Urban Simulation Using Principal Components Analysis and Cellular Automata for Land-Use Planning

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Abstract
This paper discusses the integration of cellular automata (CA), principal components analysis, and GIS techniques in simulating alternative urban growth patterns for land-use planning. The simulation of actual cities usually involves multicriteria evaluation (MCE) in tackling the problems of complex spatial factors. Spatial factors often exhibit a high degree of correlation which is considered an undesirable property for MCE. It is difficult to determine the weights when many spatial variables are involved. This study uses principal components analysis (PCA) to remove data redundancy among a large set of spatial variables and determine the "ideal point" for land development. The simulation is based on transition rules that are related to the neighborhood function and similarity between cells and the "ideal point." Principal components analysis helps to deal with a large data set of spatial variables for the implementation of the CA model.

Introduction
Cellular automata (CA) are discrete spatio-dynamic systems, which were first developed by Ulam in the 1940s and soon used by Von Neumann to investigate the logical nature of self-reproducible systems (White and Engelen, 1993). They have been increasingly used in the simulation of complex systems, such as biological reproduction, chemically self-organizing systems, propagation phenomenon, and human settlements. In recent years, a series of urban models based on CA techniques have been reported (Batty and Xie, 1994; White and Engelen, 1993; Wu and Webster, 1998; Li and Yeh, 2000; Li and Yeh, 2001b). CA models can be used for testing hypotheses, simulating urban forms and dynamics, and generating ideal land use plans. Most urban CA models are primarily focused on testing ideas and exploring the mechanisms of urban growth. It is typical to see that a series of local actions can give rise to global patterns in CA simulation. CA models are able to generate cellular cities that have features very similar to those of real cities (White and Engelen, 1993).

Attempts have been made to develop a kind of constrained CA model which can be used as a planning tool for urban planning. Planning objectives are translated into transition rules that are used for CA simulation (Ward *et al.*, 2000; Yeh and Li, 2001b; Li and Yeh, 2001a). Urban planning usually involves the comparison between a set of planning scenarios and development options before making a plan. CA models can produce various development options that are dependent on the structures of models and inputs of data. The basic strategy is to properly define the structures of CA models that can incorporate planning objectives in the simulation. Li and Yeh (2000) have used a constrained CA model to plan for sustainable urban development which aims at minimizing agricultural land loss and promoting compact development. Various urban forms which are associated with different development and energy "costs" can also be explored using constrained CA models for testing different planning options (Yeh and Li, 2001b). Ward *et al.* (2000) also present a constrained CA model which has been applied to an area in Gold Coast, a rapidly urbanizing region on the eastern coast of Australia. They demonstrate that CA models can simulate planned development as well as realistic development by incorporating sustainability in the simulation. Their study shows that economic, physical, and institutional control factors can be incorporated to modify, constrain, and prohibit urban growth.

CA models should be a good planning tool for urban growth management when the models are integrated with a GIS. Operational CA models can be built within a GIS to simulate the dynamics of actual urban systems which are driven by a series of complicated factors. GIS offer unique capabilities for data capturing, storing, and analyzing. The integration of GIS and CA can help to solve complex decision problems as they can benefit from each other (Wagner, 1997). There are numerous factors which contribute to the formation of actual land-use patterns. A GIS can be used to explore various types of factors that may play a role in determining the possible or suitable locations of land development. A series of constraints can be defined and obtained from remote sensing and GIS to address environmental concerns so that sustainable cellular cities can be simulated.

Usually, numerous factors or criteria are involved in CA models to obtain detailed simulation results and solve real-world problems. Multicriteria evaluation (MCE) techniques can be employed to handle a number of criteria in decision making. MCE techniques began to emerge to solve decision making and planning problems in the early 1970s. The planning process is becoming more complicated in technical, physical, social, and economic aspects. MCE can be used for analyzing the complex trade-offs between different alternatives (van Delft and Nijkamp, 1977).

MCE typically requires that the evaluation criteria be independent of each other (Malczewski, 1999). A high degree of correlation between evaluation criteria is considered as an unde-

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sirable property for decision making. Unfortunately, most of the spatial criteria used for CA simulation are highly correlated due to data redundancy. Principal components analysis (PCA) can be used to remove data redundancy. PCA is one of the most widely used methods for spatial data handling because of its simplicity and relative straightforward interpretation (Dunteman, 1989). The method is most suitable for representing complex relationships among a large number of variables. It can transform a set of correlated variables into uncorrelated orthogonal variables. This paper examines the integration of PCA and CA models in reducing data redundancy among a large set of spatial variables for urban simulation and planning.

The Problems of MCE in GIS Analysis and Urban Simulation

The analysis of alternative planning options is an essential part of plan making (Landis, 1995). It is useful to generate and compare a set of alternatives before planners can choose a suitable plan. The overlay of various layers of maps is a classic example of a site search exercise. GIS can be used to facilitate map overlay analysis. However, traditional GIS overlay analyses have limitations when multiple and conflicting criteria and objectives are involved (Carver, 1991). Usually, only a few factors are considered in GIS overlay analysis because there are difficulties in comprehending more than four to five factors (Janssen and Rietveld, 1990). Openshaw *et al.* (1989) applied *GIS* overlay functions to search a specified region of interest for an area suitable for the disposal of radioactive waste. The search was based on four factors—geology, population distribution, accessibility, and conservation. It identified the areas which simultaneously satisfied all the specified criteria.

Site search can be much improved by integrating MCE with GIS (Carver, 1991). MCE can provide GIS with a powerful means for performing complex trade-offs on multiple and often conflicting objectives using a large set of criteria. The integration can provide a more rational and objective approach to making decisions. Weighting spatial criteria is critical in the use of MCE. A variety of techniques have been developed for obtaining weights (Eastman *et al.*, 1995). The Analytical Hierarchy Process (AHP) developed by Saaty in the 1970s has been considered to be very useful in obtaining a relatively consistent weight for each criterion (Saaty, 1990). It uses pairwise comparisons to acquire the preference of decision makers.

Recent studies have shown that CA-based approaches have wide appeal in the study of urban and regional spatial structures (Yeh and Li, 2001b). CA simulation for real-world cities needs to deal with multiple spatial factors. It is appropriate to integrate MCE into CA for capturing decision-making behaviors. MCE can significantly enhance CA data processing capability because MCE can investigate a number of choice possibilities in the light of multiple criteria and conflicting objectives (Voogd, 1983). Wu and Webster (1998) present interesting studies that show how an integrated MCE-CA model can conveniently explore urban forms under different development regimes.

Not enough attention has been paid to the possible correlation between different layers or criteria in many GIS and CA applications. Correlation may not be apparent when only a few dimensions of spatial variables or criteria are used for decision making. However, there is a high probability for spatial factors to overlap among each other and cause data redundancy. Many problems of spatial search will inevitably involve a large range of alternatives and criteria (Carver, 1991). For example, Bauer and Wegener (1977) use 240 evaluation criteria (variables) for each zone of a city to represent the demographic, employment structure, land-use environment, and infrastructure for a spatial decision model. At least 12 spatial layers are listed in the California Urban Futures (CUF) Model, which is a GIS-based urban simulation model (Landis, 1995). Sixteen spatial factors are selected as criteria for sites evaluation for the disposal of radioactive waste (Carver, 1991). However, there is little consideration for the possible correlation between each criterion in these studies. A weighted linear combination of various layers is the most commonly used method in dealing with these multiple factors (Carver, 1991; Eastman *et al.*, 1998; Wu and Webster, 1998).

It is inadequate to carry out CA simulations based on the direct use of MCE when there are correlated spatial variables. The correlation of factors may result in the malfunction of the weighting for MCE by "double counting" similar variables. Furthermore, the models are difficult to implement because weights or parameters cannot be easily determined when too many factors are involved. It is also not easy to interpret the results by directly including all these factors in CA models.

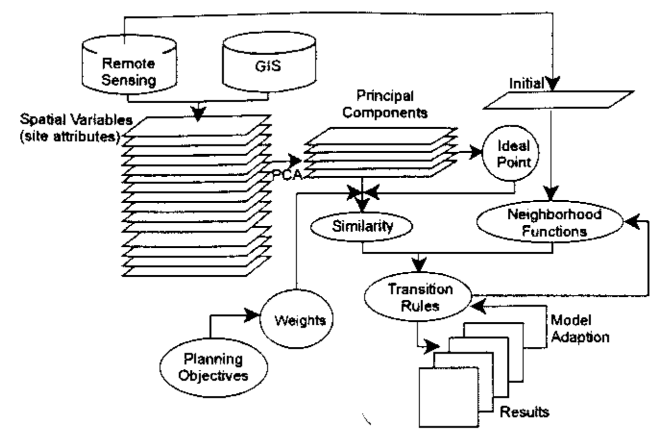

Figure 1. Flowchart of CA simulation based on principal component analysis.

Methodology

Principal components analysis (PCA) can be integrated in CA simulation to tackle the problem of correlation among many layers of spatial data. The method is especially useful in reducing the data volume of remote sensing images for better classification which have many bands or channels (Li and Yeh, 1998). The compression has practical advantages for CA simulation because principal components can pack most of the variance within a small number of eigen channels. The new variables that contain the information from the original data set can be used as site attributes for CA simulation.

The model is based on the integration of principal components analysis and CA for the simulation of various development scenarios (Figure 1). First, remote sensing and GIS are used to provide spatial information, such as various types of proximities (site attributes) and the neighborhood function in terms of development quantity. These types of spatial variables are the basis for urban simulation (Wu and Webster, 1998). Second, PCA is carried out to remove data redundancy so that the "double counting" can be avoided in the CA simulation. The "ideal point" is then defined from the component images for computing the similarity between the target cell and the "ideal point." Planning objectives correspond to different sets of weights which are also used to calculate the similarity. Alternatives of urban growth are simulated based on the transition rules that are defined according to the neighborhood function and the "similarity."

The simulation of actual urban and regional growth should involve a large number of spatial variables. The first step is to examine the criteria that are important in determining urban simulation. A set of criteria can be identified to reflect various aspects of environmental and resource settings, and different planning objectives. The criteria should be problem specific. There are no universal techniques available for selecting them. The set of criteria should be operational, complete, and understandable. If the number of decision criteria is very large, decision makers will encounter great difficulties in assigning value judgments or weights (van Delft and Nijkamp, 1977). Some form of standardization for criteria scores is necessary to enable meaningful comparisons. A common way of standardization is to transform the scores into a normalized scale (i.e., 1 = maximum, 0 = minimum) using the maximum and minimum values (Carver, 1991; Eastman, 1995).

A large set of spatial variables needs to be defined for most of the spatial decision models due to the complexity of the real world (Bauer and Wegener, 1977; Landis, 1995). It is expected that there is significant correlation between various layers of spatial information that are used to determine urban growth. Principal components analysis (PCA) can be employed to examine correlation and reduce data redundancy. PCA is a linear transformation of data which rotates the axes of variable space along lines of maximum variance. The rotation is based on orthogonal eigenvectors of the covariance matrix generated from a sample of original data. Although n number of principal components may be acquired in the analysis, the first few principal components usually account for a high proportion of the variance in the original data. Standard PCA, which has been widely used for remote sensing applications, can be integrated in the CA simulation. The transformation of n layers of spatial data can be carried out using the following equation (Gonzalez and Wintz, 1977):

$$PC_{ij} = \sum_{k=1}^{n} X_{ik}E_{kj} \tag{1}$$

where PC_{ij} is the component score of the jth principal component for cell i, X_{ik} is the value of the kth criterion or layer for cell i, and E_{kj} is the element of the eigenvector matrix at row k and column j.

The eigenvectors and eigenvalues for the linear transformation is mathematically derived from the covariance matrix by the following equation:

$$\mathbf{E}\ \mathbf{COV}\ \mathbf{E}^{\mathrm{T}} = \mathbf{\Lambda} \tag{2}$$

where **COV** is the covariance matrix, $\mathbf{\Lambda}$ is the diagonal matrix of eigenvalues, **E** is the matrix of eigenvectors, and T is the transposition function.

Principal components are used as the site attributes for the CA simulation. A "grey-cell" CA model is proposed here for urban and environmental planning based on principal components. The model can be used for a variety of environmental planning purposes. An example is to find suitable locations for land development to reduce environmental impacts. Traditionally, CA simulation only uses a binary value to address the status of conversion based on the calculation of probability. The probability of conversion is calculated based on some kind of neighborhood function. Usually, the probability is further compared with a random value to decide whether a cell is converted or not (1 for converted and 0 for non-converted). In our model, the status of a cell has a continuous "grey value" between 0 and 1 to represent the stepwise selection or conversion process. A cell will not be suddenly "selected" or converted for land development. The "grey value" is calculated based on the cumulative equation

$$G_i^{t+1} = G_i^t + \Delta G_i^t \tag{3}$$

where G^t is the "grey value" for development which falls within the range of 0 to 1 at time t, and i is the location of the cell. The simulation will stop when t reaches the final time T^0. A candidate cell will not be regarded as a developed cell until its "grey value" reaches 1. The value should be assigned to 1 when it is greater than 1 during the calculation. ΔG^t is the gain of the "grey value" at each loop.

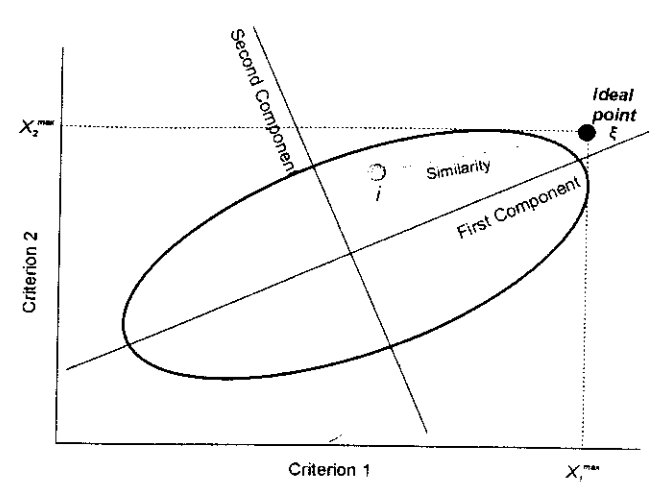

Figure 2. Transformation of coordinate systems for two variables and the "ideal point."

The "grey values" can allow various kinds of spatial criteria to be easily embedded in the CA model. The novelty of the model is to calculate the increase of the "grey value" based on the similarity between a candidate cell and the "ideal point" using principal components as site attributes. The "ideal point" is the hypothetical cell that has the best criterion scores for all criteria (Figure 2). It will generate the highest amount of gains when it is converted for development. The "ideal point" in the variable space can be expressed as

$$\xi = (X_1^{\max}, X_2^{\max}, \ldots, X_k^{\max}, \ldots, X_K^{\max}) \tag{4}$$

where $X_k^{\max}$ is the maximum score for the kth criterion.

The attributes for the "ideal point" in the principal components space can be obtained by the transformation using Equation 1. The transformed "ideal point" is

$$\xi = (PC_1^0, PC_2^0, \ldots, PC_j^0, \ldots, PC_m^0) \tag{5}$$

where PC_j^0 is the transformed score of the "ideal point" for jth principal component.

The distance from a candidate cell to the "ideal point" can be measured based on principal components. A candidate cell that is more similar to the "ideal point" in terms of site attributes will have a faster rate of urban growth. This can ensure that greater benefits can be achieved. As discussed above, the attributes have been compressed into a few major principal components, but they still contain most of the original information. The principal components are then used to calculate the similarity based on a form of Euclidean "distance." The "distance" is given by

$$d_{i\xi} = \sqrt{\sum_{j}^{m} w_j^2 (PC_{ij} - PC_j^0)^2} \tag{6}$$

where $d_{i\xi}$ is the "distance" between cell i and "ideal point" ξ based on the attributes of m components, PC_{ij} is the value of jth component for cell i, w_j is the weight for the jth component, and

PC_j^0 is the transformed score of the "ideal point" for the jth principal component. The weight w_j is used here to address the importance of a component in influencing urban growth. A component associated with a higher value of weight means that more importance has been assigned to the component. Different sets of weights can be prepared for different planning objectives.

The similarity (SIM) is given by

$$SIM = 1 - \frac{d_{i\xi}}{d_{i\xi}^{\max}} \tag{7}$$

where $d_{i\xi}^{\max}$ is the maximum value of $d_{i\xi}$.

The similarity is normalized to the range of 0 to 1. A cell with the normalized value of 1 represents that it is most similar to the "ideal point." In contrast, a cell with the value of 0 represents that it is totally not similar to the "ideal point." The essential part of the CA model is to calculate the increase of "grey value" (ΔG^t) based on the neighborhood function and the similarity.

The transition rules consist of two parts. The first part is the traditional neighborhood function which counts the number of developed cells in the neighborhood. There is a higher probability for conversion when a cell is surrounded by a larger number of developed cells (Batty, 1997). The second part is related to the similarity between a candidate cell and the "ideal point." A cell with a larger value of SIM (closer "distance") means that the cell is more similar to the "ideal point," and a proportionally higher growth rate of "grey value" should be applied to the cell.

The first part is to address the driving force of growing as usual, while the second is to reflect environmental settings and regulations for idealized growth patterns. The second part is very useful for addressing a series of environmental and resource issues that can be used to generate an idealized urban form. The increase of "grey value" should be given by

$$\begin{aligned}\Delta G_i^t &= f_i(q^t, N) \times SIM^t \\ &= \frac{q^t}{\pi l^2} \times \left(1 - \frac{d_{i\xi}^t}{d_{i\xi}^{\max}}\right)^k\end{aligned} \tag{8}$$

where q^t is the total number of developed cells in the neighborhood N at time t, l is the radius of the circular neighborhood, and k is the parameter for power transformation.

The similarity is dynamically updated at the end of each iteration. The similarity is partially determined by the neighborhood function, $f_i(q^t, N)$, which is changing during the simulation. At each iteration, the number of cells developed in the neighborhood will be counted and the neighborhood function will be recalculated accordingly.

A stochastic disturbance term is also added to represent unknown errors during the simulation. This can allow the generated patterns to be closer to reality. The error term (RA) can be given by (White and Engelen, 1993)

$$RA = 1 + (-\ln \gamma)^\alpha \tag{9}$$

where γ is a uniform random variable within the range {0, 1}, and α is a parameter to control the size of the stochastic perturbation. α can be used as a dispersion factor in this simulation.

Finally, by adding Equation 9 to the model, Equation 8 is revised as

$$\begin{aligned}\Delta G_i^t &= RA \times \frac{q^t}{\pi l^2} \times \left(1 - \frac{d_{i\xi}^t}{d_{i\xi}^{\max}}\right)^k \\ &= (1 + (-\ln \gamma)^\alpha) \times \frac{q^t}{\pi l^2} \times \left(1 - \frac{d_{i\xi}^t}{d_{i\xi}^{\max}}\right)^k.\end{aligned} \tag{10}$$

At each iteration, the increase of "grey value" will be calculated to determine urban growth. The increase in the number of converted cells in the neighborhood will cause the increase of "grey value" for the central cell. The increase of "grey value" is also subject to other site attributes by using the similarity of "ideal-point" approach. Cells that have a "grey value" equal to 1 will be converted into developed cells at each iteration. Different urban forms can be formulated when different sets of weights are used in the simulation.

According to Equation 10, it seems that urban expansion will not stop because ΔG_i^t is always positive and ultimately all cells will be developed. However, this will not happen because ΔG_i^t will become much smaller with time. The cells close to the "ideal point" will be first converted. The remaining cells will be further away from the "ideal point" and the value of similarity will drop. As a result, the growth rate will become much smaller as cities grow. This is similar to reality because cities will not encroach on all available land because of a series of constraints.

The results of CA simulation are very sensitive to the values of the modeling parameters (Wu, 2000; Yeh and Li, 2001b). A way to obtain suitable parameter values is based on calibration procedures (Li and Yeh, 2001b). Calibration is important for realistic simulation although it is difficult for dynamic models. In most situations, parameter values are intuitively given to generate plausible simulation patterns, especially for planning applications. Sensitivity analysis can be carried out to study the effects of parameter values. It is found that the parameter k can be used to generate more discriminated growth patterns. Studies have indicated that non-linear transformation of suitability or constraints is useful to discriminate growth patterns (Wu and Webster, 1998). A series of k values (e.g., k = 1, 3, 5, 7, 10) can be used in a power transformation. A higher value of k can result in more discriminated patterns (Li and Yeh, 2000). The power transformation of the similarity can be applied to generate discriminated patterns. The definition of neighborhood can also affect simulation results. A circular neighborhood is more adequate than a rectangular one because the former has no bias in all directions (Li and Yeh, 2000). The parameter l decides the size of neighborhood for counting the neighborhood effects. Usually, there are not too many choices for the determination of the value. For example, the neighborhood is only 3 by 3 cells in Wu and Webster's (1998) model. The parameter α is used to control the size of perturbation. Studies indicate that a larger value of α can result in a more random and dispersed pattern of development (White and Engelen, 1993; Yeh and Li, 2001b; Li and Yeh, 2001b). Therefore, some reasonable parameter values can be defined to generate alternative patterns for testing various planning options.

Model Implementation and Results

Study Area

The model was tested in Dongguan, a very fast growing region in the Pearl River Delta of southern China. The study area covers 2,465 km^2 and has experienced a tremendous speed and scale of urban development in the 1990s (Yeh and Li, 1997; Li and Yeh, 1998; Yeh and Li, 2001a). It consists of the city proper and 29 surrounding towns. Remote sensing and GIS data were used to provide the basic information for the simulation. The 1988 and 1993 TM Landsat images were classified to retrieve land-use and land-use change information (Li and Yeh, 1998).

The PCA-CA model can help planners to compare different development scenarios for different planning objectives. It is used to simulate alternative land development patterns of Dongguan from 1988 through 1993 according to different planning objectives. The simulation results can be compared with the actual development that has taken place in the same period to see what improvement could be made. This can provide guidance for future development and planning so that the environmental impacts can be minimized.

The GIS package, ARC/INFO GRID, was used as the platform to develop the PCA-CA model using its *Arc Macro Language* (AML). The simulation was cell-based and each cell has an area of 50 by 50 m^2 on the ground. The direct development of CA models within a GIS package can allow the model to gain access to a rich set of spatial information easily. Spatial data and modeling results can be seamlessly exchanged for further analysis based on this framework. The CA model can be treated as an extension of GIS analysis functions. Although CA models can be independently developed outside a GIS package, the integration may have some limitations, e.g., loss of map information and difficulties in data exchange.

A GIS database that contains land-use information from remote sensing and vector layers of transportation, such as the major urban center and town sub-centers, railways, roads, and rivers, was built to provide the initial condition and constraints for the simulation. Some important categories of land use, such as wetland and forest, were identified from the classification of remote sensing images.

Spatial Variables and PCA Analysis

The first step was to obtain and examine the spatial factors that play an important role in influencing urban development. Neighborhood functions are often used to address the influences of neighboring activities or services on development probability at the central cell. In most situations, the intensity of the influences can be expressed as a distance decay function. For example, the probability for residential development at a site can be related to available services and amenities, such as schools, hospitals, transportation, and parks. The proximity to these facilities should be measured for the prediction of possible land-use conversion.

Some types of benefits and costs can be identified and measured with regard to urban growth. Land suitability is a convenient indicator to measure these benefits and costs. In this study, land suitability is measured by proximity to major transportation lines, and major ecological and environmental sensitive areas. More environmental factors (e.g., soil types and slope) can be added using the PCA approach if required.

Land development that takes place in land with better suitability scores will generate greater benefits and vice versa. Development suitability is a key factor for estimating probability of land development in a general CA simulation (Wu and Webster, 1998). Various types of development suitability related to a series of spatial factors can be defined to estimate the probability of land development. The amenities for urban development may be measured by proximity to urban major centers, sub-centers, roads, expressways, railways, parks, and rivers. However, a spectrum of environmental suitability could also be used as constraints for CA simulation to reduce development costs. Environmental suitability can be defined using distance decay functions according to various objectives, such as the protection of drinking water (reservoirs), cropland, orchards, truck farms, fishponds, forests, and wetlands.

It is clear that there is frequently intensive competition and conflict for a type of land use to win the best proximity to the most desirable amenities. Conventional modeling methods have been faced with great difficulties in solving locational conflicts when many spatial variables are considered. Although MCE can be used to handle multiple variables, the method has problems in dealing with a large number of spatial variables which are usually highly correlated among themselves. The PCA method can be used to deal with such problem because it gets rid of data redundancy.

Distance-based variables can be used to indicate spatial influences. There are various parameters and options in specifying the forms of distance that affect the decision for development (Batty *et al.*, 1999). There are four typical functions of distance influences—an inverse linear function of distance, negative exponential, inverse power, or a gamma-like function which combines the exponential and power (Xie, 1996). The negative exponential function has been commonly used in CA simulations (Wu, 1998; Batty *et al.*, 1999).

This study identified a total of 13 spatial variables that were required as important site attributes for the CA model. The first set of six spatial variables was identified to address the benefits that can be obtained from a closer distance to sources of development attraction, such as the urban center, town centers, transport routes, and rivers: i.e.,

- Distance to the major urban center (city proper),
- Distance to town sub-centers (town centers),
- Distance to railways,
- Distance to expressways,
- Distance to roads, and
- Distance to rivers.

A closer distance to these sources of attraction is preferable for urban development because energy and construction costs can be saved. These spatial variables (X_{ik}) can be defined using the negative exponential function

$$X_{ik} = e^{-\beta_k \mathrm{dist}_{ik}} \tag{11}$$

where X_{ik} is the spatial variable of cell i for the positive criterion k, $dist_{ik}$ is the distance from cell i to the source of development attraction for criterion k, and β_k is its respective parameter of the distance decay function. A higher value of the parameter means that the influences will decrease more rapidly. The values of X_{ik} have been adjusted by the exponential function to fall within the range of 0 to 1. A higher value of X_{ik} means that it is closer to the source of attraction.

The same measurement was applied for environmental and resource protection considerations. The second set of seven distance variables was identified for these types of negative factors, which address greater costs for a closer distance to the sources of environmental and resource protection:

- Distance to cropland,
- Distance to orchards,
- Distance to truck farms,
- Distance to fishponds,
- Distance to reservoirs (drinking water),
- Distance to forests, and
- Distance to wetlands.

A closer distance to these sources will create disturbances or negative effects for environmental and resource protection. These spatial variables (X'_{ik}) can be defined using the following negative exponential function:

$$X'_{ik} = 1 - e^{-\beta_k \mathrm{dist}_{ik}} \tag{12}$$

where X'_{ik} is spatial variable of cell i for the negative criterion k, $dist_{ik}$ is the distance from cell i to the source of environmental and resource protection for criterion k, and β_k is its respective parameter of the distance decay function. A higher value of the parameter means that the influences will decrease more rapidly. The values of X'_{ik} have also been adjusted by the exponential function to fall within the range of 0 to 1. A higher value of X'_{ik} means that it is farther away from the source of environmental and resource protection. These 13 spatial variables will be used as the original data for PCA transformation described by Equations 1 and 2.

Information on the locations of major urban centers and town sub-centers, railways, roads, and rivers is retrieved from

TABLE 1. PRINCIPAL COMPONENTS FROM THE THIRTEEN DISTANCE VARIABLES

Principal Components	Eigenvalues	Percentage of Variance (%)
I	62.9	44.4
II	38.9	27.5
III	13.5	9.5
IV	8.5	6.0
V	6.5	4.6
VI	3.2	2.3
VII	2.6	1.9
VIII	19	1.4
IX	1.7	1.2
X	0.9	0.7
XI	0.5	0.3
XII	0.3	0.2
XIII	0.1	0.1

the vector GIS database and converted into raster format, with each cell representing an area of 50 by 50 m^2 on the ground. The proximity analysis in the GIS tool of ERDAS was carried out on the raster database to obtain the 13 distance variables that were used for the PCA analysis.

Thirteen layers of criteria, (X_{i1}, X_{i2}, X_{i3}, ..., X_{i1}', X_{i2}', X_{i3}', ...), were created by the transformation of distance variables according to Equation 11 for positive factors or Equation 12 for negative factors. A site with a higher score of a criterion will be more suitable for development with regard to the criterion. The PCA analysis was carried out to evaluate these criterion layers to see if there is any data redundancy according to Equations 1 and 2. The analysis was carried out using the PCA module of the ERDAS image processing software. Table 1 lists the principal components that were created from the 13 layers of distance variables. Although n output components can be generated in the principal components analysis, the first few components account for a high proportion of the variance in this data set. It was found that the first five components accounted for 92 percent of the variance of the original 13 variables. Even the first three components contained 81.4 percent of the total variance. Therefore, severe data redundancy is exhibited in these spatial distance variables. PCA should be carried out to remove the data redundancy in a CA simulation which deals with a lot of spatial variables.

Table 2 lists the component loadings for the 13 spatial variables. Only the first six components are used for the simulation because they contain most of the information. They are labeled according to the loadings. It is easy to see that the first component is mainly related to agriculture and the environment, such as fishponds, truck farms, and wetlands. The second component is mainly related to transport conditions, such as expressways, roads, and rivers. The third component is mainly related to population centers, such as the city proper and town centers. There are a couple of advantages for the principal components transformation. The transformation can allow similar variables to be grouped together with a large proportion of loadings in the same component. Suitable weights can be easily defined because principal components are independent of each other. This can avoid the double counting that may take place in a general MCE. Moreover, there are no restrictions for the number of variables because they can be packed into much fewer components. It is much easier to define the weights using a few variables. This can allow the CA model to explore a large spatial dataset for more realistic simulation.

The "Ideal Point" and Planning Objectives

An essential part of the CA simulation was based on the similarity between a candidate cell and the "ideal point." The "ideal point" is a virtual point which has the maximum criteria scores for each criterion with regard to development suitability. It is the best point that can be used as the reference for development. It is used to judge whether a candidate cell is suitable for development based on the similarity between the cell and the "ideal point." Therefore, the "ideal point" for development is as follows:

$$(1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1).$$

Equation 1 was used to obtain the coordinates of the "ideal point" in the principal component space. Only the first six principal components are used to calculate the similarity because the components contain 94.3 percent of the original information.

According to the PCA transformation, the "ideal point" using the six principal components in the new transformed coordinate system becomes

$$(1.2, 2.6, 1.9, -0.2, -0.4, 0.1).$$

Equations 6 and 7 were used to calculate the similarity between a candidate cell and the "ideal point." The similarity is also related to the weights for different components. A set of weights can be defined with regard to various planning objectives.

Five planning objectives are used in developing planning scenarios for the study area. They are

TABLE 2. COMPONENT LOADINGS FOR THE THIRTEEN SPATIAL VARIABLES

	Principal Components												
Distance Variables	I Ecology & Agriculture	II Transport	III Urban Centers	IV Rivers	V Expressways	VI Crops	VII	VIII	IX	X	XI	XII	XIII
City Proper	−0.10	0.07	**0.47**	−0.50	0.02	0.04	−0.03	−0.07	0.06	0.07	−0.07	−0.17	−0.69
Town Centers	−0.15	0.05	**0.45**	−0.52	−0.06	−0.05	0.01	−0.11	−0.04	−0.03	0.06	0.15	0.67
Railways	0.16	0.17	−0.07	−0.15	−0.72	0.15	0.27	0.53	−0.04	0.04	0.00	−0.13	0.01
Expressways	−0.26	**0.62**	−0.11	−0.09	0.51	0.03	0.09	0.50	−0.10	−0.05	0.03	0.05	0.01
Roads	−0.07	**0.64**	−0.34	−0.08	−0.29	−0.07	−0.10	−0.59	0.07	0.06	−0.02	−0.01	−0.02
Rivers	−0.43	**0.21**	0.54	**0.63**	−0.24	0.11	−0.05	0.00	0.07	−0.06	−0.02	0.01	0.00
Croplands	**0.18**	0.06	0.06	0.03	0.11	**0.74**	0.05	−0.22	−0.58	0.05	−0.01	−0.07	0.03
Orchards	**0.23**	0.10	0.15	0.11	0.18	0.00	0.85	−0.22	0.30	0.03	0.06	−0.01	0.02
Truck Farms	**0.49**	0.20	0.17	0.05	0.07	0.01	−0.18	0.06	0.16	−0.32	−0.71	0.07	0.08
Fishponds	**0.48**	0.19	0.17	0.05	0.03	0.10	−0.31	0.05	0.25	−0.25	0.68	0.03	−0.03
Reservoirs	**0.21**	0.09	0.14	0.08	−0.10	−0.34	0.08	0.01	−0.45	0.14	0.06	0.71	−0.21
Forests	0.16	0.09	0.15	0.10	0.02	−0.52	0.06	−0.05	−0.49	−0.17	0.07	−0.62	0.06
Wetlands	**0.25**	0.12	0.15	0.11	0.11	−0.06	−0.19	0.09	0.12	0.87	−0.06	−0.17	0.14

Table 3. Weights for the Development Objectives

Principal Components	Planning Objectives: Urban-Center-Based (city proper and town centers) Development	Transport-Based (expressways, roads, and rivers) Development	Cropland-Conservation Development	Ecology and Agriculture-Conservation (truck farms, fishpond, orchard, reservoir, and wetland) Development	Economic-Environmental Development
I. Ecology & Agriculture	0.25	0.25	0.25	1.00	1.00
II. Transport	0.25	1.00	0.25	0.25	1.00
III. Urban Centers	1.00	0.25	0.25	0.25	1.00
IV. River	0.25	0.25	0.25	0.25	0.50
V. Expressway	0.25	0.25	0.25	0.25	0.50
VI. Crops	0.25	0.25	1.00	0.25	1.00

Weights:
Most Important—1.00; Very Important—0.75; Important—0.50; Less Important—0.25; Not Important—0

- Urban-center-based (city proper and town centers) development,
- Transport-based (expressway, roads, and rivers) development,
- Cropland-conservation development,
- Ecology and agriculture-conservation (truck farm, fishpond, orchard, reservoir, and wetland) development, and
- Economic-environmental development.

This study only uses five planning objectives to illustrate the methodology (Table 3). Other objectives can also be easily defined in the same way. The first six components were used because they contain the majority of the spatial information. Different weights were assigned to these components in the simulation according to different planning objectives. The values of the weights (w_j) in Equation 6 range from 0 to 1 (1 being the most important) (Table 3). A development plan can be generated by using a set of weights for a planning objective in the simulation. Weights are assigned to the components to indicate their relative importance in a planning objective. A higher weight is assigned to a component which is emphasized by the planning objective. For example, if the planning objective is to protect agricultural land, component VI (crops) with the major loadings on crops should be assigned with the highest value of 1. Components that are less important or not important to the planning objective can be assigned with a value of 0.25 or 0, respectively.

Figure 3 shows the similarity between cells and the "ideal point" for the planning objective of transport-based development. A cell with a brighter tone means that it is more similar to the "ideal point" and therefore is most suitable for the transport-based development. Under this objective, the land development rate should be proportionally faster in a brighter cell.

The Simulation

The PCA-CA simulation was carried out using the "ideal-point" approach. Five development scenarios were simulated based on the above different planning objectives and related sets of weights. It is easy to generate more development patterns if other sets of weights are used. The initial map for the simulation was from the land-use classification of the 1988 satellite TM image (Figure 4). The model attempts to generate land development alternatives from 1988 to 1993 based on different planning objectives. For comparison purposes, the actual urban areas (built-up areas and development sited) for 1993 were also obtained from the classification of the 1993 satellite TM image (Figure 5). In the simulation of various scenarios of urban forms, the total amount of land consumption is kept to be

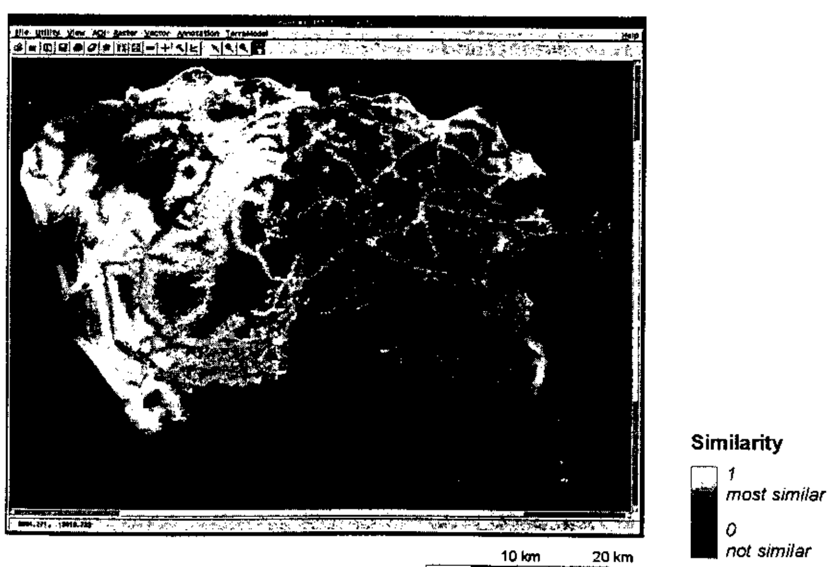

Figure 3. Similarity between a cell and the "ideal point" for transport-based development.

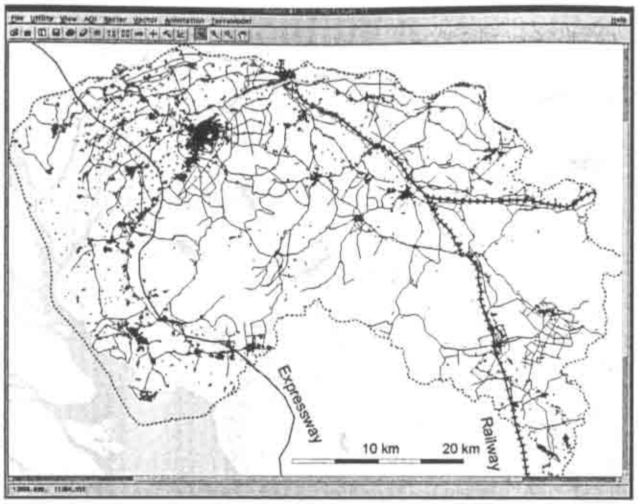

Figure 4. Urban areas of the study area classified from the 1988 TM image (initial).

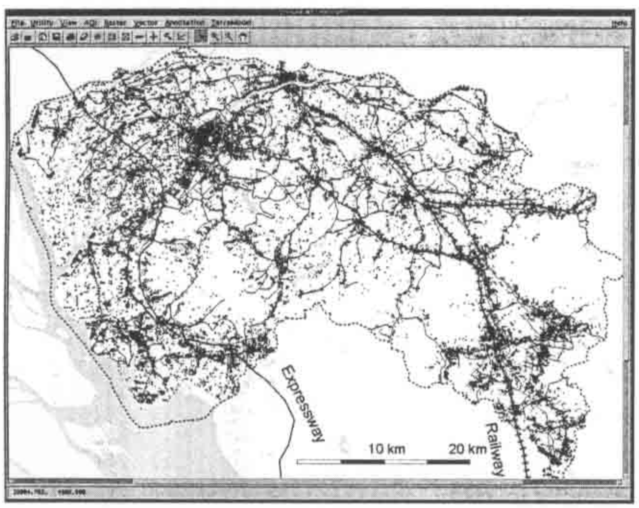

Figure 5. Actual urban areas of the study area classified from the 1993 TM image.

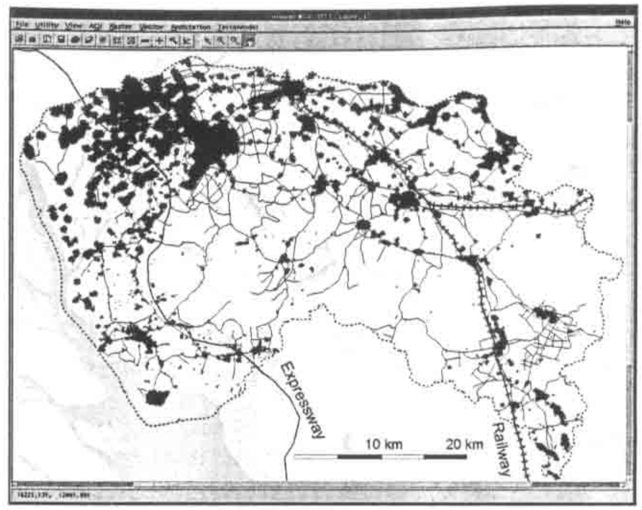

Figure 6. Urban center-based (city proper and town centers) development.

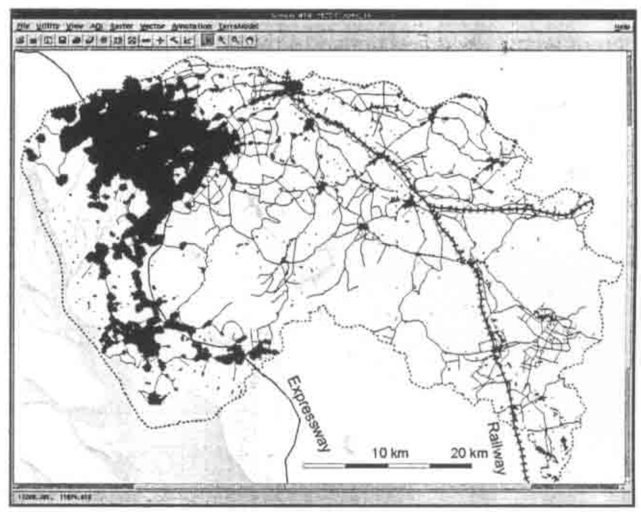

Figure 7. Transport-based (expressways, roads, and rivers) development.

the same as that of the actual development from 1988 through 1993 for comparison. The simulation will stop when the amount of land development reaches this amount. The transition rules are mainly based on Equation 10. The radius of the circular neighborhood, l, is two cells. The index of power transformation, k, is set to a high value (7) to discriminate simulation patterns. The size of disturbance, α, is set to 1 to allow only a small amount of disturbance. The final computation time (iterations) T^0 is automatically decided by the total development area which is equal to the actual land consumption from 1988 through 1993. The simulation using the above five planning objectives for the development from 1988 through 1993 was carried out using the PCA-CA model.

Urban-Center-Based (City Proper and Town Centers) Development

This objective just focuses on economic considerations with a higher weight applied for the third component (III-Urban Centers). The third component has a large proportion of loadings for the variables of city proper and town centers. In the simulation, cells closer to city proper and town centers have a higher priority for land development. There is a large amount of land development in the northwest part of the alluvial plain which is close to the urban centers (Figure 6).

Transport-Based (Expressways, Roads, and Rivers) Development

A higher weight is used for the second component (II-Transport) which has a large proportion of loadings for the variables of expressways, roads, and rivers (Table 2). Figure 7 shows the simulation result in which land development is concentrated near the expressway and rivers across the western part of the study area. As a result, most of the fertile agricultural land will

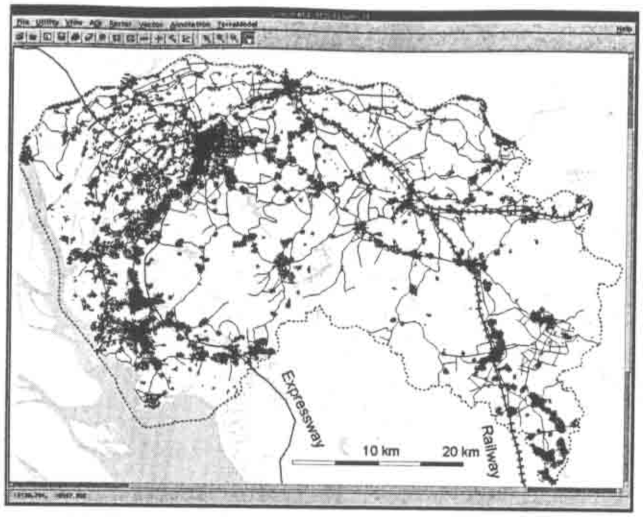

Figure 8. Cropland-conservation development.

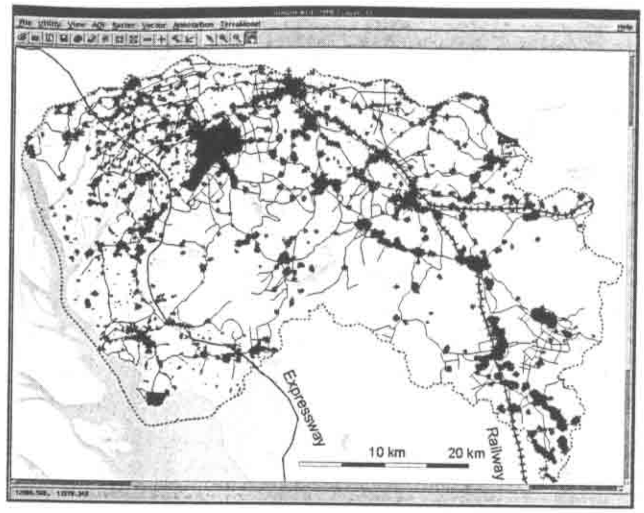

Figure 10. Economic-environmental development.

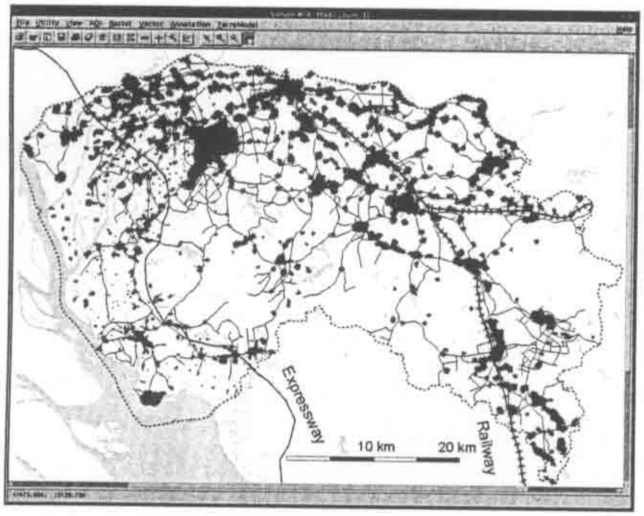

Figure 9. Ecology and agriculture-conservation (truck farms, fishponds, orchards, reservoirs, and wetlands) development.

be lost although this type of development can generate greater economic benefits in the short term. Under this situation, food has to be imported from other regions because most of the agricultural land has been consumed.

Cropland-Conservation Development

Cropland conservation can be realized by putting a higher weight on the sixth component (VI-Crops) which has a large proportion of loadings for the cropland variable. Cropland will be best protected if this alternative is realized (Figure 8). The CA model can be used to find alternative locations for development so that food production capabilities can be reserved for the region.

Ecology and Agriculture-Conservation (Truck Farms, Fishponds, Orchards, Reservoirs, and Wetlands) Development

The first component (I-Ecology and Agriculture) has a large proportion of loadings for the variables of truck farms, fishponds, orchards, reservoirs, and wetlands (Table 2). Stronger concerns for ecological and agricultural protection can be realized by putting a higher weight for the first component (Figure 9). The loss for the ecological and agricultural systems will be reduced according to this alternative.

Economic-Environmental Development

There are severe conflicts between economic development and environmental conservation for most situations. A compromise objective will help to find an acceptable solution for both environmental conservation and economic development. Higher weights are given to the first (I-Ecology & Agriculture), second (II-Transport), third (III-Urban Centers), and sixth (VI-Crops) components. The CA model is able to find suitable locations for reducing the conflicts as much as possible (Figure 10).

Assessment of the potential impacts of each scenario can be carried out using GIS overlay analysis. Table 4 shows the environmental impacts of land developments that are associated with different planning scenarios. It is found that the Cropland-Conservation Development scenario has the minimum loss of valuable cropland and forest. It consumes only 70.8 percent of what has been consumed by the actual development. This is followed by the Economic-Environmental Development scenario, which is 74.9 percent (Table 4). Planners can formulate a land development plan for the region based on the simulation results of different planning scenarios and their impacts on the environment.

The simulation shows that the model is able to generate distinctive urban forms for various specific planning objectives. A planning objective can be easily realized in the dynamic model using the "ideal point" approach. The effects of a planning objective on the simulation patterns are apparent according to field investigation. The simulation is based on a large set of spatial variables (including environmental constraints). Conventional CA models have problems because weights cannot adequately provide for correlated variables. The proposed model can deal well with the many environmental constraints which are quite commonly used in land-use

Table 4. The Loss of Important Land Resources for the Simulated Development Scenarios

Development Scenarios	Loss of Important Land Resources (in hectare)		
	Cropland	Forest	Total
a) Urban-Center-Based (city proper and town centers) Development	12,701.0 (91.3%)	1,071.2 (105.8%)	13,772.2 (92.3%)
b) Transport-Based (expressways, roads, and rivers) Development	13,168.2 (94.6%)	1,039.1 (102.6%)	14,207.3 (95.2%)
c) Cropland-Conservation Development	9,503.5 (68.3%)	1,073.0 (106.0%)	10,576.5 (70.8%)
d) Ecology and Agriculture-Conservation Development	12,129.6 (87.2%)	680.0 (67.2%)	12,809.6 (85.8%)
e) Economic-Environmental Development	10,481.5 (75.3%)	694.0 (68.5%)	11,175.5 (74.9%)
Actual Land Development	13,915.8 (100.0%)	1,012.6 (100.0%)	14,928.4 (100.0%)

*Figures in parentheses are percentage of land consumption compared with actual land development

planning. Planners can draw up land-use plans based on these simulation results in satisfying different planning objectives.

Conclusion

CA models can be used as a planning tool because they are able to produce alternatives for urban planning and environmental management. There is no single solution for a CA simulation because transition rules can be defined in many possible ways. This paper presents a CA model which is based on the integration of principal components analysis and GIS. A large set of spatial criteria is frequently used in decision making and spatial analysis which can make use of remote sensing and GIS. However, little attention has been given to the possible correlation between different spatial variables or criteria in many GIS and CA applications. In this study, 13 distance-based spatial variables (criteria) are defined to represent various economic and environmental factors that are used in the simulation of urban growth. The measurement of these criteria is facilitated by the integration of remote sensing and GIS. These criteria seem to be uncorrelated in their objectives and forms. However, the study shows that there is severe correlation between these criteria based on the principal components analysis. The PCA-CA model provides a useful planning tool for exploring various possible urban forms based on a large set of environmental constraints that could be considered in land-use planning.

This method is better than the MCE-CA method because it can remove data correlation and improve the performance of a simulation. It is easier to define weights when only a small set of components is used to replace the original large set of spatial variables. The weights can be easily defined without double counting of similar criteria. The simulation time is much faster using the compressed data. This model does not have limitations on the number of spatial variables that can be used. Furthermore, this method is not limited to CA simulation but can also be applicable to general GIS site-search applications. The PCA analysis and the "ideal point" approach can be applied to deal with the common problems of spatial correlation in site search.

The model also uses "grey cells" which have been used in our previous models to represent the continuous land development process (Li and Yeh, 2000). It is very easy to incorporate various kinds of spatial variables and calculate similarity based on "grey cells." The model can deal with complicated resource conditions and environmental restrictions that are often encountered in land-use planning. It can be developed as an extended function of GIS and can be used as a useful planning tool for urban planning and environmental management.

In this study, the criteria are rather fixed because exterior factors or interventions are not included in the model. For example, the development of new roads can change the development patterns. The model is able to deal with the changing environments by using dynamic criteria. This can be done by recalculating the principal components when environment settings have changed. Further studies should be carried out for using dynamic criteria in the simulation so that exterior factors can be incorporated in the model.

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