Modeling Urban Growth Dynamics using Cellular Automata and GIS

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Abstract

Managing and modelling urban growth is a multi-faceted problem. Cities are now recognised as complex systems through which non-linear and dynamic processes, emergence and self-organisation occur. The design of a system that can handle these complexities is a challenging prospect. This paper presents an urban planning tool for the city of Riyadh, Saudi Arabia. At the core of the system is a Fuzzy Cellular Automata Urban Growth Model (FCAUGM) which is generally capable of simulating and predicting the complexities of urban growth. This model was shown to be capable of replicating the trends and characteristics of an urban environment, in this case the city of Riyadh.

Keywords
Urban growth, urban complexity, cellular automata, genetic algorithms, simulated annealing, fuzzy logic, planning support system, GIS, satellite remote sensing, Riyadh.
1- Introduction
The city of Riyadh, Saudi Arabia, has experienced significant growth over the last 60 years increasing from a population of 30,000 in the 1940s to 2.5 million in the early 1990s. Growth has been stimulated by the discovery of oil and subsequent establishment of the commercial oil industry. The population is currently growing at around 8.1% per annum and is expected to reach 11 million by 2020. In parallel with this rapid growth in population, the urban expansion of the city has been similarly dramatic, growing from a geographical extent of less than 1 km² in the 1920s to over 1,150 km² in 2004 (HCDR, 2004).

To manage this high rate of urban growth and expansion, the Saudi Arabian government has instigated a series of master plans for the city of Riyadh. The main aim of these plans is to re-structure and direct urban expansion to achieve sustainable development in the future (HCDR, 2004). To ensure that the master plan will have beneficial effects on the urban fabric and population of the city, policymakers ideally require a planning tool that has the capability of simulating and predicting the complexities of managed urban growth over the next 15 years. Managing and modelling urban growth is, however, a multi-faceted problem. Cities are now increasingly being recognised as complex systems through which non-linear processes, emergence and self-organisation occur (Allen, 1997; Portugali, 2000; Batty, 2007). CA has to a large extent demonstrated its capability for modelling complex, self-organization and emergent systems such as urban systems. CA offers the advantages of spatiality, dynamics, simplicity and computational efficiency and capability of mimicking real spatial behaviour. This study has demonstrated that CA provides an effective spatial-temporal modelling technique for urban growth.

This paper presents a model that can assist in understanding the spatial process and patterns of urban growth and the factors involved and influencing such growth, and eventually use it to predict geographical areas where urban growth of Riyadh will occur over the next 15 years. The model used historical remote sensing images of Riyadh, land use maps, road maps, master plans and other data to simulate urban expansion over the last 18 years using stochastic constrained cellular automata, fuzzy set theory, fuzzy logic control systems and geographical information systems.

2- Derivation of Transition Rules
One of the novelties of this model is the design and development of a set of transition rules based on fuzzy set theory rather than probability theory, as applied in previous studies (Batty and Xie, 1994; Wu and Webster, 1998; Ward et al., 2000; White and Engelen, 1997; Li and Yeh, 2002). To replicate realistically the spatial dynamics and processes of urban growth, several transition rules were developed. These were constructed in two stages: (i) by identifying ten spatially-based factors; and (ii) by creating three ‘driving forces’ for urban growth (Table 1). The driving
forces were developed to reflect the main processes shaping the urban growth of Riyadh city. These drivers were derived from reviews of literature, analysis of local data and expert knowledge.

Table 1: Explanation of the spatial factors and corresponding driving forces

<table>
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<tr>
<th>Factor</th>
<th>Explanation</th>
<th>Variables</th>
<th>Driving Force</th>
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<tbody>
<tr>
<td>Local</td>
<td>Physical characteristics such as altitude, slope gradient, soil quality or geological condition</td>
<td>Slope gradient, Altitude</td>
<td>TCF</td>
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<tr>
<td>Regional</td>
<td>Measures the spatial influence of an entity and activity, for example Euclidian distance decay function such as accessibility to town centre.</td>
<td>Accessibility to Local Road, Accessibility to Main Road, Accessibility to Major Road, Urban Density, Accessibility to Town Center, Accessibility to Employment Accessibility Centers and Socio-Economic Services</td>
<td>TSF, TSF, UAAF, UAAF</td>
</tr>
<tr>
<td>Global</td>
<td>Invariant spatially but changeable temporally, e.g. zoning regulations and master plan</td>
<td>Planned Areas, Excluded Areas</td>
<td>PPRF</td>
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3- The Structure of the FCAUGM
The model is comprised of three interlinked software modules: (i) calibration; (ii) simulation; and (iii) prediction. These modules and the framework were designed to be generic, flexible and extensible. Together, the three modules form a prototype Spatial Planning Support System (SPSS). Wu (1998) argued that there is a limited link between urban CA models and an explicit decision-making process; however, the work here aims to address this gap, at least in part if not fully.

3-1 Calibration Module
The primary goal of the calibration module is the generation of optimal values or weights of the input variables. Optimisation of these values is achieved using three
algorithms: genetic algorithms (GAs), parallel simulated annealing (PSA) and expert knowledge (EK). After optimisation, the values are passed to a fuzzy logic model. This model builds transition rules for simulating urban growth (Al-Ahmadi et al., 2008a).

3-2 Simulation Module
After the transition rules have been developed, they are passed to the simulation module. Here the transition rules ‘power’ the CA model allowing replication of the spatial and temporal patterns of urban growth. Through the simulation module, the model is validated (qualitatively and quantitatively) by testing model outputs against real data from several different periods and under various scenarios.

3-3 Prediction Module
The prediction module lets users, in particular city planners, predict potential pattern and process of urban growth based on future planning policies, plans or strategies. The model has been applied to test the consequences of several different scenarios, for example, sustainable growth, the establishment of new suburban centers or the introduction of new satellite cities. The results of these simulations, and their relevance to planning policies, are presented in the paper by Al-Ahmadi et al. (2008b).

4- Results and Discussion
The spatial pattern of urban growth of Riyadh during the two periods (1987-1997), and (1987-2005) were simulated using the calibrated weights and parameters yielded from the calibration module.

In order to assess the simulated urban form, the simulated images were compared to the observed ones by visual comparison using spatial overlay of the two images. For each pair of land development images, four main categories have been produced. These include non-urban match (non-urban in observation and simulation), urban match (urban in observation and simulation), under estimate (urban in observation but non-urban in simulation), and over estimate (non-urban in observation but urban in simulation). The first two classes are correct simulations, while the latter two are incorrect. Two other classes are added for facilitating comparison including starting urban (the already developed lands before the year of simulation) and agricultural Areas.

Figure 1 shows a scenario of the overlaid outputs over the two periods (1987-1997) and (1987-2005) respectively, while Figure 2 reveals the final simulated pattern of urban growth. The urban growth for the period (1987-1997) in most areas of the city such as north, north-east or south-west is relatively well estimated (coloured in red). Nevertheless, areas located at the immediate edges of boundaries of recognised urbanized areas are over-estimated (coloured in yellow). This is not surprising because those cells are adjacent to urban land and nearby to attractions and are more likely to be urban than non-urban. Although the model simulated reasonably
well the pattern or distribution of the developed land of the city, it is noticeable and understandable that the urban CA is not able to reproduce, for example, all of the actual urban development that took place at the extreme south-eastern edge of the city (right-bottom corner of the image, coloured in black), which resulted in an underestimation of these lands. With respect to the period (1987-2005), the main result shows that there is a good visual similarity between the maps, and the simulation results resemble the real city. While some clusters of land cells were underestimated in peripheral areas such as the south-east corner of the image, overall this simulation reproduced urban growth very well. The success can be attributed to the interplay of the driving forces and to very few unusual developments. Running the simulation over a longer period has diminished the impact of leap-frog development which was an important factor in the previous simulation and a predominant characteristic of peripheral expansion.

5- Conclusion
This paper has presented a fuzzy cellular automata urban growth model (FCAUGM) for simulating the complex dynamics of urban growth in Riyadh, Saudi Arabia. This urban model differs from earlier work by its use of automated calibration routines including genetic algorithms and simulated annealing and by its construction of transition rules using fuzzy logic. The use of these methods provided a more efficient and accurate means of calibrating the model, which is described in more detail in Al-Ahmadi et al. (2008a). The inclusion of fuzzy logic allowed for the formulation of more realistic transition rules. It also allowed for a much more generic, extensible and adaptable approach than previous methods reported in the literature. The model was rigorously validated through the application of quantitative and qualitative methods. These methods were selected based on their capability to assess changes in spatial structure over time. The FCAUGM was tested by simulating the spatial patterns of urban growth over several different development stages using the calibrated values. It was found that the FCAUGM successfully replicated the empirical spatial patterns of Riyadh’s urban growth which had occurred in reality over the last 18 years, by identifying areas that broadly experienced urban development and by mapping the general urban extent. However, the results from the period 1997-2005 were not as satisfactory; this may be attributed to the patterns and characteristics of spatial growth during each period. For example, in 1987-1997 and 1987-2005, the city experienced edge-expansion or marginal urban growth which was undemanding and relatively straightforward to simulate. In contrast, during the period 1997-2005 urban growth was characterised by in-fill development as a result of strict government policy to in-fill the leap-frog development; this type of behaviour is typically highly non-linear and complicated.
Figure 1: Visual comparison of urban growth simulation for each of the study periods (A) 1987-1997 and (B) 1987-2005

Figure 2: Final simulated urban growth for each of the study periods (A) 1987-1997 and (B) 1987-2005
6- References


