Spatial Dynamic Modeling for Urban Development

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Abstract
A spatial dynamic model (SDM) in a GIS-based urban planning decision support system has been developed for the city of Beihai in southern China. The SDM was used to simulate the dynamic change of the urban spatial structure by considering urban spatial growth as the result of spatial interaction between demand and supply of urban resources. The SDM acts as an analog machine. SDM modeling provides information for decision support in urban planning and land use management. The utility function of spatial choice and a methodology for the construction of the utility function were developed to incorporate socioeconomic factors into the modeling process. Multiple scenarios of urban planning and the consequences of urban spatial growth, as well as the impacts of planning schemes on traffic flow and on the environment, were simulated. Comparisons of simulation results allowed planners to evaluate the planning schemes in decision making.

Introduction
GIS-based decision support is particularly important in rapidly developing cities in the newly emerged coastal special economic zones in China. Beihai is a major commercial port on the coast of the South China Sea. Located at the southern end of the Guang-Xi Autonomous Region, it is a traffic junction and an important foreign trade gateway for commercial goods and petroleum products (Figure 1). In 1984, Beihai was listed among the first group of 14 open cities along the east-coast special economic zones after China started economic reform in the late 1970s. The City's economic development has been rocketing since then. Between 1985 and 1991 Beihai's gross domestic product (GDP) increased 21 percent annually. The same trend continued for the 1991 through 1995 period. Accompanying economic success, the city has been expanding rapidly. The area of the city of Beihai tripled between 1983 and 1995, and its growth has continued since then. Demands in land and infrastructure for economic development, a growing population, and requirements for services, the consequences of development and restrictions of environmental regulations, have put a tremendous amount of pressure on the city's planning department. The city decided in the late 1980s to use a geographic information systems (GIS) and spatial decision support system to assist operations in urban development. It is critical for the city to maintain a practical decision support system in assisting urban planning operations and managing land use.

Spatial decision support systems have been documented in the literature (Craig and Moyer, 1991; Densham, 1991; Davis et al., 1991; Moon, 1992; Ramirez et al., 1993; Taylor et al., 1999). They are generally required in situations where complex spatial problems are either ill- or semi-structured and decision makers cannot define their problems or fully articulate their objectives (Enache, 1994). In many cases, a spatial decision support system is applied to provide the decision support for location seeking (Birkin, 1996; Sui, 1998). Popular approaches, such as location-seeking models and location-allocation models, have been developed. A location-seeking model searches for the most optimal spatial location or spatial pattern from a set of predefined schemes by considering the spatial choice behavior of individuals as an objective function. A location-allocation model searches for spatial patterns or location schemes based on multiple criteria analysis. In urban planning, an ultimate goal is to seek the most optimal urban spatial structure. Programs and models have been developed to match or optimize the decision needs on spatial locations (Parrot and Stutz, 1991; Densham, 1991; Harris and Betty, 1993).

Because of the complexities of an urban system, it would be extremely difficult to construct a mathematical expression to optimize socioeconomic spatial structure for a city of any size. Many of the spatial decision support system approaches are considered as static modeling. The spatial interactions among influencing factors and the consequences of interactions are not an integral component in decision support operations. Iteration analysis would give users a chance to add or drop variables to fit their understanding of the problem and allow users to test spatial models with new data, run "what-ifs," and achieve a first set of solutions or alternatives (Enache, 1994). However, challenges in modeling the spatial interactions among driving factors and the consequences still remain. Therefore, a dynamic mechanism-based modeling is required to simulate the change in an urban structure and to assist in planning exercises.

Dynamic system modeling has long been on the frontier in urban and regional studies (Wilson, 1981; Parrot and Stutz, 1991). Systems analysis has been applied to establish urban and regional dynamic models (White, 1985; Nijkamp and Papageorgiou, 1995). The Cellular Automata model (Chapin and Weiss, 1968; White and Engelen, 1993; Xie, 1996; Wu, 1998; Clarke and Gaydos 1998) and Master-Equation model (Haag and Dendrinos, 1983; Fischer et al., 1990; Haag, 1992) have been well documented. GIS and spatial analysis provide support for formulating operational and practical models. GIS-based spatial choice behavior models (Zhang and Ho, 1997) have been applied to predict the evolution of urban and regional spatial structure. However, most of the current models would be challenged to describe the dynamics of urban systems, particularly when spatial mutual feedback among system elements is required and when representation of the dynamic mechanism of evolution of urban spatial structure is necessary.

In this paper, we discuss a spatial dynamic model (SDM)
that presents a new simulation mechanism. The SDM reveals the dynamic changes of urban spatial structure by integration of multiple driving factors. The SDM simulates the dynamic process, predicts the change, and provides information for decision support in urban land use and management. Impacts of urban spatial growth on traffic flow and the environment from multiple urban planning schemes were simulated. Comparisons of simulation results allowed decision makers to identify the most optimal scheme in planning practices.

**SDM Design and Model Structure**

The spatial decision support system has four components:

- a database management system,
- a model-based management system,
- user interfaces, and
- the generation and evaluation of alternatives.

While the model-based management system is the core of the system, the SDM is the engine of the model-based management (Figure 2). The model-based management system consists of four modeling components in supporting SDM operations, i.e., GIS spatial models, statistical models, urban and regional models, and remote sensing models. The models are linked through object-linking-and-embedding and a dynamically linked library. An object-oriented model-based management system was designed to handle the imbedded models. The database management system provides data support for the operation of the model-based management system. The database management system stores and manipulates socioeconomic/demographic data, land use/land cover data, and environmental data, as well as analyzing driving factors and restrictions enforced by governmental policies. The planning agency interacts with the spatial decision support system to evaluate planning schemes.

**Dynamic Chain Process of the Urban Spatial System**

The spatial dynamic mechanism represents a chain interaction between spatial choice behavior, spatial processes (i.e., land-use changes), and spatial patterns (i.e., land-use patterns). The spatial choice behavior coupled with driving factors creates spatial processes. Spatial processes reshape spatial patterns. Spatial patterns, in turn, have feedback impacts on spatial choice behavior (Zhang and He, 1997). A spatial process starts at time $t$, and after a time interval $\Delta t$, reaches a new state at time $t + \Delta t$. Spatial patterns at $t + \Delta t$ represent both a temporary ending state of the previous spatial process and a starting state for a new one. Mathematical representations of the chain process of a dynamic system were developed to facilitate the execution of urban spatial dynamic modeling.

**The SDM Framework**

The SDM design follows the chain process in an urban system (Figure 3). The system consists of two dynamic components:

- spatial demand and supply of housing, and
- spatial demand and supply of facilities.

Interactions among demands and supplies change the spatial structure of an urban system. In this study, the urban structures considered included land use, spatial distribution of population, employment, public facilities, and infrastructures. The urban spatial structure alters the spatial choice behavior of investors and residents. In turn, the spatial choice behavior of investors and residents creates new interactions between spatial demands and supplies. This chain reaction is an essential mechanism of the SDM.

**Spatial Units**

We created two levels of spatial units, i.e., compartment and cell, in SDM modeling. The size and boundary of a compart-
ment were determined by multiple variables, such as administrative and natural boundaries, city zoning, land use, population, employment, and transportation lines. Fifty-five compartments were defined across the city (Figure 4). Compartments control the spatial step of simulation of urban growth. Each compartment possesses a set of state variables. The state variables are constant at a given model iteration. The urban area in each compartment is calculated at a given time interval $\Delta t$ based on the initial state at time $t$. The change of urban land, as a new state variable of the compartment, represents a new driving factor in land use change.

A 50- by 50-meter cell is the minimum spatial unit within a compartment. A cell reflects the land use status at a given time in this spatial unit. Under the control of expected urban area within each compartment at time $t + \Delta t$, the states of cells are simulated. Cells within different compartments have different controls for their expected urban land areas. Changes of a cell’s land use types alter the state variables of the compartment.

The Utility Function of Spatial Choices

Theoretical studies of applying the utility function of spatial choice have been documented (Timmerman and Borgers, 1989; Leonardi and Papageorgiou, 1992). In this study, spatial choice is a process in which investors and residents compare the attributes of the spatial units within a feasible set of choices and choose the most probable spatial unit to occupy. Urban growth represents an expansion of urban land use that is associated with the spatial choice of investors and residents. We define utility as a measurement that investors and residents can derive from the attributes within selected spatial units. A utility function, therefore, represents a relationship between the quantities of the attributes of spatial units that the investors and residents occupied and the utilities derived from the attributes. Each compartment has a utility value. The utility functions are used to derive probabilities of compartments that are to be occupied by investors and residents.

The spatial location of a compartment is defined by its central coordinates: i.e., \( z = (x_i, y_j), (x_2, y_2), \ldots, (x_Z, y_Z) \) where $Z$ is the total number of compartments. Compartments define a discrete space for the utility function of spatial choice. Spatial choice of the $i$th individual can be described by the utility function (Wang and Zhang, 2001).

For example, the spatial distribution of residents obeys a utility function of spatial choice. To construct a utility function of residents, if $P(z)$ is the change rate of the density of residents and $U$ is the utility function associated with the spatial choice of location by residents, then

$$P(z) = C \cdot U(k_1, k_2, \ldots, k_n)$$

where $C$ is a constant and can be defined as the ratio of the change rate of residents and the utility value. The $k_i$ represents the $i$th attribute that impacts the spatial choice of residents. The five attributes considered include the degree of facility accessibility ($k_1$) (Flamm and Turner, 1994), the rate of housing vacancy ($k_2$), the degree of transportation accessibility ($k_3$), the proportion of non-urban land within a compartment ($k_4$), and environmental quality ($k_5$). All five attributes were normalized to a range of 0 to 100 to facilitate the modeling calculation.

In order to implement the above discussion, a utility function needs to be constructed for each of the above attributes $k_i$ ($1 \leq i \leq n, n = 5$) by finding a set of compartments which possesses a constant attribute for all $k_i$ ($i \neq j$). Then $k_i$ is the only attribute that alters the rate of change of the density of residents.

To construct a utility function, a marginal utility needs to be defined. A marginal utility is the increment of utility caused by the unit increase of a certain attribute (Sher and Pinola, 1981; Mansfield, 1982; Peterson, 1989). A curve-fitting process can be applied to explore the marginal utility function. For example, the number of compartments that had the same influence factors of $k_1$, $k_2$, $k_3$, and $k_4$ but a different $k_5$ can be applied to calculate the ratio of $\Delta P(z)/\Delta k_5$. $\Delta P$ is the increment of the rate of change of the density of residents caused by changes in the influencing factor. $\Delta k_5$ is the increment of the influence factor ($k_5$). Given the nature of population and residential area growth, an exponential growth function was adopted (Figure 5a). In the curve fitting equation, $A$ and $B$ are constants and can be determined from $\Delta P(z)/\Delta k_5$ and $\Delta k_5$ for the selected compartments (Figure 5b). From the marginal utility function, the constructed utility function of the influence factor $k_5$ is obtained (Figure 5c). Following the same process, utility functions for other influencing factors, $U(k_1)$, $U(k_2)$, $U(k_3)$, $U(k_4)$, can be derived. By the additive rule of utility (Mansfield, 1982), the total utility function of spatial choice for residents and investors is the sum of the utility functions of influence factors.

The Spatial Growth Model

Spatial Demand of Housing

The city of Beihai’s urban spatial growth is mainly driven by new employment opportunities. Immigration from outside the area is one of the main factors that stimulate residential growth. Residential growth caused by employment increase is considered as the process of newcomers diffusing around employment centers. Spatial distance from employment centers, travel time, and availability of dwelling place determine the potential spatial pattern of housing demand. The spatial diffusion rate is obtained by

$$W(z'; t) = V\tau(t) \cdot \exp[(U(z; t) - U(z'; t))$$

If $z \in Z_1 \cap Z_2$ (2)

$$W(z'; t) = 0$$

If $z \notin Z_1 \cap Z_2$

where $W(z'; t)$ is the diffusion rate of residents from employment area $z = (x, y)$ to neighboring area $z' = (x', y')$ to neighboring area $z = (x, y)$. $V\tau(t)$ is a frequency parameter. $Z_1$ is the set of spatial compartments that have potentials to be selected by the residents, and $Z_2$ is the set of compartments that the $i$th individual can select under the constraint of travel time to work.

To represent the spatial growth of residential areas, the spatial demand of housing, $dP(z; t)/dt$, is derived as

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ties from a unit of vacant land to a housing development are presented as
\[ W_{vh}(z; t) = V^{ih}(t) \cdot \exp(\Delta U_{vh}(z; t)) \quad \text{if } L(z; t) - h(z; t) > 0 \]
\[ W_{vh}(z; t) = 0 \quad \text{if } L(z; t) - h(z; t) \leq 0 \]  
(4)

where \( V^{ih}(t) \) is a frequency parameter at time \( t \), \( L(z; t) \) is the spatial distribution of the total number of houses that could be built on the available land, \( h(z; t) \) is the spatial distribution of the total number of houses, and \( \Delta U_{vh}(z; t) \) is the expected utility gain when a unit of land is transformed into houses. Housing spatial growth is derived as
\[
\frac{dh(z; t)}{dt} = [L(z; t) - h(z; t)] \cdot V^{ih}(t) \cdot \exp(\Delta U_{vh}(z; t)). 
\]  
(5)

The \( \Delta U_{vh}(z; t) \) depends on two key factors: (1) the ratio between vacant houses and total number of houses, and (2) the expected benefit ratio in compartment \( z \). The lower the ratio between vacant and total number of houses, the higher the probability will be for conversion from available land to housing development.

**Spatial Demand and Supply of Public Facilities**

Spatial demands of public facilities represent the requirement of newly added population on public services. In this study, a Lowry-Garin spatial allocation model (Parrot and Stutz, 1991) is adopted for handling this process. The factors of attractiveness of public facilities in compartment \( z \) are introduced. The adapted Lowry-Garin model is
\[
T(z; t) = A \cdot S \cdot \Delta p(z'; t) \cdot M(z; t) \cdot \exp[-\beta \cdot C(z'z)] 
\]  
(6)

where \( T(z'z; t) \) is the newly added flow of service expenditure from compartment \( z' \) to \( z \), \( S \) is the average service expenditure for each resident, \( \Delta p(z'; t) \) is the spatial distribution of newly added residences, \( M(z; t) \) is the spatial distribution of public facilities in compartment \( z \), \( \beta \) is a spatial friction coefficient, and \( C(z'z) \) is the traffic cost from compartment \( z' \) to \( z \). From, \( \sum T(z'z; t) \), the spatial distribution of service facility \( B(z; t) \) and the spatial pattern of growth of service employment can be obtained. The above procedures quantify the basic relations between demand and supply in SDM modeling.

**Model Execution and Results**

We applied multi-year economic and industrial growth data, as well as the spatial distribution data for the city of Beihai, to establish the SDM parameters. The data include increment and growth in gross domestic product, employment, investment on industrial infrastructure, and employment-related immigrants to the city between 1980 and 1994. As for the spatial data, we applied distributions of residential areas, basic employment, service-related employment, urban land use and zoning, land price, and the transportation network for the same time period. In simulation efforts, we applied the projected gross domestic product, employment and population, and the investment plan for the city between 1995 and 2010. Upon validation, we applied SDM to simulate urban spatial growth. Using the spatial growth results, the impacts of new developments on air quality and traffic management were derived and examined.

**The Utility Function of Spatial Choice**

A key step in SDM modeling is to construct a utility function. The methodology in constructing a utility function for the spatial choice of residents is given as an example (Figure 5). Among the five considered attributes, we used the proportion of non-urban land within a compartment \( k_d \) to demonstrate...
the procedure. We applied 15 years of data in employment and residents from 1980 to 1994; land-use data in 1980, 1985, and 1994; and road network data from 1980 to 1994. The influence factors of $k_i (i = 1, 2, ..., 5)$ and the $P(z)$ between 1980 and 1994 for all compartments were derived from the above data. The final utility function for the spatial choice of residents at a given time was obtained as

$$U(x, y, t) = 35 - 13.5 \cdot \exp[-0.06k_1(x, y, t)] - 10.4 \cdot \exp[-0.07k_2(x, y, t)] - 5.4 \cdot \exp[-0.02k_3(x, y, t)] - 3.5 \cdot \exp[-0.09k_4(x, y, t)] - 2.1 \cdot \exp[-0.01k_5(x, y, t)]$$

This example indicates that the most influential factor among the five attributes on spatial choice of residents is the degree of facility accessibility ($k_1$). The rate of vacant houses ($k_2$) is in second place in affecting the spatial choice behavior. The environmental quality factor ($k_3$) has little effect on spatial choice behavior. This reveals that facility development is a main driving force that influences the spatial choice of residential development in the city of Beihai. The smaller influence from the proportion of non-urban ($k_4$) and the environmental quality factor ($k_5$) reflects that the city of Beihai is still in its development stage. The availability of non-urban land for development and relatively good environmental quality are not major concerns in residential spatial choice. By using utility functions, the spatial choice behavior of the residents was quantified and imbedded into SDM modeling.

**SDM Simulation of Urban Spatial Growth**

The city's economic development plan includes several business centers and industrial parks. Development of the centers and parks accelerates the increase of basic employment and expands the City's urban land use. Employment centers within the central city stimulate residential growth and the redistribution of population. We applied the SDM to simulate Beihai's urban spatial growth.

Compartment and cell were used in the modeling process. The SDM calculated the urban area for a compartment in modeling iterations. The conversions from non-urban to urban land use at the cell level were simulated under the control of urban area. The possibility of transition of a cell from current non-urban to urban land use depends on the land use types of the cell and it's neighboring cells, and the average transition rates from non-urban to urban land use within the compartment. A transition threshold was defined to represent the boundary value of the possibility. A cell's state transition will possibly take place when its transition possibility is greater than the transition threshold. In this study, the transition threshold was a dynamic variable. It was controlled by the expected urban land use. Therefore, whether a cell could be changed into urban land use depends on both the transition possibility and the expected urban land use within the compartment.

The algorithm of the SDM process begins by setting up an iteration of $\Delta t$ with the distribution of basic employment $E^c(z, t)$ as an input to each compartment (Figure 6). For each iteration, the demand of basic employment was derived by the basic employment growth of $E^c(z, t)$ and the supply of housing $dP(z, t)/dt$ (Equation 3) for all compartments driven by the basic employment growth of $E^c(z, t)$ is calculated. The urban land use for the spatial supply of housing $dh(z, t)/dt$ is obtained after the state-variables of urban structural changes are updated. The added urban land use for public facilities of $B(z, t)$ is derived while the spatial demand for public facilities $T(z, t)$ is calculated. The location-allocation is an iterative process under the constraint of available land. The transitions from non-urban to urban land use in cells are simulated under the control of the expected urban land use $dh(z, t)/dt$ and $B(z, t)$. The spatial distribution of the newly added service employment $E^s(z, t)$ is obtained. $E^s(z, t)$ becomes the driving force for urban spatial growth at the next model iteration. The program runs through the above steps until $\sum \Delta t = t_2 - t_1$ is achieved.

An iteration of one year was applied as the temporal step in the SDM simulation. The urban spatial structure of the city of Beihai in 1980 was taken as the initial state (Figure 7a). The dynamic urban spatial growth of the city from 1980 to 1995 was simulated. To evaluate the performance of the SDM, we used the correlation coefficients between the results from the SDM simulation and the observed spatial growth of the city in the same time period from measurements (Figures 7a and 7b). After evaluation of the SDM performance, we further applied the SDM to simulate the urban spatial growth from 1995 to 2010 according to the economic development plan of the city (Figures 7c, 7d, and 7e).

The calculated coefficients indicated that high correlation (>0.60) was obtained for the compartments that had experienced high spatial growth of urban land use. The compartments of high spatial growth were close to the edge of the central city. The correlation coefficients of 0.51 to 0.60 were achieved for the compartments that experienced moderate urban spatial growth (Figure 8). Relatively low correlation coefficients (0.20 to 0.50) were obtained for the compartments that had low urban growth. The results show that the SDM performed well for the compartments that had dramatic urban land changes.

**SDM Simulation of Traffic Flow**

Increased employment, expanded residential area, and added services alter the spatial pattern of traffic flow. Major impacts come from the designed central business district and industrial parks. Impacts can be reflected by the attraction of the developments. Other major impact comes from work-related travel from residential areas to employment centers. In this study, a GIS analysis was applied to simulate the spatial distribution of urban traffic flows under different schemes of development. We applied the dynamic process in the assignment of traffic flow (Oppenheim, 1995). A key variable is traffic cost. Under the constraint of road capacity, the increase in traffic flows will
raise the traffic cost. The ideal traffic assignment is when the traffic flows reach a state of dynamic equilibrium across the city. Traffic flows caused by the designed central business district (Plate 1a) and by one of the planned industrial parks (Plate 1b) were simulated. An overall traffic flow by the year 2010 was simulated as well according to the City’s traffic plan (Plate 1c).

SDM Simulation of Air Pollution

Urban spatial growth has significant impacts on the air quality of the city of Beihai. For example, between 1991 and 1995, the city’s energy consumption increased by 51.7 percent. The pollutants released into the atmosphere increased from 2,408 tonnes in 1991 to 4,669 tonnes in 1995. In particular, the SO$_2$ density showed a trend of dramatic increase. The dispersion pattern of air pollutants depends not only on the related industrial operations, but also on the urban spatial structure. Therefore, the spatial distribution of industrial locations and their impacts on the surrounding areas are among the key factors that need to be considered in urban planning. Based on the SDM-derived urban spatial growth, potentials of air pollution caused by different industrial operations under a variety of wind conditions were simulated.

Industrial operations include food, textile, papermaking, power plant, petroleum, chemical products, medicine, construction materials, mechanical equipment, and commercial goods. Given the energy resources and comparing the emission discharges among the industries, coal consumption is the biggest contributor of SO$_2$.

A GIS-based algorithm was developed to simulate the dispersion of SO$_2$ by both area source and point source pollution. The area-source pollution was applied for industrial compounds, while point-source pollution was applied for the locations that have discharge chimneys from industrial operations. The algorithm, based on the air pollution model (Schnelle and Dey, 1999), first divided the urban area into 50- by 50-meter cells. A threshold, which represents the density of minimum air pollutant, was set up to calculate the impact boundary of each source of pollution. For each pollution source, the density of air pollutants in every cell within the impact boundary was calculated. Accumulations of density of air pollutant for each cell from all pollution sources were derived. The sources of pollutants and wind conditions were applied. Maps of dispersion of air pollution were generated.

An example of dispersion of SO$_2$ from area-source pollution in the year 2000 by the current pattern of industrial distribution is shown in Plate 2a. The city’s coastal geographic location determined that the wind direction is predominantly from west to east. A wind speed of 1.3 meters per second was assumed for the calculation. The same wind direction and speed were applied to simulate the dispersion of SO$_2$ for the year 2010 assuming that the spatial distribution of industrial locations had not changed but that output had increased (Plate 2b). The simulation result illustrates the impact of SO$_2$ dispersion on the neighboring residential areas. Point-source pollution from major contributors, such as oil refineries and power plants, was also derived (Plate 2c). The simulation provided critical information for the planning depart-
ment to evaluate multiple planning schemes and their environmental impacts in decision support.

**Discussion and Conclusion**

This paper presents a case study of spatial dynamic modeling for urban development. The SDM is the engine of the spatial decision support system which linked with a GIS database and model-base in operations. The SDM was designed to simulate the dynamic changes of urban structures and the impacts of the changes. The simulation results provided quantified spatial effects of the urban changes under a variety of planning schemes.

In SDM modeling, the change of urban structures is considered as a result of the spatial interaction between demand and supply of urban resources. The utility function of spatial choice creates a mechanism to incorporate economic principles, and socioeconomic, demographic, and other driving factors into the simulation of urban spatial growth. The methodology in construction of the utility function creates a new paradigm in quantitative modeling of spatial choice. In a GIS-based environment and through defined spatial units, spatial features can be effectively referenced in the selection of available land for urban expansion.

The SDM acts as an analog machine that can be used not only to simulate the dynamic process of urban spatial growth, but also to depict the structure of spatial interactions between demand and supply. This allows us to simulate the urban dynamics by iteration analysis. The decision-maker will be able to evaluate "what-if" scenarios derived from the iterations and choose an optimal solution from a set of alternatives that has control of the urban dynamic spatial process.

Under the current land-use policy and city development plans, the SDM simulations demonstrate the possible spatial growth of the city of Beihai in the future. The cases of impacts of urban spatial growth and planned facilities on traffic flows and air pollution provide comprehensive projections for the city, and, therefore, well-informed decisions can be made. With the SDM and the supporting information system, additional driving factors, policies, and model parameters can be added and adjusted so that the comparison of multiple scenarios can be a routine process in urban planning practice.

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**References**


Figure 7. SDM simulation of urban land use and spatial growth of the city of Beihai. (a) Urban land use in 1980. (b) Urban land use in 1995. (c) Simulated urban growth in 2000. (d) Simulated urban growth in 2005. (e) Simulated urban growth in 2010.

Figure 8. Correlation coefficient of SDM simulated urban growth and observed urban land use between 1980 and 1995.


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