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CA City: Simulating Urban Growth through the Application of Cellular Automata

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1. Introduction

It is estimated that 3.5 billion people currently live in cities, which equates to more than 50% of the total population (UN, 2010). These cities vary in size from 500,000 to over 10 million inhabitants (termed mega-cities). The number of cities, in particularly mega-cities, are set to significantly increase by 2050. However, this rapid urban population growth is taking place at differing speeds and spatial scales across the globe. Developing countries are experiencing a much higher level of urbanisation than developed countries. For example, by 2050, it is expected that Europe will be 84% urbanised (compared to 82% in 2010), whilst Asia and Africa will be 65% and 62% urbanised by 2050, respectively, compared to 40% in 2010 (UN, 2010).

Such rapid urbanisation, normally unplanned and spontaneous, brings its own set of problems, in both the social and physical environment. These include spatial segregation of the rich and poor, shortages in urban housing and basic services, and the production of vast volumes of waste and harmful synthetic materials (Pacione, 2005), as well as urban poverty. Psychologically, urbanisation can engender feelings of loneliness, self-centeredness, loss of a sense of community, and increasing crime rates (Knox, 1994).

To mitigate for these types of problems as well as to manage and plan future urban growth, a range of modelling techniques has been applied. The development of urban theory and modelling has a long history, e.g. *Industrial Location Theory (*Weber, 1909), *Central Place Theory (*Christaller, 1933), *the Concentric Zone Model (*Burgess, 1925), *the Sector Model (*Hoyt, 1939) and the *Multiple Nuclei Model (*Harris and Ullman, 1945). These classical theories and models have formed the foundation for studying urban structure and growth, but they have been criticised for being overly simplistic, unrealistic in their assumptions, and not applicable to the structure of today's cities (Chapin and Kaiser, 1979; Briassoulis, 2000; Batty, 1994, 1996). Another major criticism levelled at these models is their static nature. They are unable to explain the spontaneous growth that has taken place in modern cities under a non-equilibrium status, which has evolved diversely from highly dispersed edge cities to

huge mega-cities (Batty, 1994). This last point reflects how, with a deeper understanding of urban phenomena, scientists have begun to recognise that cities are not uniform or a single type of phenomenon. Instead they are increasingly being recognised as complex systems through which non-linear processes, emergence and self-organisation occur (Allen 1997; Portugali 2000; Batty 2007). These processes shape the spatial growth of the city over time with structured and ordered patterns emerging (Torrens 2000a).

More recent urban models, catalysed by the availability of mainframe and desktop computers, have focused on modelling the spatial structure of urban growth processes and the notion of self-organisation. These models include large-scale urban models of land use-transportation developed using a range of analytical methods from other disciplines including linear programming, physics, human ecology, mathematics, operations research, regional science and economics (Batty, 1981; Klosterman, 1999; Torrens, 2000b). Many of these models have incorporated cellular automata (CA), whether to model land parcels or the actions of firms or organisations.

This chapter will demonstrate the potential of CA as a tool for urban planning and development using two CA models and case studies, one from Saudi Arabia and the other from the Republic of Korea. In Riyadh, Saudi Arabia, the government are planning new suburban towns to absorb future population growth. The exact location of these towns is subject to several environmental constraints. CA have been used as a planning tool to evaluate several sites and visualise the likely future growth of these towns. The impact of increased population growth is also one of the main drivers for the construction of a new city in the Republic of Korea. This chapter illustrates how CA have been used for the evaluation of different potential sites and to visualise how the city could grow over time based on various scenarios. A review of previous work in this area is first provided to place these modelling exercises in context. This is followed by a description of the case studies, the results of the model scenarios and a comparison of the two models. The strengths and weaknesses of the models are discussed including areas for further development.

2. Previous research

Cellular Automata (CA) provide a way of simulating complex systems and self-organising processes over space and time (Wolfram, 1994). As a result of their capability for generating complex patterns through local rules, and for linking rules to their consequences, CA can provide insights into the different pathways that control and form systems. The use of CA for modelling urban dynamics and growth has been the subject of considerable research over the last two decades. A comprehensive review has recently been undertaken by Santé et al. (2010), which provides a historical overview of the use of CA in urban modelling, covering CA as a largely theoretical approach to urban simulation (e.g. Itami, 1998; Batty, 1998) as well as early attempts at applying CA models to real cities (e.g. Engelen et al., 1995; White et al., 1997). Since then many different examples have emerged, which have been built using different structures and developed for diverse applications (e.g. see the work of Li et al. (2003), Barredo et al. (2004) and Stevens et al. (2007) to name a few).

In their review, Santé et al. (2010) examined thirty-three urban CA models from the literature. To compare these different models, nine main characteristics were chosen including the purpose of the model, the resolution, the predicted states, the neighbourhood, the transition rules, the constraints, the methods of calibration and validation, and any integration with other models. In addition, they also analysed the factors or drivers of urban

growth employed by each of the models. Based on these analyses, they were able to discuss some of the main strengths and weaknesses of the use of CA for urban modelling. The authors argue that the simplicity of CA models is considered both a strength and a weakness. It is difficult to capture the complexity of urban systems within such a simple representation, and for this reason, many modifications or relaxations have been made, which brings into question whether many of the models are still actually CA. The model flexibility in terms of adaptation to various real world situations is also discussed so models which have rules and parameters calibrated through data mining methods are less flexible than more generically specified transition rules. Less than 40% of the models predicted multiple land uses while most simply determined whether cells are urbanised or not. In terms of model accuracy, they found that overall this was generally very good, but one area where further research is needed is in the development of new validation methods, especially in the area of pattern recognition. Other areas where the authors suggest further research includes more integration of CA modelling with urban and spatial theory as well as integrating different modelling types such as agent-based models in a hybrid representation. Since the period of the review (which covers research published up to early 2009), a number of new papers have appeared in the literature. However, much of this research has involved the application of existing CA urban models to different areas, or modifications to improve the model performance. For example, the SLEUTH model (Clarke et al., 1997) continues to be applied to different parts of the world. Rafiee et al. (2009) used the SLEUTH model for simulating urban growth in Mashad City, Iran, Jantz et al. (2010) have made improvements to SLEUTH in the development of a fine scale regional model of the Chesapeake Bay area in the eastern US, while Wu (2009) applied the SLEUTH model to the Shenyang metropolitan area of China. Similarly, the CLUE-S model (Veldkamp and Fresco, 1996) has been used by Pan et al. (2010) and Zhang et al. (2010) for modelling areas in China with particular emphasis on the effects of scale on model outcomes, and the consideration of uncertainty. Other existing CA models used in recent work includes the research by Petrov et al. (2009), who applied the MOLAND model (Lavelle et al., 2004) to scenarios of future urban land use change in 2020 in the Algarve, Portugal, and Poelmans and Van Rompaey (2009), who applied the Geomod model (Pontius, 2001) to examine urban sprawl in the Flanders-Brussels region. Other areas of research have involved modifications to the basic CA structure, e.g. the use of a variable grid CA (van Vliet et al., 2009), a vector-based CA (Moreno et al., 2009) and hybrid model variants, e.g. Han et al. (2009), who integrated a systems dynamics model with a CA model, and Wu et al. (2010), who coupled neural networks with CA. There is also a trend towards the development of agent-based urban growth models, either in conjunction with CA (e.g. Wu and Silva, 2009) or as a new framework for modelling urban spatial dynamics (e.g. Irwin et al., 2009). Finally, recent work by Poelmans and Van Rompaey (2010) involved the comparison of a CA model against other approaches to modelling urban expansion including logistic regression and a hybrid approach that combined both individual approaches. When considering the results at only one resolution, the hybrid approach produced the best result. However, when multiple resolutions were considered, the logisitic regression proved to be superior. This work once again emphasises the importance of scale, which has been considered in more recent work as outlined above.

Thus, it is clear from the growing literature that the use of CA will continue to be used for modelling urban growth, whether building upon existing models or in hybrid formulations.

3. CA model of urban growth in Riyadh, Saudi Arabia

The first case study will assess the likely impact of several new towns and satellite centres around the city of Riyadh, Saudi Arabia. Due to the discovery of oil, Riyadh has experienced significant growth over the last 60 years. The population of Riyadh has increased from 25,000 in the 1930s to 2.5 million by the early 1990s. The current rate of population growth is around 8.1% per annum and the city is expected to reach 10 million people by 2020. The spatial expansion of the city has also seen dramatic changes, growing from a geographical extent of less than 1 km² in the 1920s to over 1,150 km² by 2004 (ADA, 2004).

To manage this high rate of urban growth and change, the Saudi Arabian government has instigated a series of master plans for Riyadh. The main aim of these plans is to re-structure and direct urban expansion to achieve sustainable development in the future (ADA, 2004). To ensure that the master plan will have beneficial effects on the urban fabric and population of the city, policy makers require a planning support tool that has the capability of simulating the complexities of managed urban growth over the next 15 years. The model outlined by Al-Ahmadi et al. (2009a,c) has been developed with this requirement in mind.

3.1 CA model details

The model, referred to as the Fuzzy Cellular Automata Urban Growth Model (FCAUGM), is a stochastically constrained CA. The model creates a new urban cell *ij* at time *t*+1 if the cell's development possibility (DP) score is greater than or equal to a transition threshold parameter, λ, as follows:

$$\text{If } DP_{ij}^t \geq \lambda \text{ Then } S_{ij}^{t+1} = \text{Urban, Otherwise} = \text{Non-Urban} \tag{1}$$

where S_{ij}^t is the state of a cell *ij* a time *t*+1; Dp_{ij}^t is the development possibility of a cell *ij* a time *t*; and λ is the transition threshold between 0 and 1, which is determined through calibration.

The model defines the state of a cell S_{ij}^{t+1} at *t*+1 as a function of its development possibility (*DP*) at time *t*, which is a function of both the development suitability (*DS*) of a cell *ij* at time *t*, and a stochastic disturbance factor (*SDF*):

$$S_{ij}^{t+1} = f\left(DP_{ij}^t\right) = (DS_{ij}^t * SDF) = (DS_{ij}^t * [1 + \ln{(\gamma)^\alpha}]) \tag{2}$$

where DS_{ij}^t is the development suitability of a cell *ij* a time *t*; γ is a uniform random variable within the range [0,1]; and *a* is the dispersion parameter which controls the size of the stochastic perturbation. The development suitability, DS_{ij}^t, of a cell *ij* is a function of four driving forces which potentially contribute and affect the spatial patterns of urban growth:

$$DS_{ij}^t = f\left(TSF_{ij}^t, UAAF_{ij}^t, TCF_{ij}^t, PPRF_{ij}^t\right) \tag{3}$$

where TSF_{ij}^t is the transport support factor of a cell *ij* at time *t*; $UAAF_{ij}^t$ is the urban agglomeration and attractiveness factor; TCF_{ij}^t is the topographical constraint factor; and $PPRF_{ij}^t$ is the planning policies and regulation factor. The four driving forces of urban growth (TSF, UAAF, TCF and PPRF) are themselves functions of fuzzy input variables as shown below:

$$TSF_{ij}^t = f\left(ALR_{ij}^t, AMR_{ij}^t, AMJR_{ij}^t\right) \tag{4}$$

$$UAAF_{ij}^t = f\left(UD_{ij}^t, AECSES_{ij}^t, ATC_{ij}^t\right) \tag{5}$$

$$TCF_{ij}^t = f\left(G_{ij}^t, A_{ij}^t\right) \tag{6}$$

$$PPRF_{ij}^t = f\left(PA_{ij}^t, EA_{ij}^t\right) \tag{7}$$

where TSF is determined by Accessibility to Local Roads (ALR), Accessibility to Main Roads (AMR) and Accessibility to Major Roads (AMJR); the UAAF is a function of Urban Density (UD), Accessibility to Town Centres (ATC) and Accessibility to Employment Centres and Socio-Economic Services (AECSES); the TCF is determined by Gradient (G) and Altitude (A); while the PPRF indicates the Planned Areas (PA) and Excluded Areas (EA). The drivers of urban growth are linked together via a set of fuzzy rules, which are determined during calibration along with the membership functions. A fuzzy inference engine combines the fuzzy rules to create a fuzzy development suitability score (DS_{ij}^t), which is then defuzzifed to a crisp value as shown below:

$$DS_{ij}^t = 1 + \frac{\sum_{i=1}^n \mu c_n(z_{ij}) * z_{ij}}{\sum_{i=1}^n \mu c_n(z_{ij})} \tag{8}$$

where μc_n is the membership function of the development suitability of a rule n and z_{ij} is the fuzzy output value (development suitability) of a cell ij of a rule n.

The model was then calibrated using a sample dataset from the study area, chosen using a disproportional stratified random sampling method consisting of 60% urban and 40% non-urban locations. A genetic algorithm and a parallel implementation of simulated annealing were used as optimisation methods. In addition, experts were used to determine the membership functions and rules as a third method for comparison. The mean squared error and the root mean squared error were used as objective functions in the calibration. They were combined into a single, weighted and standardised objective function to penalise situations where model parameters fall outside the allowable bounds. The genetic algorithm provided the best calibration results.

Once calibrated, the FCAUGM was used to simulate urban growth in Riyadh city for the following three periods: 1987–1997, 1997–2005 and 1987–2005 in order to carry out validation. Several quantitative measures to determine model performance were used such as overall accuracy (based on a confusion matrix), the Lee-Sallee index and a spatial pattern measure. In terms of overall accuracy, the FCAUGM performed well, i.e. 93% for 1987–1997, 92% for 1987–2005 and 94% for the combined period 1987-2005. However, when considering only urban agreement, the accuracy drops to 52.5% in 1987-1997, 37.6% in 1997–2005 and 74.3% in 1987–2005. For further details of the model including the full calibration and validation procedures, the reader is referred to Al-Ahmadi et al. (2009a,c).

3.2 Outline of scenarios

Two scenarios using the FCAUGM are presented in this chapter: (i) the development of new satellite towns, and (ii) the creation of new metropolitan sub-centres. These different planning scenarios form part of current Saudi government planning policy, referred to as the Metropolitan Development Strategy for Arriyadh (MEDSTAR). According to the HCDR (2004), two locations within Riyadh's urban boundary have been allocated for development as new towns. The northern town will accommodate almost 1 million people with the eastern town absorbing 900,000. The position of the towns has been selected to maximise

both business opportunities (proximity to airports and major infrastructure) and development of high quality residential areas.

Another aim of the MEDSTAR strategy is to decrease the concentration of the city's activities and services from one place to a more decentralised approach. This strategy has been translated into the designation of five metropolitan sub-centres located 25 km from the city centre. The goal of these new centres is sustainable urban development for the Riyadh metropolitan area through restructuring and urban growth. This is to be achieved through the creation of urban hubs as the focus for employment, investment, commercial facilities and governmental administrative functions.

4. CA model of new city growth in the Republic of Korea

The second case study is the development of an urban growth model for a new city in the Republic of Korea. In 2003, the Korean government announced plans to construct a new administrative capital near Daejun city. This new city would alleviate the problems that are currently caused by economic concentration and population agglomeration in the existing capital and surrounding area. The city, due for completion in 2014, will cost the Korean government approximately £4.2 billion. On completion of the city, 12 out of 18 ministries will move to the new administrative capital city. The population is projected to grow to 500,000 by 2030. To date, this is the single most important urban development ever planned in the Republic of Korea. However, there has been little modelling undertaken to determine how the city will develop or spread. Previous new city development has resulted in the spread of urban land use into conservation zones and unplanned regions. A model was therefore designed for planners to experiment with different growth scenarios to avoid these problems.

4.1 CA model details

The CA model used in this case study is called the NCGM (New City Growth Model). As with the FCAUGM developed for Riyadh, it is also a type of stochastically constrained CA urban model, operating as outlined in equation 1. However, there are a number of differences. The first is in the form of the stochastic disturbance factor, which uses a hybrid transformation function. Moreover, the input factors that drive urban growth in the NCGM have specifically been chosen for modelling new city growth and not growth due to natural processes. These factors include: urban density, road accessibilty, subway accessibility, slope, planning areas and excluded areas. The developmental suitability, referred to in this model as the composite score for a cell ij, $ComS_{ij}$, is a weighted summation of the factors as shown below:

$$ComS_{ij} = \left[(W_U * F_{ijU}) + (W_R * F_{ijR}) + (W_S * F_{ijS}) + (W_{Sub} * F_{ijSub}) + (W_P * F_{ijP}) \right] * F_{ijEx} \quad (9)$$

where $F_{ijU}, F_{ijU}, F_{ijU}, F_{ijSub}$ are the factor scores of the inputs urban density, road accessibility, slope and subway accessibility of ij respectively, F_{ijP} and F_{ijEx} are binary factors which state whether a cell is inside or outside of the planning area or the excluded areas, respectively, and $W_U, W_R, W_S, W_{Sub}, W_P$ are the weights of the inputs factors for urban density, road accessibility, slope, subway accessibility and planning areas. The composite score is then turned into a probability for development through the hybrid transformation function. The transition threshold then turns the probability into a developed or non-developed cell.

Similar to the FCAUGM, a genetic algorithm was used to determine the model parameters during calibration using the mean squared error as the objective function. In the case of the NCGM, the weights in equation 9 and the size of the neighbourhood were optimised. The data for calibration were taken from the new city of BanDung and were divided into three time periods: the Pre-Planning, the Mid-Planning, and the Post-Planning periods, respectively. Once the model was calibrated, data from the new city of IlSang were used for validation. Quantitative measures of model performance were similar to those used in the FCAUGM. The overall accuracies for the Mid-Planning and Post-Planning periods were 93% and 88%, respectively, although model performance decreased to 54% and 45%, respectively, when considering only urban areas. For further details of the structure of the model, and the calibration and validation procedures, the reader is referred to Kim (2005).

4.2 Outline of scenarios for new city growth

The first scenario, termed the baseline, simulates new growth from 2004 to 2020, which would take place without any explicit policy interventions. A default urban growth rate of 7.5% was used for both the Mid-Planning and Post-Planning periods. Due to data availability, the Mid-Planning period begins in 2004 and ends in 2012; this is according to the building plan as set out by the Ministry of Construction and Transportation (MOCT, 2005). The Post-Planning period covers the 8 years beyond the Mid-Planning period (from 2012 to 2020). A second scenario is then presented with an urban growth rate of 10%. The aim of this scenario is to estimate the potential areas to be developed if further urban growth, beyond that expected, takes place.

5. Model results

5.1 Modeling new development outside of Riyadh, Saudi Arabia

In the first scenario, the FCAUGM was run to examine the impact of two new satellite towns near Riyadh. The results of the simulation are shown in Figure 1. Here, the two proposed towns can be seen to absorb most of the urban development that is anticipated to take place to the southwest and south of Riyadh. It is highly likely that the new towns will attract residents with a preference for a calmer and more suburban living environment than is currently provided in the city. This suggests that development of the new satellite towns will be a positive planning intervention for the future of the city.

Assessing the impact of the new planned metropolitan sub-centres assumes that the development is dominated by the process of decentralisation and densification of activities and services in the different sectors of the city and particularly nearby sub-centres, i.e. the city is allowed to grow faster near sub-centres than the major urban area and town centre. Figure 2 shows that the development is more compact and concentrated around the sub-centres, resulting in more sustainable development. Thus, this scenario shows how unnecessary extended urban expansion or urban sprawl is prevented. It can be seen from the predicted urban form of Riyadh city under this scenario that the policy of designating five metropolitan sub-centres in the outer sectors of the city has to a large extent achieved the ultimate goals set by ArRiyadh Development Authority (ADA, 2004), i.e. re-structuring and direct urban expansion to achieve sustainable development in the future.
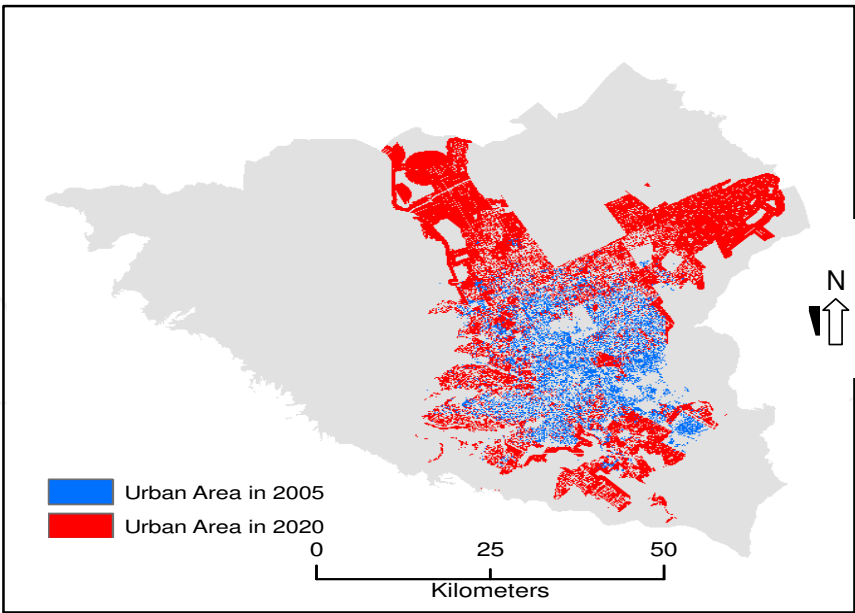
Fig. 1. Predicted urban growth of Riyadh under the New Satellite Cities Scenario
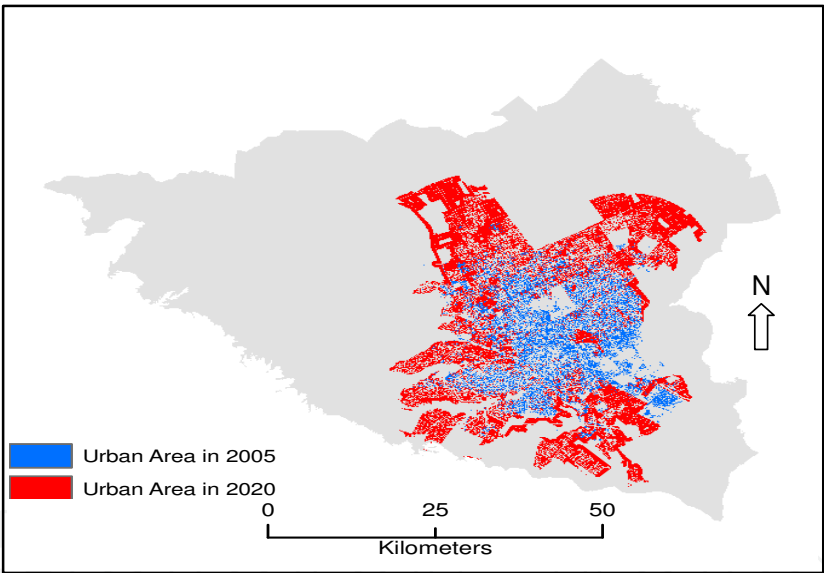

Fig. 2. Predicted urban growth of Riyadh under the New Metropolitan Sub-Centres Scenario

5.2 Development of a new city in the Republic of Korea

The results for the baseline scenario are shown in Figure 3. Figure 3a and Figure 3b are the final predicted images during the Mid-Planning and Post-Planning periods, respectively. The prediction during the Mid-Planning period started from the areas coloured in blue in Figure 3a, and the new urban areas are coloured in red in the same image. The results from Figure 3a were used as the initialisation/start point for the simulation of the Post-Planning period shown in Figure 3b. Figure 3c is an overlaid image combining urban growth during the Mid-Planning period (coloured in purple) and Post-Planning period (coloured in red). Finally, Figure 3d shows the predicted urban shape of the new administrative capital area in 2020.
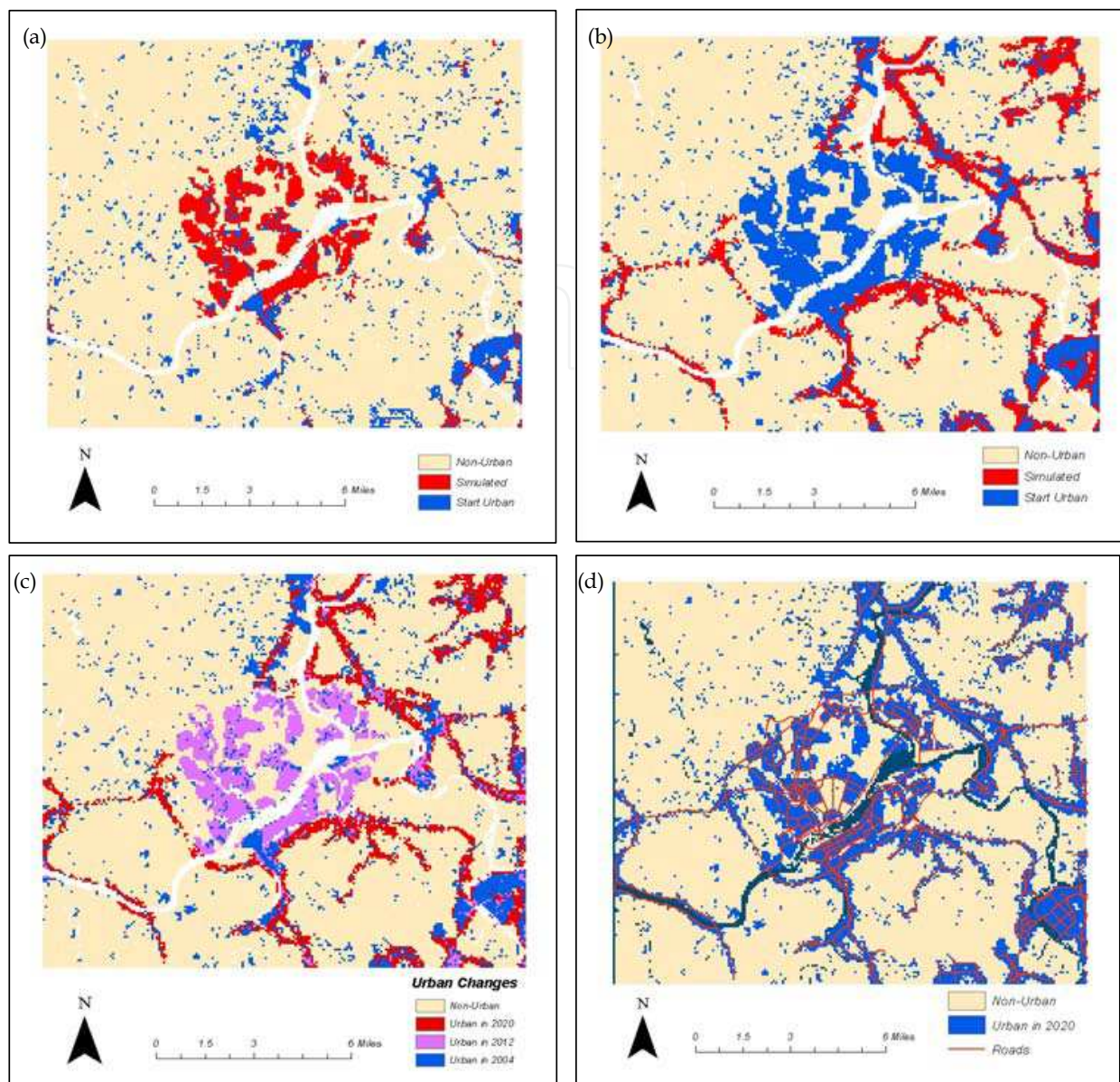
Fig. 3. Predicted urban growth of the new administrative capital area under the first (baseline) scenario during (a) the Mid-Planning period; (b) the Post-Planning period; (c) urban changes during both periods; and (d) the final urban shape in 2020.

During the Mid-Planning period, most of the urban development occurred within the area planned for the new administrative capital city with small amounts of urban clustering developing in the east and south-eastern areas (see Figure 3a). This might be considered the result of well organised and intended urban growth. However, during the Post-Planning period, further urban development would be expected to take place around the planned city, particularly along the road network (including the outer ring road and north-east corner of the image). Development pressure from the already developed area seems to cause the urban development in the south-eastern corner of Figure 3b. It is also of note that a new urban cluster has developed in the north-eastern corner of the image.

Figure 3c clearly demonstrates the differences between those urban growth patterns during the Mid-Planning and Post-Planning periods. Most urban development during the Mid-

Planning period (coloured in purple) is concentrated on the planned city. However, further urban development during the Post-Planning period would create rather sporadic forms of urban settlements along the road network (coloured in red). The predicted final urban shape in 2020 shows evidence of sporadic urban growth (see Figure 3d).

The second scenario is shown in Figure 4, where the aim is to examine the affect of a higher than expected urban growth rate of 10%. Figure 4a shows the predicted urban pattern for the Mid-Planning period. In comparison to the baseline scenario (Figure 3a), four types of urban growth can be detected. Firstly, urban development along the road crossing from the north to east edges of the image is apparent. Secondly, an urban cluster in the areas immediately to the south and south-east of the new administrative capital city develops considerably. Thirdly, two small urban clusters have grown in the north-east corner. Finally, a new urban development can be detected in the south-eastern corner of the image.
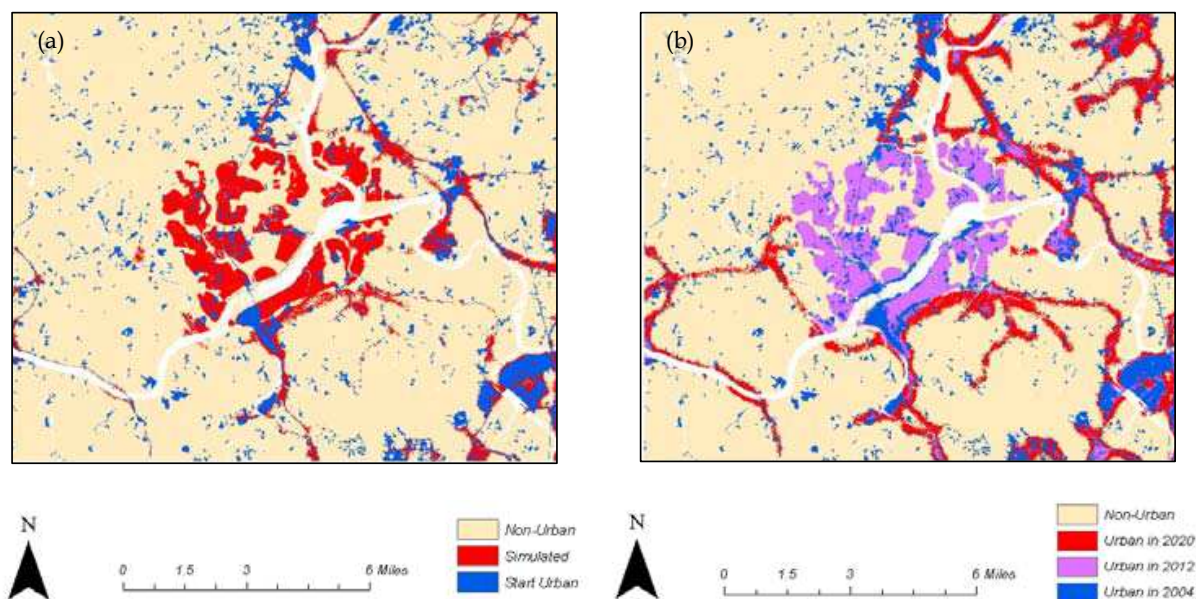

Fig. 4. Model simulation results using an urban growth scenario of 10% for a) the Mid-Planning period and b) the Post-planning period

Figure 4b shows the higher simulated level of urban growth during the Post-Planning period. Here, the result of the baseline scenario (7.5% urban growth) is coloured in purple for comparative purposes. The trends seen in the Mid-Planning period simulation are evident in this scenario. The two small urban clusters in the north-east corner that developed during the Mid-Planning period are clearly detectable, forming a large urban cluster. Away from that urban cluster, most urban development takes place along the road network linking the new administrative capital city to the other developed areas. Urban growth along the road crossing from the north to east edges of the image along with urban growth that happened in the areas immediately to the south and south-east of the new administrative capital city are now even clearer. The sporadic urban growth patterns along the road network found with the default urban growth rates (Figure 3a) is reinforced with application of a higher urban growth rate.

5. Comparison of the models

Both the FCAUGM and the NCGM have been developed independently at the University of Leeds to model urban growth for two very different areas. A comparison of the FCAUGM and NCGM is presented in Table 1 using the same characteristics as employed by Santé et al. (2010).

Model Characteristics	FCAUGM	NCGM
Objective	Descriptive + Predictive	Predictive
Cell space	20 m square cells	30 m square cells
States	Urban, non-urban	Urban, non-urban
Neighbourhood	Size is determined during calibration	Size is determined during calibration
Transition rules	Used the same exponential form as Li and Yeh (2001)	Hybrid transition rule that acts as sigmoidal in certain ranges and exponential in others
Constraints	Annual growth rate for urban land	Annual growth rate for urban land
Other methods	Genetic algorithm, parallel simulated annealing and expert knowledge used in calibration	Genetic algorithm used in calibration
Drivers of growth	Accessibility to local, main and major roads, urban density, accessibility to Town Centres, accessibility to employment centers and socio-economic services (AECSES), slope, altitude, planned areas, excluded areas	Urban density, accessibility to roads, slope, accessibility to the subway, planning areas, excluded areas
Calibration	Fuzzy membership function of growth drivers, the fuzzy rules and the transition threshold are calibrated using a genetic algorithm, simulated annealing and expert knowledge in three separate instances of the model	Weights of growth drivers and neighbourhood size are calibrated using a genetic algorithm
Validation	Visual inspection of the spatial patterns; overall accuracy from a confusion matrix; accuracy of urban areas; Lee-Sallee index; spatial pattern measure	Overall accuracy from a confusion matrix; accuracy of urban areas; Lee-Sallee index

Table 1. Comparison of the two CA urban growth models

The FCAUGM was designed to be highly generic, and can therefore be applied to any planning scenario. This is in part due to the requirements of this model to be flexible and extensible, for example modelling not only the development and growth of new towns around the city of Riyadh, but also other developments such as metropolitan sub-centres and other types of scenarios as outlined in Al-Ahmadi et al. (2009b). Santé et al. (2010) would actually consider such a model to be the least flexible when compared to other CA models because the model is calibrated using a genetic algorithm for local conditions. However, this may also explain why the accuracy of the model is high when compared to other CA models and therefore represents a tradeoff in this type of modelling. The NCGM, on the other hand, was specifically designed for simulating the likely growth of a planned new city in the future. The model is actually much simpler than the FCAUGM, with less parameters to calibrate and is therefore the more flexible of the two.

Both the FCAUGM and NCGM are predictive models as per the types of objective outlined in Santé et al. (2010). However, the FCAUGM has the added advantage of also being a descriptive model because of the fuzzy nature of the model formulation. The fuzzy logic component is intended to replicate human decision-making as well as the uncertainty around many of the drivers used in the model. The resulting fuzzy rules and membership functions are transparent so the effect of the drivers can be determined by examining the rules and the configuration of the membership functions. For example, in Al-Ahmadi et al. (2009c), different rules fired more frequently depending on which combination of drivers was tried in the model, which could then be related to the type of urban growth happening in a particular period.

The cell space or resolution of the two models is similar, with a slighter higher resolution for the FCAUGM, and both used square-shaped grid cells. As with most other urban CA models in the literature, the two models do not predict multiple land use types, just whether a cell is urbanised or not.

Both the FCAUGM and the NCGM are stochastically constrained CA but the transition rules differ. The FCAUGM uses an exponential form while the a hybrid transition rule was created for the NCGM that overcomes problems associated with calibration and the use of the mean squared error as the objective function. The hybrid rule was simpler to calibrate and can also be interpreted in terms of the rationality of the decision maker. Both models use assumptions about the annual growth rate, whether this is based on the past or an increased rate of growth depending on the scenarios run. Both models have been calibrated using a genetic algorithm although the FCAUGM was also calibrated using a parallel implementation of simulated annealing and expert knowledge. Three instances of the FCAUGM were created and it was found that the genetic algorithm gave the best result.

Both models use some of the same drivers of growth (e.g. accessibility to roads, urban density, slope, planned and excluded areas) but they differ in others (e.g. accesibility to town centers and socio-economic services, accessibility to employment and accessibility to the subway). This is partly a reflection of the difference in purpose, i.e. the more generic model that is the FCAUGM compared to the model specifically designed to examine new growth, but also a reflection of individual areas, the strategies governing development and their development history to date.

Both models used similar measures of model performance in validating the model, once calibrated. Overall accuracy is one of the most commonly used methods, and both models performed very well, especially in relation to other examples cited in Santé et al. (2010). Both performed less well when taking only urbanised areas into account but still had acceptable

performance. However, overall accuracy is a single global measure and does not take the resulting spatial patterns into account. Both models therefore also used the Lee-Sallee index, which is one method of trying to capture the urban shape of the output; however, it only works on immediate neighbours, and therefore does not capture higher level clustering or structure. The FCAUGM was further validated using a spatial pattern measure that looks at agreement within a defined neighbourhood but it is clear that measures which capture the spatial structure in a more realistic way are still needed. Finally, there were no experiments with changing the scale of the simulation and therefore determining the effects at multiple resolutions.

6. Conclusions

Figures from the UN (2010) show that the increase in urban population over the next 40 years will be dramatic (from 3.4 billion in 2009 to an estimated 6.3 billion in 2050). The ability to forecast and understand the impact of this growth on cities will be a major directive of government planning legistation and policy making. How can the growth in exisiting cities be managed so as not to create social, economic and environmental disparaties for their inhabitants? Is it possible when designing a new city, as in the Korean case study, to use modelling tools to simulate likey growth under a variety of scenarios; could this pave the way for sustainable growth? The work presented within this chapter has taken two constrasting areas of urban growth, i.e. expansion of an exisiting urban area and creation of a new city, and presented results that support the use of CA as an urban modelling and simulation tool to provide answers to some of these questions.

In the Saudi Arabian example, the FCAUGM model, a CA driven model, was presented and the impact of the development of new satellite towns, and the creation of new metropolitan sub-centres around the city of Riyadh was assessed. Both these simulations are part of current Saudi government planning policy. A separate CA driven model called NCGM, was developed and applied to the planning of a new city in the Korean example. The results from both case studies demonstrate that the models are capable of predicting plausible patterns of future urban growth. Furthermore, both models could be adapted for use as a spatial planning support tool for urban planners and decision makers in both Saudi Arabia and the Republic of Korea. Such tools can assist in testing out plans, policies and other factors underpinning and influencing processes of urban growth. This can in turn lead to a better understanding of the factors influencing urban growth and ultimately allow the evaluation of the consequences of diverse future scenarios for urban growth by answering 'what if' type questions (Yeh and Li, 2001).

The use of CA in both these examples reflects a shift in how cities are now viewed; they are not seen as static entities, but dynamic and complex systems composed of spatial and temporal interactions between the elements (people, environments, and policies, etc.). CA rooted in complexity theory, have shed light on modelling complex urban systems by allowing the components within the model to reflect spatial (neighbourhoods and constraints) and temporal (update or feedback) interactions. The FCUAGM and NCGM models are representative of a new breed of CA model that can be found in the literature. Both can be classed as hybrid models drawing on the strengths of other methodologies, for example genetic algorithms for calibration and fuzzy logic for formulation of the transition rules. Through this hybrid approach, these models can be significantly better at evaluating

the past, present and future consequences of urban planning interventions than their predecessors.

However, despite the advantages that these models bring, there are still areas that can be further improved. An obvious inclusion to both models would be an Agent-Based Model (ABM) for simulating populations. Agents are an increasingly familiar and powerful tool amongst geographers and social scientists. Within the context of these models, agents could be used to represent population dynamics at several different spatial scales such as individuals, households or neighbourhoods (it should be noted that ABMs are not just limited to representating population dynamics, they could be used for representating a varety of diverse entities such as firms, planners and governments). ABM not only compliments the bottom-up notion of modelling supported by CA, but would strengthen the realism of urban models by allowing greater detail to be included. However, this realism comes at a price. For this type of application, ABMs would require large volumes of accurate demographic and behavioural data. Often these data are not available, particularly for developing countries, and where it is available, the computational efficiency of the model (dependent on whether the model is used in academic or real world planning) should be considered as being of crucial importance.

There are other areas that to which future research should be directed. The effect of scale on these models, i.e. how to track the impacts of local neighbourhood processes on the patterns that emerge at city-wide level is an area that is ripe for investigation. How can self-organisation (a strong component of these models) be best visualised and understood? Are there better ways that these models can be validated and calibrated? Both models use genetic algorithms for calibration but are there better, more efficient optimisation methods available? How can pattern recognition techniques be used to improve validation?

Kirkby *et al.* (1992, p. 3) suggested that "models can never fully represent the real world, but can only be analogies or analogues which have some features and behaviours in common with it". The models presented in this chapter are not exceptions. Despite this caveat, both models were developed, calibrated, and tested to support different aspects of urban growth planning. Both models are driven by CA and have been shown to successfully simulate likely future growth. Inclusions of ABM and new calibration techniques can only improve the realism of these models and aid in the planning and management of sustainable future cities.

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Cellular Automata - Simplicity Behind Complexity

Edited by Dr. Alejandro Salcido

Cellular automata make up a class of completely discrete dynamical systems, which have became a core subject in the sciences of complexity due to their conceptual simplicity, easiness of implementation for computer simulation, and their ability to exhibit a wide variety of amazingly complex behavior. The feature of simplicity behind complexity of cellular automata has attracted the researchers' attention from a wide range of divergent fields of study of science, which extend from the exact disciplines of mathematical physics up to the social ones, and beyond. Numerous complex systems containing many discrete elements with local interactions have been and are being conveniently modelled as cellular automata. In this book, the versatility of cellular automata as models for a wide diversity of complex systems is underlined through the study of a number of outstanding problems using these innovative techniques for modelling and simulation.

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