ISSN XXXX XXXX © 2017 IJESC

Research Article Volume 7 Issue No.11

Prediction of Land Cover Changes of Jodhpur City Using Cellular Automata Markov Modelling Techniques

S.L. Borana[1], S.K.Yadav[2]
Scientist
Department of Remote Sensing Group
Defence Laboratory, Jodhpur, Rajasthan, India

Abstract:
This study used a CA (Cellular Automata)–Markov process model for temporal analysis of urban land use change in Jodhpur city. Land use changes area in the study were examined and calculated using Remote sensing satellite data and Geographical information systems (GIS) technology for a time period of 1990-2000. A Multi-Criteria Evaluation (MCE) used to create suitability predicted images. Transition potential matrix was derived for urban land cover distribution for future prediction for the year 2020, also the changes in pattern of urban growth are observed. Major expansions in urban areas were observed around east-south direction borders of the city. Scattered urban built-up growth was also predicted in the peripheral of the city. This study provides better approaches for environmental and urban land management for land use to make an optimised balance between urban progress and natural resources.

Keywords: CA-Markov Modelling, Land cover change, GIS, Prediction.

I. INTRODUCTION

Modeling land cover change plays a significant role for understanding impacts of the changes. This shall also help for effective environmental, development planning and also in decision making. A number of modeling approaches have come to exist in order to achieve all this. The utility of GIS, RS and modeling in urban land use change is carried out in this study. One of the normally used models, Cellular Automata Markov (CA_Markov), is applied in this study. The model output is compared and validated with base map. The model has been applied for further simulations once the results of the validation are found to be successful. IDRISI is the industry leader in raster analytical functionality covering the full spectrum of GIS and RS needs (Eastman, 2001). Some of the functionalities included in the package are image analysis, change and time series analysis, spatial modeling, decision support system, etc. These are essential for environmental modeling and natural resource management. Some of the modeling techniques embedded in IDRISI Selva is logistic regression, stochastic choice and CA_Markov chain analysis.

II. STUDY SITE DESCRIPTION

Jodhpur is centrally situated in western region of the Rajasthan state with location at 26ºN 18' latitude and 73º E 04' and at an average altitude of 224m above mean sea level. In general, the contours are falling from North to South and from North to Southeast with maximum level of 370m and minimum of 210m. The present population is about 1.05 million and admeasures 230sq.km. Alongside, Jodhpur has been functioning as one of the engines powering the Rajasthan state economy. The establishment of large-scale core industries has led to the growth of ancillary and small-scale industries in and around this industrial belt. The landscape saw significant changes with each passing year as long stretches of farmland giving way to clusters of enclosed factory campuses. The location site map is shown in Fig.-1.

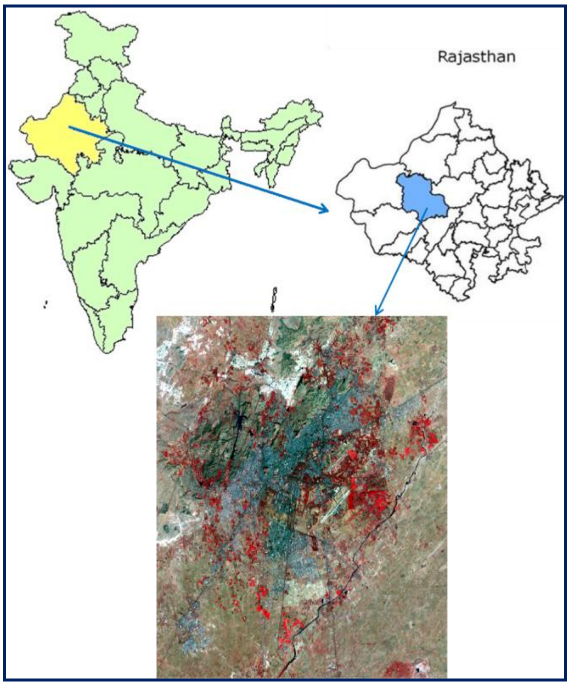

Figure.1. Study Map.

III. DATA USED AND METHODOLOGY:

Remote sensing Landsat TM satellite data scene (1990 and 2000) of False Colour Composite (FCC) and true color composite (TCC) with 30m spatial resolution were used in this study (Table-1). The SoI maps, ground truth data were used for land use classification and accuracy analysis. Ancillary data, such as a digital elevation model (DEM), major road networks were also included into the analysis. Satellite images were processed using ERDAS software for geometrical correction, noise removal and image classification. Major category of land classes used are built-up area, vegetation, open area, mining area and water body. Arc GIS software is used for Preparation of site of the study area, Kappa can be used as a measure of agreement between model predictions and reality (Congalton 1991) or to determine if the values contained in an error matrix represent a result significantly better than random (Jensen 1996). The research methodology adopted is given in Fig.2. Analysis with CA-Markov module was carried out, which uses the output from Markov Chain analysis and transition suitability image collection, and used a contiguity filter. The rule states that a pixel that is near one specific land cover built-up area is more likely to become that category than a pixel that is farther.

Table.1. The Satellite Data used.

RS Data	Resolution	Path/Row	Acquisition Date
Landsat TM	30m	149/42	Oct1990
Landsat TM	30m	149/42	Oct 2000
Landsat TM	30m	149/42	Oct 2010

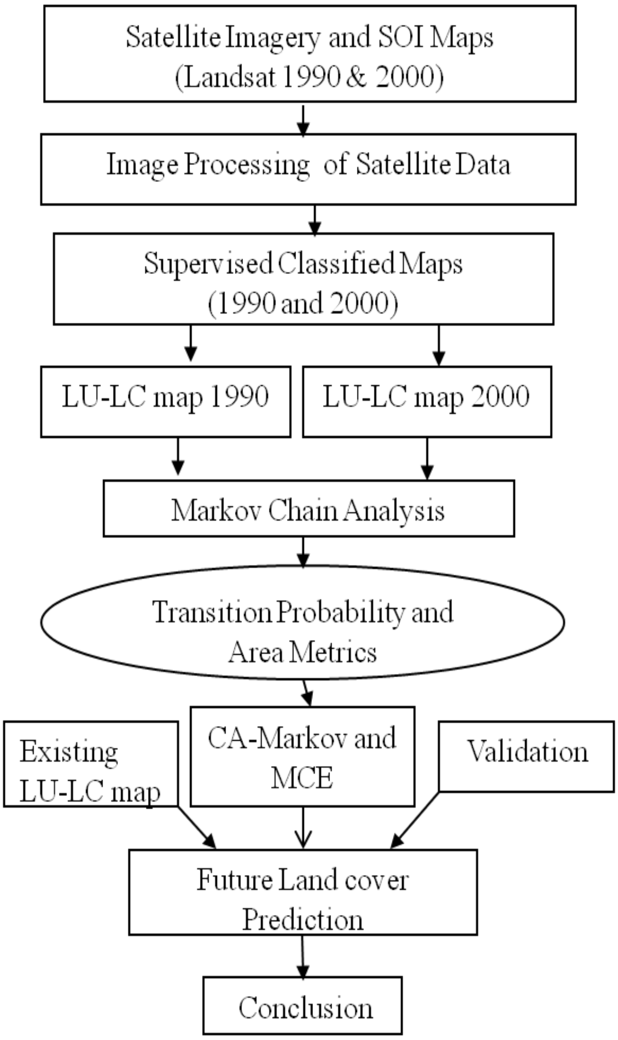

Figure.2. Research Methodology

IV. RESULTS AND DISCUSSION

Land cover classification mapping on satellite images (Fig.3) was carried out using supervised method. This method created land cover maps with high accuracies. The overall accuracy of the land cover maps for 1990 and 2000 were 84.05 %, and 85.71%, respectively. The Kappa index for the 1990 and 2000. land cover maps were found to be 0.79, and 0.81.

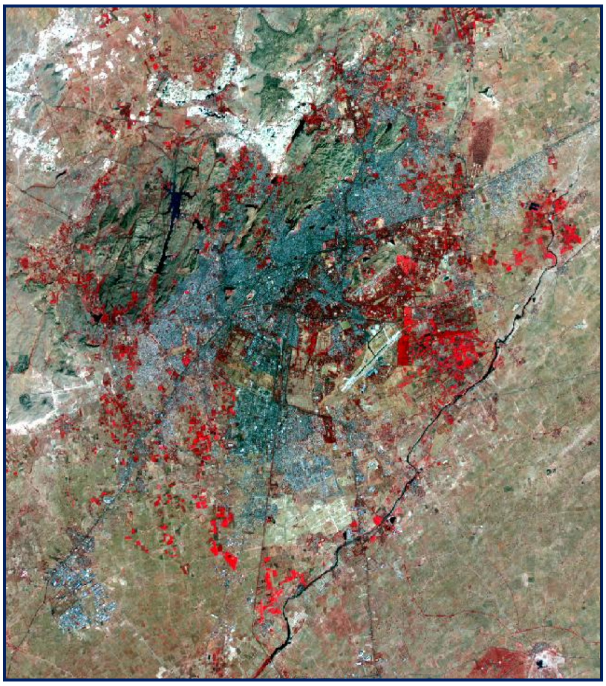

Figure.3. Satellite Image of the Jodhpur City.

- **Suitability Maps for Land Cover Classes:** Suitability map was computed using the MCE method by integrating natural driver dataset (major roads, water body, and slope). Boolean images for land cover type of Built-up, Mining area, Vegetation & other are and driver have been prepared using linear type fuzzy membership function available in IDRISI (Paegelow and Olmedo, 2005); a value 255 indicates the highest suitability and a value 0 indicates the lowest suitability of that particular category (Fig.4). The values 1 represent the areas of interest (the particular land cover type) and the values 0 represent the areas of no interest for these Boolean images. Distance images for each of these Boolean land cover images and drivers have been generated (Fig.6). These distance images are important to measure the suitability values for the pixels of land cover classes.

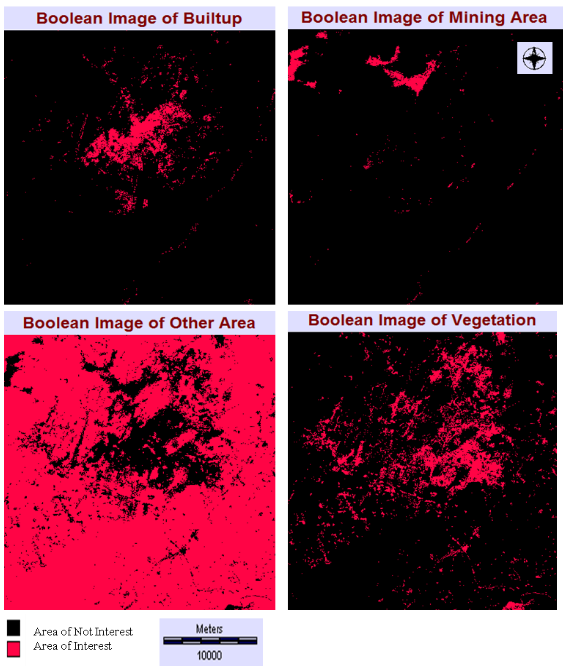

Figure.4. Boolean Images of land cover Types (2000).

The distance images are produced using simple Euclidean distance function which measures the distance between each cell from the featured image. The unit of measurement is meter. The lowest and highest values obtained from the distance images have been used as the input for fuzzy set membership analysis(Fig.7).

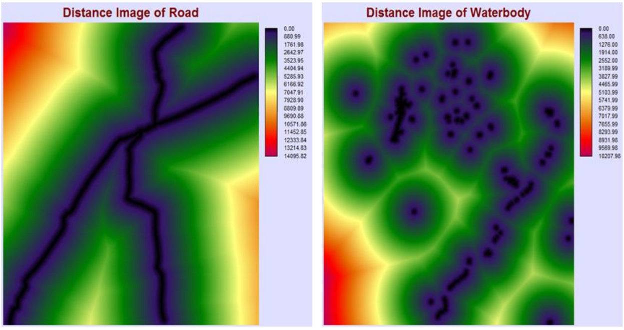

Figure.5. Distance Images of Road and Waterbody

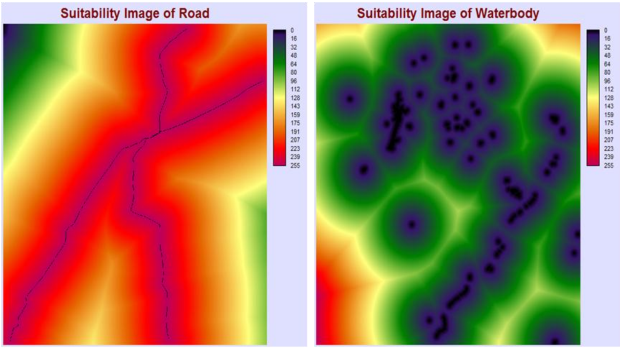

Figure.6. Suitability Images of Road and Waterbody

- **Weighed Linear Combination (WLC) Method:** All Boolean land cover images have been standardized to the same continuous suitability scale (0-255) using process of fuzzy set membership analysis.The suitability images of all land cover types are known as 'Factor Images'. Equal weights have been assigned to all the factor images for this research purpose. The reason behind this is that all the land cover types are of same importance for predicting the future. Aggregated multi-criteria output image has been generated (Fig.8) using WLC.

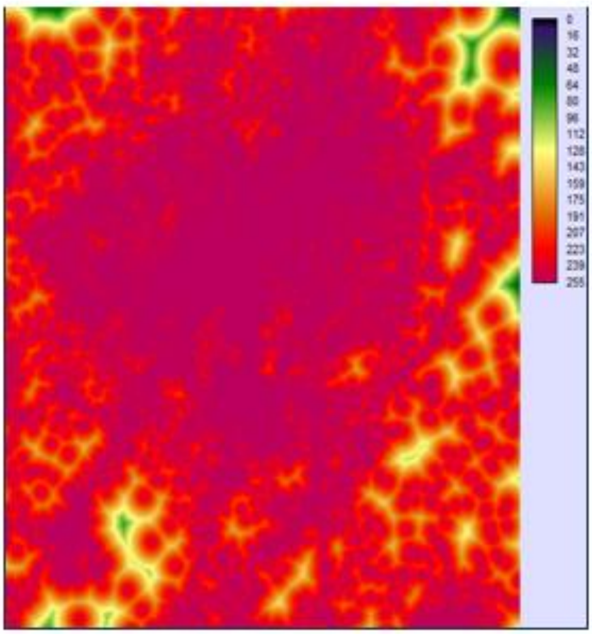

Figure.7. Aggregated Land Cover Suitability Map (2000).

- **Model Validation and Future Prediction**: The overall agreement is reported by three components: Agreement due to chance, agreement due to the predicted quantity of each land category and agreement due to the predicted location of each land category. The overall disagreement is budgeted by two components: Disagreement due to the predicted location of each land category and disagreement due to the predicted quantity of each land category. The interpretation of agreement is the proportion of pixels classified correctly, and the interpretation of disagreement is the proportion of pixels classified incorrectly. The values of allocation and quantity disagreement have been computed by entering the cross-tabulation matrix resulted from the comparison of 2010 classification result and the simulation results predicted. The assessment result is given in the table that the main disagreement between the maps was due to allocation which is around 10.79%. The quantity disagreement was only 08.46 % (Table-2). Also the results of disagreement components indicate that the disagreement due to location is greater than the disagreement due to quantity. From these values it is clear that the main part of error is associated with the simulation of location. These facts show that in our example, CA-Markov performed better at predicting the quantity of pixels rather than the location of pixels. The CA_Markov predicted final land cover image 2020 of Study area is demonstrated in Fig.10. The predicted map of 2020 reveals that 58 per cent of the total area will be occupied by built-up area cover type.

Table.2. Comparison Area statistics of Classified and Projected maps

Agreement or disagreement	Value (%)
Chance Agreement	20.00
Quantity Agreement	19.79
Quantity Disagree	08.46
Allocation Agreement	42.95
Allocation Disagree	10.79

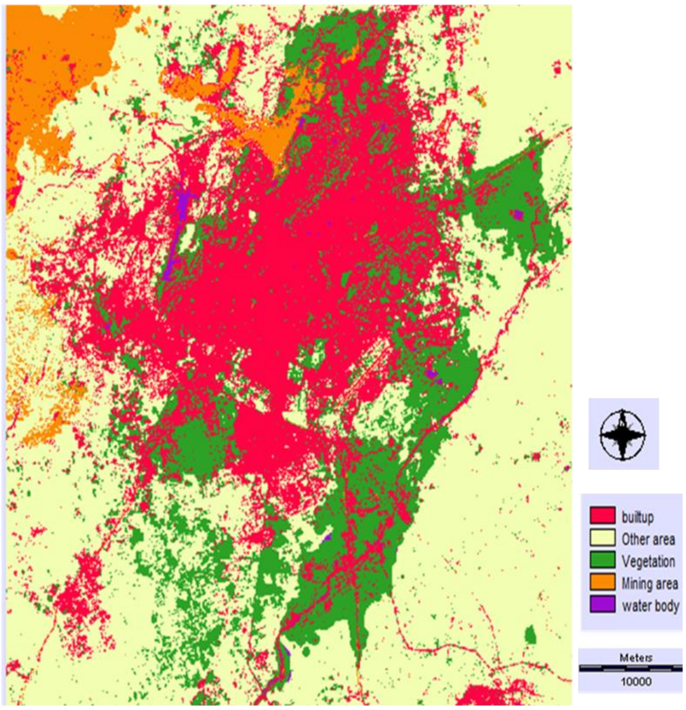

Figure.8. CA_Markov Projected Land Cover Map for year 2020.

V. CONCLUSION

Land cover changes particular in urban catchment area has been rapidly occur. Land cover changes occur as a result of increasing demand for built-up area. This study aims to predict land cover changes using coupling of Markov chains and cellular automata. Markov chains has a good ability to predict the probability of change statistically while cellular automata believed as a powerful method in reading the spatial patterns of change. combination of two methods could provide better prediction model rather than just using it separately. Urban land use change for the year 2020 was modeled using a Cellular Automata based approach. The prediction model was validated using existing land cover data and shown a satisfactory kappa coefficient. Output can easily be used future prediction of land cover changes using CA Markov modelling.

VI. ACKNOWLEDGMENT

The authors are thankful to the Director DL, Jodhpur and Head, Department of Mining Engineering, Jai Narain Vyas University, Jodhpur for help and encouragement during the study.

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