SETTLEMENT GROWTH PREDICTION USING NEURAL NETWORK AND CELLULAR AUTOMATA

Nagaratna P Hegde, * I V Muralikrishna, ** K V Chalapatirao
Associate Professor, CSE Dept, VCE, Hyderabad-500031, nagaratnaph@Yahoo.Com
*Director, IST, JNTU, Hyderabad-500075, ivm@Ieee.Org
**Dean CSE, C V R College Of Engg. Hyderabad
chalapatiraokv@Gmail.Com

ABSTRACT

The significant objective of this paper is to describe how Cellular Automata (CA) can be used to predict land use land change in the settlement growth and show the advantage of integrating the Neural Network with CA. Cellular automata have been utilized as a prediction technique in the study of an impressively wide range of dynamic phenomena. A spatial simulation model comprises an assortment of processes performed on spatial data that will produce information, by and large in the form of a map. CA models exude superior performance in simulating land changes compared to conventional models .
CA are much simpler than complex mathematical equations and produce results that are more meaningful and useful. Temporal and spatial complexities of systems can be efficiently modelled by precise definition of transition rules in CA models. GIS is a technology that is employed to view and analyse data from a geographic perspective. In practice, grid cells covers the selected area of study. Consequently, specific ground surface attribute value of interest occurring at the centre of each cell point is recorded as the value for that cell.

Simulation is carried out using traditional CA and Neural Network based CA for the settlement growth for an artificial city and real city. A number of land use sprawl parameters, and different size and shape of neighborhood with some testing constraints are used in this simulation. The results reveal that neural network CA method is more appropriate than traditional CA for predicting the settlement growth.

Key words : *Geographic Information Systems, Simulation, Cellular Automata, Neural Network*

1. INTRODUCTION

Cellular automata (CA) are a raster-based tool that can effectively be used for modelling cities and land use changes. CA models are bottom-up approaches as neighbourhood or local interactions can give rise to the formation of complex global patterns. CA models in general are used to predict land development which is a historically dependent process in which development in the past consequently influences the future through local interactions among land parcels as studied by Wu and Webster 1998. In CA simulation the outcome at the previous iteration has important effects on the outcome at the consecutive iteration. Complex global patterns can be formed after many iterations of a simulation. Wu (1998) has divulged that some unexpected features can possibly emerge during the simulation by properly defining transition rules

The prediction of land use changes by simulation can facilitate to assess development impacts, prepare land use plans and seek optimal land use patterns. It can forecast the consequences of specific human behaviour and land use policies. Land use changes are predicted in accordance with the independent spatial variables that are generated from standard GIS analysis tools.

Mathematical equations in the form of partial or ordinary differential equations have been the underlying tools behind spatial prediction models. Approaches based on cellular automata models are proposed herein to replace the conventional tools. Issues such as the definition of transition rules, computer implementation with raster geographical information systems and model verification are discussed.

1.1 CELLULAR AUTOMATA

Ulam and Von Neumann originally conceived cellular Automata (CA) models in the 1940s to provide a formal framework for investigating the behavior of complex, extended systems. CA is dynamic, discrete space and time systems. A cellular automaton system consists of a regular grid of cells, each of which can be in one of a finite number of k possible states, updated synchronously in discrete time steps according to a local, identical interaction rule. The state of a cell is determined by the previous states of a surrounding neighbourhood of cells.

The types of spatial problems that can be addressed using cellular automata are

- Spatially complex systems (e.g., landscape processes)
- Discrete entity modelling in space and time (e.g., ecological systems, population dynamics)
- Emergent phenomena (e.g., evolution, earthquakes)

CA models have better modelling capability than general GIS in the simulation of settlement growth and land use changes. CA based models are used for studying temporal dynamics. Spatial variables in CA models are dynamically updated during iterative looping so that the results are not deterministic. Some realistic and new features can emerge during the processes of simulation, e.g. formation of new aggregate centres (Wu 1998) and fractal properties as given by White and Engelen (1993).The general GIS models have snags in simulating complex land dynamics without using local rules and iterative looping and they usually use static spatial variables in the simulation.

Transition probabilities for the typical CA model depend on the state of a cell, the state of its surrounding cells, the physical characteristics of the cell like terrain, soil quality, vegetation, hydrology, demographic characteristics and the weights associated with the neighbourhood context of the cell i.e. proximity to other villages and the time since settlement. These weights and neighbourhood conditions are determined from empirical analyses of LUCC based on social survey data. The GIS database represents resource endowments of a site, and the spatial linkages between villages, land parcels, and other critical landscape features.

It is also difficult to capture non-linear features that are presented in many geographical phenomena. It is complicated to explain the theoretical and intuitive meaning when the land use change simulation is purely based on GIS modelling.

Although CA has many advantages, determining their parameter values is a major problem. Simulation of settlement growth deals with the binary state of being urbanized or not. CA models become considerably more complex when there are multiple land uses, such as vacant, residential, commercial, housing and transportation land uses. There are numerous parameters, which need to be ascertained to reflect a particular land use change to be simulated and the range of possible model types is enormous. The contribution of each spatial variable to the simulation is quantified by its associated weight . There are thus numerous parameters to be defined before the simulation can be executed. Parameter values have great effects on the results of simulation. Different combinations of parameter values will lead to a totally divergent land use form as shown by Batty *et al.* 1999, Yeh and Li 2001.

In most situations, calibration of CA models is needed to ensure that the simulation can generate the results close to the reality. There are two major types of calibration methods for CA simulation. The general statistical methods may have some limitations when spatial factors and model structures are too complicated. They are invalid when spatial factors correlate with each other. They also have difficulties in handling poor and noisy data.

The other type of calibration is based on trial and error approaches. No strict mathematical methods are required for such calibration. A simple method proposed by Clarke *et al.* 1997, Ward *et al.* 2000 is to compare the simulation results visually using various combinations of parameter values. The 'best' set of parameter values is determined from a visual comparison. However, it is difficult to define the combinations when there are many variables, and to assess the results visually because the patterns are usually very complex. White *et al.* 1997 also propose an intuitive method by means of a trial and error approach to obtain a parameter matrix for urban simulation. The method is not based on strict mathematical methods and fine-tuning the calibration to get the matrix might take too much time. Clarke and Gaydos, 1998 developed a relatively robust method for calibrating CA models based on computer comparison. It calculates the fits between the observed historical data and various simulation results. The suitable set of parameter values is found based on the 'best' outcome of the various trials. The calibration is very computation-intensive although it seems to be sound in the search algorithms. The calibration needs a high-end workstation to run hundreds of hours before finding the 'best' outcome.

Problem with CA models is to define transition rules and model structures. Transition rules and model structures are usually application-dependent. White *et al.* 1997, Wu 1998, Batty *et al.* 1999 stated that although some CA models are generic in nature these models are substantially divergent in their forms. The variations are due to the existence of many possible ways of defining the transition rules and model structures. For example, Batty and Xie.1994. use nested neighbourhood space and a distance decay function from the seed of development to determine transition probability. Wu and Webster. 1998. define transition rules based on multicriteria evaluation (MCE) methods. White and Engle. 1993. shown that a predefined parameter matrix can be used to control development probability instead. Li and Yeh 2000 propose a gray-cell-based model to accommodate gradual urban conversion process. A series of constraints can be used to define transition rules for generating idealized urban forms (White *et al.* 1997, Li and Yeh 2000). Yeh and Li, 2001 , embedded different planning objectives and options in CA models to produce alternative plans. There is a dilemma in how to choose a suitable CA model because too many choices are presented. In this study the model is chosen which best fit actual map by the visual test.

2. METHODOLOGY

Cellular automata (CA) models consist of a simulation environment represented by a grid of space (raster), in which a set of transition rules determine the attribute of each given cell taking into account the attributes of cells in its vicinities. These models have been very successful in view of their operationally, simplicity and ability to embody both logics- and mathematics-based transition rules. Even in the simplest CA, complex global patterns can emerge directly from the application of local rules, and this property of emergent complexity that makes CA so fascinating and their usage so appealing.

The CA model in general works by

- Simulating the present by extrapolating from the past using the image time-series,
- Validating the simulations via the remotely sensed time-series of past conditions and through the available collection of field observations,
- Allowing the model to iterate to the year of choice in future
- Comparing model outputs to an autoregressive time-series approach for annual conditions

Simple algorithm for simulation using CA is as follows

```
For each iteration
{
  For every cell
  {
If   cell is the same state as its group made by several adjacent   neighbour cells keep the state of the cell   unchanged
       Else   choose the majority cells' value
  }
}
```

Empirical data should be used to calibrate CA models when the simulation is for real cities. Empirical data usually include the information of location, type and amount of land use conversion. This type of information can be conveniently obtained from satellite images by employing land use change detection methods. The 1989 and 2003 TM images are used as empirical data to reveal the fast land use conversion in the region. The change in the land use, based on the satellite data is listed in the Table 1.

Table 1 Difference In The Land Use.

Description	1989	2003	Change
	Area SQ.KM	Area SQ.KM	Area SQ.KM
Forest Land	4375.27	6739.76	-28.94
Land With Scrub	367.40	914.68	-547.27
Agriculture	9611.81	7577.81	2033.99

Settlement	114.51	67.02	47.49
Water Body	245.10	510.53	-265.43

2.2 TRADITIONAL CA MODELLING FOR SETTLEMENT

The formalism of CA described in the earlier section consisting of cell space, cell state, neighbourhood, transition rule adapted to meet the needs of land use changes in several ways as discussed below.

Cell space: Of course, the idea of an infinite spatial plain is unrealistic in a land context. Cellular automata are therefore constrained in their cell space to finite dimensions. The area of study i.e. Adilabad district is considered as cell space.

Cell states: In the traditional cellular automaton, cell states are discrete (and quite often binary): alive or dead, one or zero. There is little in the city, however, that is discrete. Most conditions--land use, land value, land coverage, demographic mix, density, etc.--are continuous, and of course urban spaces are multi-faceted. . An innovative adaptation to the traditional idea of the cell state is the introduction of fixed (states that cannot be altered by transition rules) and unfixed cell states, corresponding respectively, for example, to water sites or land values.

Neighbourhoods: The idea of the neighbourhood in the formal cellular automaton is rather restrictive. For Land Change, neighbourhoods come in many shapes, configurations, and sizes. Complaining that neighbourhoods given in Fig.1 such as the Moore and Von Neumann restrict the level of spatial variation that cellular automata models can generate. The notion of 'action-at-a-distance' with neighbourhoods is included here. In this study Moore neighbours are considered and less weight assigned to corner cells than the adjacent cells like the Von Neumann neighbours.

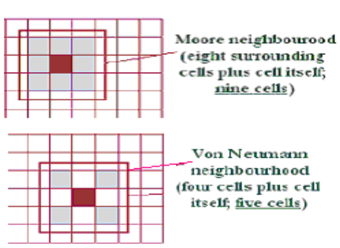

Fig. 1. Neighbourhood Used In The Simulation

Transition rules: Perhaps the greatest tinkering with cellular automata models comes in the formulation of the transition rules. It is here that cellular models of settlement change are generated with adherence to what we know in theory about land use and changes. Fig. 2. Gives the Procedure For Defining Transition Rules Within A Cellular Automata (CA) Land Use Change Model Based On An Empirical Characterization Of Neighbourhood Characteristics.

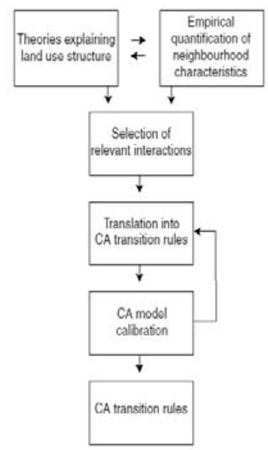

Fig. 2. Procedure followed for defining Transition rules

A generalized flowchart of the CA model used for spatial simulations of settlement growth prediction is given in Fig. 3

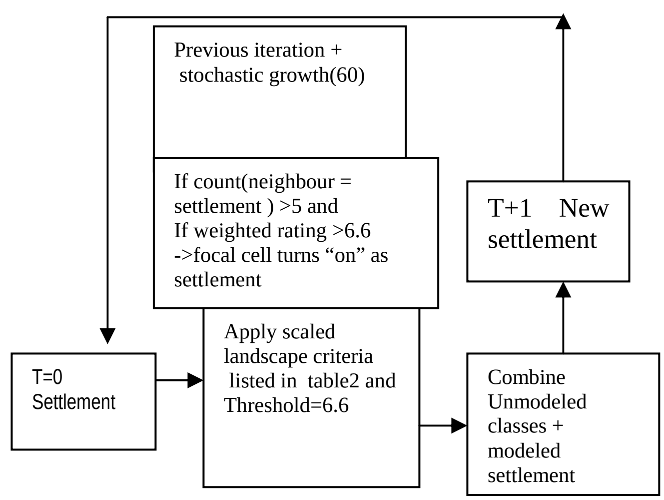

Fig. 3. Flowchart Of The Traditional CA Model

As discussed in the earlier section many site attributes affect the change in land uses.

Factors considered for the study is listed in Table 2.

CA include various distance-based variables, neighbourhood functions and physical properties. Studies have shown that these variables are closely related to agricultural land use changes. They are usually used as independent variables. These site attribute values are used in the transition rules of CA and calculated as below.

Factors considered for Modelling Settlement

- Travel distance to the nearest three communities as a measure of geographic accessibility -- lower values indicate a greater probability of change;
- Distance is computed as Euclidean distance to the nearest road -- lower values indicate a greater probability of change;
- Travel distance to the nearest tourist center as a measure of geographic accessibility -- lower values indicate a greater probability of change
- Travel distance to the nearest industry as a measure of geographic accessibility -- lower values indicate a greater probability of change
- Population of the major community is found using regression method. -- higher values indicate a greater change probability.
- Slope angle and soil moisture potential as indicators of resource endowments -- greater the slope angle, less is the probability of change, lower the soil moisture index, the greater the probability of change.
- Rain fall value at the place is considered -lower the rain fall then less chance of developing

- The model parameters included stochastic value 80 for random change.
- A 8 neighbourhood considered by 3 x 3 moving window as Moore neighbourhood

Each attribute is categorised based on the values obtained as in Table 2. Different rating is given to each site attribute depending on the category to which it belongs as in Table 3. These ratings are multiplied by weights in the transition rule. The contribution of each factor in changing land use is given by weights as in Table 4 . These weights are given by experts or calculated by literature.

Table 3 rating of the factors

Category → / Factors ↓	C1	C2	C 3	C4
Rainfall (RR)	7	8	5	0
Slope (RS)	11	10	3	2
Aspect(RAS)	7	12	4	1
Altitude(RAL)	12	8	3	2
Soil Moisture(RSM)	2	3	4	5
Dist From Road (RDR)	9	6	4	2
Dist From Water Body(RDW)	10	8	5	1
Dist From Tourist Center(RDT)	8	5	3	1
Dist From Industry(RDI)	5	4	3	0
Dist To Community(RDC)	4	8	13	15
Population(RP)	2	8	12	15

Table 4 Contribution Of The Each Factor For The Land Use

Factor	value
Rainfall(WR)	6
Slope(WS)	9
Aspect(WA)	5
Altitude(WAL)	4
Soil Moisture (WSM)	2
Dist from Road(W DR)	12
Dist from Waterbody(WDW)	4
Dist from tourist center(WDT)	5
Dist from industry (WDI)	3
ommunity(WDC)	6
Population(WP)	2

A masking threshold of 6.6 is used to specify in which cells above that value can change, whereas cells below that threshold cannot change. This threshold value is not used as probability values to derive the change itself, only as an indicator of whether change can occur. The relation among all the factors is defined with sum of weighted ratings (SW) in Equation1.

$$SW = (RR*WR+RS*WS+RAS*WAS+RAL*WAL+RSM*WSM+RDR*WDR+RDW*WDW+RDT*WDT+RDI*WDI+RP*WP+RDC*WDC+60)/12 \quad \text{---------(1)}$$

For corner cells in Moore neighbourhood value is considered as 0.5 times of the actual value. And for Von Neumann neighbourhood the actual distance only considered since it is having more effect on the center cell.

The transition rule Rule 1 is used to change to settlement if the condition is true. Otherwise cell remains in the same type.

Rule 1: -
*If weighted rating (*SW*)>6.6*
And
If count (neighbour=settlement)>5
Then focal cell change to settlement

2.2.1 CA AND GIS INTEGRATION

Most current GIS techniques have limitations in modelling changes in the landscape overtime, but the integration of CA and GIS has demonstrated considerable potential. The limitations of contemporary GIS include its poor ability to handle dynamic spatial models and poor handling of the temporal dimensions. By coupling GIS with CA, CA can serve as an analytical engine to provide flexible framework for the programming and running of dynamic spatial models.

There are two choices of developing spatial simulation models – loose-coupled integration or tight-coupled integration with GIS. If commercial GIS software meets the needs of building a simulation model, a tight-coupled integration is the ideal solution. Under this situation, spatial simulation model will be represented in GIS macro language, such as Arc/Info AML, or Arcview Avenue or ArcGIS Arcobjects VBA. When commercial GIS software could not handle the complexity of the spatial simulation model, and the model also requires some basic spatial data management, display and analysis, a loose-coupled approach usually is suggested. Loose-coupled integration develops the simulation model with C, C++, JAVA or other programming languages, and connects it with commercial GIS software. GIS saves the efforts to develop a spatial data view/analysis system.

2.2.2 THE GIS DATABASE FOR SITE ATTRIBUTES AND TRAINING DATA

A GIS database, which contains both raster and vector data built to provide the basic spatial information for the simulation. It contains the raster information of historical land use changes that are detected from satellite images. It also contains other vector layers of spatial information, such as topography, urban centres, roads, and administrative boundaries. Standard GIS buffer and overlay analyses were carried out to retrieve site attributes and training data from the database. Although the original database contains both vector and raster data, they need to be converted into a raster format for the simulation. All the data were converted into a raster format with each cell representing an area of 50 mX50 m on the ground for the simulation. Like other CA models, this model is also cell-based. Each cell is represented by a set of site attributes. These attributes are passed through the simulation model for getting the output values—conversion probabilities. Land use conversion can be predicted based on site attributes although the relationships may be quite complex.

Unlike general GIS modelling, the distance and neighbourhood variables are dynamically updated during the simulation. GIS data and functions can be directly used for the updating because the model is built within a GIS environment. The updated attributes are used as the inputs to the simulation model.

2.3 NEURAL NETWORK BASED CA MODELLING FOR SETTLEMENT

It is very tedious to calculate the parameter values in conventional CA model. To overcome the problem of traditional CA and to increase the efficiency and accuracy the Neural Network is coupled with CA.

Artificial neural networks(ANN) consists of layers and neurons which simulate the structure of human brains. The layers and neurons allow ANN to have the learning and recall abilities like human. It can be used for non-linear mapping. Simulation can be carried out after training the ANN.

During training the optimal weights are assigned from the set of training data . In this study 3 layers NNW model is used as in Fig.4. Input layer takes site attributes as the input and output layer represents the land use types. Hidden layer is responsible for the non-linearity of the network. Sigmoidal function $F(a)=1/(1+e^{-a})$ is used as the activation function to produce output in the neuron. The NNW is trained with the history data using supervised training algorithm (backpropagation). The network weights capture relation with the input and output after training the network. During simulation, for a given value of site attributes, the occurrence of land use changes is depicted.

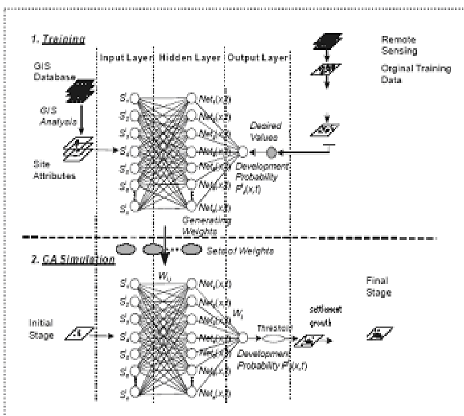

Fig. 4. Neural Network Based CA Model

It is extremely difficult to calibrate CA models when there are multiple land uses. Traditional calibration methods are not robust because they are mainly based on trial and error approaches. The Neural Network based CA model is directly developed in a GIS environment by using *ARCGIS VBA.* The GIS provides both data and spatial analysis functions for constructing the Neural Network. Real data are conveniently retrieved from the GIS database for calibrating and testing the model. . The neural network has multiple output neurons to generate conversion probabilities at each iteration. Land use conversion is decided by comparing the conversion probabilities. The model is carried out by iteratively looping the neural network for simulating multiple land use changes. Site attributes are dynamically updated at the end of each iteration. Complex global patterns can be generated from local interactions through the neural network. The simulation results are not deterministic because site attributes are dynamically updated at the end of each loop.

3 DISCUSSION OF RESULTS AND CONCLUSION

This paper has explicated use of traditional CA for simulation of settlement growth Subsequently, the process wherein neural networks can conveniently be integrated with cellular automata for simulating multiple land use changes is discussed.

A series of inherent model errors can be identified for CA models. They are related to the following aspects:

- Discrete entities in space and time;
- Neighbourhood definitions (types and sizes);
- Model structures and transition rules;
- Parameter values;
- Stochastic variables

The proposed neural network method can overcome some of the shortcomings of the multicriteria evaluation function based traditional CA models in simulating multiple land use changes by significantly reducing the tedious work in defining parameter values, transition rules and model structures. Training data from the GIS can be easily used to obtain parameter values by calibrating the model. The model has the advantages of handling incomplete and erroneous input data. The prediction surface is distinctly non-linear which is much superior to the linear surface of the popular regression models. In many geographical phenomena, spatial variables are usually correlated with each other.

Traditional methods, such as multicriteria evaluation techniques, are inadequate in providing correct weights for correlated variables. In the Neural Network(NNW) based CA model, spatial variables are not necessarily required to be independent of each other. NNW is convenient to use but these models are black box in nature. The meanings of the parameter values are difficult to explain because the relationship among neurons is quite complex. The training data required for NNW CA model is more whereas traditional method will not require training data. More expert knowledge is required in defining the rules of tradition model.

The advantage of CA model is that it allows experiment to conduct on simulated systems rather than on the real ones, which is therefore cheaper. It allows the alternative scenario to be evaluated. Different policy options can be considered and their impact on the future is considered.

In this study Traditional CA modeled for the year 1989 and 2003 for Adilabad district. The same data is used for the simulation using Neural Network based CA for the year 1989 and 2003. The patterns of land use conversions can be clearly observed from satellite images. The change from forest to settlement is dominant along main transport corridors and the conversion to agriculture is dominant along main transport corridors and near water bodies. Fig. 5 is the base map of Adilabad district, Fig. 6 is the actual map of the Adilabad district. Fig. 7 and Fig. 8 are the simulation result of traditional CA model and Neural Network Based CA model. From the results obtained it is clear that the Neural Network Based model simulates more accurately than the traditional model. The simulation carried out for the period 2003 also give similar results as given in Fig. 9, Fig. 10, and Fig. 11. The CA method has definite advantage in terms of accuracy as well as data processing facility compared to conventional methods of change detection.

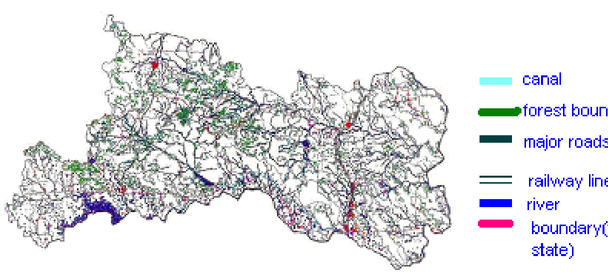

Fig. 5. Base Map Of Adilabad District

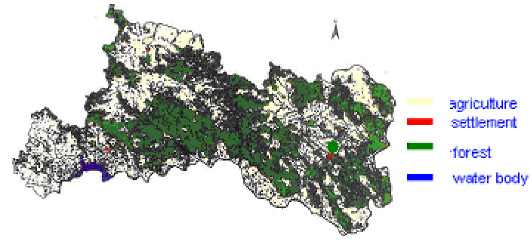

Fig. 6. LULC Map Of Adilabad District 1989

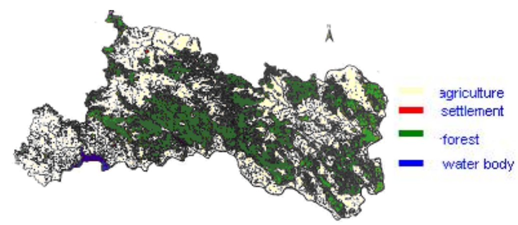

Fig. 7. LULC Map Of Adilabad District 1989 Using Traditional CA

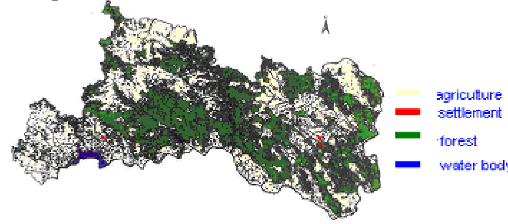

Fig. 8. LULC Map Of Adilabad District 1989 Using Neural Network Based CA

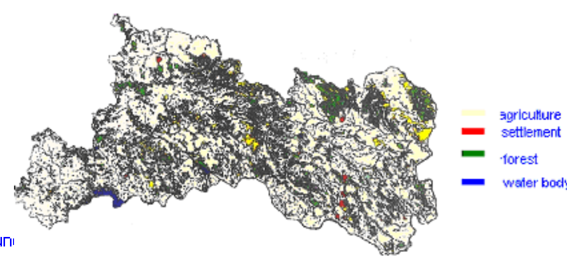

Fig. 9. LULC Map Of Adilabad District 2003

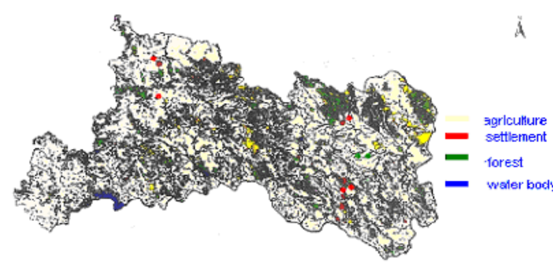

Fig. 10. LULC Map Of Adilabad District 2003 Using Traditional CA

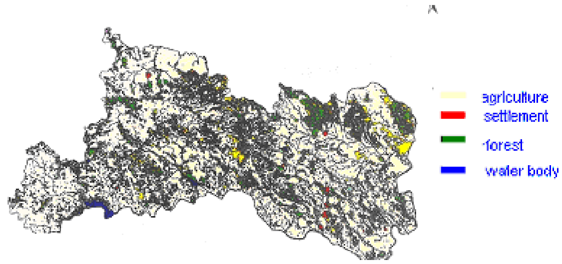

Fig. 11. LULC Map Of Adilabad District 2003 Using Neural Network based CA

4 REFERENCES

1. Anuj Kumar Singh, "Modelling land use land cover changes using cellular automata in a geo-spatial environment", M Sc Thesis, ITC Netherlands. 2003
2. Antonio S Camara, Francisco Ferreira and Paulo Castro. "Spatial Simulation Modelling ", GISDATA-4 SERIES on Spatial Analytical Perspectives On Gis, Chapter 15,201-212
3. Batty, M., Xie, Y. and Sun, Z. L. (1999) "Modelling urban dynamics through GIS based cellular automata, Computers", Environment and Urban Systems, Vol. 23, 205-233.
4. Batty, M.; Couclelis, H.; and Eichen M. 1997. "Editorial: Urban systems as cellular automata", Environment and Planning B. 24:159-164.
5. Dr David Fairbairn, Dr Sanphet Chunithipaisan, "Urban Growth Simulation with UrbanSim Sirivilai Teerarojanarat", Proceedings of the FOSS/GRASS Users Conference - Bangkok, Thailand, 12-14 September 2004
6. David O'Sullivan Paul M. Torrens, "Cellular Models of Urban Systems" CASA (Centre for Advanced Spatial Analysis University College London) Working Paper Series paper no 22 June 2000
7. Jeannette Candau "Calibrating a cellular automaton model of urban growth in a timely manner",4th International Conference on Integrating GIS and Environmental Modeling(GIS/EM4):Problems, Prospects and Research Needs. Banff, Alberta, Canada, September 2 - 8, 2000
8. O'Sullivan, D., Torrens, P. M.,. "Cellular models of urban systems", 4th Int. Conference on Cellular Automata for Research and Industry: Karlsruhe, Germany 2000
9. Olga Bandman, "Accuracy And Stability Of Spatial Dynamics Simulation By Cellular Automata Evolution", proceedings of 7th International Conference on Parallel Computing Technologies, PaCT 2003, September 2003.
10. Stephan wolfarm, "Twenty Problems in the Theory of Cellular Automata ", online http://www.stephenwolfram.com/publications/articles/ca/82-cellular/,1985
11. Stephen J.Walsh Barbara Entwisle ,Ronald R. Rindfuss, Philip H. Page ,"Spatial simulation modelling of land use/land cover change scenarios in northeastern Thailand: a cellular automata approach", Journal Of Land Use Science, Volume 1, Issue 1 , pages 5 – 28, June 2006
12. Shoufan Fang George Z. Gertner , Zhanli Sun', Alan A. Anderson," The Impact Of Interactions In Spatial Simulation Of The Dynamics Of Urban Sprawl", Landscape and Urban Planning Volume 73, Issue 4, Pages 294-306,15 December 2005
13. White, R., Engelen, G., Uljee, I., Lavalle, C. and Ehrlich, D. "Developing an Urban Land Use Simulator for European Cities.", Proceedings of the 5th EC GIS Workshop: GIS of Tomorrow, (Ed, Fullerton, K.), European Commission Joint Research Centre, 179-190, 2000.
14. Wu, F. "An experiment on the generic polycentricity of urban growth in a cellular automatic city". Environment and Planning B-Planning & Design 25(5), pp. 731-752. 1998
15. Xia Li and Anthony Gar-On Yeh "Neural-network- based cellular automata for simulating multiple land use changes using GIS", International Journal of Geographical Information Science. Volume 16, Number 4 / June 01, 2002

Table 2 Categorizing The Attributes Depending On The Actual Value.

Category → Factors Range Values ↓	C!		C 2		C 3		C 4	
Rainfall	<1030		1030-1040		1041-1045		>1045	
Aspect	N	NE	E	ES	S	SW	W	WN
Altitude	<1000		1000-1500		1500-2000		>2000	
Slope	<20		20-25		25-30		>30	
Soil Moisture	<20		21-40		41-60		>61	
Dist From Road	<200m		200--400m		401-800m		>801	
Dist From Water Body	<200m		200--400m		401-800m		>801	
Dist From tourist centre	<200m		200--400m		401-800m		>801	
Dist From community	<100m		100--300m		301-800m		>801	
population	)10,10000		01110001-		32020001-		>3>30000	
Dist From industry	<200m		200--400m		401-800m		>801	