Assessment of the Urban Development Plan of Beijing by Using a CA-Based Urban Growth Model

Jin Chen, Peng Gong, Chunyang He, Wei Luo, Masayuki Tamura, and Peijun Shi

Abstract

We developed a CA-based urban growth simulation model to emulate the city growth before 1997 and simulate possible change scenarios after that. An adaptive Monte-Carlo method was used to automate the calibration of factor weights used in the CA transitional rules. We used one scene of Landsat MSS imagery from 1975 and three scenes of TM imagery from 1984, 1991, and 1997 to classify the land-use patterns, and we used the results to calibrate the CA model. We applied the model to assess the general urban development plan entitled "disperse polycentric urban development plan" of Beijing City and found that the plan failed to meet its objectives.

Introduction

The Beijing Municipal Government initiated a general development plan entitled "dispersed polycentric urban development plan" in 1958, and subsequently revised it in 1983 and 1993. The general plan was to construct one central city and some scattered satellite cities around it. A wide range of greenbelt including truck farms, orchards, and forest lands would be set up between the central city and satellite cities (Zhou *et al.*, 2000). This general plan was meant to play a role in controlling extensive urban expansion of the central city, thus controlling such environmental problems as traffic congestion, air pollution, the heat island effect, and so on. However, during the past two decades, extensive urbanization took place due primarily to economic development and population growth. Because of an underestimation of this growth, and a lack of policy and measures to effectively implement the plan, most land-use changes did not follow the plan. Therefore, emulating the city's growth in the past and simulating possible change scenarios for the future would be helpful to the evaluation of the effects for the development plan and for its future revision.

Most existing urban growth and development models have their origin in urban economics and planning (e.g., Brotchie *et al.*, 1980, pp. 10–50; Zipf, 1949, pp. 40–90; Wilson, 1970; Makse *et al.*, 1995). For example, von Thunen (1966) proposed a model to predict the spatial distribution of land use at a very aggregated level. Zipf's rank-size rule and Christaller's central place theory can model or predict the size and economic distribution among urban systems (Zipf, 1949, pp. 40–90). Neoclassic economics with a concept of "friction of space" adapted from physics forms the basis of many later urban models, including Alonso's urban land market theory (Alonso, 1964). These economic models usually employ econometric regression, difference, or differential equations to describe the interactions of many urban growth factors. Traditional urban models have their limitations, especially in their spatial and temporal aspects. Econometric regression models often view a city as an abstract geometric shape of zones and sectors, if they employ any spatial reference at all. They are either a purely static description of the city or an aggregate prediction relying on a general equilibrium assumption. The spatial aggregate nature of the prediction results and the dependence on the general equilibrium assumption limit their usefulness in planning and decision making. Difference or differential equation based models are dynamic and can generate relatively complex results, both temporally and spatially. However, solutions that are better than a very crude spatial resolution are hard to achieve computationally. In general, several dozens of regions are the maximum number that can be handled (White and Engelen, 1993).

Recently there has been an increasing trend in applying cellular automata (CA) models in urban growth simulations. Such models view cities as complex systems based on the principle of self-organization. As has been argued by many authors, CA models can avoid many shortcomings of traditional models (Clarke *et al.*, 1997; Batty *et al.*, 1999).

Cell, state, neighborhood, and the transition rule are the primary components in CA models. The space consists of a 2D array of cells of the same size. The state variation of a cell depends on its previous state and those of its neighbors. The change of state for each cell is controlled by a set of transitional rules (functions) that are assessed at each time step. Transitional functions can be either deterministic or stochastic (Wolfram, 1984). When applied to urban growth problems, a cell corresponds to a pixel in a land-use image, and its states represent different land-use types (for both urban land and non-urban land). Time is in discrete steps. The urban growing process thus can be represented by a cell state updating process.

The key elements that define a *strict* CA as originally used in physics are that the underlying plane is homogeneous; that cells don't have intrinsic properties; that rules must be uniform, and they must apply to every cell, state, and neighborhood; and that every change in state must be local, which in turn implies that there is no action-at-a-distance effect. When

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Photogrammetric Engineering & Remote Sensing
Vol. 68, No. 10, October 2002, pp. 1063–1071.

0099-1112/02/6810–1063$3.00/0

applied to land-use modeling, CA models are often relaxed to adapt to real problems at hand. Common relaxations include adopting heterogeneous underlying planes; extending the immediate neighborhood definition from a Moore or Neumann neighborhood to a larger extent; incorporating action-at-a-distance effects, or broad-scale factors, etc.

The primarily dynamics generating mechanism of CA-based urban growth models is based on local interactions. It has a strong analogy with how cities evolve in the real world—numerous individuals make decisions about the use of their own piece of land, and the overall landscape pattern is an aggregate outcome of these individual locally based decisions. In the planning field, there is a general cry for "bottom-up" models and CA models. CA models seem to be the perfect tool to reflect this concern (Batty *et al.*, 1997). Their easy integration with GIS and remote sensing algorithms also facilitates their implementation. The success of CA models in simulating realistic urban growth has been demonstrated by many authors (e.g., Couclelis, 1985; Phipps; 1989; White and Engelen, 1993; Batty and Xie, 1994; Couclelis, 1997; Batty and Xie, 1997, Clarke *et al.*, 1997; White *et al.*, 1997; Wu and Webster, 1998; Wu, 1998; Batty *et al.*, 1999; White and Engelen, 2000; Li and Yeh, 2000; Wang and Zhang, 2001).

Cellular automatic (CA) models are being adapted to reflect realistic economic and social theories. Economic, geographic, and planning theories and models can serve as guidelines for the construction of CA models. For instance, traditional geographical models such as spatial interaction models are used to control the growth rate for different regions in a CA model (e.g., White and Engelen, 2000). On the other hand, the local interaction concept and the dynamic feature of CA models offer a way to augment traditional urban models and theories. With the help of CA models, classical urban economic and planning models can be re-phrased and made more explicit both spatially and temporally.

We developed a modified CA model to investigate the urban growth history of Beijing from 1975 to 1997. In addition to involving the common approaches of relaxing the strict CA model formalities, we focused on calibrating the factor weights used in the transitional function, especially between local effect factors and broad-scale effect factors. Differing from traditional approaches relying on the modeler's experience, we developed an iterative procedure based on the goodness-of-fit between the model prediction and the real data. In the rest of this paper we describe the model calibration process with land-use data derived from remotely sensed data and the assessment of the general urban plan for the near future with the modeled urban growth results for Beijing.

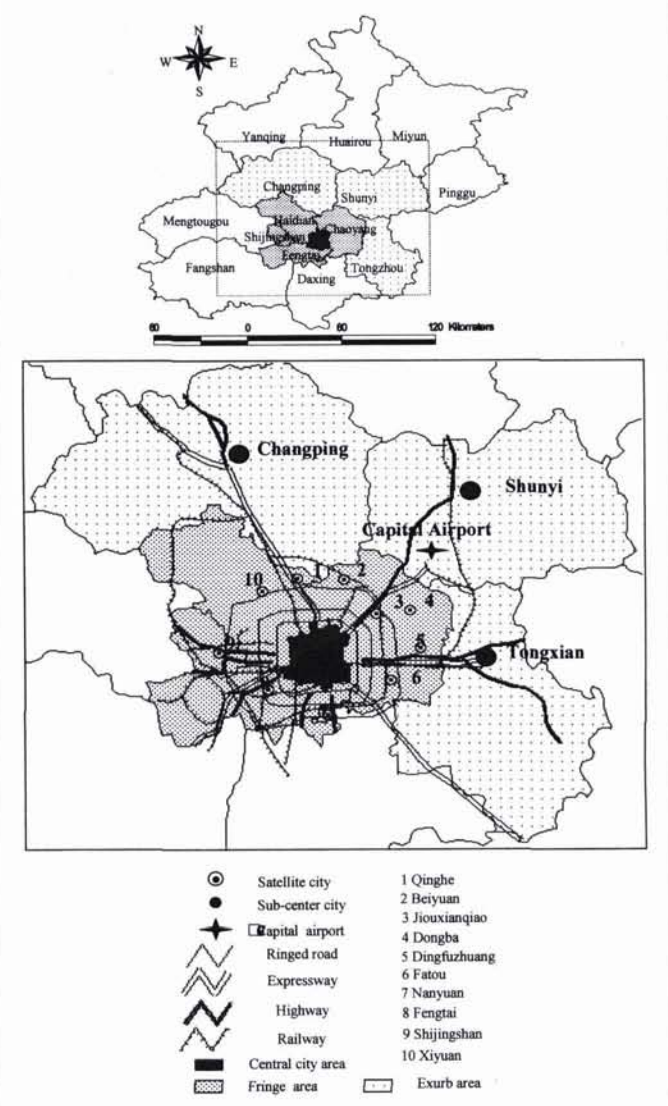

Figure 1. Study area and location.

Study Area and Data

Our study area (115.8347°E to 116.9859°E and 39.5977°N to 40.3832°N) covers 4499.6 km^2, approximately 27 percent of Beijing City (Figure 1). The total population in this area is approximately 9.19 million. Although covering a small portion of Beijing, it provides the most representative "profile" of this city in terms of development levels and land-use diversity. The study area includes all land-use types of Beijing and nine of its ten satellite cities.

For an area of this size, aerial photographs would have been suitable for model development to investigate the urban growth history. However, complete coverage of aerial photographs was not available to us. Therefore, the urban growth history was recovered from a land-use/land-cover classification mode using one scene of Landsat Multispectral Scanner (MSS) data (06 May 1975) and three scenes of Landsat Thematic Mapper (TM) data (02 October 1984, 06 May 1991, and 16 May 1997), which cover the whole study area with relatively high quality. Transportation networks cannot be accurately identified from satellite images at a 30- to 80-m resolution. This led us to concentrate only on general land-cover and land-use types.

Because the spatial resolution and spectral bands of MSS data in 1975 are different from TM data, and the TM data in 1984 have obvious seasonal differences from other data, the images were carefully registered to a 1:100,000-scale topographic map using more than 30 ground control points. The root-mean-squared errors were less than 1 pixel. The images were classified separately using a supervised maximum-likelihood classification. The resultant land-use maps consist of six land-use/land-cover types: urban land, water (including fish pounds), cultivated area (mainly including irrigable land, truck (vegetable) farms, and paddy fields), orchard land, shrub land, and forest land. After post-processing and verification with ground survey data, the Kappa coefficients of classification were 0.71, 0.76, 0.80, and 0.82 for 1975, 1984, 1991, and 1997, respectively (Plate 1). The lower land-use mapping accuracy for 1975 was partly due to the lack of spectral details in the MSS data while the relatively low accuracy for 1984 was partly caused by the greater amount of shade and shadow during the fall season. It appears to us that for six land classes a kappa coefficient

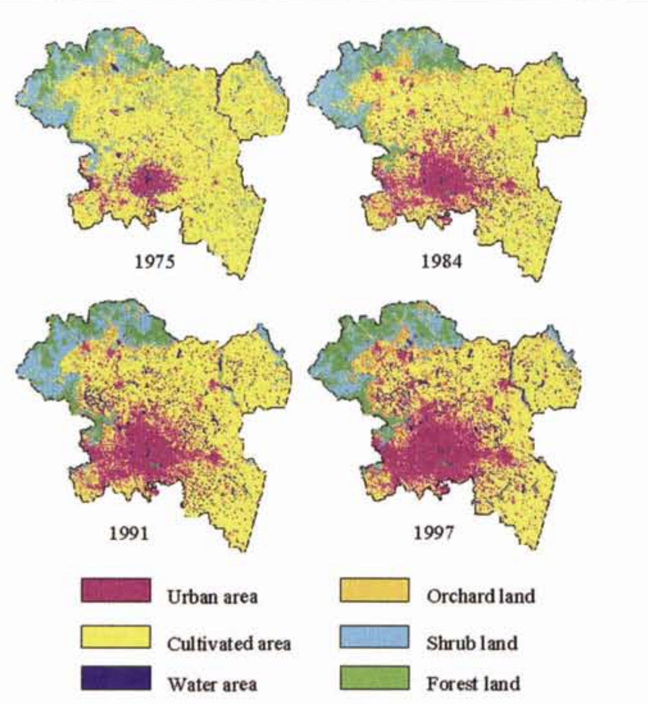

Plate 1. Land-use/land-cover maps for 1975, 1984, 1991, and 1997 classified from remotely sensed data.

exceeding 0.7 is acceptable for the purpose of this analysis.

Other ancillary data included a topographic map at a scale of 1:100,000; maps of transportation networks for the early 1980s, early 1990s, and 1996; a DEM; and a map of the land protection plan in which the flood plain areas of rivers, existing green areas within the central city area, reservoirs, and lakes are prohibited from urban development (Zhou and Mong, 2000, pp. 127–129, 237). Considering the differences in spatial resolution of the MSS data, TM data, and ancillary data, we resampled all data layers to a cell size of 150 m by 150 m using the nearest-neighbor method. This further reduced the image misregistration effect.

CA-Based Urban Growth Model

Model Framework

The transitional function is the core of CA models. There are two groups of factors in the transitional function. The first group includes local factors, such as interactions between adjacent land uses. The second group includes broad-scale factors such as regional interactions based on transportation networks. In transitional function calibration, there is a need for evaluating their relative importance. In this study, we consider calibration of weights as an inverse problem, in which the result of urban growth is known and some parameters (weights) influencing the result need to be determined. We used an adaptive Monte Carlo method to solve this inverse problem (Ichimura and Wakimoto, 1974). We made the following modifications to the formal CA framework to reflect the realistic situation (Figure 2):

(1) *External Land Demand Control.* Urban growth takes place when demands for land development arise, which is a function of economic and population factors. General CA models depend solely on the states of a cell and its neighborhood to allocate land demands into the space. Because economic and population factors were not included in the CA model, urban land demands need to be predicted elsewhere. A function of land demand can be built based on the economy and population data. Sometimes only the total urban land demand for a certain period is available, but the CA-based model needs urban land demand in each year as input. Therefore, we selected the sustainable land development model (Yeh and Li, 1998) to derive the optimal allocation of urban land demand to each year based on Tietenberg equity (Tietenberg, 1992).

(2) *Transition Potential from Non-Urban Land to Urban Land Based on Land Suitability and Neighborhood Effect (Urban Agglomerative Effect).* Because urban growth may depend on its inherent suitability for urban land use determined by land location, traffic conditions and physical conditions, our model quantified land suitability and neighborhood effects and incorporated them into a transition potential through a weighted linear combination as follows (White *et al.*, 1997; Wu, 1998a):

$$P^t_{ij} = A \times \left(\sum_{k=1}^{m-1} w_k \times s_k + w_m \times N\right) \prod_{r=1}^{n} C_r \qquad (1)$$

where P^t_{ij} is the transition potential to an urban land use for a cell ij at time t. $\sum_{k=1}^{m-1} w_k \times s_k$ is the inherent suitability of the cell for urban use, in which s_k is a standardized suitable score [0,100] of factor k $(1, \ldots, m-1)$ and w_k is its weight. N represents the neighborhood effect and w_m is its weight. The weights $(w_1, w_2, \ldots, w_{m-1}, w_m)$, reflecting different contributions of the above factors, were determined using an adaptive Monte-Carlo method based on realistic urban growth history. C_r is a binary variable representing imperative constraints to urban growth extracted from the land protection plan. If $C_r = 0$, the cell may be a river, lake, or protected land that cannot be used as urban land. A is a scalar that standardizes transition potential into the range of [0,100].

(3) *Definition of Neighborhood Effect Was Relaxed to Involve the More Distant Influence of Neighbors.* Agglomeration in urban expansion results from the benefit of conveniences for exchange of material, information, and money, and cost saving for infrastructure construction when urban land is agglomerated. Theoretically, the magnitude of the agglomeration effect largely depends on the difference between the benefits and increased cost caused by urban land agglomeration. The agglomeration effect of urban expansion could be enhanced by the neighborhood effect in a CA-based model. As a relaxed definition of neighborhood in this study, Moore neighborhood was expanded from eight cells in eight directions to 224 cells with a radius of seven cells (Li and Yeh, 2000). The neighborhood effect N is defined by

$$N = \sum_{n=1,m=1}^{7} \frac{1}{d_{i\pm n,j\pm m}} \times I_{i\pm n,j\pm m} \qquad (2)$$

where $d_{i\pm n,j\pm m}$ is the distance from a neighbor cell (m, n) to the center cell (i, j) in cell units as $1, \sqrt{2}, 2, \ldots$ Its reciprocal reflects the distance-decay effect. As a binary variable, $I_{i\pm n,j\pm m}$ represents the state of a neighborhood cell (1 for urban and 0 otherwise). Based on the above definition, it is easy to find that the neighborhood effect N depends on the number of urban cells within a neighborhood and their distances to the center cell.

According to Figure 2 and the above considerations, simulation of urban growth is a process of allocating urban land demands to potential cells based on transition potentials. This process was divided into two parts in our model: (1) calibrating weights in the transition potential formula using an adaptive Monte Carlo method based on historical data of urban growth, and (2) simulating urban growth in the future based on the calibrated CA-based model and land demand prediction.

Calibration of Weights in Transition Potential Using Adaptive Monte-Carlo Method

The goal here is to estimate the weights so that the simulation result is as close to the realistic urban growth as possible. By doing so, we expect that the model would allow us to identify the different contributions (weights) of various driving factors in the urban growth process. We define the weights to be positive integers and normalize them to sum to 100. The inverse

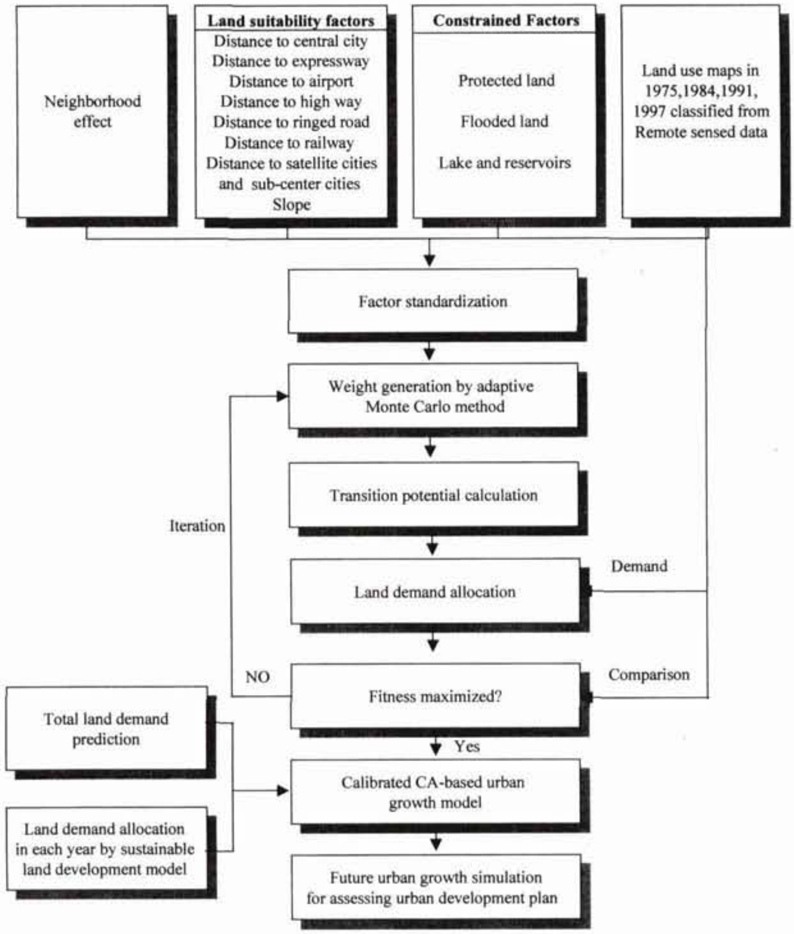

Figure 2. Framework of CA-based urban growth model.

problem then becomes a constrained maximization (minimization) problem as follows:

$$\text{Constrained Condition:} \quad \sum_{k=1}^{m} w_k = 100 \tag{3}$$

$$\text{Objective function:} \quad \text{Max } F(w_1, w_2, \ldots, w_m) \tag{4}$$

where $w_k > 0$, and F is a fitness function between simulation results and the actual situation. Our objective is to find optimal weights so that a fitness index reaches its maximum. This inverse problem can be solved using an adaptive Monte Carlo method (Ichimura and Wakimoto, 1974; Carmone *et al.*, 1997). Compared to other models in which weights of the driving factors are determined beforehand based on the experience of modelers or experts, the adaptive Monte-Carlo method is more objective and can avoid the difficulties in finding experts. The weight of a driving factor calibrated from urban growth history reflects its contribution to urban growth. "What-if" scenarios in the future can be modeled when the same role of each driving factor is played. The procedure of weight determination is described as follows:

(1) A constrained random number generator is used to generate the weights (Miyatake and Wakimoto, 1978, pp. 31, 32, 60). First, the random numbers ($L_1, L_2, \ldots, L_{m-1}$) are generated from a uniform distribution between 1 and $100 + m - 1$. Then $L_1, L_2, \ldots, L_{m-1}$ are sorted in an ascending order ($L_{(1)} < L_{(2)}, \ldots, L_{(m-1)}$). The weights are

$$\begin{aligned} w_1 &= L_{(1)} \\ w_2 &= L_{(2)} - L_{(1)} \\ &\ldots\ldots\ldots\ldots \\ w_m &= 100 - L_{(m-1)} \end{aligned} \tag{5}$$

(2) Based on these weights, the transition potential of each cell is calculated using Equation 1. The total land demand during a certain period (the difference of urban land areas between the beginning and ending years) is then allocated in the order of the ranked transition potentials, starting with the highest. Then a fitness index κ is calculated to assess the simulation performance based on a cell-by-cell comparison between the simulation results and the land-use map of the ending year that is derived from remotely sensed data. Because the simulation results and the land-use maps were georeferenced, the cell-by-cell comparison included location information of the pixels. During each simulation we used the changes of urban areas between the starting and ending years determined from remotely sensed data as the total newly urbanized areas. Therefore, the ratio between the number of simulated urban pixels, C, and the total number of newly urbanized pixels during the period of simulation, D, is sufficient to be used as a fitness index: i.e.,

$$\kappa = \frac{C}{D} \times 100\%. \quad (6)$$

The above steps were iterated many times to fit the real data (land-use maps), and the weights corresponding to the highest κ were chosen as the optimal weights, which reflect the contributions of driving factors during this period. They were then used for new urban growth simulation. According to Miyatake and Wakimoto (1978, pp. 31, 32, 60), when the iteration times reach 500, the probability for the Monte Carlo simulation approaching ± 1 percent of the true maximum is approximately 0.995. Therefore, 500 was selected as the minimal number of iteration times, ensuring that the Monte-Carlo method can obtain reliable weights in this study.

Land Demand Prediction for Future Urban Growth Simulation

In order to simulate future urban growth with the calibrated CA-based model, the total land demand on a yearly basis is needed. Assuming that Beijing will adopt a sustainable land policy, the total urban land demand can be estimated as a tradeoff between economic growth and environment protection under the control of available land resources. The optimal allocation of land demand to each year can be obtained using the sustainable land development model.

According to Tietenberg (1992), land resource can be treated as a depletable, non-recyclable resource. Its demand and supply are influenced by price. Thus, the optimal allocation of land resources is to maximize the net benefit. The maximum net benefit can be obtained when the marginal benefit function is equal to the marginal cost function. Because the marginal benefit falls as land consumption q_t or land consumption per capita q_t/P_{ta} increases (P_{ta} is additional population in year t) (Yeh and Li, 1998), the marginal benefit function (MB) in year t can be given by assuming the land demand curve is linear and stable over time (Tietenberg, 1992): i.e.,

$$\text{MB} = a - bq_t/P_{ta} \quad (7)$$

where a is the maximum value of the marginal benefit in theory and b is the slope of the marginal benefit curve. The total benefit TB for a period is the integral of Equation 7, and is given by Equation 8 when the additional population P_t is fixed: i.e.,

$$\text{TB} = \int (a - bq_t/P_{ta})dq_t = aq_t - bq_t^2/2P_{ta}. \quad (8)$$

The marginal cost for a period is further assumed to be a constant c. The total cost TC is

$$\text{TC} = cq_t. \quad (9)$$

Because the optimal allocation of land demand Q over n years is to maximize the net benefit that equals the total benefit minus total cost, it should satisfy the following maximization condition:

$$\max_{Q_t} \sum_{t=1}^{n} (aq_t - bq_t^2/2P_{ta} - cq_t)/(1+r)^{t-1} + \lambda\left(Q - \sum_{t=1}^{n} q_t\right) \quad (10)$$

where Q is the total land demand; q_t is allocated land demand in year t; c is the marginal cost constant, which is less than a; r is interest rate; and λ is a constant to be solved for. Maximization can be achieved by solving the following equations:

$$(a - bq_t/P_{ta} - c)/(1+r)^{t-1} - \lambda = 0$$
$$t = 1, \ldots, n \quad (11)$$

$$Q - \sum_{t=1}^{n} q_t = 0 \quad (12)$$

where P_{ta} is the projected additional population in year t, which can be estimated with a logistic model based on historical data. The solution of Equations 11 and 12 yields a stream of q_t, which is the optimal allocation of total land demand in each year. After the total urban land demand and optimal allocation are achieved, urban growth in the future can be simulated using the CA-based model.

Urban Growth Simulation During 1975–1997

Simulation of the urban growth history can improve our understanding of the urban growth mechanism in the past. The changes of land use in Beijing were influenced by a large number of factors. Population and economic growth driven by the development of the tertiary industry and infrastructure construction propelled urbanization as a whole (Gu, 1999; Sun, 1992), while such factors as traffic condition, distance to central city, slope, and so on determined the spatial distribution of urban growth. In the case of Beijing, the most important nine factors associated with land suitability and neighborhood effect were selected and incorporated in the calculation of transition potential. These factors were distance to central city, distance to satellite cities and sub-center cities, distance to expressway, distance to airport, distance to highway, distance to ring road, distance to railway, slope, and neighborhood effect. Because the traffic system and neighborhood effect changes each year, factors related to the traffic system and neighborhood effect were calculated for each year by taking into account the newly built traffic lines and newly urbanized pixels. Because the above nine factors were measured in different units, a standardization method was used to translate them into a normalized scale (0 to 100). Fuzzy membership functions were adopted to accomplish the standardization (Figure 3). For each factor, the form of and coefficients in the membership function were determined based on buffer analysis and

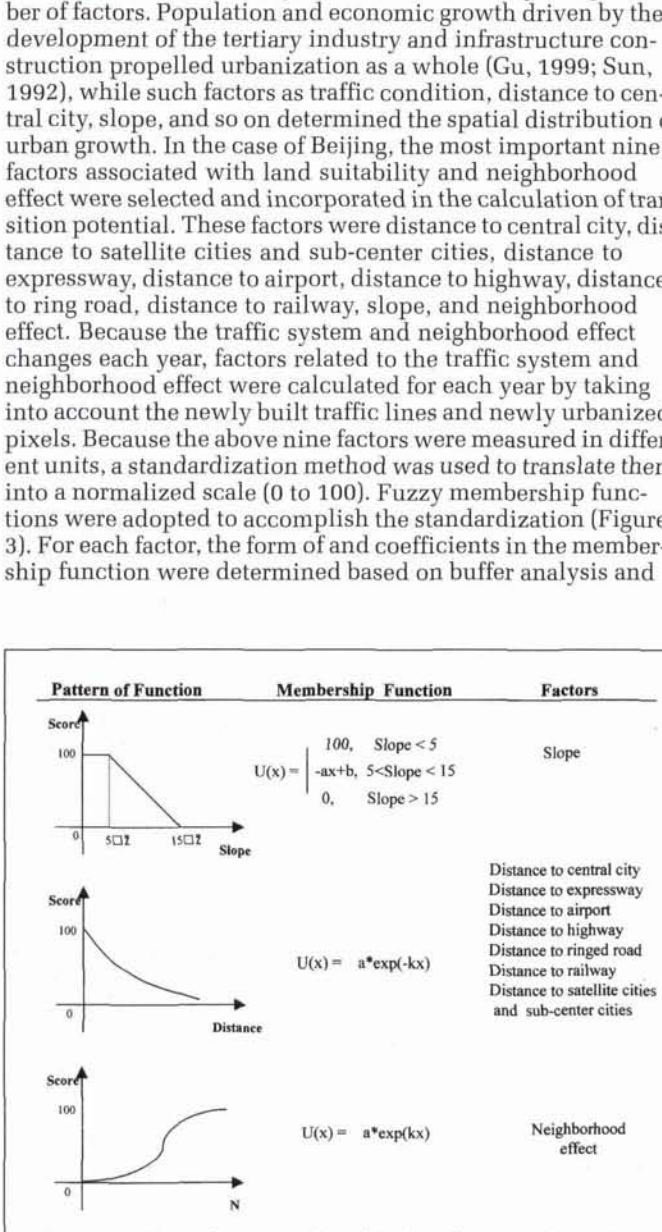

Figure 3. Three fuzzy membership functions used to standardize the driving factors.

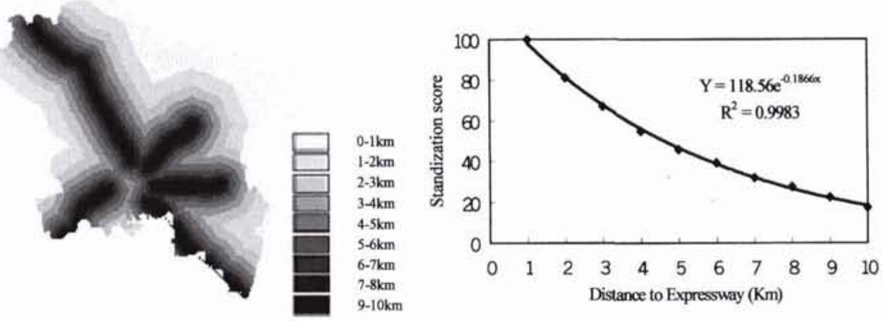

Figure 4. Standardization of the factor of distance to expressway. (a) Buffer regions from expressway. (b) Fuzzy membership function for standardization.

regression analysis. For example, the distance-to-expressway factor was standardized in the following steps (Figure 4):

(1) The nearest distance to expressway was calculated for each pixel in a GIS. Then, buffer analysis was carried out with the distances from 1 to 10 km. The nine buffer regions from expressway were extracted as 0 to 1 km, 1 to 2 km, . . . , 9 to 10 km.
(2) In each buffer region, the change probability was calculated, which was defined as the percentage of the number of urbanized pixels to the total number of pixels in the region. Here the urbanized pixels were those pixels that changed from non-urban land to urban land during a certain period.
(3) A membership function between the change probability and distance to expressway was developed based on regression analysis, and the range of the function was translated to [0,100] by normalizing the change probability with the maximum probability.

Based on the model and standardized factors in each year, the urban growth during the periods of 1975–1984, 1984–1991, and 1991–1997 was simulated, respectively, about 500 times using the adaptive Monte Carlo method. For each simulation in one period, the simulation result was compared with the urban land map derived from remote sensing. Then the fitness index (κ) was calculated to measure the overall performance of the simulation. Among all 500 simulations for each period, the highest fitness indices achieved were 0.59 for the period of 1975–1984, 0.65 for 1984–1991, and 0.67 for 1991–1997, respectively. The best fitness simulations for 1975–1984, 1984–1991, and 1991–1997 are shown in Figure 5. It is evident that the simulation results are similar to the urban patterns mapped with remote sensing as a whole but do not entirely match the scattered and small-scale urban patches. There could be several reasons for the relatively low fitness indices and clustered growth patterns: (1) some important factors associated with urban growth were not captured by the model because land rent data were not available and some policy factors were difficult to represent in a spatial context; (2) the decision criteria on land use by individuals have both commonality and diversity, but the CA-based models only capture the commonality; and (3) imperfect information and other uncertainties also affect the model performance.

From Figure 5, it is obvious that the urban spatial pattern of Beijing had not been developed in accordance with the "dispersed polycentric urban development plan" during 1975–1997. Specifically, the central city was not controlled effectively and expanded quickly to its fringe areas, where the dispersed satellite cities developed slowly. As a result, there was a trend that satellite cities were absorbed into the central city to form one "big city," and greenbelts between the central city and the satellite cities were encroached gradually by urban land. Obviously, the "dispersed polycentric urban development plan" has not brought its function into full play during this entire period. Some reasons can be drawn from the calibrated weights (Table 1) in our urban growth model.

(1) The strong attractive power of the central city and the agglomeration effect stimulated by the economic development and population growth in Beijing has been underestimated in the general plan. The fact that the distance to central city and neighborhood have higher weight scores shows their primary contribution to urban growth during the three periods. The sum of the weights of these two factors is about 67 in 1975–1984, 54 in 1984–1991, and 44 in 1991–1997, respectively (Table 1). The strong agglomeration effect is largely strengthened by the planned economic system adopted in China for some time and by use of bicycles as a primary means of transportation in Beijing. On the other hand, there were too many satellite cities of small scale in the general plan, causing the investment in infrastructure construction to be dispersed, and resulting in the slow growth of the satellite cities. As a result, the satellite cities had a low attraction (weights are 5, 9, and 11, respectively, for each of the three periods) and were found difficult to restrict the expansion of the central city because of their incomplete infrastructures and unfavorable living conditions.
(2) Ring road construction accelerated the central city expansion. The traffic system in the study area consists of two parts, the ring road structure within the central city and its fringe area and the linear structure linking the central city and the suburbs (see Figure 1). It is shown in Table 1 that the linear traffic system, including expressways and highways, played a less important role in urban growth (total weights of these two factors are only 12, 15, and 15 for each period, respectively).

Table 1. Calibrated Weights During 1975–1984, 1984–1991, and 1991–1997

Factors	Weights During 1975–1984	Weights During 1984–1991	Weights During 1991–1997
Distance to central city	12	11	8
Distance to expressway	7	8	11
Distance to airport	1	1	2
Distance to high way	5	7	4
Distance to ring road	10	14	21
Distance to railway	4	5	3
Distance to satellite cities and sub-center cities	5	9	11
Slope	1	2	4
Neighborhood effect	55	43	36

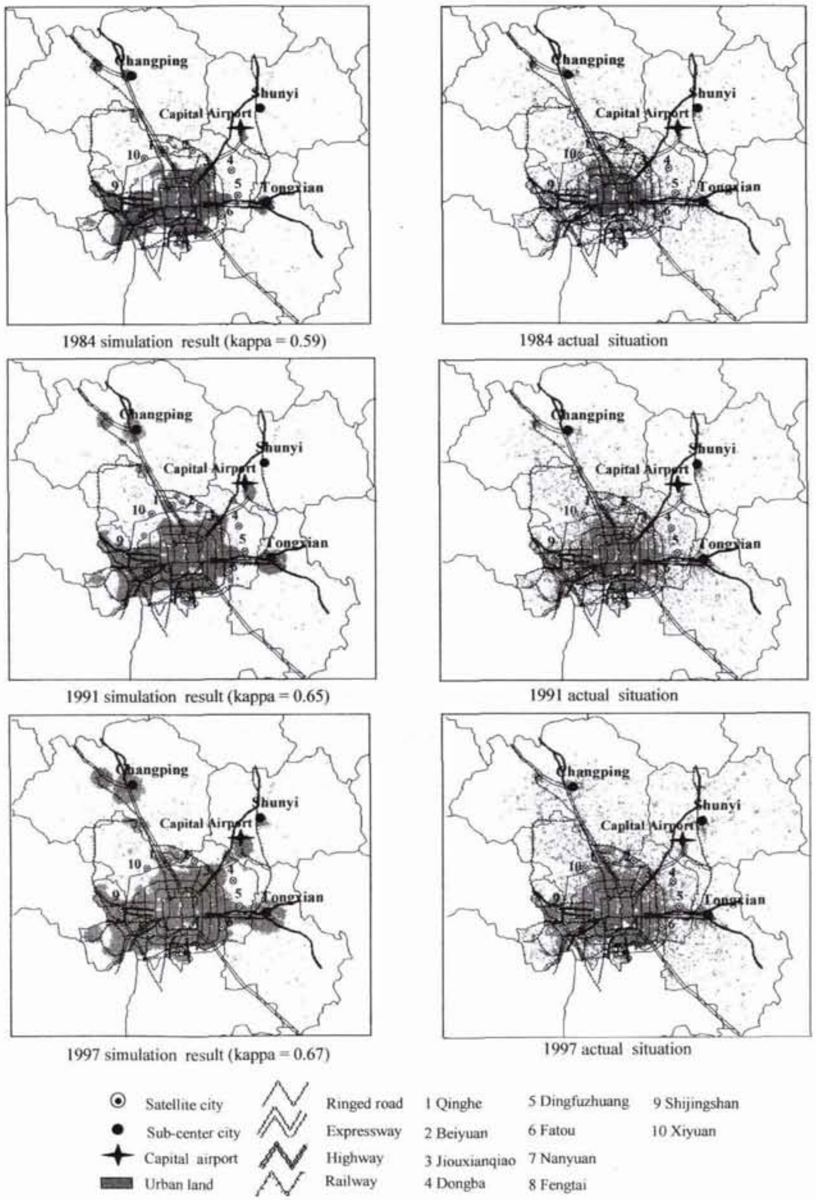

Figure 5. Urban growth simulations from 1975 to 1997.

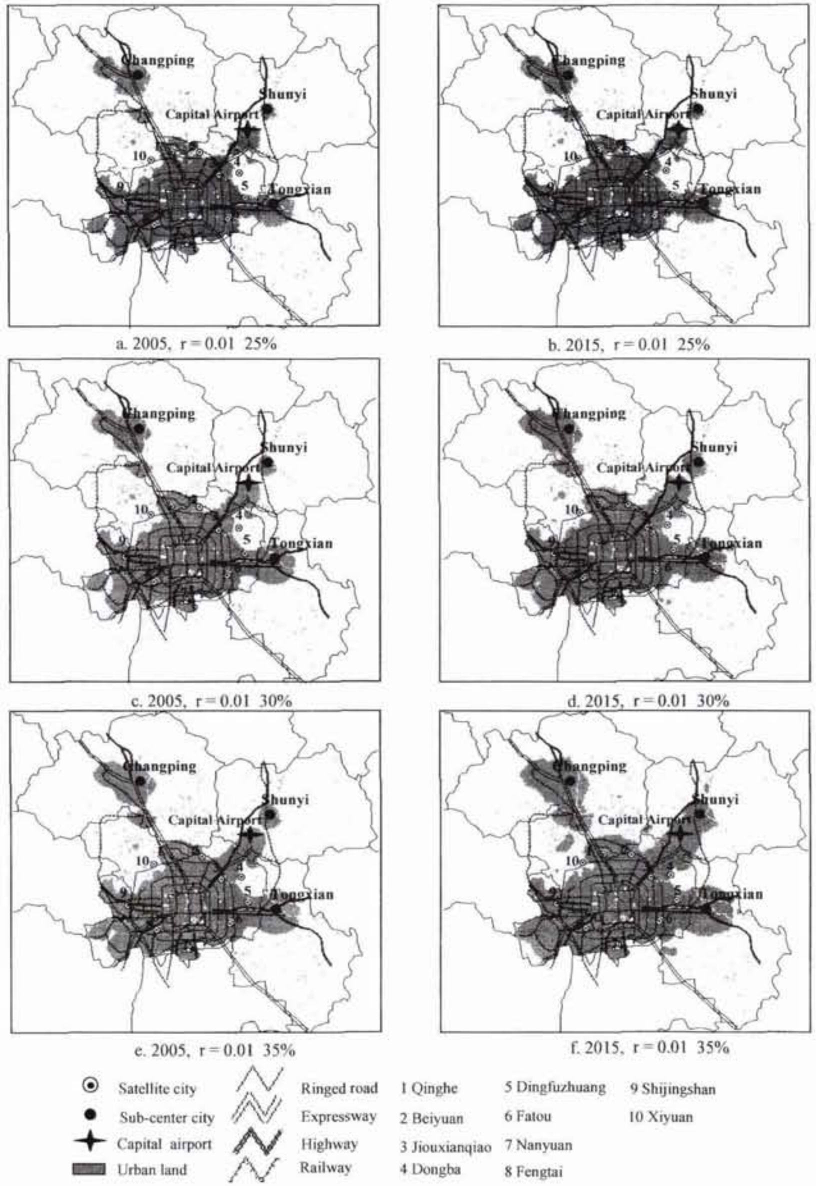

Figure 6. Urban growth simulations from 1997 to 2015. (a) and (b) are results for Scenario 1: total urban land demand = 101.34 km^2. (c) and (d) are results for Scenario 2: total urban land demand = 326.32 km^2. (e) and (f) are results for Scenario 3: total urban land demand = 551.30 km^2.

In contrast, the weight of the ring road system shows an increasing trend from 10 to 21 with the construction of the third and fourth ring roads at the urban fringe area. Due to the construction of the ring roads, the accessibility to the central city was considerably improved at the urban fringe areas in every direction. The central city expansion was accelerated remarkably. On the other hand, the railway and airport had little to contribute to urban growth between 1975 and 1997.

The fact that greenbelts between the central city and satellite cities were not protected effectively is another cause of the failure of the general plan. Truck farms and cropland constituted a major part of the greenbelt. They not only provided food, mainly vegetables, to the city but also played a role in the environmental adjustment of the city by increasing humidity and alleviating the heat island effect. However, they did not gain enough attention and no effective action was taken to protect them. Thus, the greenbelts became the dominant area to be encroached by the expansion of the central city because of their close location and low rental costs.

Urban Growth Simulation from 1997 to 2015

The simulation of the trend of urban growth in the future will help assess the future effect of the general plan and provide a base for making reasonable development strategies. In 1997, the total area of urban land was 1023.55 km^2, approximately 22.5 percent of the study area. Because the increase in urban land would lead to a decrease in greenbelts and likely produce additional environmental problems, we assumed that the government would adopt a strict land policy to control urban growth. Therefore, we set three scenarios: by 2015 the area of urban land will only occupy 25 percent, 30 percent, or 35 percent of the total area. Thus, the additional amount of land conversion in 2015 is set to 101.34 km^2, 326.32 km^2, and 551.30 km^2, respectively. Based on the 1997 figure, the annual rate of increase of urban land will be 0.5 percent, 1.7 percent, and 2.9 percent, respectively. Because the annual rate of increase in the region was 13.6 percent, 4.4 percent, and 5.0 percent in 1975–1984, 1984–1991, and 1991–1997, respectively, the three scenarios are all very conservative. After the total land demand in the future is determined, the optimal allocation of land demand for each year was obtained based on the sustainable land development model and the population prediction using a logistic model, which was built by using historical population data of Beijing between 1980 and 1998: i.e.,

$$y(t) = 1220.05419/(1 + 0.9019*\exp(-0.0418*t)) \quad (t = 0,1,2,3,\ldots) \tag{13}$$

where $y(t)$ is the total population, which is the sum of the registered population and the floating population. $t = 0$ indicates the year 1980.

Based on the calibrated model (the weights calibrated from 1991–1997 were used here) and the above land demand scenarios (Table 2), urban growth in 2000, 2005, 2010, and 2015 was simulated by assuming that those driving factors would play the same roles and no new traffic line would be added between 1997 and 2015. The results of 2005 and 2015 are shown in Figure 6. It can be seen that almost all satellite cities will be merged into the central city and the greenbelts will disappear completely by 2015, even using the most restrictive scenario. These suggest a failure of the "dispersed polycentric urban development plan" in the not too distant future. Although there are continuing debates on whether urban forms should be compact or dispersed (Ewing, 1997; Gordon and Richardson, 1997), we believe it is necessary to control urban growth and protect greenbelts around the city.

Table 2. The Prediction of Urban Land Demand and Additional Population from 1998 to 2015

Period	Additional population (10,000 persons)	25% urbanized land (hm * hm) r = 0.01	30% urbanized land (hm * hm) r = 0.01	35% urbanized land (hm * hm) r = 0.01
1998–2000	28.0559	2909.09	6977.24	11045.39
2001–2005	48.1109	3682.86	10220.43	16758
2006–2010	43.0473	2348.18	8504.99	14661.8
2011–2015	37.9759	1193.87	6929.09	12664.31
Total	157.19	10134	32631.75	55129.5

Note: r is the interest rate

Conclusions

We incorporated a new weight calibration method into a cellular automata (CA) model that allowed model parameters to be estimated from the history of urban growth. The application of this model to Beijing indicates that the spatial pattern of urban development in Beijing has not been developed in accordance with the "dispersed polycentric urban development plan" during 1975–1997. There was a trend that satellite cities were absorbed into the central city to form one "big city," and greenbelts between the central city and satellite cities were encroached gradually by urban land. The calibrated weights provided some reasonable explanations for the failure of the urban development plan. Three primary reasons are summarized here: (1) underestimation of the strong attractive power of the central city and the agglomeration effect in the general plan, (2) strong effects of ring road construction, and (3) the shortage of effective means to protect the greenbelts between the central city and satellite cities. The simulation of urban growth suggested that almost all satellite cities would be merged with the central city and the greenbelts in-between would disappear completely by 2015, even when using the most restrictive scenario. In order to realize sustainable development in Beijing, a new urban development plan and effective measures for implementing the plan are needed. The CA-based urban growth model developed here can play an important role in developing the new plan.

Acknowledgments

This research was partially supported by the Watershed Environments and Management Research Project at the National Institute for Environmental Studies, Japan, the project of Ecosystem Restoration Mechanism and Optimized Eco-productive Paradigm of Grassland and Farming-pastoral Zone of North China (G2000018600), a grant from NASA (NCC5-492), and a grant (49825511) from the NSF of China.

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