.178
Vegetation	159.707	32.35 %	166.723	33.86 %	7.015	4.393
Scrubs	34.570	7.00 %	35.360	07.19 %	0.789	2.283
Fallow land	110.440	22.38 %	52.317	10.63 %	-58.123	-52.629
Waste land	3.9357	0.80 %	30.507	6.20 %	26.571	675.143
Built-up area	12.278	2.49 %	38.209	7.76 %	25.930	211.185
Water bodies	25.497	5.17 %	9.909	2.02 %	-15.588	-61.138
River bed	9.750	1.98 %	5.069	1.03 %	-4.680	-48.006

Change detection analysis using LCM method

A number of LUCC models have been developed; however it is difficult to compare which one gives more accurate representation (Wu & Webster 2000). Among the numbers of land use modeling tools and techniques, the commonly used models are the modeling techniques embedded in IDRISI. These are Land Change Modeler (LCM), Cellular Automata (CA), Markov Chain, CA_Markov, GEOMOD, and STCHOICE (Eastman, 2006). But LCM is widely used modeling tool.

Land Change Modeler was used to analyze the land use/cover changes for various classes during the period 1988-2010. The basic principle behind this module is to evaluate the trend of the change from one land use category to other, the influencing factors such as roads, slope, aspect and soil type, and finally predict the land use pattern based on the previous change trend. The LCM module works on neural network and needs to reach higher accuracy, but accuracy depends much on influencing variables. The land use changes were evaluated by gains and losses by different classes. For the present study LCM in IDRISI Selva was used and the flow chart in the figure 2 describes the methodology applied to calibrate, simulate and validate the model

Most of the classes have both gains and losses. During the period 1988-2010, river bed has been lost 86.99% and gained 73.24%, with a net loss of 13.75%. Water bodies has been lost 84.52% and gained 55.25%, with net loss of 29.27%. Built up area has been lost 53.71% and gained 80.50%, with net gain of 26.79%. Waste land has been lost 85.54% and gained 97.52%, with a net gain of 11.98%. Fellow land has been lost 88.24% and gained 64.61%, with net loss of 23.63%. Scrubs has been lost 91.85% and gained 88.11%, with net loss of 3.74%. Vegetation has been lost 64.03% and gained 49.41%, with a net loss of 14.62 %. There is no loss or gain for agriculture land with a net gain of 100% (Figure 5).

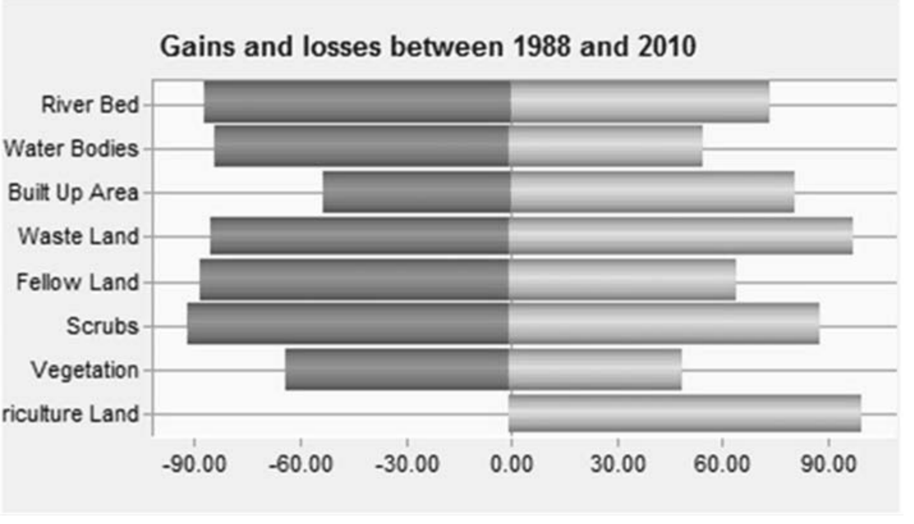

Figure 5. Gains and losses of land use/cover categories between 1988 and 2010.

From figure it is clear that there are significant changes and transitions among various land use/cover classes during the period from 1988 to 2010. The main changes and transitions are basically among agriculture land, vegetation and built up area.

Transition potentials modeling with LCM

The main goal of this tab is to create transition potential maps with acceptable degree of accuracy to run the actual modeling. Hence, the transition potentials tab allows us to group transitions into a set of sub models and explore the potential power of explanatory variables. Variables can be added to the model either as static or dynamic components (Eastman, 2006). Static variables express aspects of basic suitability for the transition under consideration, and are unchanging over time. Dynamic variables are time-dependent drivers such as proximity to existing development or infrastructure and are recalculated over time during the course of a prediction.

Transition sub-model status

This step provides the list of all minor to major transitions that has occurred from time t1 to time t2. In the case of Alaknanda basin, based on major transitions that occurred among the land use cover classes and the major concern of transitions to built ups between 1988 and 2010 has been considered. Although the major concern of the study is on the transitions that occurred from all other classes to built up, it is important to incorporate the major other transitions that have happened and played a role in the dynamics of the study area. This also enhances the performance of MLP (Eastman, 2006). The total three transitions that have been selected are, vegetation to built up, fallow land to agriculture land and river bed to water bodies.

Model assumptions

In LCM, there are two options of modeling algorithms that are used to model these selected transition variables. These are logistic regression and Multi-Layer Perceptron (MLP) neural network. MLP uses minimal parameters and it is more easily approachable. Also the MLP neural network has been extensively enhanced to offer an automatic mode that requires no user intervention. Hence, MLP neural network has employed in this study. The selected eight transitions are collected into a sub-model. Then the important decision the analyst does is to develop variables that explain these transitions. In the present study both static and dynamic variables have used.

Constraints and Factors

Constraints are the criteria that limit the expansion of built up land use. Physical constraints can be existing built up area, water bodies (streams), road network etc. The constraint map developed is shown in Figure. Factors are not ‘hard rule’ like constraints; they allow the analyst to determine the degree of suitability from very low to high. The low to high suitability in LCM can be in real (0.0 to 1.0) or in byte (0 to 255 ranges). It is unnecessary to do this for a simple LCM prediction. All factors may maintain their original values-elevation, distance to roads, etc. do not need to be standardized to work effectively in the model.

Factors are a criterion that enhances or diminish from the suitability of a specific alternative for the activity under consideration (Eastman, 2006). But in case of factors, it is different and they give a degree of suitability for an area to change (mostly on distance basis). The following factor have been created for the modeling: distance from major roads network (Figure 6). This tab is the final transition modeling step. It provides us two land change modelers; the MLP neural network and the logistic regression. For multiple variables to model at the same time MLP is chosen. Moreover, MLP neural network is quite capable of modeling non-linear relationships and the most robust land cover change models (Eastman, 2006).

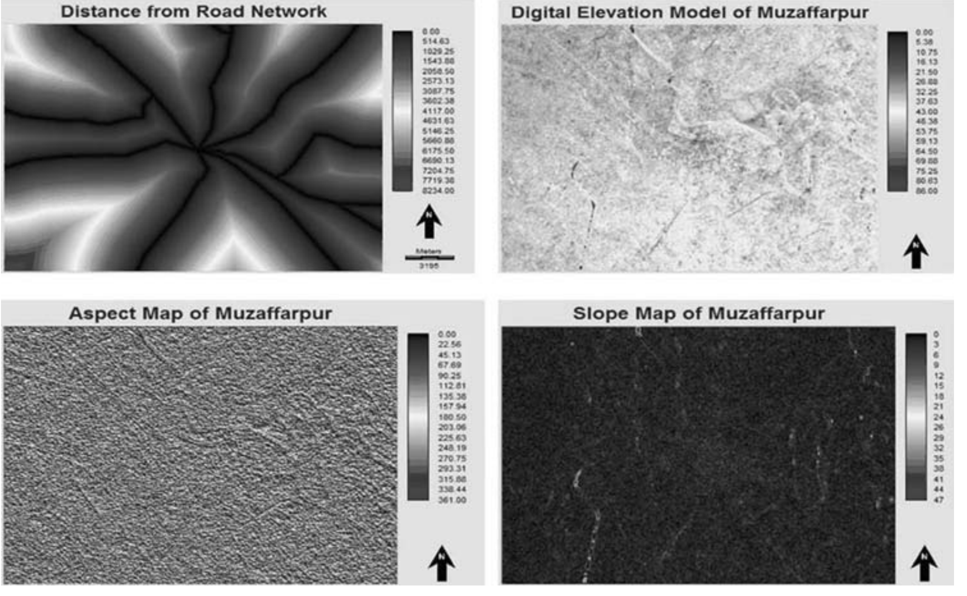

Figure 6. Factor distance from roads network, DEM, aspect and slope map.

Transition sub-model structure and running the model

Multi-Layer Perceptron (MLP) neural network

The Multi-Layer Perceptron (MLP) neural net as described by Rumelhart et al. 1986 is one of the most commonly used Artificial Neuron Networks (ANN). The multilayer perceptron neural network training is based on the Backpropagation (BP) algorithm that is a supervised training algorithm. It is a common method of training Artificial Neural Networks. From a desired output, the network learns from many inputs. A Multi-Layer Perceptron (MLP) is a feed forward artificial neural network model that maps sets of input data onto a set of appropriate output. An MLP consists of multiple layers of nodes in a directed graph, with each layer fully connected to the next one. The perceptron is an algorithm for supervised classification of an input into one of several possible non-binary outputs. MLP undertakes the classification of remotely sensed imagery through a Multi-Layer Perceptron neural network classifier using the back propagation (BP) algorithm. The calculation is based on information from training sites.

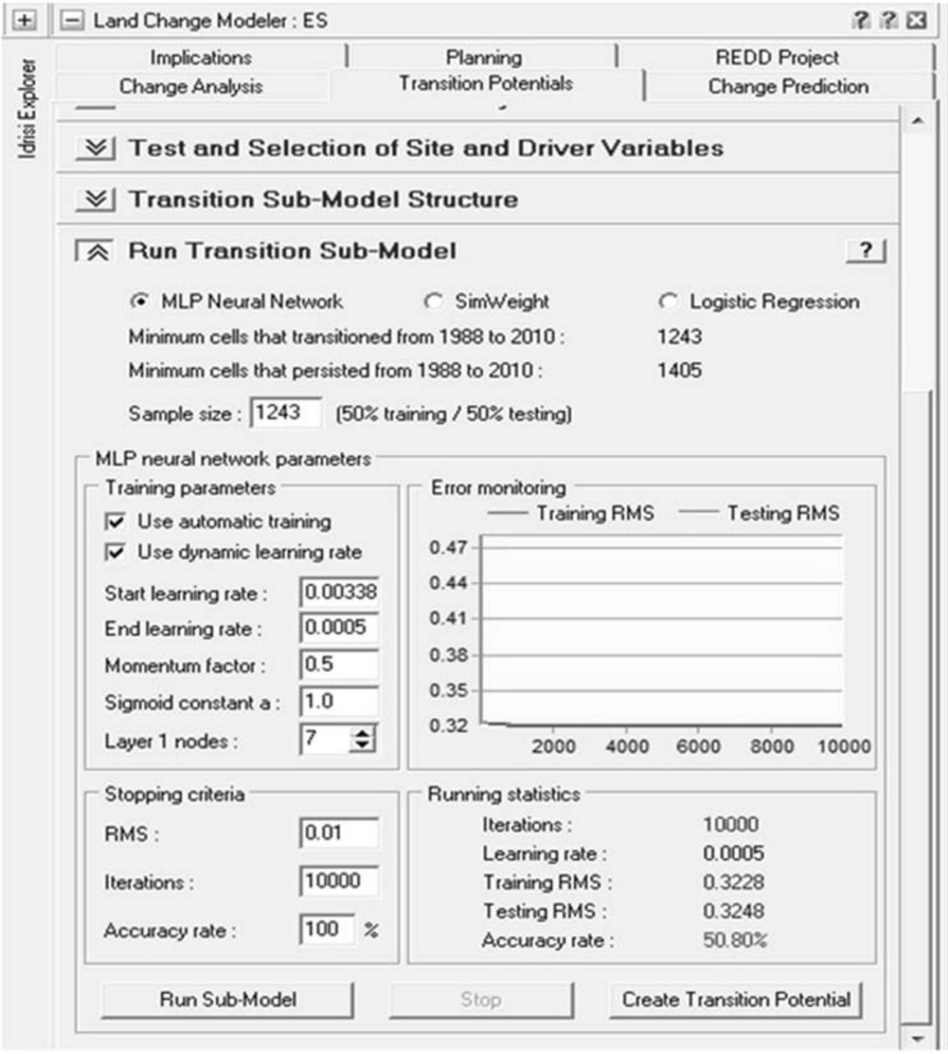

Figure 7. Multi-Layer Perceptron (MLP) neural network classifier process.

The variables were loaded into the sub-model structure to execute the model, the neural network created random sample of cells that experienced each of the transitions selected in this modeling. It also builds network of neurons with weights, in which it uses to compute its error of training and adjust the weight and improve accuracy (i.e., the RMS error decreases as the weight is adjusted). Accuracy rate around 80% is acceptable (Eastman, 2006). In this study, when the MLP has finished 10000 iteration (default) of training and testing with an accuracy of 50.80% then transition potential maps were obtained (Figure 7).

Markov Chain Modeling

Markov Chain determines the amount of using the earlier and later land cover maps along with the date specified. The procedure determines exactly how much land would be expected to transition from the later date to the predicted date based on a projection of the transition potentials into the future and creates a transition probabilities file. The transition probabilities file is a matrix that records the probability that each land cover category will change to every other category. A Markov Chain is a random process where the following step depends on the current state. Markov produces transition matrices (Table 2 and 4), a transition area matrix and a set of conditional probability image by analyzing two land use and land cover images (Figures 8, 9 and 11) from two different dates (1988 and 2010). In table the rows stand for the older land use and land cover categories and the columns stand for newer land use and land cover categories (Table 2 and 4).

Table 2. Markov prediction to 2025 based on land use and land cover maps of 1988 and 2010 (given probability of changes to the values in bold)

LU/LC Class	Agriculture land	Vegetation	Scrubs	Fallow land	Waste land	Built up area	Water bodies	River bed
Agriculture land	0.0000	0.1429	0.1429	0.1429	0.1429	0.1429	0.1429	0.1429
Vegetation	0.3799	0.4341	0.0491	0.0720	0.0394	0.0244	0.0010	0.0000
Scrubs	0.3051	0.2960	0.0972	0.1433	0.0539	0.0731	0.0314	0.0000
Fallow land	0.2600	0.3348	0.0756	0.1386	0.0817	0.0922	0.0072	0.0100
Waste land	0.2241	0.1603	0.0266	0.0423	0.1775	0.0698	0.1248	0.1746
Built-up area	0.0629	0.1083	0.0994	0.1171	0.0439	0.5565	0.0061	0.0057
Water bodies	0.2064	0.1734	0.0830	0.1455	0.0784	0.0679	0.2091	0.0362
River bed	0.1770	0.1730	0.0307	0.0578	0.1725	0.0876	0.1316	0.1698

Table 3. Projected land use and land cover statistics of the study area for 2025

LU/LC Class	Agriculture land	Vegetation	Scrubs	Fallow land	Waste land	Built up area	Water bodies	River bed
Area (Sq.Km.)	167.830	174.745	26.642	36.381	22.887	48.868	10.865	4.103
Area (In %)	34.08	35.50	5.41	7.39	4.64	9.92	2.20	0.83

Projected land use and land cover statistics of the study area for year 2025 and 2035 are given in the table 3 and 5. Projected Markov conditional probability image for year 2035 is also shown in the figure 11. Area statistics of different land uses categories among years 1988, 2010, 2025 and 2035 is given in the figure 12.

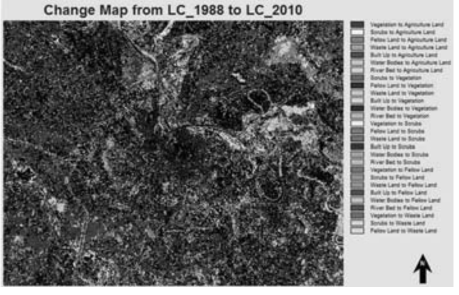

Figure 8. Combined LU/ LC change map of 1988. and 2010.

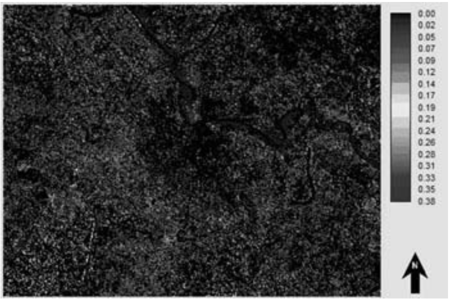

Figure 9. Projected Markov conditional probability matrices for 2025.

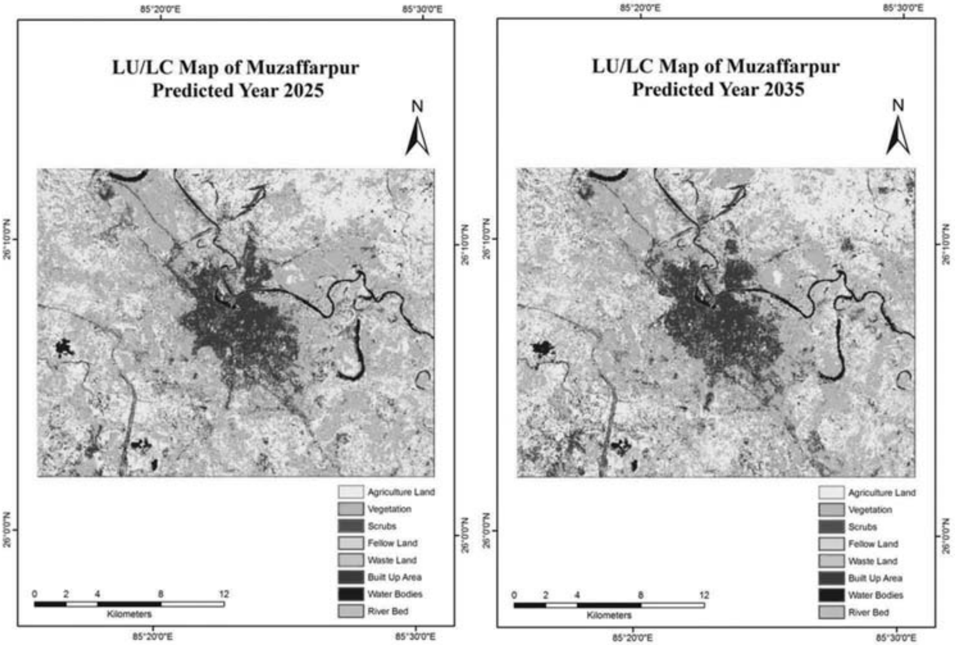

Figure 10. Projected land use and land cover maps of 2025 and 2035.

Table 4. Markov prediction to 2035 based on land use/cover maps of 1988 and 2010 (given probability of changes to the values in bold)

LU/LC Class	Agriculture land	Vegetation	Scrubs	Fallow land	Waste land	Built up area	Water bodies	River bed
Agriculture land	0.0000	0.1429	0.1429	0.1429	0.1429	0.1429	0.1429	0.1429
Vegetation	0.3979	0.2812	0.0657	0.0992	0.0628	0.0669	0.0142	0.0122
Scrubs	0.3211	0.3091	0.0627	0.1027	0.0639	0.1005	0.0244	0.0156
Fallow land	0.3199	0.3032	0.0642	0.0932	0.0669	0.1073	0.0228	0.0226
Waste land	0.2475	0.2221	0.0542	0.0863	0.1066	0.1047	0.0950	0.0838
Built-up area	0.1612	0.1876	0.0849	0.1118	0.0552	0.3714	0.0151	0.0128
Water bodies	0.2690	0.2585	0.0697	0.1117	0.0797	0.1015	0.0738	0.0360
River bed	0.2469	0.2237	0.0559	0.0881	0.1055	0.1114	0.0896	0.0789

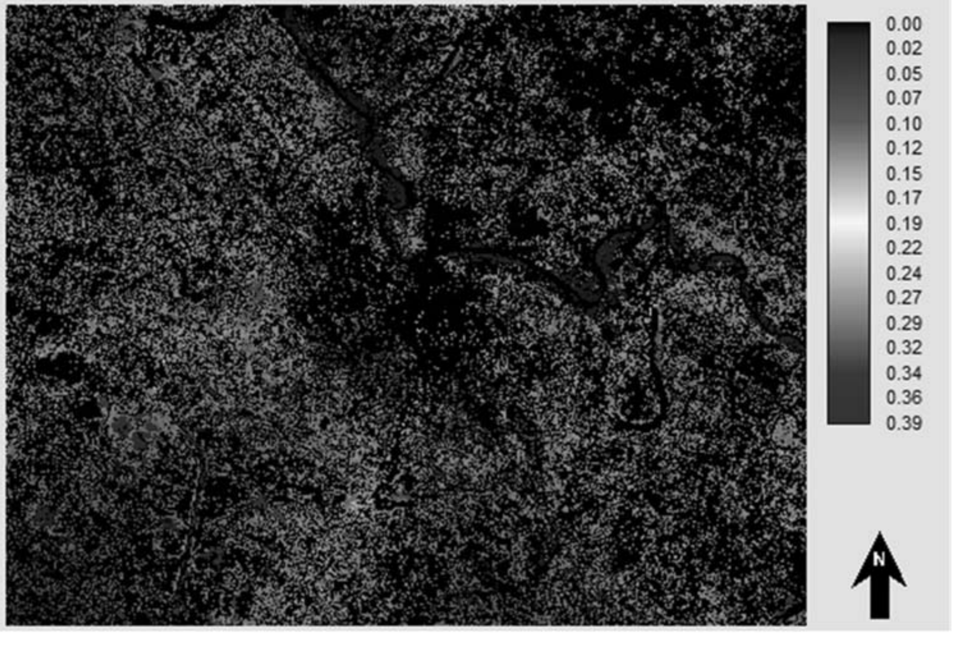

Figure 11. Projected Markov conditional probability matrices for 2035.

Table 5. Projected land use and cover of the study area for 2035

LU/LC Class	Agriculture land	Vegetation	Scrubs	Fallow land	Waste land	Built up area	Water bodies	River bed
Area (Sq.Km.)	181.5093	162.3726	24.1398	30.2382	22.9347	55.7298	11.0988	4.302
Area (In %)	36.87	32.97	4.90	6.14	4.66	11.32	2.26	0.87

Source: All the information given in the tables are collected based on satellite data classification & analysis.

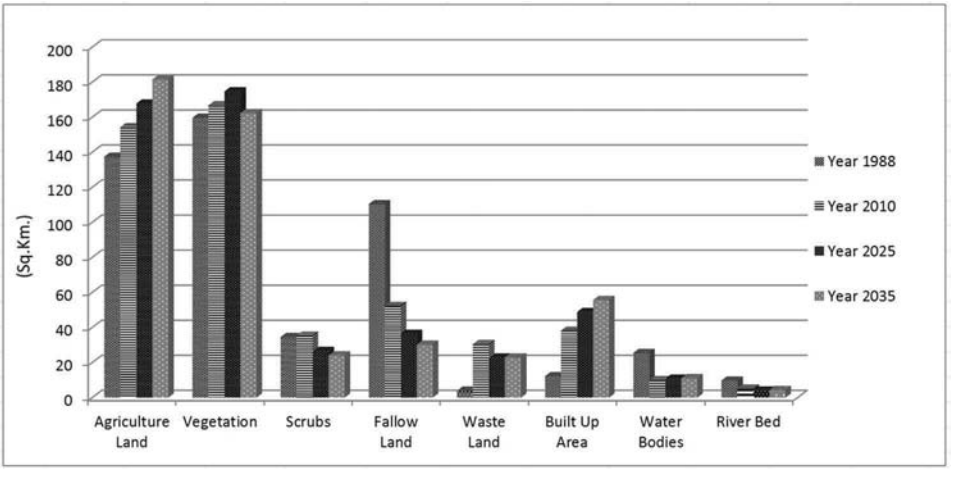

Figure 12. Area statistics of different land uses categories among 1988, 2010, 2025 and 2035.

Accuracy Assessment

There are always ambiguities in acceptability of the result, particularly when the result predicts future scenario based on disturbed variables. But there are again some scopes of checking the results in GIS techniques. The location accuracy of land use change model of Landsat TM image of 1988 and 2010 was done using the road network which was generated using Google Earth.

The prediction of land use land cover change was done on neural network built-in module in the Selva version of IDRISI. Iterations considered were 10000-sufficient for running the data. The accuracy was obtained as 72.28% for all the conversion types (Figure 13).

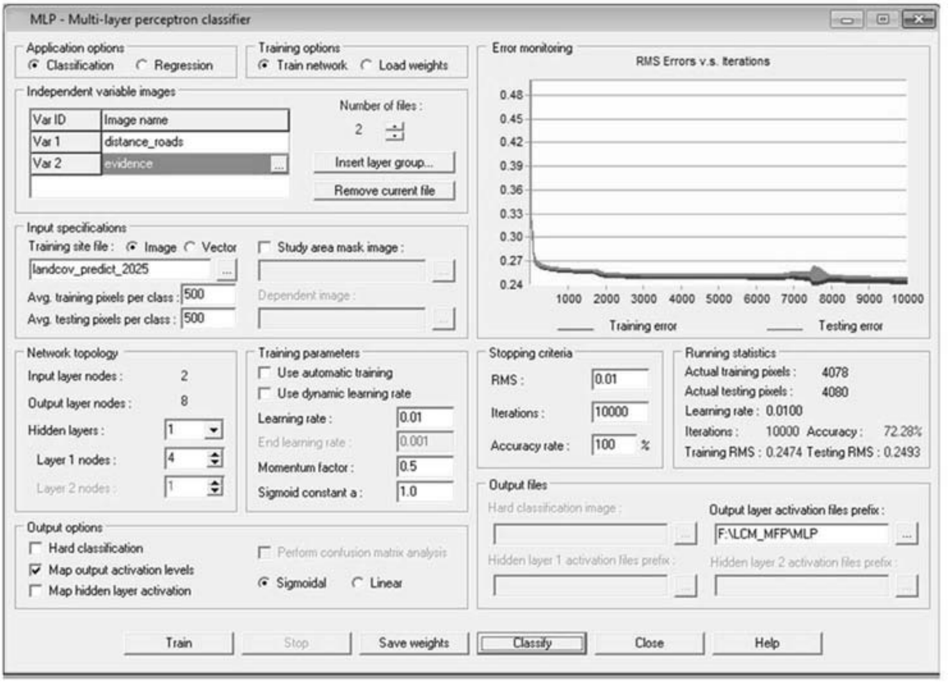

Figure 13.Process for accuracy assessment of MLP classifier.

Conclusion

This study has revealed that there are changes in many land use cover categories over the year (1988- 2010). This paper is described a method named as "Multi-Layer Perceptron Markov Chain (MLP_Markov)" model to simulate the land cover map of 2010 being persistent with the inherent changing characteristics. Then this model has been used to predict future land use and land cover maps of year 2025 and 2035 based on the data. It clearly shows that built up area and agriculture land is increasing, while there are fluctuating trends for other land cover categories.

Also the present study demonstrated the efficiency of remote sensing data in the study of land use and land cover changes. It gives a fairly good understanding of land use/land cover changes for a period of two decades, which in turn will be very helpful for local administrative bodies for decision makings in the district.

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