Chapter 4
Cellular Automata in Urban Spatial Modelling

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Abstract Cities and urban dynamics are today understood as self-organized complex systems. While the understanding of cities has changed, also the paradigm in modeling their dynamics has changed from a top-down to a bottom-up approach. Cellular automata models provide an excellent framework for urban spatial modeling of complex dynamics and the accumulation of local actions. The first part of this chapter describes the basic concepts of cellular automata. The second part discusses the definition of complexity and the complex features of cellular automata. The history and principles of urban cellular automata models are introduced in the third part.

4.1 Preliminaries

The contemporary city, consisting of numerous strongly interconnected structures, multiple centers and continuous flows, although spatially scattered, has developed into a complex structure that cannot be understood with traditional methods. The interpretations about this new urbanity of the third modernisation (metapolisation) emphasizes continuous mutual competition between cities. Fast communication technologies, on one hand, connect cities and their districts together stronger than ever, and on the other hand, it enables scattering of their physical structure so that global centers do not by definition determine their development. Thus local dynamics has increasing meaning for competitiveness of cities (Ascher 2004). Cities of third modernity are considered as entities pursuing dynamic change in a state of continuous disequilibrium (Batty 2005) rather than entities pursuing some equilibrium state. For example, economic activity driven by comparative advantage

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searches continuously for new locations and modes, and thus produces a polycentric recentralized structure that disperses the traditional monocentric city.

Accompanying these new concepts and city structure, the paradigm has also changed in urban modeling: from aggregates to individuals and from equilibrium to far-from equilibrium. Complex models and concepts of Cellular Automata (CA) offer tools for understanding these dynamics.

The history of computing and CA are intertwined with each other and this affinity makes the foundations of CA-based modeling particularly firm. Attractiveness of CA is largely based on the simplicity of its basic concepts that are accessible to a wider audience but are still also intellectually fascinating. Due to the digital revolution through the 1990s when competent computing capacity and graphics became accessible for almost anyone, there was a rise in computational modeling of urban development. Numerous CA-based simulation methodologies for urban dynamics have been created during the past few decades. The process begun in the geographical sciences in the 1960s with so called raster models and continued as development of truly cellular models that were based on the idea of complexity. Understanding of urban entities as self-organizing systems, and the demand for tools to discern, control and predict these emergent phenomena, ensures interest towards computational modeling of urban development.

4.2 Basic Concepts of CA

4.2.1 Origins of CA

The history of CA leads back to John von Neumann's (1966) theory of self-reproducing automata and his co-operation with Stanislaw Ulam at the time when they were working with concepts of artificial life and idealizations of biological systems. The theory of self-replicating automata describes conceptual principles of a machine that was able to self-replicate. Alan Turing was also already working with automata in the 1930s and defined in his paper "On computable numbers, with an application to the Entscheidungsproblem", a simple abstract computer later known as the *Turing machine* (Turing 1936) where the idea of the automaton comes close to what we today consider as CA.

A cellular automaton is a dynamic discrete system and can be defined as a lattice (or array) of discrete variables or "cells" that can exist in different *states*. Usually the lattice is considered as infinite and the number of different states is finite. Cells change their states in discrete time steps according to local rules which define the cell's state on the basis of states of the cell itself and the neighboring cells in previous time steps. These *transition rules* are deterministic. Graphically, simpler forms of the cellular automaton lattices are represented as grid format but also other tessellations have been used. Due to the conditions described above, three fundamental features of CA have been defined: uniformity, synchronicity and locality. *Uniformity* means that all cell states are transformed by the same set of rules. *Synchronicity*

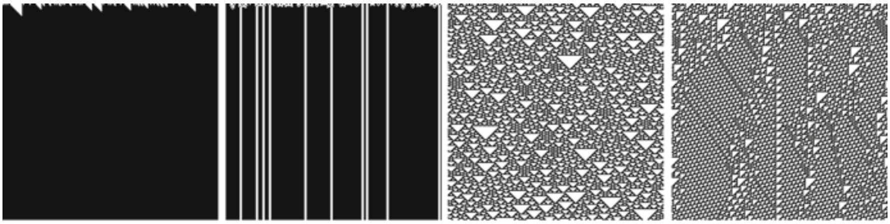

Fig. 4.1 Wolfram classes of 1-D CA dynamics

means that all the cell states are transformed simultaneously. *Locality* means that all the transformation rules are local in nature (Schiff 2008). In the next section, the characteristics of CA are discussed using one-dimensional CA as an example.

4.2.2 One-Dimensional CA

The simplest form of CA, i.e. elementary CA as Stephen Wolfram defines it, is usually considered as a one-dimensional CA consisting of an array of cells that can exist in two states 1/0 (or black/white or alive/dead) in which local rules are applied in the neighborhood of the cell itself and its immediate adjacent cells (r = 1). Thus the neighborhood of one cell consists of three cells, and since they are varying in two values, there are $2^3 = 8$ different neighborhood states. For each neighborhood state, a transition rule is defined. These rules can also be presented as eight-digit binary numbers, and thus $2^8 = 256$ possible transformation rules exist in a one-dimensional two state 'r = 1'-neighborhood cellular automaton.

Wolfram was one of the first who really systematically generated and examined the behavior of one-dimensional CA. In this work, which started in the early 1980s, he classified CA in four universality classes mostly according to the qualitative complexity in their behavior (Wolfram 1984). An analysis of the qualitative features of CA rules was mainly based on visually observable properties of CA evolution patterns (Wolfram 2002). The four Wolfram classes (Fig. 4.1) are as follows:

The class I – fixed – CA evolve to the homogenous state after a finite number of time steps independently from the initial state. Hence this class of automata is irreversible, which means that after a certain convergence point where all the cells have the same value, it loses all the information from the initial state. However, some exceptional configurations can be found that do not converge to a homogenous state, but the number of these exceptions approaches zero as the size of the automaton approaches infinity. Class 1 CA are comparable with dynamical systems that tend to a fixed-point attractor.

The class II – periodic – CA evolve to periodic structures that repeat after a fixed number of time steps. The size of the possible periods increases while the number of possible states increases. This class is naturally analogous with periodic behavior in dynamical systems.

The class III – chaotic – CA evolve to aperiodic patterns almost regardless of the initial states. In these chaotic automata, the number of initial cells that affect the value of a particular cell increases as new generations evolve. The class III CA are analogous with chaotic dynamical systems that are converging to strange attractors (Wolfram 1984).

The class IV – complex – CA evolve to complex localized structures. This class, with a mixture of chaos and randomness, is the most interesting one of the Wolfram classes. However, the definition for this class is not as rigorous as for the other classes. Localized structures that arise as the automaton progresses can move and interact, but the exact prediction of this behavior is impossible. For this class, no equivalent can be found in dynamical systems. The class IV CA behavior can also be defined as emergent, which is typical for complex systems in general (Wolfram 1984).

In his book "A New Kind of Science", Wolfram (2002) discusses the possibility that all CA can be divided into these four classes, which have been discovered by exploring one-dimensional CA. He also states that results obtained from idealized mathematical models can tell us some more general results about complex systems in nature.

4.2.3 Two-Dimensional CA

After discussing one-dimensional CA, one can ask: what happens if more dimensions are added? Wolfram discusses this question in his papers and his book "A New Kind of Science" and concludes that there is no remarkable difference in occurrence of complex phenomena as dimensions are added (Wolfram 2002). At least from a spatial modeler's point of view, two dimensions naturally look more interesting because of its similarity with maps. If the complexity of two dimensional CA are perceived by taking one dimensional slices, then the behavior of the automaton resembles pretty much pure one-dimensional CA. But what is maybe more interesting and a new feature after increasing the number of dimensions, is the *overall shape* of the pattern that emerges. There are many two-dimensional CA whose overall shape approximates a circle, but also rules that lead to more complicated overall shapes and it seems that usually these differences in overall shape are very sensitive to the initial configurations. Even more fascinating is when these shapes start to move in two dimensional space as in the most famous CA, John Conway's "Game of Life", which is discussed later.

Another thing that changes with the dimension of the automaton is the space of possible rule sets, and also the form of the neighborhood can vary in more than one dimension. The most typical form of two-dimensional CA is an orthogonal square lattice of cells. In this space, the locality is typically defined as two alternative neighborhoods: *von Neumann* and *Moore neighborhoods* (Fig. 4.2).

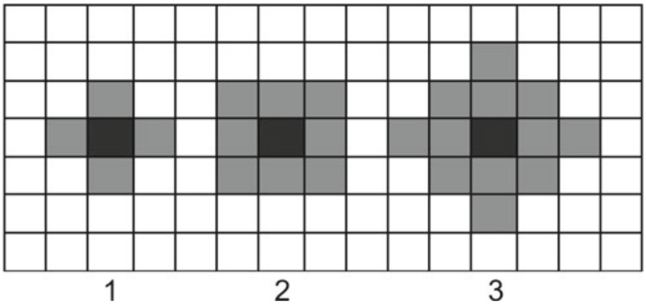

Fig. 4.2 Typical neighborhoods in 2D CA: (*1*) von Neumann 1-neigborhood; (*2*) Moore 1-neighborhood; and (*3*) von Neumann 2-neighborhood

Also, a few typical rule categories have been defined: *general*, *symmetric* and *totalistic* rules. General rule type means all the possible combinations in a given neighborhood, e.g. in a five-cell von Neumann neighborhood with two possible cell states, there are $2^{32} \approx 4 \times 10^9$ possible transition rules. The number of possible rules can be reduced if different symmetries – like rotational, reflectional or complete – are adopted. Sometimes only sums of cell values in the neighborhood are considered as in the Game of Life. This group of rules is called totalistic rules. If the value of the cell itself is taken into account, then the rule set belongs to the category of outer totalistic rules.

4.2.4 *Game of Life*

Developed by British mathematician John Horton Conway, the popular CA application the Game of Life was first published in Martin Gardner's (1970) column in the October 1970 issue of Scientific American. Operating in a two-dimensional lattice, the rules of the game are defined by two cell states and the eight-cell Moore neighborhood. The Game of Life belongs to the Class IV category of CA, and its rule set is an example of outer totalistic rules. There are three rules in the Game of Life:

- Rule 1 – Survival: a live cell with exactly two or three neighbors stays alive
- Rule 2 – Birth: a dead cell with exactly three live neighbors becomes a live cell
- Rule 3 – Death: owing to overcrowding or loneliness, in all other cases a cell dies or remains dead.

The popularity of the Game of Life rests on the outstanding variation of the behavior and in the patterns it can produce with these simple rules. It is also easily accessible to the general public through the internet. Several applications of the Game of Life in other tessellations, e.g. triangular, hexagonal, have been developed but they have not surpassed the original one in richness of behavior.

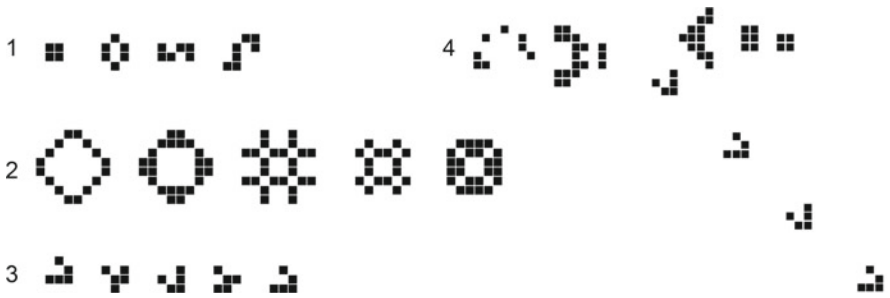

Fig. 4.3 Different life forms: (*1*) invariants, (*2*) oscillator (*5 steps*), (*3*) glider (*5 steps*) and (*4*) glider gun

4.2.5 Life Forms

Since the invention of the Game of Life, a significant amount of work and creativity has been devoted to the development of different "life forms" (Fig. 4.3). The very simple patterns, like one or two cell configurations, disappear after one generation in the Game of Life but there are a huge amount of patterns that continue their lives. Life forms that reach an unchangeable state are called *invariant* forms. Patterns showing periodic behavior between a fixed number of configurations are defined as *oscillators*. Oscillators with two periods are the most common but oscillators with more periods have also been developed. Configurations that not only repeat themselves but also move in the lattice are called *gliders*. One step more complex in the structure and behavior in the Game of life is represented by *glider guns* that are configurations constantly producing new gliders. Some of the glider like behavior is called *puffer trains* which are objects moving vertically and leaving stable configurations behind them. *Methuselah configurations* are initial patterns that achieve stable states after a remarkably long evolution, say after several hundreds of generations (Schiff 2008). There are still more mathematically interesting features of the Game of Life, which are not discussed here.

The life forms have proven that the Game of life is capable of self-reproduction. The self-reproducing system exploits the information that has been stored in it, in the form of instructions and the data to be copied (Casti 1997). In urban spatial modeling, this means that the occurrence of certain initial states is copied to other locations as the system evolves.

What makes CA a special case within other automata and agent based models is the stationary structure of the agents (cells). The automata offer a framework for abstraction of "behaving systems" in which agents, behaviors, relationships and time can be represented formally (Benenson and Torrens 2004). A number of definitions and characteristics of CA have been represented in the previous sections. However, it is not necessary to fulfill all of these conditions to achieve certain system dynamics. In spatial modeling, many conditions have been relaxed to achieve a better correlation with the system. CA have been tested in varying spatial tessellations, like triangular and hexagonal, as well as a graph form CA. The usage of different spatial tessellations has not shown any remarkable difference in automata behavior except some cellular automata classes (or types). In these (exceptional) classes, the neighborhood relations (i.e. tessellation) can change (or vary) as the system evolves (i.e. CA proceeds) (Benenson and Torrens 2004). The L-systems (Lindenmayer 1968) are an example of this kind of CA.

4.3 CA as Complex Systems

CA have become a standard example of complex systems, although there are no rigorous definitions of complex systems. However, among different disciplines under the umbrella of complexity science, the principle of emergence as an indication of a complex phenomenon is widely agreed (Holland 1998; Casti 2002). The emergence arises when simple interaction rules of objects at lower level create unforeseeable phenomena that cannot be derived straight from the objects' qualities at a higher level. As we have seen earlier, the CA obey this kind of self-organizing behavior. Despite fluctuating initial states, the class IV CA systems organize themselves through dynamical evolution, spontaneously generating complicated structures (Wolfram 1988). Irreducibility is another distinguishing characteristic of complex systems. They must be studied as a whole, as there are no means to explore the system or predict the behavior of the system by looking separately at the parts.

Casti (2002) describes three kinds of complex systems. The first one has a complex structure but the behavior of the system is simple; as an example he gives a mechanical clock. The second system has a simple structure but complex behavior, where the toy rotator is provided as an example. In the third type, both the structure and the behavior are complex, as in a human brain. Obviously it is the second type that is interesting and CA belong to this category. Casti (2002) also presents four "fingerprints of complexity": instability; irreducibility; adaptability; and emergence.

Instability refers to the modes of behavior of the system. For the complex system it is typical to have different modes of behavior depending upon small changes in the initial conditions or the interactions of the system. The four classes of CA can be interpreted as well as modes of behavior, and thus CA fulfill this criterion of complexity.

Irreducibility means that the system is infrangible, i.e. if the system is dismantled, it loses some of its essential characteristics. This is against the classical view of science where typically properties of the higher level system can be explained by properties of the parts and laws governing the behavior of the parts. In CA systems, irreducibility is engaged with the capability of universal computing. If some algorithm is used to effectively predict the behavior of the system, it should perform more sophisticated computation than the system itself, which is impossible for universal computers. Thus, because the class IV CA – the complex class – is considered to be a universal computer, they are computationally irreducible.

Adaptability becomes apparent in systems that consist of several intelligent agents. Typically these agents change their interaction rules on the basis of information rules. For example, in traffic models, one agent such as a driver can change one's decision rules according to the information about the environment. With CA, it is also possible to create adaptive agents by considering a cell as an agent and by creating for them an internal mechanism that controls the behavior of the cell.

Emergence is often considered to be the most fundamental property of complex systems. The organized behavior or structure that is generated at a global level as the system evolves according to simple local rules is an emergent phenomenon. This self organization cannot be predicted or derived from the properties of the isolated parts of the system. In CA this is a feature of the class IV systems, and self-organization is intrinsic (Casti 2002; Wolfram 1988).

Efforts have also been made to measure complexity. Ilachinski (2001) discusses a list of different measures of complexity that fall into static and dynamic classes. The four static measures are graph complexity, hierarchical complexity, Shannon's information and simplicial complexity, while the four dynamic measures are algorithmic complexity, computational complexity, logical depth and thermodynamic depth. The static measures refer to structural properties of an assembly of the system and the dynamic measures refer to the dynamic or computational effort that is required to describe the information content of an object or a state of the system (Ilachinski 2001). However none of these measures alone, or even together, delineate complexity unambiguously. Defining and observing is largely based on the human ability of visual perception regardless of all the mathematical and technical analysis that has been developed. If our standard methods of perception and analysis cannot find a short description of the phenomenon, it is considered complex (Wolfram 2002). Wolfram also discusses human pattern and texture recognition and goes even further by comparing this process to simple computer programs. The strong visual nature of the representations of CA models is clearly a strength and also one of the reasons for the success of CA in spatial and urban modeling.

From a wider perspective, complexity has influenced the predominant scientific world view. Kauffmann (2007) challenges the reductionist way of doing science and offers emergence instead. He discusses the power of creativity in nature, in the "biosphere" and in the "econosphere". Moreover, ontological phenomena, which exist in the universe, cannot be deduced from physics. He also states that "our inability to state how novel functionalities come to exist in nature is an essential limitation to the way Newton taught us to do science" (Kauffmann 2007). This comes close to the world of urban planners and architects, who under the functionalist tendency have dismantled the intermeshed traditional city structure to monofunctional enclaves. What was lost was the rich spectrum of connections in neighborhoods with mixed use and diverse functions that, for example, Jane Jacobs has written about in her book "The Death and Life of Great American Cities" (Jacobs 1961).

4.4 Urban CA

CA include intrinsic spatiality and therefore offer an excellent instrument for simulations of urban spatial dynamics. The huge number and popularity of urban simulation models based on CA is evidence of this usefulness. With a relatively simple structure and model construction, CA also provide support for large parameter spaces (Torrens 2009). A self-evident advantage is also the natural affinity with raster data in GIS and alternatively different urban morphological or functional tessellations, e.g. plots of land can be quite easily represented as cells in simulation models.

In urban modeling, the concept of CA is mainly understood in quite a broad sense, and the majority of the applications do not follow all of the conditions of strict CA. Some of the rigorously defined components of CA can be relinquished according to the requirements of the phenomenon that is being examined. Benenson and Torrens (2004) have defined these extensions as follows:

- Neighborhoods can vary in size and shape.
- The cell states can be defined in different ways: nominal, ordinal, continuous, fuzzy or multi-parameterized.
- Transition rules can be deterministic, stochastic, fuzzy, given by equations or other predicatives.
- Factors above-neighborhood level urban hierarchy can be used to control development in the model.

4.4.1 History of Urban CA

The history of urban and geographical CA models dates back to the 1950s and 1960s. Already in 1952, Hägerstrand (1952) had developed a high-resolution model of spatial diffusion, in which the dynamics were already based on local interaction. But the crucial step towards CA was not yet realized while geographical modeling concentrated on regional models. However, during the 1960s, some cell space models and raster models were introduced (Lathrop and Hamburg 1965; Chapin and Weiss 1968). Most of the models applied cellular presentation of urban space, and their principles were close to the idea of CA models. In cellular space, there was a certain state defined for each cell, which was updated at every time step. However, the raster models did not follow the bottom-up approach, at least not in the sense of how we understand this today. The transition rules in those models were mainly based on higher level functions and only some of them were based on neighborhood relationships.

The first true CA model was introduced by Tobler in his article "Cellular Geography" (1979), where he classified five types of models using a geographical array. The first four models were representations of earlier models, but the fifth model – the geographical model – had a new feature: the transition of a cell state was based on the von Neumann neighborhood. He also mentions the complex properties of Conway's Game of Life as an example of CA dynamics. Nevertheless the boom of CA based modeling did not begin until the late 1980s when the formal background of CA was established within mathematics, computing and natural sciences. Also, the development of computer graphics was crucial for CA to become common in spatial and urban modeling. One of the central papers was written by Helen Couclelis (1985) where she stated that CA combined with progress in system theories can be utilized in studying urban systems. She realized the possibilities of emergent characteristics of the global structure that arises from the dynamism of local events and presented a framework for cellular modeling of land use. By the end of the 1980s, several other papers concerning CA as simulation methods in urban dynamics were published (Itami 1988; Phipps 1989 among others).

The next level in the development of CA models took place when White and Engelen (1993) published the first constrained CA model. The idea of the constrained CA model was to combine micro and macro scale mechanisms in cell state transition rules. The constrained model enabled merging of traditional top-down and emerging bottom-up methodology. After this development stage, the interest towards the paradigm exploded rapidly. Numerous models based on CA have now been developed. There is no rigorous classification of models although Santé et al. (2010) have made a recent attempt at classifying over 30 urban CA models. In this chapter, some areas for distinguishing different models are outlined. More theoretical models, which focus on the fundamentals of the modeling mechanisms, can be distinguished from the more realistic simulation models whose intention is to generate plausible scenarios for real environments. The modeling methodologies used and the examined phenomena define their own reference groups.

4.4.2 Theoretical Urban CA Models

The development of theoretical urban CA models concentrates on revealing the properties and effects of the modeling techniques, where the interest is in the theory of CA in an urban context. Michael Batty writes in his book Cities and Complexity (2005) about hypothetical models. He has developed an extensive variety of models in this category with his collaborators. These models are simple idealized city models in which the growth starts from reduced initial conditions, typically from a single seed. The idea of the simple models is to reveal special features of growth mechanisms in their purest form in laboratory-like conditions.

One of the interesting and salient features of these theoretical models is how the concept of geographical potential appears in them. Lots of dynamics in urban development is based on "action at a distance" and Batty discusses "action at a distance" as an emergent phenomenon that arises as the influence of cell transitions propagates in the lattice as the system evolves (Batty 2005). This is a key issue in the theory of urban dynamics and in differences between strict CA models and more general urban models. The demand for simple strict CA models arises from the "action at a distance" question that can be enlightened by examining single cells in those models.

4.4.3 Real City CA Models

Several urban CA models have been developed with the intent to create future scenarios for real urban environments. Therefore, many of their features have a pragmatic explanation. For instance, they can be configured according to the availability of data. The division between models into a theoretical or real category is not that rigorous. Rather there is a spectrum of models between these extremes. The differences between urban CA models can be differentiated by how they are configured to the five basic elements of CA: spatial tessellation, cell states, neighborhoods, transition rules and time (Liu 2009). The most significant differences between urban CA models seems to be based on differences in the transition rules, as they actually define the logic of how the modeled phenomena are handled. All these features have been stressed differently depending upon the purpose for which the simulation model was created. In the following sections we will discuss some examples of models developed for the simulation of urban growth, land use, sprawl, gentrification, etc.

4.4.3.1 Land Use Change in Constrained CA

The constrained CA model developed by White and Engelen (1993, 2000) has been used to simulate land use change. The operational principle of the model is based on the transition potential of the cell, which is derived from the properties of the cell and its neighboring cells. The potential is based on the intrinsic properties of the cell and the influence of the neighbors weighted by distance from the central cell. All cells are then ranked by their potential and the macro scale mechanisms are applied by determining the overall amount of cells to be transformed according to demand for certain land use at an aggregate level. The aggregate level transition operations, which utilize population data, were developed separately from the CA model.

The land use change is represented as a transition of 16 different cell states that are classified as active, passive or fixed state categories. The transition potential of the cells is defined as the vector sum of the components of attraction or repulsion of other land uses, accessibility to transportation networks, and the intrinsic suitability for the particular land use and zoning regulations. In the model, the size of the neighborhood is relaxed to a circular template of 113 cells. The cell size in the model is 500 m × 500 m (White and Engelen 2000).

The principle of combining the above neighborhood structures into transition functions has also been introduced by others (Xie 1996; Batty and Xie 1997; Phipps and Langlois 1997). How the constraints are formulated varies between the different models. The challenge in constrained modeling is how to implement the constraints so that the local dynamics are not destroyed.

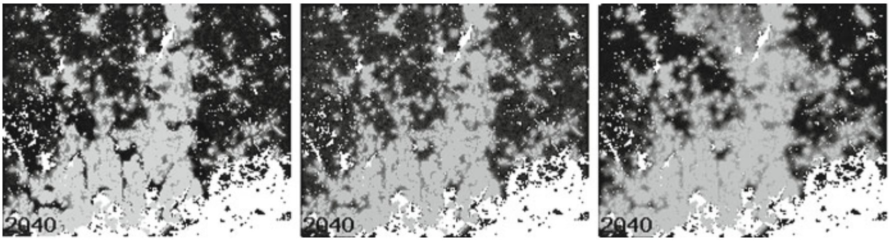

Fig. 4.4 Sleuth-model simulations of Helsinki city region. Three predictions for the hypothetical year 2040 with different input data. Taken from Iltanen (2008)

4.4.3.2 Diffusion-Based Urban Growth

The *Sleuth* model represents a diffusion-based view of urban development (Benenson and Torrens 2004). The model was developed to simulate urban growth for the San Francisco Bay area by Keith Clarke and colleagues during the 1990s (Clarke et al. 1997; Clarke and Gaydos 1998). The model is based on a self-modifying cellular automaton and can be calibrated according to predominant trends of urban development. The growth dynamics consist of four growth rules executed in the following order in every growth cycle: (1) spontaneous; (2) new spreading centre; (3) edge; and (4) road influenced growth. The spontaneous growth defines the random urbanization of a cell by giving a certain probability to every cell regarding urbanization. The new spreading centre growth determines with certain probability the newly urbanized cells to become a spreading center. The edge growth defines the growth on the edge of the existing urban structure by giving a certain probability to a cell to be urbanized if it has at least three neighbors. The road influenced growth is based on the urbanization in earlier steps, on the input data of the transportation infrastructure and a random walk component.

The model also includes an optional *Deltatron*-module, which simulates land use change. The core model can be used without this module. The number of newly urbanized cells, generated in the core model, is the driver for land use transitions. However, the *Deltatron*-module generates only nonurban land use transitions (Clarke 1997).

The calibration is carried out by using historical cross-sectional data as input to the model, and the Monte-Carlo method is used in iteration. The calibration phase produces five growth coefficients as a result. These growth coefficients control the growth rules that are typical for each simulation area and the input data used in the simulation. The input data needed for the model consist of five (or six if the *Deltatron*-module is implemented) layers: slope, land use (*Deltatron*), excluded, urban, transportation and auxiliary hill shade. The name *Sleuth* is comprised from the first letters of the layer names. After the calibration phase, the predictions (Fig. 4.4) can be executed using growth coefficients (Clarke et al. 1997).

The *Sleuth*-model combines a CA approach with different statistical methods to achieve higher realism in simulations. The features of the excluded layer enable the top-down control of growth to be combined with the bottom-up growth dynamics in a way that the level of top-down regulation can be defined by the user. The definition of urban and non-urban areas can be utilized in terms of density to catch sprawl like development (Iltanen 2008, 2011).

4.4.3.3 Urban Sprawl in CA

One interesting exploration concerning urban growth and polycentricity was introduced by Batty and Xie (1997). Their model was based on the idea of development potential, which is a driving force of urban growth. The positive feedback in land use transformations creates growing clusters that break the monocentric structure. This model was implemented in cellular space where the potential of the cell evolves on the basis of itself.

Different grades of urbanization and growth were modeled by Batty and Xie (1997). They also used an epidemic model and generalized it to a spatial context (Batty 2005).The model exploits aggregate models as a part of the simulation process, embedding them in the CA model *Duem* (Batty et al. 1999). The *Duem* model is a CA model that simulates urban growth and the land use change of five different categories. The five land uses of the model are housing, industry, commerce, services and vacant land. The transport network is also represented in cellular form. The model utilizes different decision methods and life-cycle processes of land use.

4.4.3.4 Fuzzy Urbanization

Fuzzy logic and fuzzy set theory have also been utilized in modeling urban growth. It has been argued that fuzzy methodologies are suitable for urban modeling since both physical factors and human decision making are characterized by uncertainty and fuzziness (Wu 1996; Liu 2009). Many urban conditions are continuous rather than discrete by their nature, which points to the appropriateness of using fuzzy logic in modeling urban dynamics. Fuzzy set theory has been developed to extend crisp set theory by defining membership of a set gradually instead of through a binary definition; 0 (=non member) or 1 (full member). Wu (1996) developed a methodology that utilized fuzzy logic in CA transition rules. He applied linguistic modeling with the idea to couple behavioral considerations of decision making to the simulation process. Liu (2009) developed an urban fuzzy constrained CA model in which fuzzy set theory has been used in the definition of cell states and their grade of urbanity. Liu (2009) found that more realistic simulation results were produced in terms of the human decision-making process. Moreover, fuzzy logic has been used in the representation of drivers and in the transition rules for an urban growth model in the city of Riyadh, Saudi Arabia (Al-Ahmadi et al. 2009a; 2009b; 2009c). One of the main advantages of using fuzzy logic was the ability to interpret the resulting model and the rulebase, and to understand which drivers are important and which rules fire most frequently during different periods of urban growth.

4.5 Conclusions

The increasing connectedness of urban structure, both locally and globally, makes it more and more difficult to understand and control the development of cities. CA models, as part of the modeling toolkit, can enlighten the complex interactions and relations in networked urban structure. The better we know the theoretical behavior of our models, the better we can adjust them to real world situations. Thus, there is still space for both theoretical and applied explorations of the models of urban dynamics. The knowledge concerning theoretical aspects of the model also enhances their transparency. This transparency is required for keeping the basis of the model simple enough to catch the complex features in the system.

The strength of CA models is fast processing of information and the illustrative nature of the results, which can be effectively interpreted by human visual perception. Many possibilities also lie in the exploitation of the urban morphological elements in CA modeling. New dimensions could be added to the modeling scheme by using suitable urban morphological elements to add more coherence between the model and reality. The quantitative analysis of urban morphological objects and configurations could be incorporated within the automata models and also the utilization of suitable morphological tessellations could be developed to achieve more sensitive representation of the environment.

Simulations do not necessarily represent the behavior of real urban systems, yet they reveal to us some essential mechanisms that are part of the overall dynamics. The models can be used as tools within urban planning to produce unforeseeable development paths and to help generate scenarios for the basis of decision making. By exploiting simulation models, suitable boundary conditions can be outlined to achieve eligible development, although the modeling always leaves the final state open. The challenge in the wider utilization of simulation models is a tradeoff between the ease of accessibility and understanding the inner logic of these models.

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