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Simulating spatiotemporal dynamics of urbanization with multi-agent systems—A case study of the Phoenix metropolitan region, USA

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ABSTRACT

Urbanization is a human-dominated process and has greatly impacted biodiversity, ecosystem processes, and regional climate. To understand the socioeconomic drivers of urbanization and project future urban landscape changes, multi-agent systems provide a powerful tool. We develop an agent-based model of urban growth for the Phoenix metropolitan region of the United States, which simulates the behavior of regional authorities, real estate developers, residents, and environmentalists. The BDI (Beliefs–Desires–Intentions) structure is employed to simulate the agents behavior and decision models. The heterogeneity of agents is reflected by adjusting parameters according to the agents' beliefs, desires and preferences. Three scenarios, baseline, economic development priority and environmental protection, are developed and analyzed. The combination of multi-agent system and spatial regression model is employed to predict the future urban development of the Phoenix metropolitan region. Landscape metrics are used to compare the spatial patterns of the urban landscape resulting from different scenarios in different times. In general, with the rapid urban expansion, the shape of urban patches will become more regular as many of them become coalesced. The spatial analysis of urban development through modeling individual and group decisions and human–environment interactions with a multi-agent systems approach can enhance our understanding of the socioeconomic driving forces and mechanisms of urban development.

1. Introduction

Land use and land cover change has been widely recognized as the primary driver for global ecosystem changes as well as a key factor in global climate change (Lambin and Geist, 2006; Ojima et al., 1994). Urbanization is the most severe form of land use and cover change, profoundly influencing biodiversity, ecological processes, and ecosystem services (Grimm et al., 2000; Grimm et al., 2008; Tian et al., 2007a; Wu, 2008). For example, the surface change to asphalt and cement has resulted in urban heat islands, which is the phenomenon of higher temperatures at the urban core compared with the surrounding rural area (Brazel et al., 2007; Buyantuyev and Wu, 2010). It is of great importance to understand how the urban land use and land cover change occurs and to project its future changes for the purpose of urban sustainability (Wu and David, 2002; Wu, 2008).

To acquire a better understanding of urban dynamics, researchers have developed different kinds of modeling approaches. Among them, cellular automata (CA) models have been widely used to simulate urban growth (Batty and Xie, 1994; Berling-Wolff and Wu, 2004; Clarke et al., 1997; Wu and Webster, 1998). CA models are usually implemented through transition rules which are heuristically defined according to the intuitive understanding of the process (e.g., Jenerette and Wu, 2001). One of such models is PHX-UGM (Berling-Wolff and Wu, 2004), developed to simulate urban growth of Phoenix, in which four different types of urban growth—spontaneous, diffusive, organic and road-influenced are distinguished. Although CA models, to a certain extent, have been successful to simulate urban land use change, there are problems that restrict their further application. In particular, the urban dynamic process is so complex and ill-defined that it is impossible to propose universal transition rules to control the processes in different places (Wu and David, 2002). Also, CA models have rather limited capacities for incorporating decision processes of individuals and organizations (Torrens and Benenson, 2005).

Human behavior and interactions are key to understanding urbanization process (Bousquet and Le Page, 2004). Although there

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is an extensive literature on urban dynamic simulation, few papers addressed human planning and decision processes because, to a large part, of their high degree of complexity. As a promising method to fill this gap, the multi-agent system (MAS) modeling approach provides a more capable tool to simulate multi-level decision making processes that produce urban dynamics over time (Parker et al., 2003; Sengupta and Bennett, 2003). With adaptive agents that interact with one another and with their environment, a MAS model has great potential in its application to spatial-policy making as it allows for dynamic learning through scenario analysis (Ligmann-Zielinska and Jankowski, 2007; Matthews et al., 2007; Couclelis, 1989; Ligmann-Zielinska and Jankowski, 2007).

Agents that are used to represent organizations and interest groups rather than mere individuals provide a more realistic way of modeling the urbanization process. On the one hand, taking individual people as building blocks of a model may result in formidable complexity, and on the other hand, organizations and interest groups are often the decision-makers at the level of multi-actor regional planning. The MAS approach is particularly suitable for dealing with heterogeneous actors across scales. It models desires, beliefs, intentions and preferences of agents in the planning process and translates them into visions of agents (Ligtenberg et al., 2004), and can strengthen the understanding of social processes by modeling decision making processes and human–environment interactions. Agents that represent various individual or group entities have differing influences on the emergent results of the system. In most, if not all, situations, government, real estate developers, residents, and environmentalists all play a role in shaping the urban landscape. MAS-based models provide quantitative and empirically verifiable accounts of how individual decisions lead to group formation pattern, contagion, and cooperation, so that collective behavior can be predicted, manipulated, and improved (Goldstone and Janssen, 2005).

In this study, we developed a MAS model to simulate the urban dynamics of the Phoenix metropolitan area, as an alternative to previous models developed by our research group (Jenerette and Wu, 2001; Wu and David, 2002; Berling-Wolff and Wu, 2004). The main goal of this study is to project the urban dynamics of the Phoenix region through simulating the decisions and behavior of individuals, groups and organizations, so as to achieve a better understanding of the driving forces and mechanisms of urbanization in this area. The behavior of agents in our model is a function of urban planning process, land use policy, water use policy and environmental measures, the major factors influencing land use dynamics in the Phoenix region. We also conducted scenario analysis to illuminate multiple alternative possible futures and to examine their impacts on economic, social and environment.

2. Study area and data

The Phoenix metropolitan area is the fifth most populous and the fastest-growing city in the United States. It is located in the northern Sonoran Desert, with a warm and arid climate (Jenerette and Wu, 2001; Luck and Wu, 2002). Phoenix exemplifies automobile-oriented urbanization (Gober and Burns, 2002), with a network of mass transit systems connecting people from the downtown and industrial areas to the surrounding open space (Greater Phoenix, 2003). The metropolitan area is characterized by a decentralized pattern of dispersed new towns connected by a regional network of highways. Phoenix has been changing places with Los Vegas as the fastest growing city in the USA in recent years (Wu et al., 2010), with a population growth rate of 6.38% between 1995 and 2000 (Maricopa Association of Governments, 2005). About two-thirds of the population growth was due to immigration from other regions.

Most data used in the study were obtained from the Central Arizona-Phoenix Long Term Ecological Research (CAP-LTER) project (Jenerette and Wu, 2001; Luck and Wu, 2002; Berling-Wolff and Wu, 2004). Land use maps for the years of 1990, 1995 and 2000 were selected, with four categories—agricultural, desert, urban and recreational (Knowles-Yánez et al., 1999). Information on major roads, rivers and reservoirs, land ownership, and open spaces was also extracted from the CAP-LTER database. In addition, topographic data were derived from the United States Geological Survey (USGS) digital elevation model.

3. A multi-agent systems model of the urban growth of Phoenix

3.1. Conceptual framework and rules for the behavior of multiple agents

The conceptual framework for our MAS model is based on the BDI (Beliefs–Desires–Intentions) structure (Rao and Georgeff, 1995). Agents have several important characteristics: goal-directed, autonomous, social, reactive and pro-active, which can interact with one another and with the environment to complete tasks autonomously. Beliefs refer to information obtained by agents about their environment and other agents, and are constructed by perceiving relevant relations between the desired states and the real environment. The agents obtain the information of their environments. For example, the topography, the distance to the road, etc. Desires represent agents' various objectives to be completed. For example, the economic development, environmental protection, etc. Intentions are related to a set of selected goals together with their state of processing, enacted by the currently chosen course of action (Fig. 1). The agents make their beliefs through obtaining the environmental information including the physical factors, states and neighborhoods. They make intentions according to economic development and environmental protection desires. They adjust the weights of the variables by the different desires and beliefs. Then they impact on the land use conversion probability through adjusting the weights of the variables (Fig. 1).

Every city-dweller may influence urban dynamics in some way, but it is impossible and unnecessary to explicitly consider every individual given the purpose of our model. Individuals participate in organizations, and the actions of these organizations affect and are affected by individual behavior (Goldstone and Janssen, 2005). Individuals can be grouped in terms of some common property, and the groups can be represented as agents. Heterogeneity, one of the main characteristics of complex adaptive systems (Levin, 1999), is embodied by the diverse agents (Benenson and Torrens, 2004). According to their roles in urban dynamics, the agents in our model are classified into four groups: regional authorities, real estate developers, residents, and environmentalists.

Constrained by different rules, agents are allowed to compete in a variety of environments and act solely to maximize their own expected utility. These group-level agents act and interact in a dynamic environment (Bousquet and Le Page, 2004). Environmental, economic and social factors affecting urban dynamics are difficult to characterize at the regional scale (Manson, 2005). So, our model represents these factors in terms of the parameters and rules that reflect the agents' desires, social norms, policies, and strategies. We analyze the preferences of the four kinds of agents, their behaviors and decision models at first.

3.1.1. The regional authority behavior

Decision making is carried out at two levels: the individual and joint decisions among all agents. The hierarchical structure of social organization indicates that the lower-level processes are con-

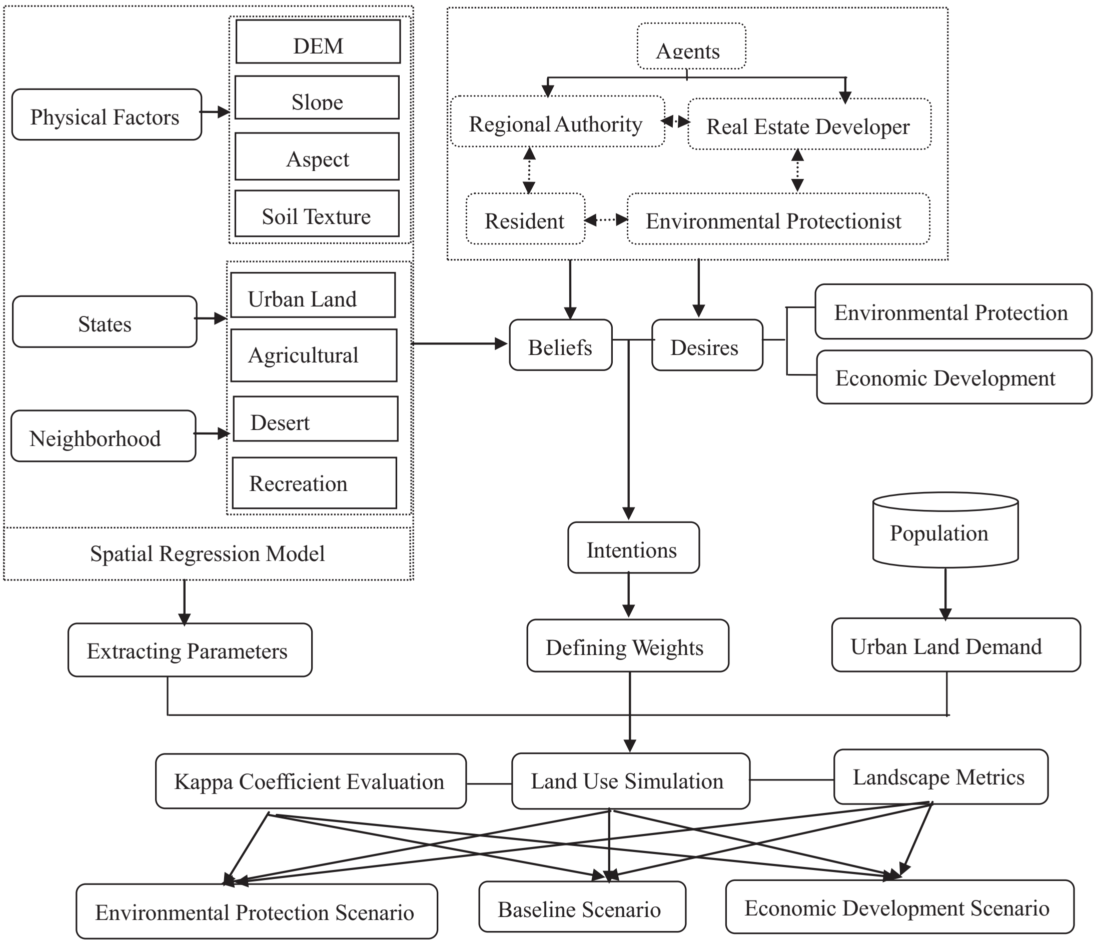

Fig. 1. The workflow of multi-agent system model.

strained by higher-level dynamics (Wu, 1999; Wu and David, 2002; Verburg, 2006). For example, national and regional authorities usually have more power than local authorities in decision making, and national and regional policies tend to have a broader impact on urbanization (Tian et al., 2002, 2005, 2007b; Berling-Wolff and Wu, 2004). Regional authority agents consider spatial and temporal efficiencies in using land resources, and decide whether land development can be approved according to a number of criteria. For example, urban development in water bodies and land owned by Native American Indians is quite unlikely.

Government policy on water rights provides the most significant explanation for the agricultural to residential land transformation (Keys et al., 2007). The person who puts water to its first beneficial use acquires the rights to the water, which is defined in the Public Water Code enacted in 1919 (Maricopa Association of Governments, 2005). This law mandates that a person must apply in order to appropriate surface water. Therefore, agriculture is more likely to be transformed to urban land. We derived rules and policies from comprehensive planning of Maricopa Associations of Governments (MAG), policy and statistics. The local government and social organizations will cooperatively establish the comprehensive planning for the Maricopa County for 5 or 10 years. They establish the basic principles that assist in translating the assumptions and goals into progressive community action, so as to prevent land degradation and protect forests, parks, and Native American communities.

The government intervenes with urban development by controlling land consumption in the spatio-temporal dimension. The government pays more attention to economic development and employment opportunity increment. We assume that compact development is encouraged to concentrate as much as possible around existing urban conglomerates, and that agricultural land is preferred (e.g., Wu, 2002). The comprehensive plan for Maricopa County encourages infill within existing development.

3.1.2. The real estate developer behavior

The main objective of property developers is to achieve a certain amount of profit which is the difference between housing price and the total amount of land price and development cost. The development probability lies in developer agents and their investment profit. The provision of public facilities is an important factor to affect the decisions of real estate developers. And convenient freeway and highway access also has a positive impact on the construction of houses and commercial offices (Berling-Wolff and Wu, 2004). Real estate developers encourage the urban growth of residential, commercial and industrial development, and guide compatible land use patterns. They acquire new development to fully utilize the existing infrastructure and city services, and develop the land near major roads first.

3.1.3. The behavior of residents

The general plan incorporates the knowledge about various combinations of beliefs. The preference of an agent influences and is influenced by those of other agents. All agents input their individually generated desired state of the environment into a voting procedure. Consultation is a common step in the planning process, in which the planners will consult with the citizens. The behavior of resident agents is determined by their location and status factors.

Households are the basic decision units in the studies of residential location and mobility, consisting of persons living together in dwelling units (Gober, 1986). Households with different income have different preferences of houses in terms of location, density and environment. In our model the location factors include the distance to hospital, park, and public facilities.

3.1.4. The behavior of environmentalists

The conservation of national forest, park, wild space and lake is important to maintain biodiversity and ecosystem functions in urban regions. The Native American Indian tribes have a culture closely tied to their land; to date they have not sold their land for non-Indian community use, and only in the last few decades have they begun to lease their lands for commercial and industrial development (Maricopa Association of Governments, 2005). So, the Indian reservations have rather small likelihood for urban development, and the national forest, park, wildland and water bodies also have limited possibilities to be developed. So, we set the following preferences: (1) establish adequate buffers and transitions of open space to protect the natural beauty of the land and water; (2) coordinate land management and planning activities with neighboring Native American Indian communities and federal, state and private interests, and forbid urban development near the Indian Reservations; and (3) buffer recreational area from urban development and support lower density development.

The agents of regional authorities, real estate developers, residents and environmental protectionists make their beliefs through observing the environment, such as 'close to urban land', 'close to open space', and 'close to highway' (Fig. 1). They make their intentions based on their beliefs and different desires. For the economic development objective, they pay more attention to the infrastructure utilization. But for the environmental protection objective, they will pay more attention to the open space protection, etc. The behaviors of the agents were decided by the preferences and policies. Then they decide the weights of the factors, and the different combinations of the factors and their weights shape the different intentions that emerge from the agent behavior (Fig. 1).

3.2. Model implementation

Our model is a specific real-world application of the MAS modeling approach, and it shares some fundamental aspects similar to other spatially explicit systems. In general, the spatial resolution of a model determines how much spatial detail to be included in the model as well as what kinds of landscape changes to be considered. In this model, we use a regular grid with cells of 100 m × 100 m, based on the appropriateness of most processes of interest and the availability of data. At each time step, decisions of various agents affect land conversion on a cell-by-cell basis. The location of each cell is represented by the coordinates of its center (i,j). Agents have spatial characteristics and make decisions that may change the states of the affected cells.

The model uses population growth as a global driver of urban growth, as in Berling-Wolff and Wu (2004). Population growth was predicted before the appropriate land use conversion could be obtained for each time step of the model implementation (Fig. 1). As Berling-Wolff and Wu (2004) described, the urban growth of Phoenix area has been taking place at an exponential rate. Thus, a regression model was established for estimating the population growth, based on the population data in 1960–2000:

$$P(t) = 1.7343 \times 10^{-30}\, e^{0.0383t} \tag{1}$$

where $P(t)$ is the population in year t. The square correlation coefficient of population and year t is 0.9986. Hence, there is a strong correlation between them. The standard error of the projection is 70.666.

Table 1
The land use in 1995 and 2000 and the projected in 2010 and 2020 of Phoenix metropolitan area (ha).

Land use type	1995	2000	2010	2020
Urban land	54,290	73,012	101,452	105,591
Agricultural land	30,827	18,536	6252	3814
Desert	187,691	180,451	163,638	161,258
Recreational land	12,865	13,674	14,331	15,010

The area of urban land is regressed with the population in 1960–2000 as shown below.

$$UL(t) = 2563\, e^{0.0008P(t)} \tag{2}$$

where $UL(t)$ is the area of urbanized land in year t.

We projected the urban land in 2010 and 2020 by Eqs. (1) and (2) (Table 1). According to the projection, the urban land will reach 101,452 ha in 2010 and 105,591 ha in 2020 (Table 1). There are four land use types considered in our model (1995–2000): urban, agricultural, desert, and recreational. We projected the agricultural land, desert and recreational land according to their growth rate between 1995 and 2000 and keep the balance of the total land (Table 1). Several factors including topography, and the distance to railway, major roads, rivers, open spaces and public facilities are considered in this model as the determinants of the probability of land use types. For example, the proximity to major roads has a positive impact on the urban growth.

In this MAS model, we defined the probability of land use conversion of a cell as:

$$\frac{P_{ij}^t}{1 - P_{ij}^t} = f(S_{ij}^t, C_{ij}^t, \Omega_{ij}^t) \tag{3}$$

where P_{ij}^t is the probability of the cell (i,j) for the occurrence of a land use type at time t; S_{ij}^t includes the biophysical state of the cell (i,j) at time t; C_{ij}^t is a constraint factor; and Ω_{ij}^t is the neighborhood of the cell (i,j) at time t.

The bio-physical factors that impact the land use conversion include elevation, slope, aspect, and soil texture, denoted by $S_{ij,1}^t$, $S_{ij,2}^t$, $S_{ij,3}^t$ and $S_{ij,4}^t$, respectively (Berling-Wolff and Wu, 2004). The constraint factor is land ownership represented by $C_{ij,1}$. For example, Indian reservations will not be developed. The definition of the Moor neighborhood (i.e., the 8-neighbor rule) is adopted in this model, meaning that the eight surrounding cells all influence the state of the focal cell. The number of cells for each of the land use types (urban, agricultural, desert and recreational) is denoted by $\Omega_{ij,1}$, $\Omega_{ij,2}$, $\Omega_{ij,3}$ and $\Omega_{ij,4}$, respectively. These variables are standardized in order to avoid the impact due to different scales. For example, the variables of the biophysical factors can be standardized by the following Eq. (4):

$$S'_{ij} = \begin{cases} \text{if } \max(S_{ij}) = \min(S_{ij}), & 1 \\ \text{else}, & \dfrac{S_{ij} - \min(S_{ij})}{\max(S_{ij}) - \min(S_{ij})} \end{cases} \tag{4}$$

Logistic regression is often used to study the relations between land use dynamics and a combination of its driving factors (Verburg and Chen, 2000; Geoghegan et al., 2001; Serneels and Lambine, 2001; Verburg et al., 2002; Li and Liu, 2006, 2008). It is regarded as an effective method of the land use conversion with only a limited number of explanatory variables and complex distributed land use conversions (Wu, 2002; Li and Liu, 2006, 2008). It can explain the land use dynamic pattern based on our knowledge. We used stepwise logistic regression to help determine the probability of a certain cell to be converted to each of the four land use types (Verburg et al., 2002). Specifically, the regression equation is as

Table 2
The regression beta values of the variables for land use pattern in Phoenix metropolitan area for the baseline scenario.

Factors	Variables	Urban land	Agricultural land	Desert	Recreational land
Constant		−1.461	−2.059	2.831	−5.297
DEM	X_1	0.002	0.147	−0.009	0.075
Slope	X_2	0.011	0.027	−0.04	−0.032
Aspect	X_3	−0.002	0.003	0.02	−0.001
Soil	X_4	−0.002	0.005	−0.001	−0.005
Neighborhood of urban land	X_5	0.772	−0.635	−0.963	0.023
Neighborhood of agricultural land	X_6	−0.391	0.771	−0.999	−0.047
Neighborhood of desert	X_7	−0.405	−0.608	0.417	−0.14
Neighborhood of recreational land	X_8	−0.564	−0.622	−1.112	1.285
Distance to urban land	X_9	−12.068	0.018	−1.112	−0.002
Distance to agricultural land	X_{10}	−0.012	−9.225	0.229	−0.02
Distance to desert	X_{11}	−0.037	−0.015	0.014	0.019
Distance to recreational land	X_{12}	0.034	−0.009	−11.223	−10.136
Distance to water body	X_{13}	−0.004	−0.030	−0.026	0.002
Distance to major road	X_{14}	0	0	0.014	0
Distance to railway	X_{15}	0.002	0.018	0	−0.003
Distance to open space	X_{16}	0	0	0	0
Distance to residential area	X_{17}	0	0	0	0
Distance to commercial area	X_{18}	0	0	0	0
Distance to industrial area	X_{19}	0	0	0	0
Distance to school	X_{20}	0	0	0	0
Distance to public facilities	X_{21}	0	0	0	0

follows:

$$\log\left(\frac{P_{ij}^t}{1-P_{ij}^t}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n \qquad (5)$$

where P_{ij}^t is the probability of the cell (i,j) for the occurrence of a land use type at time t; $X_1, X_2, \ldots, X_n$ are the driving factors, and $\beta_0, \beta_1, \beta_2, \ldots, \beta_n$ are corresponding coefficients. These beta values were obtained through stepwise logistic regression by using the land use data of 1995 and 2000 (Table 2). The regression standard errors of the variables for land use spatial distribution were listed in Table 3.

The behavior of agents significantly affects land use conversion probabilities, which is represented in our model by changing the coefficients of these driving factors. The coefficients of variables for baseline scenario are considered unaffected by behavior of agents. After we parameterized Eq. (5) for the baseline scenario, the coefficients of these driving factors were adjusted according to the preferences of the agents for the other two scenarios considered—environmental protection priority scenario and economic development priority scenario. For any driving factor, each agent group has distinct preferences. The preferences of different agent groups were obtained using Saaty's pairwise comparison procedure (Eastman, 1999; Li and Liu, 2008).

The combined preference of agents PR^k for factor k is described as:

$$PR^k = \frac{PR_{ra}^k \cdot PR_{re}^k \cdot PR_{rs}^k}{PR_{ep}^k} \qquad (6)$$

where PR_{ra}^k is the preference of regional authorities for factor k, PR_{re}^k is the preference of real estate developers for factor k, PR_{rs}^k is the preference of residents for factor k, and PR_{ep}^k is the preference of environmental protectionists for factor k. The combined preferences were calculated as the weights of the factors (Tables 4 and 5).

Combining all these together, the probability of the cell (i,j) to be converted into a land use type was adjusted as:

$$P_{ij}^{t+1} = \sum_{k,l,m} (W_{ij,k}^t \beta_{ij,k}^t S_{ij,k}^t + W_{ij,l}^t \beta_{ij,l}^t C_{ij,l}^t + W_{ij,m}^t \beta_{ij,m}^t \Omega_{ij,m}^t) \qquad (7)$$

Table 3
The regression standard error of the variables for land use pattern in Phoenix metropolitan area for the baseline scenario.

Factors	Variables	Urban land	Agricultural land	Desert	Recreational land
Constant		0.315	0.409	0.289	1.429
DEM	X_1	0.01	0.026	0.01	0.020
Slope	X_2	0.009	0.027	0.009	0.011
Aspect	X_3	0.001	0.003	0.001	0.002
Soil	X_4	0.002	0.006	0.002	0.004
Neighborhood of urban land	X_5	0.034	0.038	0.032	0.158
Neighborhood of agricultural land	X_6	0.034	0.037	0.034	0.164
Neighborhood of desert	X_7	0.034	0.038	0.03	0.158
Neighborhood of recreational land	X_8	0.035	0.077	0.036	0.159
Distance to urban land	X_9	25.213	0.028	0.015	0.030
Distance to agricultural land	X_{10}	0.005	13.312	0.006	0.011
Distance to desert	X_{11}	0.009	0.025	51.311	0.013
Distance to recreational land	X_{12}	0.005	0.01	0.005	13.106
Distance to water body	X_{13}	0.01	0.013	0.008	0.022
Distance to major road	X_{14}	0	0	0	0
Distance to railway	X_{15}	0.002	0.005	0.002	0.005
Distance to open space	X_{16}	0	0	0	0
Distance to residential area	X_{17}	0	0	0	0
Distance to commercial area	X_{18}	0	0	0	0
Distance to industrial area	X_{19}	0	0	0	0
Distance to school	X_{20}	0	0	0	0
Distance to public facilities	X_{21}	0	0	0	0

Table 4
The preferences of regional authorities, real estate developers, residents and environmental protectionists on the variables of the urban land spatial distribution in Phoenix metropolitan area for environmental protection scenario.

Variables	Regional authorities	Real estate developers	Residents	Environmental protectionists	Total
X_1	1.78	0.99	3.56	0.37	17.00
X_2	1.92	1.08	0.84	0.96	1.82
X_3	0.50	0.50	0.50	0.25	0.50
X_4	0.51	0.73	0.65	0.24	1.00
X_5	0.98	0.69	1.34	0.97	0.93
X_6	0.75	1.54	1.07	0.99	1.24
X_7	0.73	0.83	1.62	0.75	1.30
X_8	0.91	1.33	1.24	1.17	1.28
X_9	0.83	0.96	1.05	0.89	0.94
X_{10}	1.13	1.48	1.77	0.91	3.25
X_{11}	0.95	1.07	1.23	0.86	1.46
X_{12}	1.05	0.97	0.89	0.93	0.97
X_{13}	0.92	0.91	0.85	0.95	0.75
X_{14}	0.00	2.00	2.00	1.00	0.00
X_{15}	2.06	1.49	1.06	0.93	3.50
X_{16}	0.23	0.52	0.91	2.87	0.04
X_{17}	0.00	0.00	0.00	0.00	0.00
X_{18}	0.00	0.00	0.00	0.00	0.00
X_{19}	0.00	0.00	0.00	0.00	0.00
X_{20}	0.00	0.00	0.00	0.00	0.00
X_{21}	1.00	1.00	1.00	1.00	1.00

where $W^t_{ij,k}, W^t_{ij,l}, W^t_{ij,m}$ are the weights of factors $S^t_{ij,k}, C^t_{ij,l}$ and $\Omega^t_{ij,m}$ at location (i,j), respectively.

4. Model simulation and evaluation

4.1. Scenarios

We designed three scenarios for simulation analysis, which represent different development patterns (Fig. 1):

- Scenario 1 (baseline scenario): In this scenario urban land will increase according to the current trend. The government, real estate developers, residents and environmentalists do little to change the status quo. Accordingly, there are no changes in the parameters of economic development and environmental protection. Thus the model in this scenario includes cell state, constraint and neighborhood factors. The parameters of the model were derived from land use data of 2000 for the baseline scenario (Table 2). The preferences of agents are considered not to impact the land use dynamics for this scenario.
- Scenario 2 (environmental protection priority scenario): In this scenario the regional authorities attach more importance to environmental protection. Representatives from business, government and other groups have developed an alternative approach to land use planning and growth management called the "Growing Smarter Initiative" (Heffernon and Melnick, 1998). This initiative calls for slowing down the economic development to protect open space, water body and recreational land. Preservation of open space is a growth mitigation measure. Thus, in the environmental protection scenario, the weights of driving factors are adjusted to reflect this alternative development possibility. Particularly, the weights of the factors such as distances to residential, industrial and commercial land are decreased, whereas the weights of distance to open space, water body and recreational land are increased. At the same time, the Indian reservations are prohibited from urban development.

For any factor, each group of agents has distinct behavior and preferences for environmental protection priority scenario and economic development priority scenario. For example, as to 'distance to open space', the residents attach more importance to

Table 5
The preferences of regional authorities, real estate developers, residents and environmental protectionists on the variables of urban land spatial distribution in Phoenix metropolitan area for economic development scenario.

Variables	Regional authorities	Real estate developers	Residents	Environmental protectionists	Total
X_1	1.95	0.97	2.48	0.26	18.00
X_2	2.06	0.87	0.99	0.93	1.91
X_3	0.50	0.50	1.00	0.50	0.50
X_4	1.50	1.00	1.00	1.00	1.50
X_5	0.75	0.78	1.53	0.97	0.93
X_6	1.35	0.69	0.95	0.71	1.25
X_7	2.03	0.98	0.65	0.99	1.31
X_8	0.79	1.36	1.19	1.00	1.28
X_9	1.21	0.75	0.98	0.94	0.94
X_{10}	1.62	1.68	1.53	1.25	3.33
X_{11}	1.67	0.66	1.75	1.32	1.46
X_{12}	1.00	0.74	1.23	0.97	0.94
X_{13}	1.00	1.00	1.00	1.00	1.00
X_{14}	2.00	0.00	2.00	1.00	0.00
X_{15}	2.61	1.87	1.04	1.27	4.00
X_{16}	0.00	0.00	0.00	0.00	0.00
X_{17}	0.24	0.64	0.31	2.64	0.02
X_{18}	0.29	0.52	0.46	1.87	0.04
X_{19}	0.27	0.23	0.16	1.43	0.01
X_{20}	0.12	0.37	0.86	2.74	0.01
X_{21}	0.14	0.33	0.67	2.85	0.01

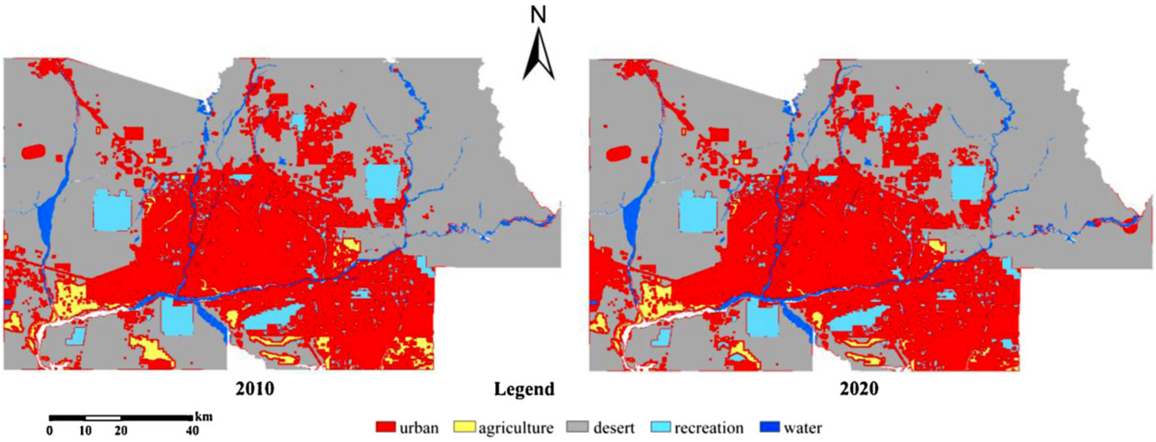

Fig. 2. Land use simulation of Phoenix metropolitan area for baseline scenario in 2010 and 2020.

open space than real estate developers and regional authorities, but the environmental protectionists think the open space should be protected. The preferences of regional authorities, real estate developers, residents and environmental protectionists for environmental protection priority scenario, which are 0.23, 0.52, 0.91 and 2.87 respectively (Table 4), do reflect the difference. Their combined preference can be calculated by Eq. (6). All the combined preferences will be normalized into the range of [0,1] as the weights of the factors. The probability of the cell (*i*,*j*) to be converted into urban use is calculated by Eq. (7).

- Scenario 3 (economic development priority scenario): The third scenario emphasizes the priority of economic development. Based on this priority, the weights of driving factors including distances to residential, commercial, industrial land, schools and public facilities are increased in the model. The combined preferences of the four agent groups will decide the weights of the driving factors by Eq. (6) (Table 5). The probability of the cell (*i*,*j*) to be converted into a land use type is calculated by Eq. (7) using the parameters used in the baseline scenario and the weights of the factors.

4.2. Model evaluation

Before simulating the three scenarios, we evaluated the model by comparing the projected results with the empirical land use map for 2000, with a commonly used method in remote sensing and landscape ecology, the Kappa coefficient (Congalton and Green, 1999; Pontius et al., 2001). Kappa is calculated based on the predicted and observed values over the entire area (Congalton and Green, 1999):

$$\text{Kappa} = \frac{P_0 - P_c}{1 - P_c} \qquad (8)$$

where P_0 is the percent correct for the model output, and P_c is the expected percent correct due merely to chance.

The value of Kappa ranges from ≤0 (no agreement between the predicted and observed maps) to 1 (perfect agreement between the predicted and observed maps). Although there is no universally accepted standard, a value of Kappa greater than 0.80 has been considered as indicating a strong agreement between the predicted and observed maps (Landis and Koch, 1977; Congalton and Green, 1999; Pocewicz et al., 2008).

We computed the Kappa statistic based on the settings of Scenario 1 (baseline scenario), Scenario 2 (environmental protection priority scenario) and Scenario 3 (economic development priority scenario), and the values of Kappa were 0.8375, 0.8373 and 0.8369, respectively.

4.3. Results from the three scenarios

We simulated the model to project the land use maps for 2010 and 2020 following the three scenarios. In 2000, urban land accounted for 25.56% of the total area. Scenario 1 projected that the urban land would reach 35.44% in 2010 and 36.71% in 2020 (Fig. 2). In Scenario 2, urban land percentage would reach 30.74 in 2010 and 31.85 in 2020 (Fig. 3). In Scenario 3, urban land percentage would reach 39.13 in 2010 and 41 in 2020 (Fig. 4). The urban growth in Scenario 2 is evidently slower compared with the other two because the emphasis of environmental protection would impose more restrictions on the land use conversion to urban use. Urbanization is encouraged in Scenario 3 such that the urban area would increase the fastest.

In order to further compare the simulated results of the different scenarios, we used landscape metrics (Jenerette and Wu, 2001; Luck and Wu, 2002; Berling-Wolff and Wu, 2004; Seto et al., 2007) to describe the size and complexity of urban form in 2000, 2010 and 2020 for the three scenarios. Four landscape metrics were calculated by using FRAGSTATS (McGarigal and Marks, 1995): the number of urban patches (NP), urban edge density (ED), mean urban patch size (MPS), and area weighted mean patch fractal dimension (AWMPFD) (see Table 6). These and other landscape metrics have been used extensively to quantify the spatial and temporal patterns of urbanization in the Phoenix region (Luck and Wu, 2002; Wu et al., 2002, 2010; Wu, 2004; Buyantuyev et al., 2010). These previous studies have shown that NP is expected to increase when urban growth is dispersed and to decrease when urban patches expand and merge. During the urbanization process, the merger of smaller urban centers decreases MPS while emergence of new small urban areas increases it. Aggregated urban patches lead to lower ED values as compared to dispersed ones, and more irregular or complex shapes of patches tend to lead to higher AWMPFD.

From the simulation results, the values of NP for all the three scenarios decline dramatically from 2000 to 2010, and continue to do so to a lesser degree between 2010 and 2020 (Fig. 5a). Conversely, the values of MPS tend to increase for the three scenarios (Fig. 5b). Thus the changes in NP and MPS suggest that urban areas expand and coalesce during urbanization. As expected, the urban growth reflected by NP and MPS is accelerated in Scenario 3 because of the priority of economic development, and slows down in Scenario 2 due to the emphasis on environmental production.

The value of ED goes up first from 2000 to 2010 and then down from 2010 to 2020 for both Scenarios 1 and 2 (Fig. 5c and d). The reason for the larger increase in ED between 2000 and 2010 is probably that the expansion of urban patches is more irregular in shape

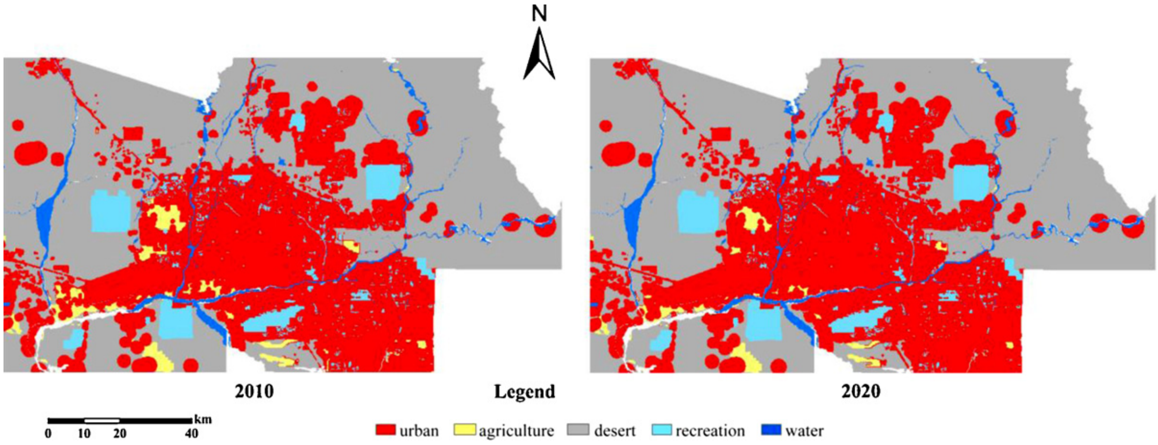

Fig. 3. Land use simulation of Phoenix metropolitan area for economic development priority scenario in 2010 and 2020.

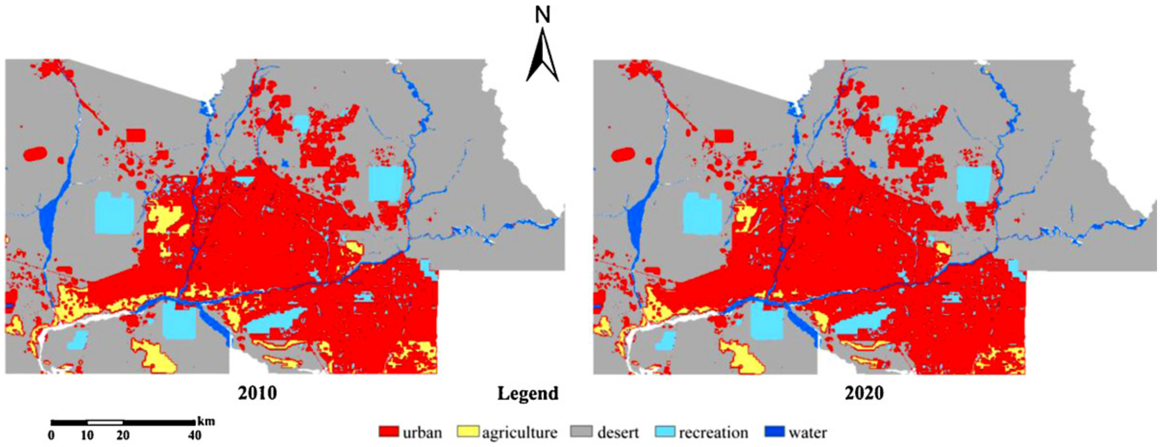

Fig. 4. Land use simulation of Phoenix metropolitan area for environmental protection priority scenario in 2010 and 2020.

than between 2010 and 2020. ED continues to decrease in Scenario 3 because of the coalescence of urban patches (corresponding to increasing MPS and decreasing NP). The results of AWMPFD are consistent with ED (Fig. 5d).

5. Discussion

MAS models are increasingly recognized as a powerful tool to simulate social systems because they can capture important human decision and behavior that are difficult to formulate by using other tools (Lempert, 2002). In our MAS model, the agents are equipped with land use related preferences and beliefs extracted from comprehensive planning and strategic policies. Economic development and environmental protection behavior are incorporated in the model by properly defining agents' behavior. The behavior of regional authorities, real estate developers, residents, and environmental protectionists is adaptive. These agents may change their behavior in response to their environmental change based on their beliefs. The heterogeneity of agents is reflected by using different sets of weights according to GIS data. It simulates the urbanization process by adjusting parameters according to the agents' preferences.

Through simulating the decision process and behavior of regional authorities, real estate developer, residents and environmental protectionists, this model is different from Markov-cellular automata model (Jenerette and Wu, 2001) and PHX-UGM in (Berling-Wolff and Wu, 2004). In the Markov-cellular automata model, the current states of each individual cell are dependent on states of the focal and neighborhood cells. They are updated based on the pre-defined rules. PHX-UGM is also a CA-based model, in which the urbanization is controlled by diffusion coefficient, breed coefficient, spread coefficient, slope resistance and road gravity. The cells in CA-based models are endowed with goal-directed decision rules, while MAS models offer a more flexible way to simulate urban dynamics, in which agents are proactive and their decisions and behavior influence the states of related cells.

Table 6
List of landscape metrics used for comparing the simulated and empirical land use maps.

Landscape metrics	Abbreviation	Description
Number of patches	NP	The total number of urban patches in the landscape
Edge density	ED	The total length of all edge segments per hectare urban patches (unit: m/ha)
Mean patch size	MPS	Mean urban patch size (unit: ha)
Area weighted mean patch fractal dimension	AWMPFD	Averages the fractal dimensions of all patches by weighting larger land cover patches: $\text{AWMPFD} = \sum_{i=1}^{n}(2\ln 0.25P_i/\ln a_i)(a_i/A)$, where P_i is the perimeter of patch i, a_i is the area of patch i, n is the number of land patches, and A is the total landscape area.

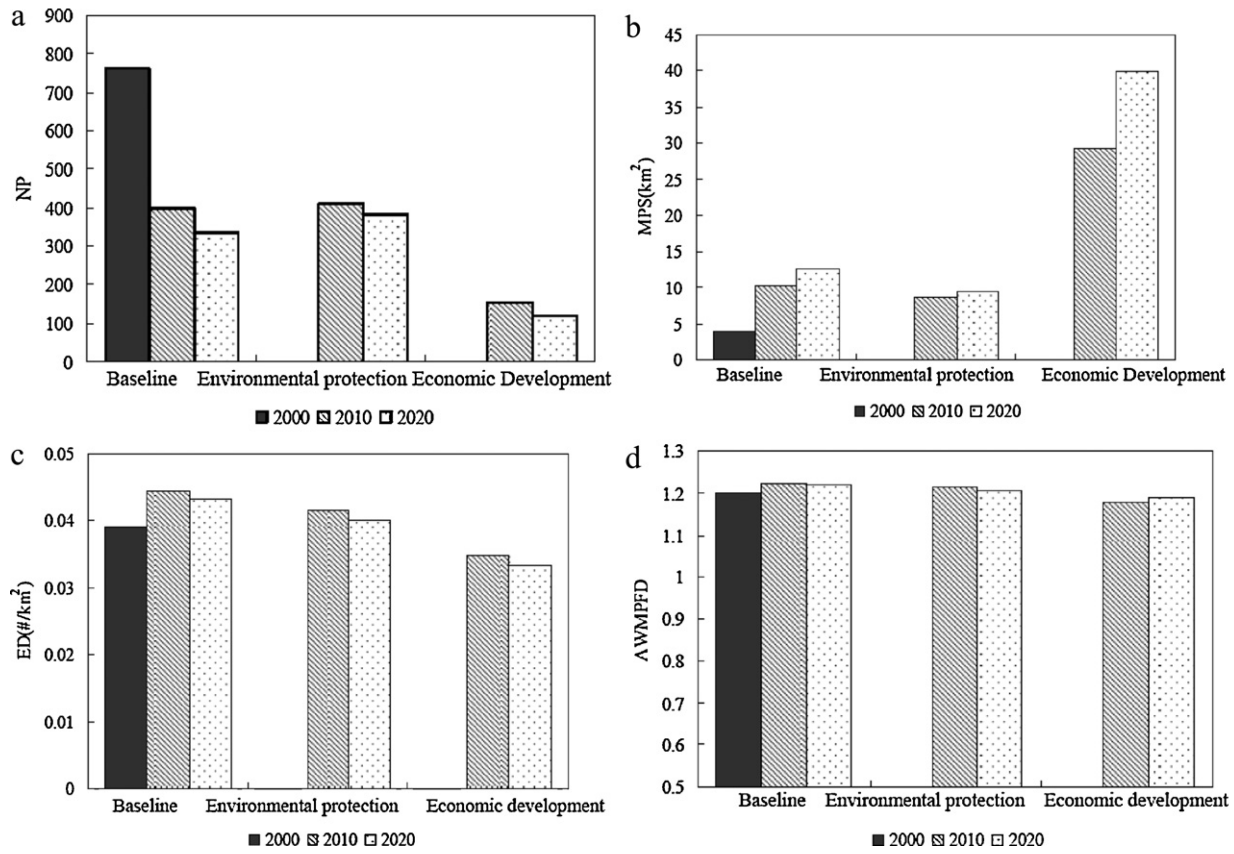

Fig. 5. Results of landscape metrics used to compare the land use patterns among the three different development scenarios for 2000, 2010, and 2020: (a) the number of urban patches (NP), (b) mean urban patch size (MPS), (c) urban edge density (ED), and (d) area weighted mean patch fractal dimension (AWMPFD).

In our MAS model, economic and environmental objectives necessary to understand the biophysical and socioeconomic interactions in urban dynamics are included. Three scenarios based on the current trend, economic development priority and environmental protection priority are considered. Decision and behavior of regional authorities, real estate developers, residents and environmental protectionists are crucial for those scenarios. Our model combines MAS and the spatial regression model to simulate the human–environment system in Phoenix metropolitan area. The simulation results indicate that urban patches would increasingly expand and merge during the urbanization process in all three scenarios. Urban land use will increase faster from 2000 to 2010 and slow down a little between 2010 and 2020. The urban growth in Scenario 3 is faster than that in Scenario 1 because of its economic development priority. And the urban growth in Scenario 2 is slower than Scenario 1 due to more restrictions from the emphasis on environmental protection.

This case study is a primary attempt to use MAS models to simulate urban dynamics. Greater effort is required to unleash the full potential of MAS to understand the urbanization mechanisms and to offer more support for policy-making based on scenario analysis.

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