CELLULAR AUTOMATA AND STATE SPACE REPRESENTATION APPLIED TO URBAN LAND-USE MODELING: NORFOLK

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Abstract

The combination of cellular automata (CA) and system dynamics were used to predict the evolution of individual components in urban growth. Feasibility was also considered for use in the study of industrial or commercial growth development. Numerical simulations were performed using the city of Norfolk, Virginia, as a test case. The simulation results show that industrial activities are distributed around the railroad.

Introduction

Urban change is a complex spatial phenomenon controlled by many factors. The geographical conditions of area, socio-economic status, infrastructure supply, demographic features and the potential of population growth, planning and zoning constraints, environmental protection regulations as well as group and individual behavior, all play a role in the process of urban development. The development of a predictive science of urban structure has been characterized by a multitude of approaches from a variety of disciplinary perspectives. Different approaches are dependent on how to treat urban structure and urban change in terms of space and time. One interesting method is the use of cellular automata (CA).

Cellular automata have two characteristics that make them inherently attractive for application to geographical problems. The first is that they are, as noted, intrinsically spatial; the second is that they can generate very complex forms by means of very simple rules. CA was combined with fuzzy logic control to predict urban growth [1]. Fuzzy logic control was used to calculate the development of each cell. Calibration is a time-consuming process in CA. To overcome this, neural network was utilized with CA to reduce the time requirement [2].

This study used the combination of CA and a linear state space model to predict the development of housing, industrial, and commercial activities in the area of interest. CA was used to find the transition possibility of the considered cell as functions of its own state and the state in neighborhood cells. The linear state space equation represents the dynamics of each component in the area under consideration.

Cellular Automata

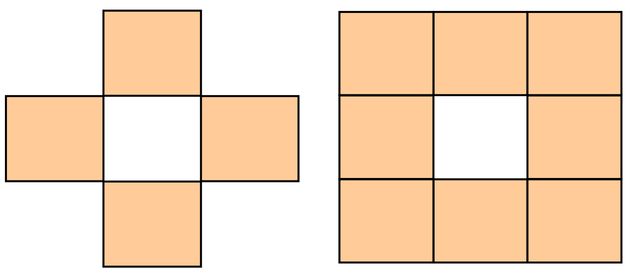
White and Engelen [3] used CA to predict the evolution of land-use development. The area was divided into small sub-regions referred to as cells. Each sub-region had its own state, which could be changed by effects of its present state and those of neighborhood cells. For example, an area is divided into a rectilinear grid. The size may be varied from 10 to 500 meters. Smaller sizes have smaller error in state representation, but higher computational times would be required. Cell states most commonly represent land cover and land use, but they may also be used to represent any spatially-distributed variable. In keeping with the spirit of the simplicity of CA, applications most often adopt either the Von Neumann neighborhood (consisting of the four cells directly adjacent to the sides of the cell), or the Moore neighborhood (the eight adjacent cells), as shown in Figure 1.

The transition rules are the heart of CA. They represent the logic of the process which is being modeled and, thus, determine the resulting spatial dynamics. Since they are as varied as the processes they represent, it is difficult to generalize them. They may be simple, as in the "Game of Life" or spatial voting models where a cell takes the state of the majority state in its neighborhood, or complex; in the limit the rule may consist of an entire sub-model. Rules developed to apply to neighborhoods with a large cell radius will typically represent local spatial processes that include a distance-decay effect. For example, a rule relating the future land use of a cell to the actual land use within an eight-cell radius will represent the attraction and repulsion effects of the various land uses in the neighborhood, but with an attenuation of the effect of the more distant cells. In models of human systems, it is usually appropriate, or even necessary, to introduce a stochastic element into the transition process in order to capture the effects of imperfect information and differences among individuals.

Again, noting the simplicity of CA, applications most often adopt spatial modeling. In CA models, time is normally discrete, with a simultaneous updating of all cell states after the rules have been applied to each cell using the current configuration. For many applications, the appropriate time step is a matter of convenience; e.g., iterations representing 1 year may be adequate in a model of land use change.

Component Development

The changing of each component in the urban model was considered in this study. As well, Markov chain and linear state space methods were utilized to predict the number of each component. Weng [4] used the first-order Markov chain to predict the land use in the Zhujiang Delta of China, and Lopez et. al., [5] used it to predict the land-use changes in Moelia City, Mexico. Aaviksoo [6] compared the first- and second-order Markov chain to predict the plant cover and land-use types. The changing of components in the cellular-automata analysis is controlled by either Markov chain or linear state space systems.



Von Neumann Neighborhood **Moor Neighborhood**

Figure 1. Neighborhood Cell

Urban growth is considered in its own state by how developed it is; i.e., is it urban, suburban, or rural? The factors of interest are: distance between any given cell and whether it is urban or suburban, a road, expressway or railroad; if there are neighborhood states; and, its agricultural suitability.

Markov Chain

Markov chains are stochastic processes that can be parameterized by empirically estimating transition probabilities between discrete states in the observed systems. For a Markov chain of the first order, the next state depends only on the present state. In a Markov chain of second or higher order, the next state depends on the present state and one or more of the previous states. The first order transition matrix can be represented [4];

$$P = \begin{bmatrix} p_{11} & p_{1,2} & \cdots & p_{1,m} \\ p_{21} & p_{2,2} & \cdots & p_{2,m} \\ \vdots & \vdots & \ddots & \vdots \\ p_{m,1} & p_{m,2} & \cdots & p_{m,m} \end{bmatrix} \quad (1)$$

$$[p_1 \ \ p_2 \ \ \cdots p_m]_{futu} = [p_1 \ \ p_2 \ \ \cdots p_m]_{pres} P$$

The transition probabilities, p_{ij}, of any state vary between 0 and 1. The summation of transition probabilities in a row equals 1.

Linear State Space Model

The evolution of various components in the city, e.g., housing, industrial, and commercial developments, are represented by the Lotka-Volterra model:

$$\dot{x}_i = k_i x_i + \sum_j g_{ij} x_i x_j$$

where

x_i = population i

$k_i x_i$ = the growth ability of population i

$g_{ii} x_i x_i$ = environmental pressure or resource on population i

$g_{ij} x_i x_j$ = the influence of population j on population i

g_{ij} = the properties of the influence are varied by time

$g_{ij} > 0$ has promotional effects on population i, and if

$g_{ij} < 0$ then the action is inhibited.

For more applicability, the extended Lotka-Volterra model can be represented [7], [8] as

$$\dot{x}_i = k_i x_i + \sum_j g_{ij} x_i x_j + \sum_k \alpha_{ik} x_i u_k$$

where

u_k represents a forcing function on the compartments

α_{ik} is coefficient varied by time

The linearization model will be

$$\dot{z} = Az + Bu$$

where

$$a_{ii} = k_i + \sum_j g_{ij} x_{j0} + \sum_k \alpha_{ik} u_{k0}$$

$$a_{ij} = \sum_j g_{ij} x_{i0} \delta x_j, i \neq j$$

$$b_{ij} = \sum_k \alpha_{ik} x_{i0}$$

a_{ii} is the growth ability of population i, environment pressure or resource on population i, and the influence of population j on population i; a_{ij} is the influence of population j on population i; b_{ij} is depended on the population.

As a discrete model, it can be written as

$$z(k+1) = Fz(k) + G\mathbf{u}(k) \quad (2)$$

The state will be number of housing, industrial, and commercial units. This study used the Markov chain of Equation (1) and the extended Lotka-Voltera model from Equation (2) to control the population in the area under consideration. The state status of each cell was calculated using the CA.

State Transition

The next state of each cell was calculated using the transition potential [9];

$$P_{ij} = s_j a_j S\left(1 + \sum_{h,k,d} m_{kd} I_{hd}\right) + H_j$$

where

P_{ij} = the transition potential from state i to state j

m_{kd} = the weighting parameters applied to cells in state k in distance zone d

h = the index of cells within a given distance zone

I_{hd} = 1, if the state of cell $h = k$, otherwise $I_{hd} = 0$

s_j = suitability of the cell state for j, $0 \le s_j \le 1$

a_j = accessibility by transportation $a_j = \left(1 + \frac{D}{\delta_j}\right)^{-1}$

δ_j = the coefficient expressing the importance of accessibility for desirability of the cell for land use j

D = Euclidean distance from the cell to the nearest cell of the network.

H_j = inertia parameter, $H_j > 0$ *if* $i = j$

S = a stochastic disturbance term

$S = 1 + (-\ln R)^{\alpha}$

where $0 < R < 1$ uniform random variation, α is a parameter that allows control of the size of the stochastic perturbation.

The stochastic S has a highly skewed distribution so that most values are near unity, and much larger values occur only infrequently. Most of the potentials, P_{ij}, are close to their unperturbed deterministic values; i.e., the transition parameters dominate the determination of the transition potentials. As $P_{ij} \ge 1$, every cell in the array has a nonzero chance of transition. In general, cells within the neighborhood are weighted differently depending on their state and also on their distance from the reference cell, and the m_{kd} may be specified to represent, for example, a standard negative exponential distance-decay relationship. Vacant cells do not receive a weight and, thus, do not contribute directly to the transition potential.

At each iteration, sufficient cells are converted to each use so that the net increase in the number of cells in each non-vacant state is equal to the exogenously specified increase, N_i (i = *H, I, C*). The cells converted to each state are those with the highest potentials for that state. To begin with commerce, the N_c cells with the highest potentials for commerce are identified. If some of these cells are also in the lists of the cells with the highest potentials for industry or housing, then those cells will change to commercial. If for industry, some of the cells are also in the lists of the cells with the highest potentials for housing, then those cells will change to industrial.

Numerical Simulations

The city of Norfolk was the test case for the study. The aerial photo is divided into a 62×100 square grid. The railroad, road, bridge and river are mapped in the grid, as shown in Figure 2. The transition weighting parameters are the same as those found by White et. al., [9]. The simulations were performed using MATLAB.

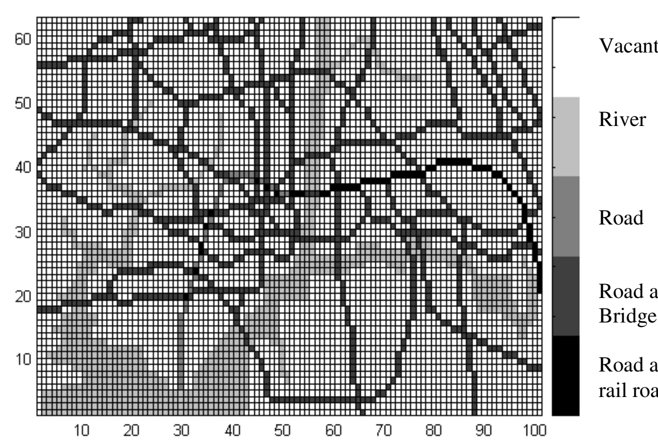


Figure 2. Railroad, Road, Bridge, and River

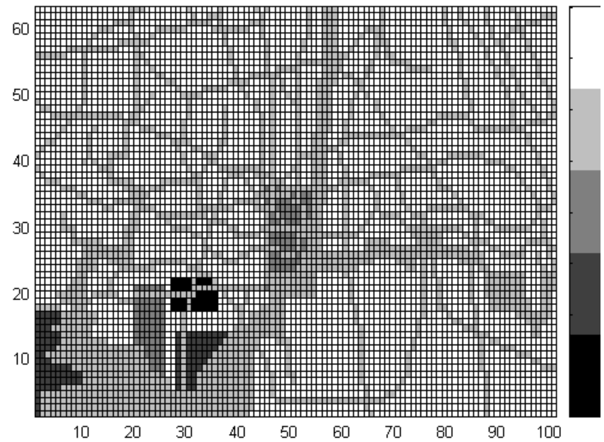


Figure 3. Initial Condition

The first-order Markov chain transition matrix is

$$P = \begin{bmatrix} 0.9 & 0.06 & 0.03 & 0.01 \\ 0.0 & 0.8 & 0.1 & 0.1 \\ 0.0 & 0.5 & 0.4 & 0.1 \\ 0.0 & 0.6 & 0.32 & 0.08 \end{bmatrix}$$

The results of these simulations are the same as for the linear system representation.

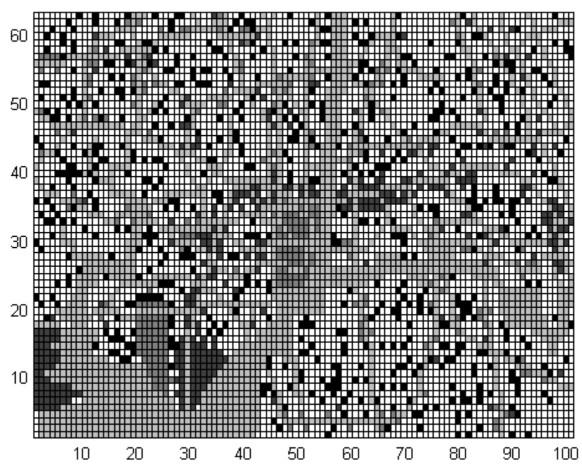


Figure 4. 20^{th} Iterations

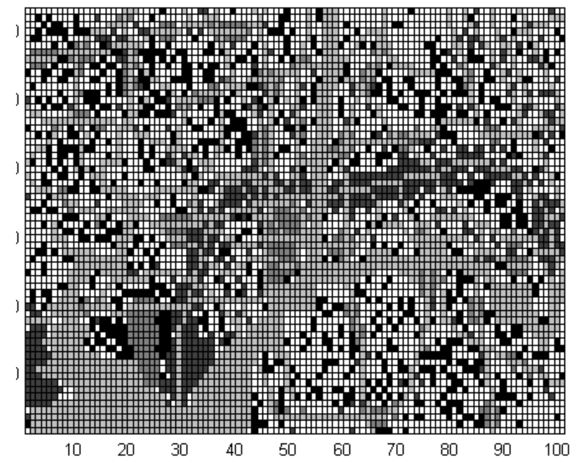


Figure 5. 50^{th} Iterations

For the linear system representation, the linear system parameters are

$$F = \begin{bmatrix} 0.94 & .01 & 0 \\ .05 & 0.9 & 0 \\ 0 & 0 & 0.94 \end{bmatrix}, \quad G = \begin{bmatrix} 50 \\ 15 \\ 20 \end{bmatrix}$$

Numerical simulation results are shown in the Figures 3-7. Figure 3 is the initial condition for simulation. Figures 4, 5, and 6 show the distribution of housing, industrial, and commercial sites at the 20^{th}, 50^{th}, and 100^{th} iteration, respectively. One iteration represents a one-year change of the compartment. Figure 8 shows the number of each compartment's history.

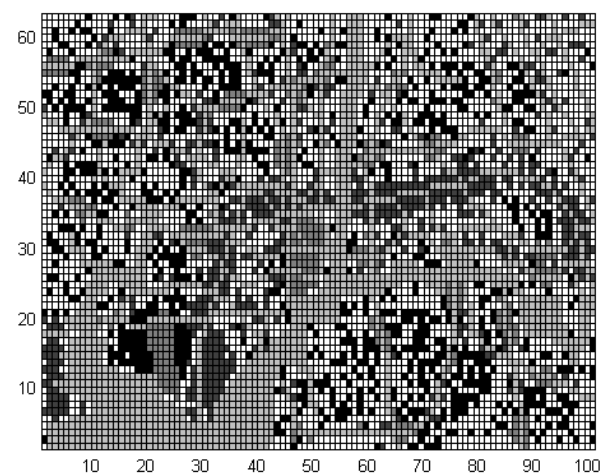


Figure 6. 100^{th} Iterations

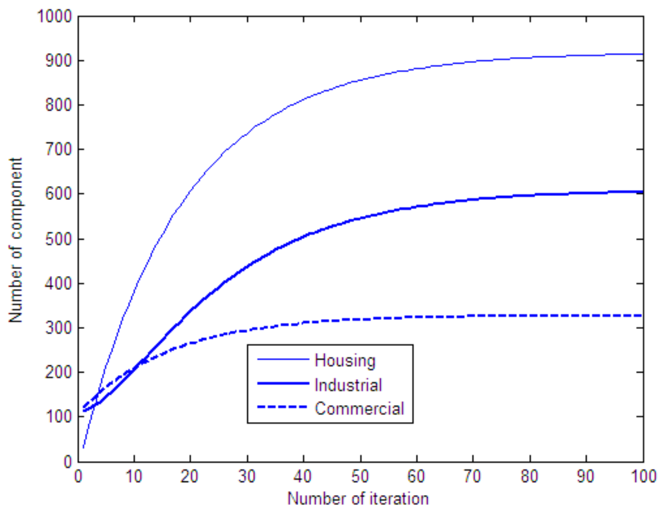


Figure 7. Simulation time history of number of housing, industrial and commercial

Conclusions

Urban land-use dynamics can be divided into two parts: cell state change, which is dependent on neighborhood cells, and the total land use of each compartment. The linear state space model is more flexible to use than the Markov chain model for the prediction of the past growth data. For linear state model representation, it is easy to change the new equilibrium of the state of each compartment. In this study, cellular automata were used to predict the area of each cell and state space to represent the number of each compartment at each point in time. When it becomes necessary to change the equilibrium points, the state space equation is easier to manipulate than the Markov chain. If more accurate predictions are needed, the identification should be done to find parameters used in the CA and state space equations.

References

[1] Liu Y. and Phinn S. R., 2003. Modelling urban development with cellular automata incorporating fuzzy-set approaches, Computers, Environment and Urban Systems, Vol.27, pp 637-658.

[2] Li, X. and Yeh, A. G. O., 2001. Calibration of cellular automata by using neural networks for the simulation of complex urban systems. Environment and Planning A, 33(8), pp. 1445-1462.

[3] White R., and Engelen G. 1993. Cellular automata and fractal urban form: a cellular modeling approach to the evolution of urban land use patterns, Environment and Planning A, 25, pp1175–1199.

[4] Weng Q., 2002. Land use change analysis in the Zhujiang Delta of China using satellite remote sensing, GIS and stochastic modeling, Journal of Environmental Management, Volume 64, Issue 3, pp 273-284.

[5] López E., Bocco G., Mendoza M., and Duhau E., 2001. Predicting land-cover and land-use change in the urban fringe: A case in Morelia city, Mexico. Landscape and Urban Planning, Volume 55, Issue 4, pp 271-285.

[6] Aaviksoo K., 1995. Simulating vegetation dynamics and land use in a mire landscape using a Markov model, Landscape and Urban Planning, Volume 31, Issues 1-3, February 1995, pp 129-142.

[7] Huang J., Systems Evolutionary Analysis for Urban Industry System, Systems, Man, and Cybernetics, 1998 IEEE International Conference, 11-14 Oct 1998, San Diego, CA , USA

[8] Magyar A., Szederkenyi G., Hangos K.M., Globally stabilizing feedback control of process systems in generalized Lotka–Volterra form, Journal of Process Control 18 (2008) pp80–91.

[9] White R., Engelen G., and Uljee I. 1997. The use of constrained cellular automata for high-resolution modeling of urban land-use dynamics, Environment and Planning B, 24, pp323–343.

Biographies

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