A Compound-type Neighborhood Cellular Automata Model for Land Use Dynamics

Zhongqiu Liu[1], Yangjie Guo[2], Yaolin Liu[3*]

[1] School of Resource and Environment Science, Wuhan University, Wuhan, China

Telephone: (+8618986247127)

Email: zoneq6@163.com

[2] School of Resource and Environment Science, Wuhan University, Wuhan, China

Telephone: (+8615172482868)

Email: guoyj-021@163.com

[3] School of Resource and Environment Science, Wuhan University, Wuhan, China

Telephone: (+8613871298058)

Email: yaolin610@163.com

Abstract

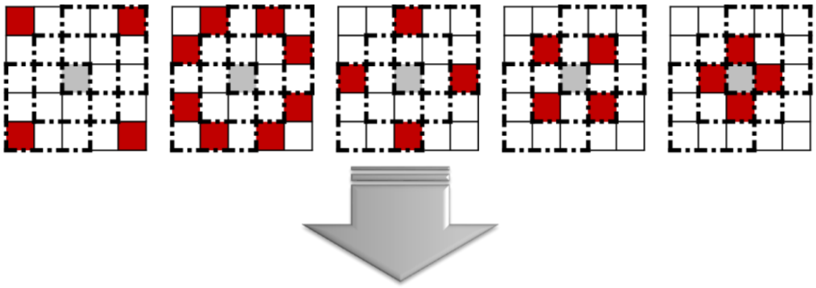
Land use is considered as a major interface between socio-economic and environmental processes (Letourneau *et al.* 2012). Land use occurs in local places, considered a local environmental issue generally, but it is becoming a force of global important. Activities of land use have transformed a large proportion of the planet's land surface, mainly for acquisition of natural resources to meet immediate human needs at the expense of environmental conditions (Foley *et al.* 2005). Since the "land use and cover change" (LUCC) science plan was proposed together, land-use change has become the front and hot point task of the global change and many projects and studies have focused on LUCC (Turner *et al.* 1995, Lambin *et al.* 1999, Lambin *et al.* 2001). For recent decades, researchers have tried to simulate land-use changes at different temporal and spatial scales, with different geographical models and for different purposes (Li *et al.* 2002a, Matthews *et al.* 2007, Verburg *et al.* 2008, Schweitzer *et al.* 2011, Verburg *et al.* 2011). The favored techniques for implementing model of spatial dynamics is cellular automata (CA) (White *et al.* 2000).

Cellular automata is dynamic model originally introduced by Ulam and Von Neumann in the 1940s as a possible idealization of biological systems (Neumann 1966). However, CA was not considered as a modelling paradigm until Wolfram presented his contributions to CA modelling (Wolfram 1983, Wolfram 1984). CA has been linked to the work of spatial diffusion and segregation modelling approaches (Hägerstrand *et al.* 1967, Schelling 1971). In 1979 Waldo Tobler first introduced CA into the scope of geographical modelling (Tobler 1979). CA, a bottom-up approach, can well capture complex spatially distributed processes and provide insights into a wide variety of local behaviors and global patterns, in addition CA can be well integrated and programmed

in raster-based geographic information system (GIS) environments (Wolfram 1984, Kocabas *et al.* 2006). Due to the advantages of CA in geographical spatiotemporal dynamics, CA models have been increasingly used for simulating various geographical phenomena, especially used in land-use/land-cover change (Jenerette *et al.* 2001, Li *et al.* 2002b, Wu *et al.* 2002, Maria de Almeida *et al.* 2003, Menard *et al.* 2007) and in modelling urban spatial dynamics (Clarke *et al.* 1997, Couclelis 1997, Batty *et al.* 1999, Li *et al.* 2000, Li *et al.* 2002b).

A basic CA essentially consists of five components: a grid space on which the model acts; cell states in the grid space; transition rules that determine the spatial dynamic process; a neighborhood that influences the central cell, and time steps (White *et al.* 2000). We can model the spatial complexity and dynamics of land use change with these basic element of the CA model design. With more than 70 years development, CA model has been improved continuously by scholars aimed at developing the technique as one which can be applied to practical problems, mainly from three aspects as follows: (1) the scale sensitivity of CA model to grid space extent, size of cells and neighborhood; (2) the impact of cell type and neighborhood type on the behavior of CA model; (3) coupling other models or methods to make the transition rules more automatic and realistic. Geographical CA, up to now, has got very great improvement in scale sensitivity, the types of cell and neighborhood, and transition rules. However there are still some deficiencies to be solved, such as, most researchers focused on discussing which factor results in what impact in scale, but few studies were carried out aimed to eliminate or minimize the scale sensitivity; And some new-type and complex cells and neighborhoods were difficulty in popularization due to their pertinence and complexity. As an example, the neighborhood space may be defined differently for each cell, a relaxation is widely acknowledged, but seldom implemented (Sante *et al.* 2010). There is not a uniform method for determining distance-weight until now, when the distance-decay is considered in neighborhood. Besides, the quantity of cells is the only factor, which is taken as the measurement of the influence of the neighborhood, in current research on geographical CA. However, the spatial distribution characteristics are rarely taken into consideration, e.g. spatial compactness, in spite of their importance and universality in the evolution of complex geographical phenomena.

In this paper we tried to improve the two-dimensional raster-based CA by proposing compound-type neighborhood and drawing the spatial compactness factor into neighborhood. Compound-type neighborhood with the multi-level weights considers the distance-decay effect, and the weight-determining is implicitly included in neighborhood computation (see fig. 1). Since the explicit weight assignment is not



Count times of the cells with different distances				
1	2	3	4	6

Figure 1. Distance-decay effect

required, it reduces the interference of artificial element and has good scalability. In addition, the spatial compactness factor is introduced into the neighborhood impact assessment, which enhances the representation of spatial characteristics in CA model and may provide a more realistic simulation of LUCC. (1)Compound-type neighborhood based on Moore neighborhood consists of influence neighborhood and computation neighborhood (see fig. 2), which depicted in mathematical equation 1:

$$\Omega = \Omega_{5\times5} \cap \left\{\Omega_{3\times3} \times \left([L \quad C \quad R] \times \begin{bmatrix}T\\M\\B\end{bmatrix}\right)\right\} \tag{1}$$

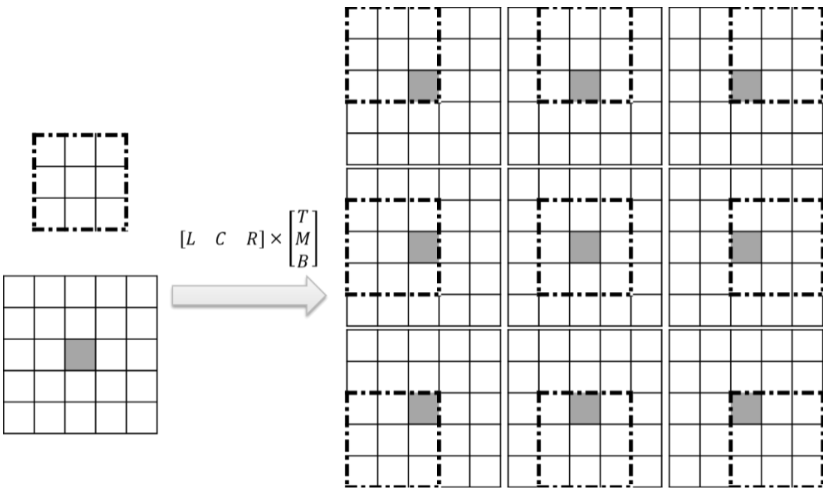


Figure 2. Structure of the compound-type neighborhood

Influence neighborhood represents the local extent of the adjacent cells impacting on the transition of center cell, it is a (2n-1)*(2n-1) Moore neighborhood with the side length of computation neighborhood as radius; and computation neighborhood is an n*n Moore neighborhood, which is used directly for counting the adjacent cells. According to the relative position of the center cell in the computation neighborhood, the influence neighborhood is divided into n^2 computation neighborhoods. The center cell can be localized anywhere in computation neighborhood because of its non-symmetrical structure, and the development state of the influence neighborhood depends on the statistical values of all computation neighborhood. In this paper we employed 5*5 Moore and 3*3 Moore as the influence neighborhood and computation neighborhood respectively. (2) The spatial compactness factor reflects the spatial distribution characteristics of different land use types in influence neighborhood, the comprehensive effect of neighborhood is determined by both quantity and spatial compactness (see fig. 3), which breaks the tradition CA model that takes quantity of

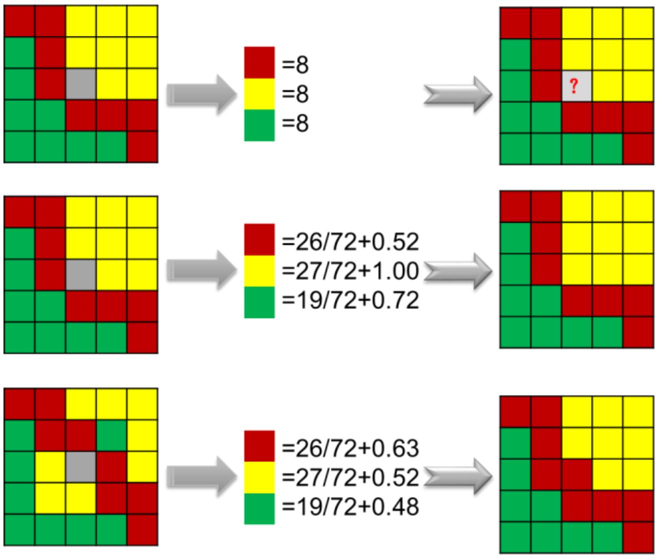
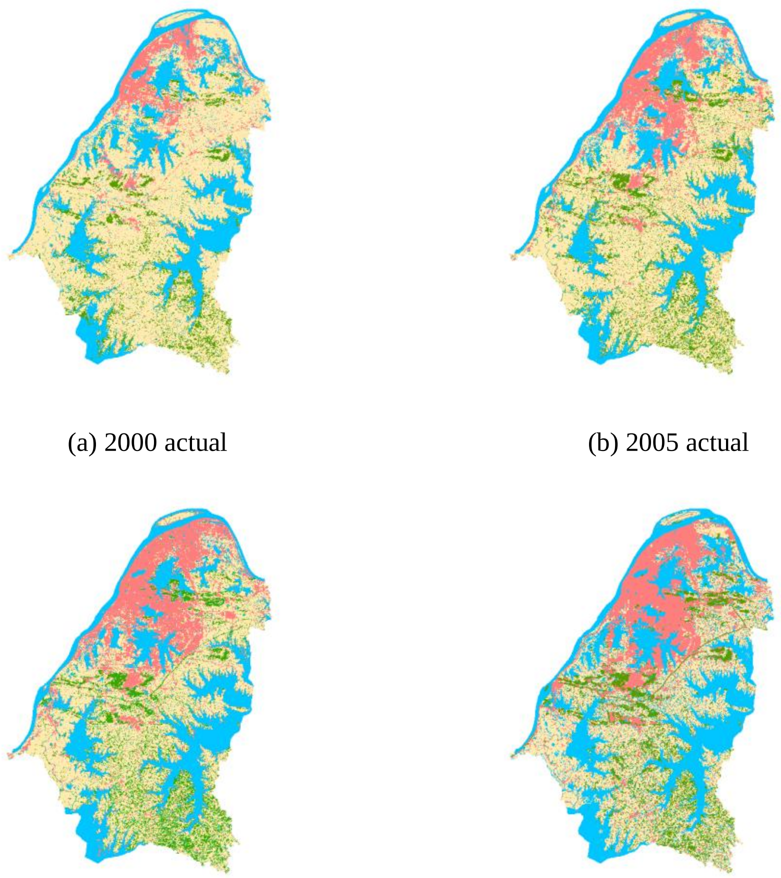


Figure 3. Determined both by quantity and spatial compactness

cells as the only calibration for development of neighborhood. In practice situation the effect of the spatial compactness on the land use change is not a simple positive correlation or negative correlation, but the complicated nonlinear relationship. For instance, it is very possible to have different two development patterns during the urban sprawl: the spatial compactness is in favor of urban development when its value is below than a certain value γ; while if the spatial compactness is higher than value γ it will show the opposite situation, the transition probability of construction land decreased with the increase of spatial compactness, which is the result of the shortage of land resource and the saturation of building density. BP neural network is employed to obtain the transition rules of CA model due to its ability of effectively representing these nonlinear relationships between spatial compactness and land dynamics, and it does not require the researchers thoroughly understanding the complex relationship between inner neurons, which greatly simplifies the rule establishment during modeling geographical CA. In the paper we verified the improved CA model by taking the 4 districts of Wuhan (WuChang, HongShan, QingShan, and JiangXia located in south of Changjiang River) as an example. By interpreting three remote sense images of the study area (2000ETM, 2005ETM, and 2010ETM), basic data about area of the Land Use/Cover Type of the basin in the last three periods are extracted, and combining with other GIS data, such as DEM, transportation, the basic farmland protection zone, agro type, and land use planning, we have modeled the geographical CA and simulated the land use change (see fig 4.). By comparing with the tradition CA through Kappa and Moore indices, the improved CA shows its superiority and the results indicate that the improved CA is more precise in simulation and can better reflect the spatial distribution features of land use.



(a) 2000 actual (b) 2005 actual

(c) 2010 actual (d) 2010 Simulation

Figure 4. Results of the land use dynamics

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