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Using Cellular Automaton to Simulate Urban Expansion in Changchun, China

[1, 2] Jing MA, [3] Qiang BI, [4] Jingxia ZHANG, [1] Hongmei ZHOU

[1] School of Prospecting and Surveying Engineering, Changchun Institute of Technology, 3066 Tongzhi Street, Changchun 130021, China

[2] Key Laboratory of Geo-informatics of National Administration of Surveying, Mapping and Geoinformation, 28 Lianhuachi West Road, Beijing 100830, China

[3] Jilin Province Water Resource and Hydropower Consultative Company, 7135 South Lake Road, Changchun 130012, China

[4] Sinohydro Bureau 11 Co., Ltd., 9 Lianhua Street, Zhengzhou 450001, China

[1] Tel.: +86-431-85573039, fax: +86-431-85573035

E-mail: majing615@163.com

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Abstract: Urban expansion is a complex spatial transformation process over time. It converts various land-use types into urban lands, therefore gradually increase the size of urban areas. The research in simulation and prediction of urban expansion can provide us with two benefits: one, we would be able to grasp the pattern of the complex process of a city's expansion; and the other, we may be able to foresee a possible problem that may occur during expansion, and deal with it ahead of time to create the best suitable plan for the city's structure and layout. In our experiment, we designed a Visual Basic (VB) program, and applied binding conditions and random factors to simulate the process of urban expansion using Cellular Automaton (CA) as a model. This experiment was based on selected previous research, and used the city of Changchun as an example. Our results indicate that it is feasible to model urban expansion with the sprawling process of CA. *Copyright © 2014 IFSA Publishing, S. L.*

Keywords: Cellular automata, Urban expansion, Transition rules, The rules of urban sprawl, Simulation.

1. Introduction

Urbanization is an integral part of China’s ongoing industrialization process. In the Urbanization Work Conference held by the Chinese Central Government near the end of 2013, it was clearly stated that the governing and development of urbanization must consider the unique conditions of the country being in the early stages of socialism. It needed to follow the natural process of growth. If the governing body recognized that and regulated accordingly, urbanization could be a smooth and progressive transition. The evolution of land is affected by natural, social, cultural, economic, legal and political factors. Therefore it is a very complex process. As a complicated dynamic system, many characteristics of urban expansion cannot be modelled using classical Newtonian theories of static mechanics (CHEN Gan et al., 2000, [1]).

Cellular automaton (CA) is a discrete dynamic modelling system. It consists of a grid of cells, each of which only interacts with its neighborhood cells to reveal the evolution of the system. Space and time are considered discrete units and space is often represented as a regular lattice of two dimensions.

CA models are built from bottom to top, thus have the ability to represent non-linear, spatial and stochastic processes. Many works have already demonstrated CA's capability to accurately simulate complex time-space sprawling patterns (LI Xia et al., 2007; LIU Haojie et al., 2012; Wolfram S, 1994, [2-4]).

The rapid development of Geographic Information System (GIS) has encouraged the use of CA to simulate urban expansion. GIS provided a valuable set of data for creating CA transition rules (Couclelis H, 1997, [5]). The "bottom-to-top" nature of CA makes it suitable for modeling the dynamic evolution of urban expansion. However, when using CA models to simulate geographical entities, how to define transition rules remains a challenge due to the large number of spatial variables involved (LI Xia et al., 2004; LUO Ping et al., 2004; LI Xia et al., 2007, [6-8]). The parameters used to define transition rules can greatly affect the result of simulation. There are many existing methods to define these parameters, such as Multi-Criteria Evolution (MCE), Logistic Regression, Principal Component Analysis, Gray Method (LIU Yaolin et al., 2004, [9]), Neural Network Model, Genetic Algorithm, Data Mining (LI Xia et al., 2007; LIU Haojie et al., 2012, [8, 9]) etc. We designed a CA model based on these methods, and used it to simulate and study the spatial expansion of urban areas. It aims to provide some references and examples for studying urbanization.

2. CA Transition Rules

2.1. Parameter Definition

The rapid growth in social economy, population, commercial and industrial development would inevitably lead to an expansion of a city. With the demand of urban land increasing, the city would gradually expand around its boundary. This is called Boundary Sprawling Growth. This can be represented in CA as follows: for a particular non-urban land cell, if its neighborhood cells yield a certain number through a series of calculations, then it would have a higher probability to be converted into urban land in the next time interval. Sprawling Growth reflects the agglomeration effects of urbanization. We have chosen Sprawling Growth as the transition rules, and designed a model such that, in the next time interval the possibility of converting a cell from other use to urban land depends on a function of C^t_{ij}, P_y and RA values (LI Xia et al., 2007, [8]). That is, at time t+1:

$$\mathrm{P}^{t+1} = F(C^t_{ij}, P_Y, RA), \tag{1}$$

where P^{t+1} is the possibility of cell transition; C^t_{ij} is the Neighborhood Constant; P_Y is the Cell Constraint; *RA* is the Random Disturbance.

Different modelling parameters will yield very different simulation results. Defining a set of appropriate parameters is critical to maximizing the accuracy of simulated results.

2.1.1. Neighborhood Constant C^t_{ij}

The Neighborhood Constant is vital in the transition rules used for simulation model. It controls the neighborhood cells' influence to the center cell, and prevents spatial chaos. The Neighborhood constant utilizes a 3×3 matrix to calculate the interactions between various land-use types. It is defined as:

$$C^t_{ij} = \frac{\sum_{3\times3} con(s_{ij} = urban)}{3\times3-1}, \tag{2}$$

where *con*() is the conditional function: if the state of cell S_{ij} is the urban land, it returns 1, otherwise it returns 0.

2.1.2. Cell Constraint P_Y

The possibility of turning into urban land is lower if the cell is located in water, mountain, high-yield farmland, nature reserve or designated green belt land that prohibits urban use. Therefore, it is necessary to introduce a constraint parameter that is specific to a cell into the model. The Cell Constraint values used in this experiment were mainly calculated based on data from slope map layer and city planning layer.

2.1.3. Random Disturbance *RA*

Urban expansion can be affected by many factors, such as political, economic, and other man-made or natural random interventions. Among these, man-made factors tend to make modeling very unpredictable. Therefore, in order to make the result of the CA model more accurate, we introduced the Random Disturbance parameter to accommodate the randomness of urban growth pattern. It can be expressed as:

$$RA = 1 + (-\ln\gamma)^{\alpha}, \tag{3}$$

where γ is the random decimal in (0, 1); α is the control factor of Random Disturbance, and is defined as an integer within [1, 10].

2.1.4. Probability Threshold

With the above parameters, we can determine the probability of a cell transition at time t+1. To ensure the rationality of the CA model, we defined a threshold value for converting the probability to a discrete state. In this experiment, we have taken the following approach: we created a random decimal between 0 and 1, then we compared the calculated probability with this random decimal: if the probability was larger than the random decimal, then the cell was converted to urban land, otherwise it remained in its original state.

2.2. CA Modeling Methodology

In this experiment, the spatial data was obtained through Multi-Temporal Landsat Thematic Mapper (TM) imaging, and technologies such as Remote Sensing (RS) and GIS. Landsat image processing software ERDAS 9.2 was used to analyze and map land-use types. GIS processing software ArcGIS 9.3 was used to convert spatial data and map it into the required format for CA simulation. We used our CA software to simulate historical urban expansion, then analyzed results and verified the model's accuracy. With the most optimum set of parameters validated by historical data, we ran the simulation based on the latest Landsat data and predicted the future expansion of the city.

3. CA Simulation

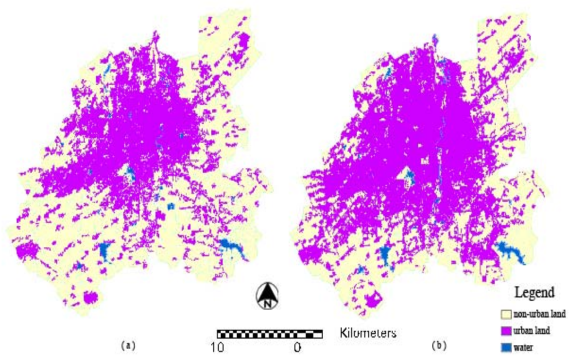
3.1. Geographical Information of the Area Being Studied

Changchun is located in the mid-latitude zone of the Northern Hemisphere. It lies in the Northeast Plain on the east coast of the Eurasian continent. Its coordinates are: 43 ° 05 '~ 45 ° 15' N, 124 ° 18 '~ 127 ° 05' E. It is the geographical center of the Chinese Northeastern region. The city lies on the transitional terrace between mountains to the east, and plains to the west. Due to this fact its eastern area is higher than the west side. The geomorphologic surface consists of 70 % platforms and 30 % plains. The two different geomorphological types would contribute different binding factors in the city's development and growth.

3.2. Data Processing

The geographical data used as CA seed data was mainly obtained from Landsat TM images (30 meter resolution), acquired in 1993, 2005 and 2010. The corresponding Path/Row used was from 118-29 and 118-30. After the two sets of images were combined, the resulting image covers the entire city of Changchun. In addition, we obtained the land-use database from the city of Changchun, and used it to provide classified land-use data. This database also includes slope map and city planning information.

Using ERDAS 9.2 and ArcGIS 9.3 software for image analysis and processing, we enhanced the Landsat images through linear contrast stretching and histogram equalization, rectified the TM images by identifying ground control points to the common Gauss-Kruger projection based on 1:100,000 topographic maps. For each TM scene, at least 20 evenly distributed ground control points (GCPs) were defined and used to register these images. To increase the speed for running the CA simulation, the image data was trimmed to the built-up urban area boundary. We applied the widely accepted supervised classification method to the combined data from TM 2, 3, 4 and 5, and identified three main categories for land use: urban land, non-urban land and water. We ran cluster analysis and removal functions, and filter analysis in post classification processing of image, to eliminate small chunks of abnormities, and identify the effective boundaries of the study area. See Fig. 1.



(a) 1993 (b) 2005

Fig. 1. Remote sensing classification maps.

We extracted slope map and city planning information from the land-use database, and generated slope map layer and city planning layer, each with 30 m × 30 m raster pixels. They provided control layer data used for modeling.

3.3. CA Software Design

The CA software used in this experiment was written in Microsoft Visual Basic 6.0. The CA simulation is realized through the following 9 steps: cell initialization; data conversion; seed data creation; control layer data creation; neighborhood cell determination; transition rules establishment; parameters determination; model simulation; and result analysis. Describing the CA model as a conceptual model helps reducing the complexity of the simulation. In this experiment, we did not consider the transition within urban land-use types, instead, we focused on the conversion among urban land, non-urban land and water. The types of land use in the entire simulation are of three categories: urban land, non-urban land, and water.

We chose CA's basic attributes at cell initialization stage, namely cell space and neighborhood types. Using Microsoft Visual Basic 6.0, we created a new project with a form, coded program, set the basic attributes of CA model, then went to the simulation interface. We imported the seed data files as the baseline for simulation data, then selected control layer data from slope map layer and city planning layer. We also defined the path and name of simulation result file to be saved.

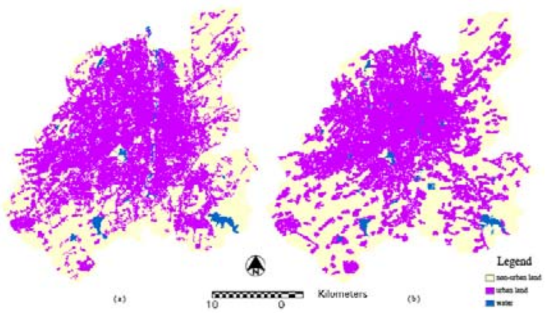
The experiment used data from 1993 and 2005 as baselines, and simulated city expansion using CA as a model. The resulting data was saved, and after it was dynamically processed in ArcGIS, we were able to review it visually, and analyzed it spatially, using methods such as raster computation.

3.4. Parameter Adjustment and Accuracy Validation of CA Simulation

3.4.1. Parameter Adjustment

In order to determine the parameters used for CA, we first used existing historic data to verify simulation results. After repeated tests, we were able to find a set of parameters. We then set the simulation ending time to the reference data's time, and obtained simulation result from this time. Lastly, we compare the simulated result with the reference data, and adjust the parameters to make them align.

The detailed steps are as follows: we input seed data and control layer data to the model, then start simulation. During the experiment, we first set 1993-2005 time period as simulation duration. We compared our simulation results with the actual city expansion data from 2005 (see Fig. 2.), and obtained the best set of modeling parameters.



(a) 2005 remote sensing image classification map;
(b) 2005 simulation map

Fig. 2. Comparison of landsat data and simulation results.

We then set 2010-2020 as simulation duration, and used 2005's data as seed data. We input control factors (city planning information), and compared the simulated result of 2010 with the classified Landsat data collected in 2010. The classification of Landsat data was achieved through Index-based Built-up Index (IBI) simulation method (XU Hanqiu et al., 2008, 2010, 2011, [10-12]), and the result was the city's classified land-use data. With the simulated result as a baseline, we adjusted the parameters further and obtained the most optimal set of parameters, which we used to predict the urban expansion map in 2020.

3.4.2. Accuracy Validation

Setting up the criteria to determine the accuracy of the model is a vital step. In our experiment, we took the simulated 2005 and 2010 results, and overlapped them with corresponding Landsat data collected in the same time period (see Fig. 3), through ArcMap software. We divided the number of urban land cells from the simulated data over that of the reference data, and yielded the accuracy of that particular simulation. Through calculation, we found that our model for 2005 and 2010 simulation has reached accuracies of 95.4 % and 94.3 %, respectively. Based on this result, we found the CA modeling did provide realistic results, and we could use to predict the future trend of urban expansion in Changchun.

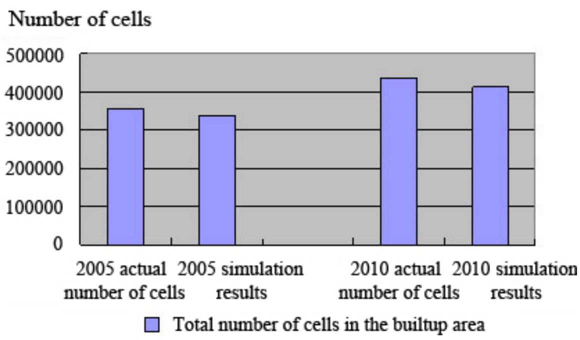


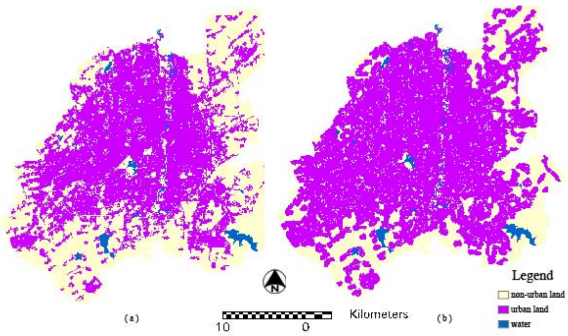
Fig. 3. Comparison of actual number of cells vs. simulation results.

3.5. Results and Analysis

With classified data from 2005 remote sensing image as a baseline, and the set of parameters we obtained through our experiment, we input Changchun's city planning data for 2011-2020, and predicted the city's urban expansion map in 2020. The simulation result can be seen in Fig. 4.

We created an urban land area growth chart based on the simulated result and reference data. In this chart, one notes that the simulated urban land growth is in line with the actual urban land growth. See Fig. 5.

From the above chart, we can see that as a whole, urban expansion simulation with CA model has yielded a result very close to the actual urban expansion in Changchun. The city's expansion has the following characteristics: the core of Changchun has been growing exponentially; the area of urban land has been increasing and occupying more agricultural land. Comparing to the Landsat data collected around the same time, we found out the total area of cells being converted from non-urban to urban land: the total urban land area was 233.3 km^2 in 1993, and it was increased to 318.9 km^2 in 2005. We predict it will grow to be 433.2 km^2 in 2020. These figures show that Changchun is going through the early stage of rapid urban expansion. With increased speed of the city's urbanization and industrialization, the demand for urban land will continue to rise.



(a) 2005 remote sensing image classification map
(b) 2020 simulation map

Fig. 4. Comparison of simulation results.

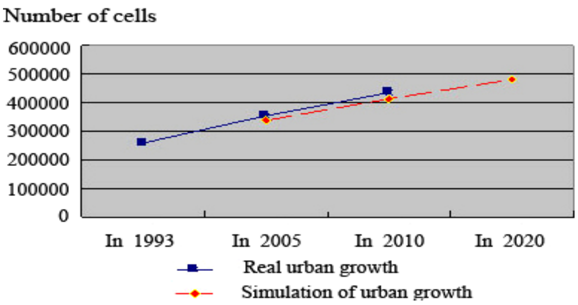


Fig. 5. Comparison of urban growth.

4. Conclusions and Discussion

The research in simulation and prediction of urban expansion can provide us with two benefits: one, we would be able to grasp the pattern of the complex process of a city's expansion; and the other, we may be able to foresee a possible problem that may occur during expansion, and deal with it ahead of time to create the best suitable plan for the city's structure and layout. With the application of various software such as ArcGIS and ERDAS, we created a CA model to simulate and analyze urban expansion, and obtained excellent results.

Our study has shown that there are several factors effecting accuracy in CA simulation:

- Quality of seed data. Using Landsat data collected at various time intervals, we are able to understand the city's growth during these time intervals, and get a pattern of the city's evolution process. The most vital step here is to obtain high resolution Landsat data. The accuracy of classification is inevitably restricted by the quality of seed data.

- Quality of control layer data. The location of rivers, reservoirs, mountain, and city planning information defined by the municipal government are all control and binding factors. Such data is very dynamic and can be scattered in many locations, therefore very difficult to collect. An up-to-date and complete set of control layer data will lead to an accurate simulation result.

- CA transition rules. The transition rules describe the logical relation within the model. It is used to determine the result of spatial change. We have found the traditional methods of defining CA model rules and parameters were not adequate. Our future research would focus on how to create dynamic and adaptive transition rules.

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