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Dynamic Spatial Modeling of Urban Growth through Cellular Automata in a GIS Environment

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ABSTRACT: Urban settlements and their connectivity will be the dominant driver of global change during the twenty-first century. In an attempt to assess the effects of urban growth on available land for other uses and its associated impacts on environmental parameters, we modeled the change in the extent of Gorgan City, the capital of the Golestan Province of Iran. We used Landsat TM and ETM+ imagery of the area and evaluated possible scenarios of future urban sprawl using the SLEUTH method. The SLEUTH is a cellular automaton dynamic urban-growth model that uses geospatial data themes to simulate and forecast change in the extent of urban areas. We successfully modeled and forecasted the likely change in extent of the Gorgan City using slope, land use, exclusion zone, transportation network, and hillshade predictor variables. The results illustrated the utility of modeling in explaining the spatial pattern of urban growth. We also showed the method to be useful in providing timely information to decision makers for adopting preventive measures against unwanted change in extent and location of the built-up areas within in the city limits.

Key words: Urban growth, Dynamic modeling, Cellular Automata, SLEUTH, Landsat, Gorgan

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INTRODUCTION

Urbanization is one of the most evident global changes. Small and isolated population centers of the past have become large and complex features, interconnected, economically, physically and environmentally (Acevedo, *et al.*, 1996). One hundred years ago, approximately 15% of the world's population was living in urban areas. Today, the percentage is nearly 50%. In the last 200 years, while the world population has increased six times, the urban population has multiplied 100 times (Acevedo, *et al.*, 1996). Urban settlements and their connectivity will be the dominant driver of global change during the twenty-first century. Intensely impacting land, atmospheric, and hydrologic resources, urban dynamics has now surpassed the regional scale of megalopolis and must now be considered as a continental and global scale phenomenon (Acevedo, *et al.*, 1996).

Theoretical and descriptive explanations of urban growth have been well developed and documented in the literature since the middle 1950s. A half century of development in the field has involved great advances and significant changes in the theory and methodology, particularly the evolution of computer graphic technologies, and the introduction of new paradigms. During the 1950s and 1960s, research on urban modeling attempted to build large scale urban models (LSUMs), which Lee (1994) defined as models that seek to describe, in a functional/structural form, an entire urban area, in spatial, land-use, demographic and economic terms. According to Batty (1994), these modeling attempts were part of an effort to transform planning from an architectonic and intuitive art into an objective and rational activity. The LSUMs were severely criticized during the early 1970s.

However, large scale urban models have been blamed for problems such as hyper-comprehensiveness; grossness; hungriness wrong-headedness; complicatedness; mechanicalness; and expensiveness (Lee, 1973). Geographic information systems were a central component of these developments and there was much effort in linking these systems to traditional spatial models (Batty, 1994).

Understanding land use change in urban areas is a key aspect of planning for sustainable development. It also helps in designing plans to counter the negative effects of such changes. According to Clarke *et al.*, (1997), simulation of future spatial urban patterns can provide insight into how our cities can develop under varying social, economic, and environmental conditions. Since the late 1980s, applications of computers in urban planning have changed dramatically. The traditional top-down approaches described before were replaced by bottom-up approaches where complexity, self-organization, chaos and fractals are taken into consideration. The advances in the computing technology have contributed very much to make the approach a reality (Batty and Densham, 1996). In the bottom-up approach, system behavior is rendered deterministic and small changes at the micro-level can result in dramatic changes at the macro-level. Some examples of these new concepts and techniques in urban modeling include fractals and cellular automata (CA). Batty *et al.* (1989), were the pioneers of the application of these new paradigms in the urban dynamics research field.

The study of CA goes back to the late 1940s with the research of Neumann and Ulgam. Some examples of CA-based models developed and applied to the simulation of urban evolution are found in White and Engelen (White *et al.*, 1993;1994; 1997; Engelen *et al.*, 1995;1997), US Geological Survey (Clarke *et al.*, 1997; 1998), Li and Yeh (2000), AUGH-Generalised Urban Automata with help on line (Cecchini, 1996), Wu (1998), Phipps and Langlois (1997), Sembolini (1997), DUEM (Dynamic Urban Evolutionary Modeling developed by Batty *et al.*, 1999) and Barredo *et al.*, (2003).

Markov Chain Analysis has also been used to model change in land use and land cover (Mahiny, 2003 a). A Markovian process is simply one in which the future state of a system can be modeled purely on the basis of the immediately preceding state and will describe land use change from one period to another (Eastman, 2001b). This is accomplished by developing a transition probability matrix of land use change from time one to time two, which will be the basis for projecting to a later time period. The output from Markovian process has only very limited spatial knowledge (Eastman, 2001).

Cellular automata can be used and linked to the Markov chain results to compensate the lack of spatial knowledge. A cellular automaton is a cellular entity that independently varies its state based on its previous state and that of its immediate neighbors according to a specific rule. In the process, only a transition rule is applied that depends not only upon the previous state, but also upon the state of the local neighborhood (Eastman, 2001). Cellular automata (CA) are discrete dynamic systems whose behavior is completely specified in terms of a local relation. They are composed of four elements: cells, states, neighborhood rules and transition rules. *Cells* are objects in any dimensional space that manifest some adjacency or proximity to one another. Each cell can take on only one *state* at any one time from a set of states that define the attributes of the system. The state of any cell depends on the states of other cells in the *neighborhood* of that cell, the neighborhood being the immediately adjacent set of cells that are 'next' to the cell in question. And, finally, there are *transition rules* that drive changes of state in each cell as some function of what exists or is happening in the neighborhood of the cell (Batty and Xie, 1997).
According to Dietzel and Clarke (2006), of all the CA models available, SLEUTH may be the most appropriate because it is a hybrid of the two schools in CA modeling—it has the ability to model only urban growth and incorporate detailed land use data. Reasons attributed to choosing this model are: (1) the shareware availability means that any researcher could perform a similar application or experiment at no cost given they have the data; (2) the model is portable so that it can be applied to any geographic system at any extent or spatial resolution; (3) the presence of a well-established internet discussion board to

support any problems and provide insight into the model's application; (4) a well documented history in geographic modeling literature that documents both theory and application of the model; and (5) the ability of the model to project urban growth based on historical trends with urban/non-urban data.

The main component of the SLEUTH is the Clarke Urban Growth Model (UGM) which drives a second component, the Deltatron land cover model. SLEUTH is the evolutionary product of the Clarke Urban Growth Model that uses cellular automata, terrain mapping and land cover deltatron modeling to address urban growth. The name SLEUTH was derived from the simple image input requirements of the model: Slope, Land cover, Exclusion, Urbanization, Transportation, and Hillshade.

In order to run the model, one usually prepares the data required, verifies the model functions, calibrates the model, predicts the change and builds the products. The user can implement SLEUTH modeling in different modes. The test mode is intended to give the user an easy way to execute a single run on a data set to confirm that the model is performing correctly, or produce output files for a specific set of coefficients.

In calibration mode, the large number of possible coefficient sets is narrowed down to a reasonable estimate of best fit values using brute force calibration methods. Typically the calibration of SLEUTH is a three-step process. In the first step which is a coarse calibration, a variety of spatial metrics are produced, the most common being the Lee–Sallee metric. The Lee–Sallee metric describes the degree of spatial matching between the simulated data and the input historical data, and is a rigorous measure of the ability of a parameter set to replicate historical urban growth patterns. The tested parameter sets are sorted based on their goodness of fit, and the parameter values are narrowed to values around the parameter set that produced the best fit between the historical and simulated data.

In the fine calibration step, the narrowed range of parameters from the previous step is used to simulate the historical growth patterns. Results of these simulations are evaluated using spatial metrics of fit, and the range of parameters is narrowed one last time. Finally, the historical data is simulated one last time using the re-narrowed set of parameters, and the one that best recreates the urban growth is then used in model forecasting. After calibration, a set of five parameters or coefficients are produced that describe the historical growth patterns of the system over time based on a fixed set of transition rules. Five coefficients (with values 0 to 100) control the behavior of the system, and are predetermined by the user at the onset of every model run (Clarke et al., 1998). These parameters are diffusion that determines the overall dispersiveness nature of the outward distribution, breed coefficient which is the likelihood that a newly generated detached settlement will start on its own growth cycle. Spread coefficient is another parameter that controls how much contagion diffusion radiates from existing settlements. Slope resistance factor influences the likelihood of development on steep slopes, and finally road gravity that is produced to show the attraction roads create in drawing new settlements towards and along them. These parameters drive the transition rules that simulate four types of urban growth. These are spontaneous growth showing the urbanization of land that is of suitable slope, yet not adjacent to preexisting urban areas, diffusive growth when newly established urban areas begin to transform the land around them from other uses into urban land cover, organic growth at the urban fringe and as infill within areas that may not have fully made the transition from another land use to urban. Road influenced growth is another type of growth that takes into account the influence of roads over urbanization and land use change while prediction growth type is a collection of Monte Carlo simulations.

The prediction mode of the SLEUTH model uses the best fit growth rule parameters from the calibration to begin the process of ''growing'' urban settlements, starting at the most recent urban data layer. The resulting forecast of future urban growth is a probabilistic map where each grid cell has the chance of being urbanized at some future date, assuming the same unique ''urban growth signature'' is still in effect as it was in the past, while allowing some system feedbacks termed self-modification (Herold *et al.*, 2003). Due to its scientific appeal, availability and relative ease of use, we adopted the SLEUTH for modeling Gorgan City change through time, a first time event in Iran.

MATERIALS & METHODS

Gorgan is the capital city of the Golestan Province in the north east of Iran. The economic growth in the area in the recent past has led to a large increase in population, driving dramatic urban expansion and land use change.

We used the SLEUTH modeling method to simulate and project the change in the area of the city. SLEUTH requires an input of five types of image files (six if land use is being analyzed). For all layers, zero is a nonexistent or null value, while values greater than zero and less than 255 represent a live cell.

We geo-registered and re-sampled a 10 meter DEM of the area obtained from National Cartographic Center of Iran to 20 meters resolution using Idrisi 32 software (Eastman, 2001). Then, we derived the slope and hillshade layers from the DEM layer. Landsat TM and ETM+ scenes of the Gorgan City covering around 1316 Km^2 were selected for this study. The scenes which dated July 1987, September 1988, July 2000 and 2001 were imported into Idrisi 32 software (Eastman, 2001), geo-registered to the other layers and re-sampled to 20 meters resolution. Then the scenes were classified using knowledge from the area and Maximum Likelihood supervised classification method. We identified seven classes: water, agriculture, fallow lands, built-up areas, dense broad-leaved forest, thin forest, pastures and needle-leaved woodlands. A post-classification comparison was conducted to detect the change in land use and land cover of the area. The urban extent was derived through reclassification of these detailed land cover classifications into a binary urban / non-urban map (Fig. 1)

For deriving the transportation and excluded layers, we used visual image interpretation and on-screen digitizing to generate individual vector layers that were transformed into raster layers with 20 meters resolution. We ensured that all data layers followed the naming protocol for SLEUTH, were in grayscale GIF format and had the same projection, map extent, and resolution.

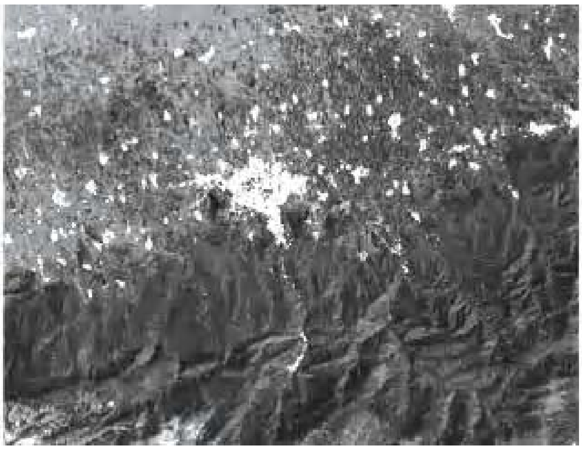

Fig. 1. Gray scale color composite image of the study area, bands 2, 3, and 4 of ETM+ sensor of Landsat satellite, 30th July 2001, with lighter spots showing the residential areas

Model calibration was conducted in three phases: coarse, fine and final calibration. The algorithm for narrowing the many runs for calibration is an area of continuous discussion among users, and so far no definitive “right” way has been agreed upon. Examples of approaches used thus far include: sorting on all metrics equally, weighting some metrics more heavily than others, and sorting only on one metric. In this investigation, the last method, namely sorting on one metric, was applied. Simulations were scored on their performance for the spatial match, using Lee-Sallee metric.

Adopting the procedure used by Leao *et al.*, (2001 and 2004) and Mahiny (2003) we devised two different urban growth scenarios for model prediction. One scenario described the city as growing following historical trends, according to the parameters calibrated based on historical data. The second scenario described a more compact growth as a response to hypothetical policies and the shortage of land to reduce urban spreading. This was done by manipulating the value of some of the calibrated growth parameters. In the historical growth scenario, when the final calibration process was completed, the best selected parameters were run through the historical data many times and their finishing values were averaged considering the self-modification parameters. In the simulation for a compact city, the spread and road-gravity coefficients were reduced to half of the calibrated and averaged best values were derived in the process.

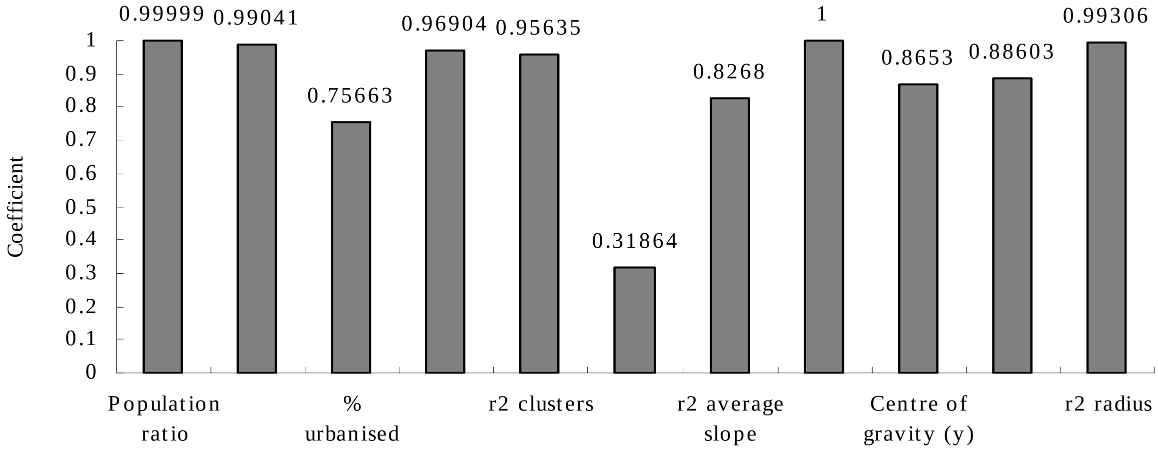

Fig. 2. Statistics of the best fit parameters for modeling Gorgan City Expansion

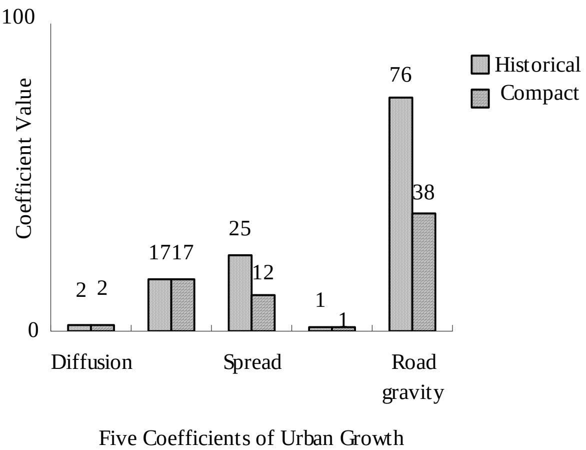

Fig. 3. Best fit parameters for final calibration.

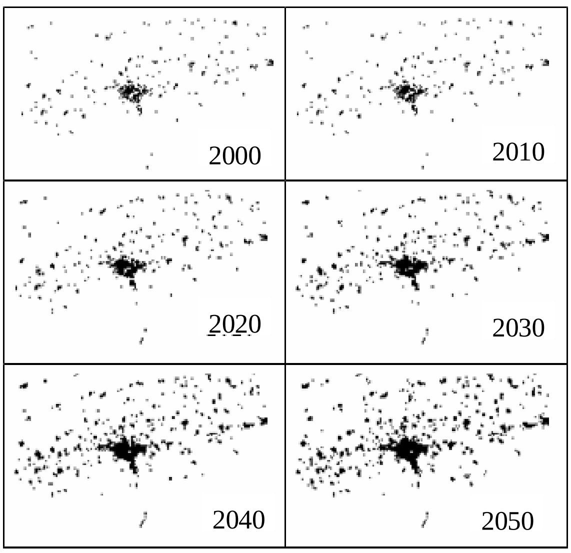

Fig. 4. Simulated urban growth of Gorgan in historical scenario

During final calibration, statistics were produced for best fit parameters for the Gorgan City. Some of the statistics are related to the 'amount' of growth experienced in the region (number of cells urbanized). These include the indexes *population ratio, r^2 population* and *%urbanized*. Other indices are mainly related to the 'shape' of the growth simulated by the model, such as *r^2edges*, *r^2clusters* and the *Lee-Sallee* index.

The resulting forecast of future urban growth was produced as a probabilistic map. In the map, each grid cell will be urbanized at some future date, assuming the same unique ''urban growth signature'' is still in effect as it was in the past, while allowing some system feedbacks termed self-modification. For both the back-cast and projected urban layers, a probability over 70% (given 100 Monte Carlo simulations) was used to consider a grid cell as likely to become urbanized. The final results of the model application were annual layers of urban extent for the historical time frame (1987–2001) and projected future urban growth (2002–2050).

RESULTS & DISCUSSION

We conducted 5 Monte Carlo iterations for the coarse calibration of the model in 3124 runs which took around 15 hours on a Pentium 4 with 2 GHz CPU speed. For fine calibration, 8 iterations in 6479 runs were conducted taking around 15 hours on the same computer. The final calibration was done using 10 iterations in 2999 runs on the same computer that took around 9 hr.

Most of the statistics for best fit parameters of the simulation results of Gorgan present high values of fit, indicating the ability of the model to reliably replicate past growth (Fig 2). This suggests that future growth predictions can also be used with confidence. There was a high match for the amount of urban cells and clusters and the shape of urban edges between the simulated and control years (Fig. 2). It can be seen in Figure 2 that the slope has a low coefficient, translating into a small effect on the possibility of area becoming urban.

For the simulation of Gorgan city expansion, the final averaged parameters used in the prediction phase are presented in Figure 3. Each parameter in Figure 3 reflects a type of spatial growth. For Gorgan City, the diffusion coefficient is very low, which reflects a low likelihood of dispersive growth. The low value for the breed coefficient reinforces it, given low probability of growth of new detached urban settlements. The spread coefficient stimulates growth outwards of existing and consolidated urban areas. The high value of the road gravity coefficient denotes that the growth is also highly influenced by the transportation network, occurring along the main roads. Slope resistance affects the influence of slope to urbanization. In Gorgan area, topography was shown to have a very small effect in controlling the urban development, where even the hilly areas are likely to urbanize (Fig. 3). This was also clear in Figure 2 where the statistic of the parameter was found to be low. Inspection of the newly developed areas in the Gorgan City proved this to be reality.

Fig. 4 .illustrates the future urban form and extent of Gorgan City area according to the model simulation using the historical scenario. Looking at the Figure 4, managers and decision makers can easily find the locations where the city may increase and their corresponding intensities. This information is of great importance, as it gives the managers an upper hand in controlling the unwanted situations from happening.

Fig. 5. shows the extent of urban development over time for the two growth scenarios. Quite expectedly, the compact city scenario predicts a smaller increase for the future as compared to the historical scenario. However, the choices are open to the users to construct different scenarios and immediately assess their effects on the fate of the city. Modification of the driving parameters of city change, as defined in this study, can help in defining the best method for preventive measure in terms of feasibility and economy.

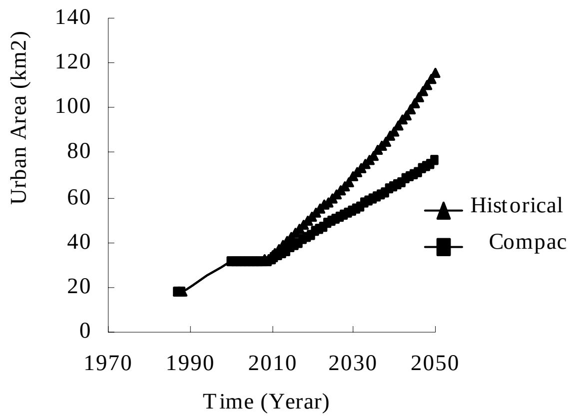

Fig. 5. The area of city expansion for the two scenarios

CONCLUSION

Planning and management are based on generic problem solving. They begin with problem definition and description, and then turn to various forms of analysis, which might include simulation and modeling, and finally move to prediction and thence to prescription or design, which often involves the evaluation of alternative solutions to the problem (Batty and Densham, 1996). According to Rubenstein-Montano and Zandi (2000) modeling tools form the majority of approaches developed to assist decision-makers with planning activities and according to Leao *et al.*, (2001 and 2004), spatial modeling of urban growth permits systematic and formal studies of *possible future worlds* and provides a basis for the preparation and evaluation of urban policies.

Models allow the simulation of the real system, thus allowing the user to get a better insight into the actual decision domain and particular decision situations. They also allow the user to forecast alternative and comparable future states, and thus constitute an instrument to investigate the likelihood of a desired situation through experimentation. Spatial models of urban growth have the ability to play an important role in the planning process; if not in aiding in policy decisions, then in processes such as visioning, storytelling, and scenario evaluation (Dietzel and Clarke, 2006).

We successfully modeled the change in the extent of the Gorgan City using the SLEUTH method for the first time in Iran. The process was found feasible, considering the time, facilities and the background knowledge it requires. The results, although not tested thoroughly, were found very useful in terms of providing insight into the process of city change to the managers and decision makers. Using this information, the authorities can take preventive measures for controlling negative effects of the predicted change. They can also use the information for preparing the infrastructure required in near future and mitigate the unwanted changes through possible means. Using a combination of the past, present and future city sizes and their impact on the surrounding land use and land cover, information can be also compiled for other studies such as a proper cumulative effects assessment in the area.

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REFERENCES

Acevedo, W., Foresman, T. W. and Buchanan, J. T., (1996). Origins and philosophy of building a temporal database to examine human transformation processes. Proceedings,ASPRS/ACSM Annual Convention and Exhibition, Baltimore, MD, **I**, 148–161.

Barredo, I. J., Kasanko, M., McCormick, N. and Lavalle, C., (2003). Modeling dynamic spatial processes: simulation of urban future scenarios through cellular automata. Landscape and Urban Planning, **64**, 145-160.

Batty, M., Longley, P. and Fotheringham, S., (1989). Urban growth and form: scaling, fractal geometry, and difusion-limited aggregation. Environ. Plan. A., **21**, 1447–1472.

Batty, M., Xie, Y. and Sun, Z., (1999). Modeling urban dynamics through GIS-based cellular automata. Computers, Environment and Urban Systems, **23**, 205-233.

Batty, M., (1994). A Chronicle of Scientific Planning: the Anglo-American Modelling Experience. J. Am. Plan. Assoc., **60** (1), 7–16.

Batty, M. and Densham, P. J., (1996). Decision support, GIS, and urban planning. Available at: http://www.geog.ucl.ac.uk/~pdensham/SDSS/s_t_paper.html

Batty, M. and Xie, Y., (1997). Possible urban automata. Environ. Plan., B., **24**,175-192.

Cecchini, A., (1996). Urban modelling by means of cellular automata: generalised urban automata with help on-line (AUGH) model. Environ. Plan. B., **23**, 721-732.

Clarke, K., Gaydos, L. and Hoppen, S., (1997). A self-modifying cellular automaton model of historical urbanisation in the San Francisco Bay area. Environ. Plann. B., **24**, 247-261.

Clarke, K. and Gaydos, L., (1998). Loose-coupling a cellular automaton model and GIS: longterm urban growth prediction for San Francisco and Washington/Baltimore. Int. J. Geo. Inform. Sci., **12**(7), 699-714.

Dietzel, C. and Clarke, K., (2006). The effect of disaggregating land use categories in cellular automata during model calibration and forecasting. Computers, Environ. Urban Sys., **30**, 78-101.

Eastman, R. J., (2001). Guide to GIS and Image processing, Vo.2. Clark university, USA. 144.

Eastman, R. J., (2001). Idrisi 32, Release 2. Tutorial. Clark university, USA. 237.

Engelen, G., White, R., Uljee, I. and Drazan, P., (1995). Using cellular automata for integrated modelling of socio-environmental systems. Environ. Monitor. Assess., **34**, 203-214.

Engelen, G., White, R. and Uljee, I., (1997). Integrating constrained cellular automata models, GIS and decision support tools for urban planning and policy-making. Available at: http://www.citeseer.ist.psu.edu/371266.html

Herold, M., Goldstein, N. C. and Clarke, K. C., (2003). The spatiotemporal form of urban growth: measurement, analysis and modeling. Remote Sens. Environ., **86**, 286-302.

Leao, S., Bishop, I. and Evans, D., (2001). Assessing the demand of solid waste disposal in urban region by urban dynamics modeling in a GIS environment. Resources, Conservation and Recycling, **33**, 289-313.

Leao, S., Bishop, I. and Evans, D., (2004). Simulating urban growth in a developing nation's region using a CA-based model. Journal of Urban Planning and Development, **130**(3), 145-158.

Leao, S., Bishop, I. and Evans, D., (2004). Spatial-Temporal model for demand and allocation of waste landfills in growing urban region. Computers, Environ. Urban Sys., **28**, 353-385.

Lee, D., (1973). Requiem for large-scale models. J. Am. Inst. Plan., **39**, 163-178.

Lee, D., (1994). Retrospective on Large-Scale Models. J. Am. Inst. Plan., **60**(1), 35–44.

Li, X. and Yeh, A. G. O., (2000). Modelling sustainable urban development by integration of constrained cellular automata and GIS. Int. J. Geo. Info. Sci., **14**(2), 131-152.

Mahiny, A. S., (2003). A modeling approach to cumulative effects assessment for rehabilitation of remnant vegetation, PhD Thesis, SRES, ANU, Australia.

Phipps, M. and Langlois, A., (1997). Spatial dynamics, cellular automata, and parallel processing computers. Environ. Plan. B., **24**, 193-204.

Rubenstein-Montano, B. and Zandi, I., (2000). An evaluative tool for solid waste management. J. Urban Plan. Develop., **126**(3), 119-135.

Sembolini, F., (1997). An urban and regional model based on cellular automata. Environ. Plan. B., **24**, 589-612.

White, R. and Engelen, G., (1993). Cellular automata and fractal urban form: a cellular modelling approach to the evolution of urban land-use patterns. Environ. Plan. A., **25**, 1175-1199.

White, R. and Engelen, G., (1994). Cellular dynamics and GIS: Modelling spatial complexity.Geo. Sys., **1**(2), 237-253.

White, R. and Engelen, G., (1997). Cellular automata as the basis of integrated dynamic regional modelling. Environ. Plan. B., **24**, 235-246.

White, R., Engelen, G. and Uljee, I., (1997). The use of constrained cellular automata for highresolution modelling of urban land use dynamics. Environ. Plan. B., **24**, 323-343.

Wu, F., (1998). SimLand: a prototype to simulate land conversion through the integrated GIS and CA with AHP-derived transition rules. Int. J. Geo. Info. Sci., **12**(1), 63-82.