Application of Cellular Automata and GIS Techniques in Urban Growth Modelling: A New Perspective

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Abstract

This present paper undertakes a critical review of traditional urban models and identifies their shortcomings. The advantages of using Cellular Automata or CA models as compared to the traditional models have then been highlighted. The concepts and issues in CA based urban growth modelling with an emphasis on combining CA models with GIS have also been discussed. The paper forms a basis of understanding the existing work done in the area of CA based urban growth modelling. It is also apparent from the paper that the integration of GIS and CA is the way forward to gain better insight into the process and form of urban dynamics simulation and modelling.

1. INTRODUCTION

India is undergoing a rapid pace of urbanization. Urban population of India increased from 217.6 million to 285 million in the last decade and presently constitutes 27.8 percent of the total population (Census of India, 2001). It is expected to increase to 40 percent of the total Indian population by the year 2021 (GGIM, 2005). Urban growth has two contradictory facets: on one hand, cities act as engines of economic growth and on the other they are accompanied by environmental degradation as the surrounding agricultural lands, forests, surface water bodies get converted into urban uses and are irretrievably lost (Gowda and Sridhara, 2000; Tayal and Bharat, 1997). Faced with these severe negative impacts, there is an urgent need for urban planners to develop predictive models of urban growth. These models not only provide an understanding of the urban growth process, but also provide realizations of the numerous potential growth scenarios that an urban area may take in the future. This kind of information can be very helpful in regulating urban growth, and proper planning can also be done for the future urbanizable areas (Routray, 1993, 2000).

Although, the traditional urban modelling approaches are based on sound theories, they have significant weaknesses such as poor handling of space-time dynamics, coarse representation of data and top down approach, which ultimately fails to reproduce realistic simulations of urban systems. Most of these models conceive the city as static and attempt to simulate how land uses are located with respect to each other at a cross section of time. Linear econometric models, in which spatial interaction is implicit, form one class of models, in contrast to the non-linear models such as Lowry Pittsburgh model which attempt to model spatial interaction

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explicitly (Reif, 1973). However, all these spatial interaction models are static and operate at a fairly coarse level i.e. census tracts and traffic zones form the levels at which cities could be represented. These models were criticized by Lee (1973) for being hyper comprehensive, data hungry and complicated. Thus, towards the mid 1980s, Cellular Automata (CA) based models were proposed as an alternative to these traditional models due to the following reasons (Sullivan and Torrens, 2000a):

• Simplicity;
• Potential for dynamic spatial simulation;
• Capability of detailed or high resolution modelling; and
• Affinity to Geographic Information Systems.

This integration of CA with GIS opens up new vistas to improve urban modelling. The aim of this study as reported in this paper is to present the state of knowledge on urban modelling, specifically in relation to GIS based urban CA modelling.

2. TRADITIONAL MODELS OF URBAN GROWTH

Since the beginning of 19th century, various models and theories have been proposed to explain urban growth. Burgess's Concentric Zone Theory in 1925 was based on the idea that the growth of a city took place outwards from its central area to form a series of concentric zones of various land uses. However, discrepancies between the Concentric Zone Model and the actual distribution of urban land use patterns encouraged the formulation of various theories, notable among these were the Sector Theory proposed by Hoyt and Davie in 1939. According to this theory, patterns of urban land use were influenced by the road networks radiating outwards from the city centre. The accessibility to roads created a sectoral pattern of land values, which in turn influenced the urban land use pattern. However, both the Concentric Zone Theory and Sector Theory assumed that the city grew around single nucleus, but actual pattern of urban growth is generally far more complex and varied than any of the models suggested. Consequently, Harris and Ullman in 1945 proposed the Multiple-Nuclei Theory, and suggested that urban growth in large cities took place around a number of nuclei rather than a single nucleus (Knowles and Wareing, 1976).

Thus, with the help of these theories, attempts were made to formulate comprehensive models of urban growth. However, none was entirely satisfactory, as these theories were rigid and static in nature and sought only to represent visually the spatial arrangement of urban socio-economic systems (Ramachandran, 1991).

Urban growth modelling bloomed in the 1950s and 1960s. Most of these models developed were spatial interaction models. Spatial interaction models drew from

the original efforts of Reilly in 1931 and Zipf in 1946 to model human activities. The model formula, in its most basic form, was based on Newton's Law of Gravitation. Models included in this group were the well known gravity type models and their reincarnated formulations such as Lowry and Grain-Lowry Model. The spatial interaction models were used to study a variety of intersections arising out of human activities within the urban system such as journey to work, land use transport interactions and urban growth in general. However, these models had significant limitations namely, they were very complicated, required lot of data, their resolution was coarse and they were static in nature.

Forrester (1969) introduced the concept of industrial dynamics for simulating industrial processes in firms and attempted to apply this idea to model the growth dynamics of an abstract city using differential equations referred to as stock and flow equations. Since the model was developed for an abstract city, it was not calibrated for real world. Besides, the model also ignored the spatial dimension of urban growth. According to Batty and Torrens (2001) it was not appropriate to treat this model as a generalized model of a city. Although Forrester's model played an important role in introducing the dynamic view of the urban systems, but it was Lowry Model with extensions and modifications that found widespread use. However, all these models were criticized by Lee (1973) for being hyper comprehensive, data hungry and complicated.

3.   CELLULAR AUTOMATA OR CA FOR URBAN GROWTH MODELLING

Towards the mid 1980s, Cellular Automata (CA) based urban growth models were proposed as an alternative to the traditional models as the CA based models were inherently spatial, dynamic and has a natural affinity towards GIS and remote sensing data (Couclelis, 1997; Torrens, 2000, 2001).

Cellular automata (CA) were originally conceived by Ulam and Von Neumann in the 1940s to provide a framework for investigating the behavior of complex systems (Torrens, 2000). The concept of self-organization, which is one of the main characteristics of complex systems, is central to CA based modelling. Self-organization refers to the tendency of system to spontaneously develop ordered patterns, often on a large scale from local decision making processes (Torrens and Sullivan, 2001). Thus, CA are able to simulate processes such as urban growth where global or centralized order emerges as a consequence of local or decentralized rules.

At the most rudimentary level, a CA is an array or lattice of regular cells. At any given time, a cell is in one of the finite number of allowed states. The cell changes its state based on the state of its neighboring cells in the lattice as per uniformly applied set of transition rules. Cells change their states iteratively and synchronously through repeated application of these transition rules. CA is thus composed of five principal elements (Torrens, 2000, 2001),

- **Lattice:** A regular uniform and infinite 'lattice' or 'array' with discrete variables at each cell. Lattice space can have *n* dimensions, but two-dimensional CA is the most common in urban simulation.

- **State**: A state is a variable, which takes different values at each cell. It can be a property, a number or word (0 or 1, urban or non-urban).

- **Cell**: A cell is the sub-unit of the lattice or the regular geometrical grid. A cell at any instant of time can be in only one state out of a given number of states. The states of all cells in a grid are updated during CA iterations.

- **Neighbourhood**: In a lattice, there are normally the cells that are physically closest to the central cells, which influence the state of the central cell in the next step. The neighbourhoods cells act as immediate areas of interest for the central cell, as the transition rules which decide the state of the central cell in next step are based on the neighbourhood values. The neighbourhood also includes the central cell itself. The two commonly used neighborhoods are the Von Neumann and Moore neighborhoods. A 3x3 cell Von Neumann and Moore neighborhoods are shown in Figure 1. The black cell (which represents the cell under consideration) and the surrounding grey cells (4 in case of Von Neumann and 8 in case of Moore neighbourhood) together constitute the neighbourhood. The neighborhoods can also be extended from their 3x3 cells size to other larger odd numbered sizes (e.g. 5x5, 7x7, 9x9 and so on).

- **Transitional rules**: These are a set of conditions or functions that define the state of change in each cell in response to its current state and that of its neighbors. The future state of cells is determined by the transitional rules in a discrete time frame.

Thus, an urban cellular automata consists of a two dimensional lattice of cells that represents the urban landscape. Every cell in the lattice has a single value or state which corresponds to the land uses i.e. built up and non-built up. Each cell changes its states in the time steps as a function of the states of its immediate adjacent neighbors, which are updated at each iteration. The function, which is used to change the cell states between the time steps, is called as transition rule and gives a chance to infuse urban theory directly into model. In the sequence of time (t, t+1, t+2...) which are treated as discrete, each cell in the CA lattice updates its state based on the transition rules. The general definition in mathematical notation is:

Fig 1: Von Neumann Neighborhood and Moore Neighborhood
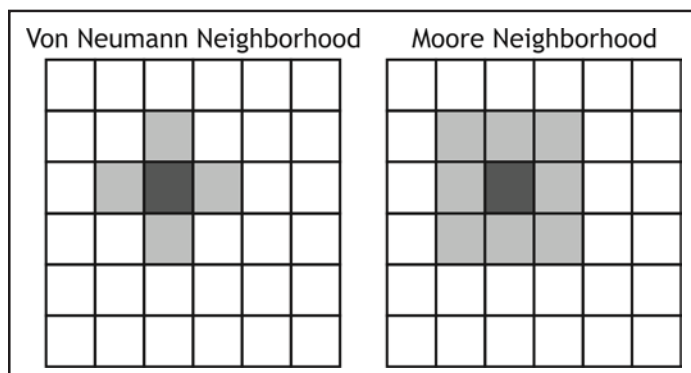
$\{S_{t+1}\} = f \ (\{S_t\}\{I^h_t\})$

Where

$\{S_{t+1}\}$ is the state of the cell in the CA at time (t+1)

$\{S_t\}$ is the state of the cell in the CA at time (t)

$\{I^h_t\}$ refers to the neighbourhood,

f () denotes the transition rules

t is the time steps in temporal space

h is the neighbourhood size

Hence, it is this capacity to integrate spatial and temporal dimensions that makes CA appealing for the development of robust and reliable urban dynamics models.

3.1   Role of GIS in CA based Modelling

In order to be useful and realistic, urban models depend on real-world data such existing urban land uses and growth patterns, existing road network, location of various facilities, availability of infrastructure facilities etc. that can be integrated and mapped in a modelling scenario. Geographic Information Systems has emerged as a prime framework for the integration and management of a range of spatial real world data. However, to use GIS alone as modelling tool have been received with skepticism as it has limited modelling functionalities and has constraints in handling temporal data sets. Nevertheless, GIS and CA in combination can be used as a strong couple to model the urban growth to take advantages of both the techniques. For example, although the capacity of CA to explore complex systems has been well established (Itami, 1994), its capacity to represent real patterns is yet to be proven. In case of GIS, its spatial data analysis capacities may be insufficient to handle complex urban dynamics. The integration of the dynamic strength of CA with the effective spatial representation found in GIS thus may be beneficial to achieve realistic representation of a phenomenon such as urban growth (Wolff and Wu, 2004).

A number of important points have been raised in the literature about the benefits of linking GIS and CA to improve urban dynamics modelling. GIS and CA have been argued to have significant common features and complementary functionalities, and can therefore supplement and complement each other (Wagner, 1997; White, 1998). Couclelis (1985, 1989) discussed the theoretical considerations for the integration of GIS and CA as well as their potentialities in improving the quality of spatial urban dynamics models. Couclelis (1997) also pointed out the natural affinity between CA and GIS and advocated more interactive and visual integration of GIS and CA to improve the patterns of realism in urban modelling and simulation.

Sui and Zeng (2001) recognized the advantage of GIS based CA urban modelling and simulation. One of the advantages cited is the bottom up approach of CA, which

enables the incorporation of various local factors into the modelling process in order to better represent their evolution. In doing so, the model can generate realistic urban dynamics thereby correcting the static representation of GIS.

In many ways, the deficiencies of GIS and CA can be compensated by each other. For example, although the capacity of CA to explore complex systems is well established (Wolfram, 1984; Itami, 1994), its capacity to represent real patterns has still to be proven. In case of GIS, its predictive and analytical capacities are insufficient to handle complex urban dynamics. The integration of the dynamic strength of CA with the realistic temporal and spatial representation found in GIS and remote sensing is, therefore, appealing as a practical means to achieve realistic representation. On one hand, GIS has much to offer in this integration as it can perform data pre-processing, sorting, storage and retrieval of data, data base querying, graphical display, input and output editing. On the other hand, CA may provide the power for database analysis, temporal dimensionality (for instance by handling multiple iterations), and the flexibility to assign transitional rules and definition of the spatio-temporal neighborhoods.

3.2   Limits and Strengths of CA

Conceptually and theoretically, CA for urban studies has some limitations and strengths with regard to the development of an urban dynamics framework. This section first discusses some of the limitations of CA and then expands on its strengths to model complex phenomena like urban growth.

The original framework of CA is not appropriate to support realistic urban dynamics (Wolfram, 1986). For instance, the overall original structure of CA is too simplistic and constrained to apply in real urban applications (Sipper, 1997). Similarly, it is not reasonable to apply the concept of an infinite space plane (two-dimensional) and uniform regular space to the city because cities are not infinite, regular, or uniform. Moreover, the notion of neighbourhood is too coarse and does not take external factors and distance-decay actions into consideration.

Another criticism is that CA only assumes the bottom up approach, and accounts for local specificities that ultimately define the overall representation of the space generally. All constituents of urban systems, however, do not exhibit bottom up behavior like, urban planning decisions, national policies, macro-economy, and so on. These factors operate from top to bottom and serve to constrain the urban growth.

In the original CA, transition rules were universal and applied synchronically to all cells. In real urban growth processes, however, no single rule governs the behavior of the entire system. To solve the rigid transitional rules, urban dynamics CA transition rules are formulated using Boolean statements, and probabilistic expressions such as {< IF >, < THEN >, < ELSE >}. The flexibility thus gained in these expressions simplifies the representation of more complex systems (Batty, 2000).

Turning to strength, the simulation of urban dynamics is an area of research where CA has been recently implemented. Here, CA represents a useful tool for understanding urban dynamics, improving theory, achieving realistic and operational urban models (White, 1998). White and Engelen (1993) have demonstrated that a cellular automata approach can lead to a better understanding of spatial patterns as well as representing realistic patterns. In the spatial modelling perspective, the strengths of CA lie in their capacity to perform dynamic spatial modelling over a discrete and continuous Euclidean space. Similarly, CA has the ability to exhibit explicit spatio-temporal dynamics. Several studies (For example Bivand and Lucas, 2000; Openshaw and Abrahart, 2000) have shown how CA models can be integrated with other spatio-temporal models to improve the representation of urban features. Finally, the flexibility of transitional rules embedded into CA architecture favors an effective control over the dynamic patterns that are generated.

Role of CA is to discover, understand and explain how cities emerge and change (Couclelis, 1985; White and Engelen, 1994; Portugali, 2000; Ward *et al.*, 2000). Introduction of CA approaches in Geography may be traced back to the work of Hägerstrand (1968) who highlighted the major components of current CA architectures as discrete time and state, cell, neighbourhood, uniform transitional rules and lattice. Investigation of Hägerstrand was limited by the capacity of the simulation (e.g., less than 200 cells), yet it was theoretically and conceptually well formulated. Tobler (1970) further developed a forecasting model based on urban growth. In fact, Tobler's study laid the theoretical and conceptual foundation of CA for future applications in Geography. In 1979, he published a paper formalizing the concept of CA (Tobler, 1979) in which he opened the gates for geographers to use CA for urban planning applications, spatial modelling and simulation. However, the temporal dimension of Tobler's CA was considered weak because the simulated maps developed for each year were very different from the actual growth simulation (Wegener, 2000).

Tobler's work was improved by Couclelis (1985, 1989, 1997), Batty and Longley (1986, 1994) and Batty and Xie (1994c, 1997), who enhanced the theoretical and methodological aspects of CA for analyzing and modelling complex urban dynamics. In the same spirit, Couclelis (1989) demonstrated the use of CA as a metaphor to study different varieties of urban dynamics. Couclelis claimed that although CA was not originally intended to produce realistic representations of urban dynamics, it could be reformulated and integrated with some spatial models to form better predictive models. White and Engelen (1993, 1994) went further to advocate that CA was capable of generating real patterns of urban land use change. Thus, it is during the last two decades that impetus on the use of CA models for urban growth simulation can be seen. The following section describes the uses of CA in the simulation of urban growth.

4   MODELLING THE REAL CITIES WITH CA

White and Engelen (1993) used CA to explore the spatial structure and temporal dimension of urban land use and to test general theories of structural evolution. The cellular model generated patterns for each land use type, which were then, compared with data from a set of US cities using fractal dimension. The results showed realistic representations of actual urban form. In another example, White and Engelen (1997) and White *et al*. (1997), implemented CA, to model and predict the land use of the Caribbean Island of St. Lucia and in USA. In both studies, the transition rules were based on the suitability value of a cell for different land uses and neighbourhood information. The model for Cincinnati was calibrated by trial and error process, whereas in case of St. Lucia, the final calibration was not done and one scenario was described in order to illustrate the behavior of the model. In all the three models thus far discussed, the neighbourhood used was of circular shape and included the cell itself and the cells lying within a radius of six cells.

Barredo et al (2003, 2004) also developed a CA model for predicting land use of Dublin and Lagos, Nigeria respectively. The model was based on 22 states, which were classified as fixed classes (water bodies, airport, rail and road network etc.), passive states (arable land, forests, shrub, sparsely vegetated and wetlands) and active states (different categories of residential areas, industrial, commercial, public services, port areas and abandoned lands). The transition rules were based on accessibility, neighbourhood, suitability of a cell and zoning status. The neighbourhood used was of circular shape and included the cell itself and the cells lying within a radius of eight cells. The model parameters were determined heuristically.

Clarke et al (1997) developed the Urban Growth Model (UGM) based on integration of GIS and cellular automata approaches. The UGM simulates the urban growth transition from non-urban to urban land. In UGM, the input factors were the local (roads, existing urban areas and slope), and temporal (historical patterns of growth). The simulation was controlled by five parameters, which carry respective weights or coefficients: slope resistance, road gravity, breed, dispersion and spread. The coefficient of each parameter was determined by running four rigorous calibration phases: coarse, fine, final and averaging best results. The weighted probabilities of each parameter were then used as input into the growth prediction. Clarke and Gaydos (1998) gave the SLEUTH model, which is a CA-based urban growth model(UGM) coupled with a land cover change model (US Geological Survey 2003).The SLEUTH, stands for slope, land cover, exclusion area, urban extent, transportation network and hill shade. These characters constitute the five main categories of data input. Whereas UGM was designed for local application, the SLEUTH was more ambitious and claimed to be used for forecasting urban growth at a regional and continental scale.

UGM and SLEUTH models have been applied in the study of many planned cities in North America such as San Francisco (Clarke *et al.*, 1997), Chicago, Washington-Baltimore area (Clarke and Gaydos, 1998), Sioux Falls, California, and Philadelphia (Varanka, 2001); Lisbon and Porto (Silva and Clarke, 2002) in Portugal (Europe); and Porto Alegre (Leao, 2002) in Brazil South America.

Li and Yeh (2001, 2002) developed CA and artificial neural network (ANN) based urban growth models for Dongguan city of China. The ANN derived weights acted as the transition rules derived directly from the database, instead of the user defining them as in case of MCE based CA models. Li and Yeh (2001) applied the ANN based CA model to predict the urban growth in Dongguan city. The model was based on the dichotomy of built up and not built up areas. The ANN was first trained and then using this trained network, the urban growth was simulated. Li and Yeh (2002) used the same model to simulate land cover classes, like cropland, construction sites orchard built-up areas, forest and water in Dongguan city.

4.1 GIS and CA integration: A review of some studies

Urban researchers in principle have agreement on the usefulness and necessity to link CA with GIS to achieve more realistic and informed urban dynamics models. However, implementation strategies are divergent in identifying the appropriate way to achieve optimum results. One approach consists of building a CA modelling application using the programming language within a GIS language protocol (Batty and Xie, 1994a; 1994b; Yeh and Li, 2001). This requires a certain level of familiarity with the programming language embedded in the GIS package in use. The flexibility of the language, however, is not always guaranteed and the scope for application of the skills learnt in the process is limited.

Another approach to integrate CA and GIS is to develop a standalone CA program that can use data from GIS. Data interchange and compatibility can be achieved through file conversion protocols (Yates and Bishop, 1998; Yeh and Li, 2002, 2003). However, if the program cannot access and modify the data to and from the GIS environment, then the process of reformatting the input and output is not only more likely to mislead the representation, it may also be time consuming and error prone. For these reasons, 'loose' or 'tight' coupling are more likely to produce better integration models (Bivand and Lucas, 2000; Almeida *et al.*, 2003; Couclelis, 2002).

The integration of GIS and CA approaches may be successfully achieved through tight coupling. That is, new extensions, functionalities or dynamic tools are encoded into the GIS environment to expand its capabilities to perform tasks for which it has not been originally designed. In the perspective of urban spatial modelling by means of GIS, the tight coupling group supports the view that future GIS should be equipped with spatial dynamics modelling. This can, however, be achieved by incorporating GIS functionalities into a type of analytical engine of cellular

automata; The CAM modelling machine developed by Toffoli and Margolus (1987) is one such example. Although, models generated through tight coupling are often suitable for a specific application, these are poorly replicated in different contexts. Moreover, spatial models developed within GIS remain less flexible and the capabilities of handling other modelling functionalities are also weak. Thus, there are thresholds for the extension of CA or GIS functionalities and capacities. At least in the case of GIS, it is clear that the technology has not yet been designed to perform complex modelling operations (Longley and Batty, 1996; Alberti, 1999; Waddell, 2002).

An alternative view on the integration of GIS and spatial modelling approaches is that it should be envisaged in respect of the sole strength and contribution of each set of tools. This technique is known as loose coupling. In loose coupling, both GIS and CA maintain their fundamental structure and functionalities, and only execute the operations where they perform the best. In case of CA and GIS, for instance, a loose coupling approach is the first pragmatic choice when it comes to dynamics modelling and simulation of real data (Clarke and Gaydos, 1998). In case of loose coupling, there are many variants: from using GIS purely as the display environment to a more expanded coupling where the contribution of GIS is much wider (Batty *et al.*, 1999). In a sharing task, GIS may act as a data management, storage, retrieval and static visualization interface, whereas CA may perform other functions that cannot or are less effectively handled by GIS, such as dynamic exploration and data analysis, interaction with commands and functions, insertion of weighting parameters, iterations, calibration, modelling, dynamic visualization and simulation.

The loose coupling can also be achieved through the development of a macro language. Conceiving and building scripts using macro languages may achieve optimum and flexible integration of CA and GIS. This supplementary programming task, which takes place outside the GIS and CA environment, has advantages since programming languages can be used and the knowledge gained may be reused or expanded for other applications. Moreover, the scenario can be easily updated or adjusted. Also, many of these programs support conditional statements such as Boolean logic based ('if...then') iterations, calibration possibilities, and many other functions which help in modelling. In that respect, properties of Object-Oriented Programming (OOP) have been reported as appropriate for realistic urban modelling and simulation (Benenson and Torrens, 2004).

In the Indian context, very few attempts have been made to develop CA based models for urban growth simulation. Jacob et al (2006) developed a CA model for simulating land use dynamics for degradation prone areas in the State of Andhra Pradesh. In the unpublished works of Maithani (2008), Singh (2003) and Sudhira (2004), CA models for urban growth simulation in Dehradun and Saharanpur planning areas, Shimla District and Mangalore city respectively have been developed. Thus, not much work has been reported on urban growth simulation using CA based models

in India. Nevertheless, the CA based models can be quite useful in the Indian context, as the present day focus of the Indian Government is on infrastructure development in urban areas.

5 CONCLUSIONS

In developing countries like India, there is an urgent need for sustainable urban development. CA based models, which simulate urban growth realistically, can be used and operated as an urban planning tool to build projected growth scenarios and answer "what-if" questions. The CA models can be used as a planning tool for developing alternative scenarios and the urban planner can take more rational and scientific decisions by looking at the various scenarios generated, thus providing a scientific basis for implementing decisions.

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