

Integration Of Spatial Agents And Markov Chain Model In Simulation Of Urban Sprawl

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ABSTRACT

In this research, in order to simulate urban sprawl in Tehran metropolitan area, an agent based modeling model was developed through GIS functionalities in ArcGIS software. The most efficient agents were classified into 3 categories such as developer agents, government agents and resident agents. Firstly, it was assumed that resident agents have their own preferences to choose a location to live; therefore, possible locations for settlement by these agents were identified. An AHP weighting system was carried out to differentiate between the effective variables. Secondly, it was assumed that the developer agents look for locations, where they can earn more money arising from their investment. A function was employed to create the probability surface of development in the study area. The final assumption was the government agent considers whether the development applications should be approved or rejected. All predefined agents were combined together through a customized overlay function. A probability surface of development was produced by this combination. Markov chain model was employed to retrieve the amount of changes and afterwards, the amount of change was allocated.

Keywords: *Land use change, Spatial Agents, Geosimulation, Agent Based Modeling, Tehran*

INTRODUCTION

Urban sprawl is defined as a complex system which is determined by the interactions of environmental and demographic factors in space and time at different scales (Barredo, 2003; He, 2006). There are several models that essentially rely on a limited number of methods and assumptions (Koomen, 2007); for instance, Cellular Automata (e.g. Clarke, 1997), Markov Chain model (e.g. López, 2001), Spatial logistic regression, economical models (e.g. Irwin, 2001), statistical models (e.g. Veldkamp, 2001), optimization techniques (e.g. Pijanowski, 2002), rule based models (e.g. Klosterman, 2005), multi agent models (e.g. Torrens, 2006), and Microsimulation. Agent based modeling (ABM) differs from Cellular automata in one particular respect, individual automata are basically free to move around, i.e. they are not fixed agents and their movements do not have to take place cell by cell. This feature has obvious consequences for the representation of spatial systems (Longley, 2003).

A recent pervasive approach to consider and simulate human decisions in land use change studies is the use of multi-agent systems (Matthews, 2006; Parker, 2003). Multi-agent systems (MAS) are defined as modeling tools that entities make decisions by the predefined agents. Importing human agents' activities in explaining land use change has been becoming gradually more pervasive and useful in land use modeling. In Multi-Agent System models, in general, the agents could be residents, land owners and administrative organization which play critical roles in the land change decision-making process (Bakker, 2009).

STUDY AREA

In this study, Tehran metropolitan area was picked as an ideal case for this research, whereas it had a lot of changes within last decades. Tehran is the capital and the largest city of Iran and the Middle East and also the administrative center of Tehran province with more than 13 million inhabitants (Fardi, 2010). The center of study area is located at latitude and longitude of 35.6962°N, 51.423°E.

Resident Agents

In this study area, two kinds of residents exist; firstly, those who are moving into the metropolitan area from other cities to live, and secondly, current residents relocate themselves to either better places or worse places. The behaviors of the residents can influence the type of change. Furthermore, these behaviors can justify the investment plans for developer agents. These resident agents and their interactions are the main keys in urban expansion.

Several variables were picked to estimate residents' preferences to live (e.g. favorite elevation, favorite slope, accessibility to some variables such as medical services, educational centers, metro stations, orchards, to sport centers, road networks, recreation points, commercial centers, and distance to railways and disposal areas). Therefore, a utility function of location (ij) for resident agent k was employed as equation 1.

$$F(k, ij) = W_{education} B_{education} + W_{elevation} B_{elevation} + W_{slope} B_{slope} + W_{medical} B_{medical} + W_{metro} B_{metro} \cdot E \quad (1)$$

Where W are the weights of the factors. The mentioned factors were considered according to their weights for resident k and location (ij). Each resident agent has his/her own preferences for choosing a place for settlement.

Implementation of AHP Weighting System

The Analytic Hierarchy Process (AHP) is a well-known methodology for specifying appropriate weights by cross-comparing of all factors versus each other. The AHP function was applied to the imported factors in ArcGIS environment. The achieved weights after satisfaction of the consistency ratio were input into the model (Saaty, 1980). By means of implementing this weighting system as well as applying the designed formula (equation 1) in the ArcGIS environment, a categorical probability surface was produced which identifies the preferable locations for residency by resident agents.

Developer Agents

The developer agents consider the preferences of residents in home buying as well as the governmental policies in land resources supervision. In other words, the developer agents can be affected by resident agents' preferences and government agents' restriction which proves the interaction between these agents to conduct the developer agents where to invest their resources in order to reach maximum benefits. This criterion was used to conclude the decision behaviors of developer agents. Equation 2 was used for the reflection of development potential (Li, 2007):

$$D_{Profit}^t = H_{price}^t - L_{price}^t - D_{cost}^t \quad \text{Eq. 2}$$

Where D_{Profit}^t represents the investment profit, H_{price}^t is housing price, L_{price}^t is land price and D_{cost}^t is development cost. These prices were calculated in domestic currency units (i.e. Rial). The probability of development by the developer agents can thus be represented as following equation:

$$P_{developer}^t(k, ij) = \frac{D_{profit}^t - D_{tprofit}}{D_{mprofit} - D_{tprofit}} \quad \text{Eq. 3}$$

Where $P_{developer}^t(k, ij)$ represents the development probability related to the developer agents, D_{profit}^t is a threshold value and $D_{mprofit}$ is the maximum value of the investment profit. Developer agents will invest in the site if the estimation is in favor of the development according to equation 3 (Li, 2007). A probability surface of probable development by the developer agents was the result. Changes will be applied after approving the application through the government agents; thus, government agents play an important task in this matter.

Government Agents

Government agents have this authorization to prohibit construction in any area in order to have sufficient control on cities. Besides, the government agents are able to decide approval on any application for development according to multiple criteria. An application will be approved providing no conflicts exist with the current planned land policy. The behaviors of government agents can also

be affected by any unexpected behaviors of resident agents and developer agents such as high migration rate, unexpected population growth, new interchange expansion, request increase or new development plans due to new policies approval. Hence, the following function was defined to consider the behavior of this agent.

$$GAB = f(\text{RSRZ}, \text{RNB}, \text{HB}, \text{ASB}, \text{MFRZ}, \text{PFRZ}, \text{PB}, \text{NSS}) \quad \text{Eq. 4}$$

The *Government Agents Behavior* is a function restricted by the following mentioned components (i.e. *River Streams Risk Zone, Roads Network Buffer, Highways Buffer, Airports Risk Buffer, Parks Buffer, Non Suitable Slope*). Therefore, the prohibited areas by these agents were discovered by expert knowledge. These variables acted in a binary type. Challenges between resident agents and developer agents are not the final step of the decision to be made for land development. Government agent is the final decision maker that can either approve applications or reject them.

Nonetheless, this agent does not concern only the environmental factors, but also by resident agents and developer agents' interaction. It also considers the suitability of any residency and construction based on current land use situation, surrounding environment, transportation supplies, affordable general facilities, and educational benefits. In fact, the government agents' behavior is a function restricted by those components that were mentioned before. These factors were input as a binary type. A binary surface indicating late policies issued by government was created.

Combination of the Agents

Three main agents in formats of developer agents, resident agents and government agents were created, also the potential behaviors of those agents were considered. Each agent type was modeled separately to consider possible behaviors and actions. According to the previous definition of agents, agents have internal interaction between themselves as well as external interaction between other existing agents (Benenson, 2004; Li, 2007).

Thus, in this research the interaction between agents had to be considered by agents' combination. The possible interactions between agents were taken into account, besides the change demand factor was also another variable which has control over the final output. In other words, the agent combination will produce a potential map of change that has to be coordinated with the change demand. Change demand was already calculated through a Markov model. This method was applied to obtain predicted land use maps of 2016 and 2026. The potential cells for change were chosen and converted according to the change demand through a Cellular Automata function.

RESULTS

All possible behaviors of resident agents were taken into account to maximize the efficiency of the model. It was aimed to maximize the accuracy of change allocation model. Fuzzification of existing factors was another approach that has been carried out to adopt the critical points of each factor to treat in a different way. Thus, applying fuzzy membership functions seemed to be innovative. Certain thresholds were applied for multiple factors which were mentioned before. The other important approach was to weight each variable based on its importance. These weights were manipulated by the AHP method. It was mandatory to assure the value of the consistency ratio does not exceed more than 0.1 which verifies the accuracy of weighting (Saaty, 1980).

The extracted weights were taken into account in the overlay process; therefore, a categorical probability surface was produced that identifies the preferable locations for residency. The produced probability surface map demonstrates the most preferable area for settlement by resident agents. Government agents are the final decision makers that can either approve applications or reject them and prohibit any construction. A function was designed to acquire their output. These factors were input as a binary type.

The interaction between agents had to be considered by agents' combination. Accordingly, some actions and decisions will be in conflict with other agents' favorites. Hence, an overlay function comprising some rules was designed. The overlay function was in charge to run the module as long as reaching the change demand variable. Consequently, the agent combination process produced a potential map of change. Change demand was already calculated by Markov model. The retrieved amount was applied to obtain predicted land use maps of 2016 and 2026. The simulated land use maps of 2016 and 2026 are illustrated in figures 5 and 6.

Although, there is no evidence of future to compare the achieved maps with the reality, a visual interpretation can be beneficial to challenge the output maps. As it is illustrated in the maps, the expansion intends to fill the gap cells in the vicinity of city core in 2016, i.e. it has not been predicted to observe considerable changes out of city core. However, it has been predicted to observe more changes in surrounding area in 2026.

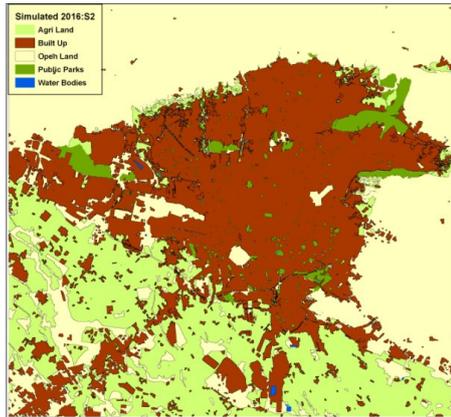


Figure 5: Simulated land use map of 2016

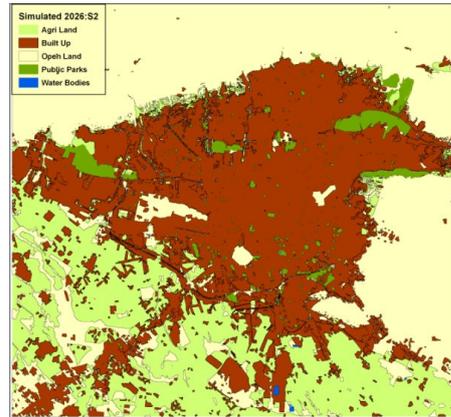


Figure 6: Simulated land use map of 2026

CONCLUSIONS AND DISCUSSIONS

The simulation of built-up development can afford helpful and valuable information about future land demands and landscape changes. However, cities are treated as complex systems that are complicated to characterize by means of mathematical equations (Li, 2007). There is a large and upward amount of researches over using “bottom-up” techniques to simulate urban areas. The major problem in using the CA models is to integrate the human, social and economic factors to incorporate in the simulation, which can be considered in ABM systems. Three major agents were classified to implement land change modeling through Multi Agent based modeling such as government agents, property developer agents, resident agents.

Each predefined agent had its own specific behavior and effect on land change matter. In other words, developer agents have their own concern to build new housings based on their financial benefits. Resident agents have their preferences to choose an area for life according to multiple preferred variables. It is considerable that developer agent has this influence to lead resident agents to choose their houses due to some financial points of view. Furthermore, the developer agents consider the appropriate circumstances which are in favor of resident agents in terms of easiness. Resident agents choose where to live in their preferred districts and to achieve their requirements. Thus, if the purchase and rent prices exceed their affordable threshold, they have to look for other places for residency. Therefore, property developers have to alter their investment policies and plans according to the residents’ purchasing behavior. However, the developers must get the appropriate approval from the government before any place converts. Government is the final decision maker who is able to approve the accuracy of site development by considering the environmental circumstances and internal policies.

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