Markov Method Integration with Multi-layer Perceptron Classifier for Simulation of Urban Growth of Jaipur City

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Abstract: - The aim of this study is to simulate urban growth using multiple land use data of 1989, 2000 and 2002 by integration of multi-layer perceptron (MLP) neural network and markov model. Simulation of urban growth using markov model, is difficult to integrate spatial variable and transition rules within it. In this research, MLP used to create transition potential areas for each land use class by including spatial variables or factors those affect and influence the urban growth. Multi-layer perceptron neural network approach has been used to calculate conversion probabilities for urban growth. These conversion probabilities have been used in markov model for urban growth simulation. This method has been implemented to Jaipur city of India to find out urban growth. The simulated urban growth for 2002 is cross tabulated and validate with actual urban growth of 2002. Urban area class in actual data of 2002 is 12,630 hectare, where as 12,200 hectare in simulated data. Results indicating good matching between actual and simulated urban with difference of only 3% in total urban area and 94% accuracy in 1*1 pixel matching in both data.

Key-Words: - Urban Growth, Multi-Layer Perceptron classifier, Remote Sensing, and Markov Method

1 Introduction

Urbanization is the social process whereby cities grow and societies become more urban. Modeling of urbanization requires spatially explicit factors. There are many factors which influence the urbanization like population growth, good prospects for livelihood, good availability of facilities etc. The concentration of urban population is becoming particularly characteristic for developing countries [7], [10], [18]. According UN-HABITAT in 2010, 30% of total populations live in cities and which will increase up to 34% in 2020 in India. Cities in the developing countries are already faced by enormous backlogs in shelter, infrastructure and services and confronted with increasingly overcrowded transportation systems, insufficient water supply, deteriorating sanitation and environmental pollution [11], [14], [18].Urban growth evaluation and estimation is very important for urban environment. Urban growth knowledge helps to planning infrastructure development of city [7],[10],[18], [22].

The conventional surveying and mapping techniques are time consuming and costly and these information are not readily available for most of the urban centers, especially in the developing countries [7],[10], [18]. Because of it there is increase in research interest towards the use of remote sensing techniques. Remote sensing techniques for mapping urban areas have been used since 1950s. Mapping from remote sensing techniques have very much advantage because it is synoptic, repetitive and multi temporal. It is a versatile tool for mapping and monitoring of natural features as well as manmade features [6], [9], [10], [12], [14], [18].

Artificial neural networks (ANN) are powerful tools that use a machine learning approach to quantify and model complex behavior and patterns [1], [5], [11], [16], [17], [21]. Multi-layer perceptron (MLP) classifier is based on ANNs used for remote sensing data interpretation. It has been motivated by the realization that the human brain is very efficient at processing vast quantities of data from a variety of different sources. Multi-layer perceptron classifiers are more efficient and require less data for training [1], [4], [5], [14].The use of MLP has increased substantially over the last several years because of the advances in computing performance and the increased availability of powerful and flexible software [1], [4], [11],[16], [17], [21].

To understand the stochastic nature and simulate the urban growth, Markov model is very useful, to simulate landscape change analyze land use conversions, trends and dimension of changes [2], [9], [15], [22]. Due to advancement in GIS technology and its interconnectivity with remote sensing Markov model has become more popular [3]. Most of the researches used remote sensing data, classified using supervised and unsupervised method for land use/land cover data preparation [7], [15], [22]. Markov method has been used for simulation of land use on those classified data. These researches did not consider the policies and variable that affect the transition of land use. So this study focuses to simulate and verify urban growth by including of variables those influence the urban growth, such as proximity to city centre, distance from road, proximity to city urban, slope etc. To include these variables and find out transition potential areas, multi-layer perceptron neural network approach has been used.

2 Methods and Material

2.1 Data used

Jaipur city is located in India approximately between Latitude 27.88 N, Longitude 74.88 E / Latitude 26.42N Longitude 76.29 E. Jaipur, the pink city was founded in 1727 by Maharaja Sawai Jai Singh II at that time total area was approx. 4.80 km sq.

Landsat satellite data of 1989, 2000 and 2002 has been used for land use data preparation using supervised maximum likelihood and K-means clustering unsupervised method[4],[7],[9],[10],[18], [22].Digital elevation model (DEM) has been prepared using toposheets. Slope and hill shade generated using DEM. Road data has been created using toposheets and then updated using satellite data.

supervised and unsupervised technique. To maintain accuracy and similarity in classification same method has been implemented for land use classification for all the three years data. The land use change analysis performed using 1989 and 2000 data then potential changes for each class have been demarcated. Spatial maps of different variables have been created based on distance and land use categories such as distance from road, distance from city centre, and distance from urban periphery of 1989. Slopes and hill shades maps are prepared using digital elevation model.

Samples has been selected for each class transition are extracted from the multi land cover maps provided of areas that underwent the transitions being modeled as well as areas that were eligible to change, but did not change during the period.

Different variables are selected using Cramer's V method and inserted as layers in MLP classifier for each transition of each land use class to other class such as transition from forest to urban area during 1989-2000 [19], [20].

The multi layer perceptron neural network is used for each transition among classes of land use to locate the transition potential areas by integrating these variables.

For simulation of land use, markov model has been used on these transition potential areas of land use. Flow chart of research flow has been shown in Figure 1.

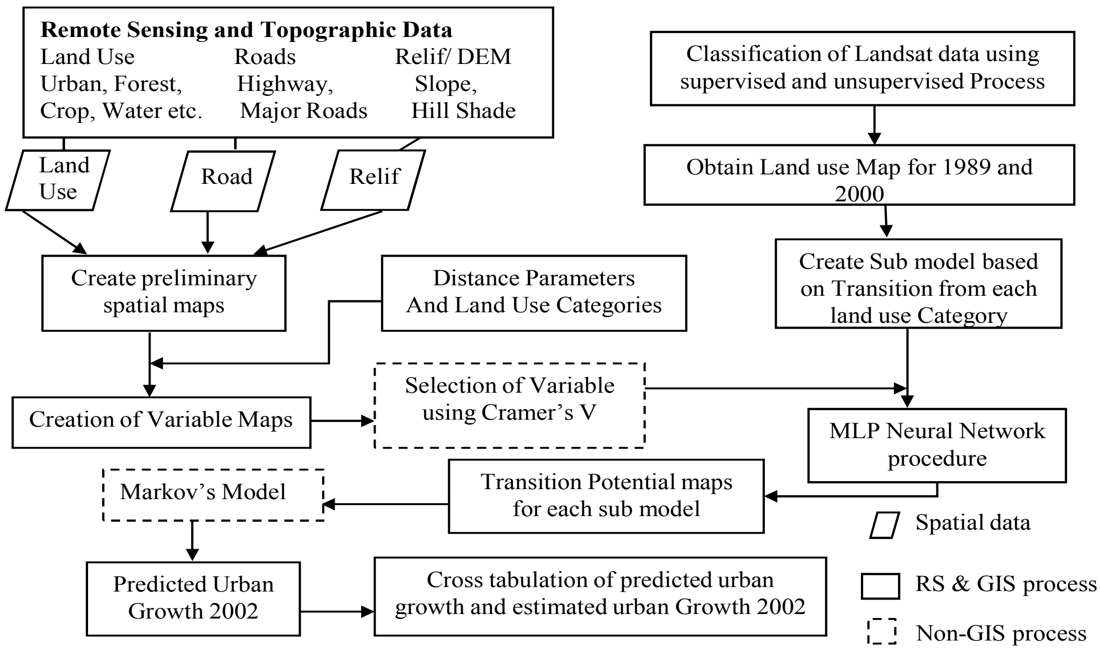

Fig. 1 Method Flow Diagram

2.2 Simulation of Urban Growth

The urban growth is simulated by classifying land use data in urban area, forest, crop land and barren land of 1989, 2000 and 2002 satellite data using combination of

2.2.1 Test and selection of variable using Cramer's V

Cramer's V is a statistic measuring the strength of association or dependency between two categorical variables. It is used as post-test to determine strengths of association after chi-square has determined [19], [20].

V is calculated by first calculating chi-square, then using the following Eq. 1.

$$V = \mathrm{Sqrt}\,(c^2 / (n\,(k - 1))) \quad (1)$$

Where c^2 is chi-square and k is the number of rows or columns in the table.

2.2.2 Multi-Layer Perceptron Neural Network

Artificial neural networks (ANN) have undergone vigorous development in the last decade, and the most widely experimented ANN with remotely sensed data is multi-layer perceptrons (MLP) using back propagation (BP) as a training algorithm. A neural network consists of a number of interconnected nodes. Each node is simple processing element that responds to the weighted inputs it receives from other nodes. A typical BP algorithm contains input layer, hidden layer and output layer [1], [5], [8], [11].

Back propagation algorithm involves two major steps, forward and backward propagation. During algorithm, the input layer fed by sample i.e. feature within a single pixel and the receiving node sum up the weighted signals received from all nodes from which it is connected in the preceding layer. The weight for each node receives is according to Eq.2.

$$net_j = \sum_{i=1}^{m} w_{ij} o_i \quad (2)$$

Where w_{ij} represents weight between node i and node j, and o_i is the output from node i. The output then from a given node j is then computed from Eq.3.

$$o_j = f(net_j) \quad (3)$$

The function f is a non-linear sigmoidal function that is used for inputs before the signal passes to the next layer [1]. The activities of the output nodes are compared with their expected activities after completion of the forward pass. Each node is associated with a class in the output layer. Each output node will generate a value when a pattern introduced to the network that shows the similarity between the input pattern and the corresponding class. In some circumstances, the calculated output will differ from the expected outcome; The difference is associated with error in the network. The weights are modified after all observations are introduced to the network, according to delta rule shown in Eq. 4, so the total error is distributed among all the nodes in the network.

$$\Delta w_{ji(t+1)} = \eta \delta_{ji} o_i + \mu \Delta w_{ji(t)} \quad (4)$$

Where η is learning rate, μ is a momentum factor, and δ is the computed error.

The target of network training is to build a model of the data generating process so that the network can generalize and simulate outputs from inputs [1]. The forward and backward passes continue until the network has "learned" the characteristics of all the classes and until the error stabilized at an acceptable magnitude.

2.3 Simulation of Urban Growth using Markov Model

A Markovian process is one in which the state of a system can be determined by knowing its previous state and the probability of transitioning from each state to each other state. The earlier and later land cover maps has been used in markov process, markov helps to figures out exactly how much land would be expected to transition from the later date to the simulation date based on the transition potentials into the future [3], [7], [10]. Transition potential area prepared using MLP has been used in markov model to simulate land use.

3 Result and Discussion

Land use data prepared for 1989, 2000 and 2002 with accuracy of 92%, 91% and 94% respectively. These land use data has been used for land use change analysis and verification of simulated data for 2002. Urban growth simulated and verified for 2002 using 1989 and 2000 data. Generated spatial variable data used in MLP for creation of transition potential areas as distance from roads, distance from city urban, slope, hill shade, digital elevation model and distance from forest. Cramer's V is checked for all the variables to select important variables. Overall value of Cramer's V is highest for distance from city urban (0.1481) followed by distance from roads (0.1207), distance from forest (0.0876) and so on. MLP classifier used for each sub transition from one class to other class and accuracy level for each classification of transitional area is maintained minimum to 85%. Sample size for training pixel has been selected on the basis of cells of each class transitioned during 1989-2002.Transitional potential areas have been prepared for transition of each class of land use. On the basis of those areas transition matrix has been prepared and used in markov model to simulate land use. Simulated land use map and actual land use map have shown in Figure2. Urban growth from 2000 is mostly on the periphery of current urban and mainly along the roads. There are few new developments in sub urban area showing impacts of road and infrastructure developments in southern part of city. Urban growth simulated for 2002, due to availability of data and this also allow to verifying the methodology adopted for the simulation of land use data. By looking at the both maps in Figure 2 one can say that there is no much difference in dimension and magnitude of actual land use map and simulated land use map. There is a very little difference in density of urban area in both

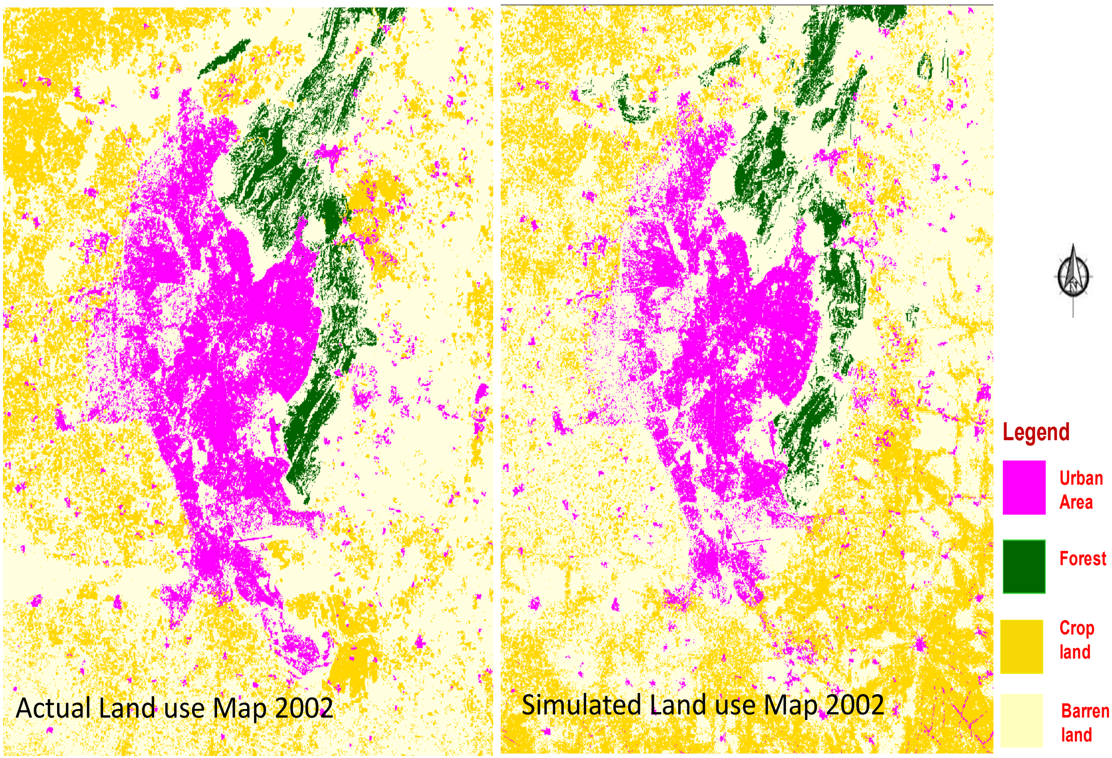

Fig. 2 Difference between actual and simulated land use map of 2002

Table 1 Change scenario of actual and simulated land use of 2002 (Unit – Hectare)

Land Use Change Data for 2002					
Land Use Class	**Actual Land use Data (Ha.)**	**%from Total Study Area**	**Simulated Land Use Data (Ha.)**	**%from Total Study Area**	**% Accuracy between Two data**
Forest	4444.47	4.10	3843.36	3.55	86.47
Urban Area	*12630.69*	*11.69*	*12200.94*	*11.27*	*96.59*
Crop Land	21533.49	19.90	25958.70	23.99	82.95
Barren Land	69357.69	64.10	66195.09	61.17	95.44

data, where as actual land use showing high density of urban compares to simulated urban area. In the southern part of city actual data is showing more density in urban area class compare to simulate one, this may be due to implementation of policies for that area such as industrial zone development, as cross checked with Google Earth and found it is a industrial development. Total urban area in actual land use data is 12,630.69 hectare and which is just 3% less than the simulated data i.e. 12,200.94 hectare shown in Table 1. Instead of urban area class, in other land use classes, there is quite big difference in their area, especially in the vegetation cover classes such as crop land and forest land. This is may be due to seasonal variation of data used. The main concentration in this research was urban growth so seasonal variation didn't considered much. Random points are generated for the urban area to check the accuracy between actual and simulate urban area. In 750 random points only 625 points are true for both data. The pixel accuracy has been validated and cross tabulated for the urban area between actual and simulated data using GIS tools. One by one pixel accuracy for this data is 94.1% as shown in Table 2. Urban area annual growth rate for simulated urban of 2002 was 6.2%, where as 8% for actual urban of 2002 from 2000. This is referred to steady and consistent urban growth for the city.

Table 2 Cross Tabulated data for Urban Area Class 2002

Cross Tabulation of Actual Urban and Simulated Urban -2002				
		Pixels in Actual Urban		Total Pixels in Simulated Urban
		Non-Urban	Urban	
Pixels in Simulated Urban	Non-Urban		12919	
	Urban	8144	127422	135566
	Total Pixels in Actual Urban		140341	
Pixel Matching Percentage (based on simulated data)			94%	
Value = No. of Cell/Pixels 1 Cell/ Pixel = 0.09 hectare				

4 Conclusion

Jaipur city is going through fast urban growth. The city area grew by 145% from 1989 to 2002 in just 13years. The urban growth is maximum on sub urban areas but as well as density is also increased in city centre areas. Urban growth has been found in the almost all the direction of city. Mostly sub urban growth showing impact of highways and industrial developments of city.

Urban growth estimation and simulation in developing countries can be dependent on data availability, which can be easily gathered using widely available Satellite data and it can be integrated with GIS and automated databases with good quality levels.

Multi layer perceptron classifier approach used here has shown good results for urban growth by integrating variables those that not only affect but also influence the transition of land and urban growth. The analysis results of MLP integrated with markov model are showing high level of accuracy for the simulation of the urban growth. Markov chain is widely used model, which help to describe pattern of urban growth.

The results are satisfactory enough to retain this method for the starting point to next step to simulate urban growth for near future. However it is also important to simulate urban growth and checked with the actual urban growth for some other years and also need to include more policies that lead urban growth of city. Urban growth estimation and find out the dimension of growth is necessary for urban planning and infrastructure development. This methodology shows good simulation results for the urban area of 2002 and can be used for optimal planning of the land and urban growth. It would be more interesting to use this method with high resolution satellite data such as 5m and 10m spatial resolution.

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