Multi-agent Simulation for Modeling Urban Sprawl In the Greater Toronto Area

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Abstract: The use of Multi-agent Systems/Simulations (MAS) can help to represent human-environment interactions in dealing with complex land-use problems by examining how different entities influence the process of land development. In this paper, we simulate the urban growth of the Greater Toronto Area (GTA) from 1985 to 2005 using MAS. After analyzing the driving force in this area, three different types of agents are defined: residents, developers and government, in terms of their diverse characteristics in real society. Considering different even opposite demands of residents in residential development, we divide residents into two parts: new residents and existing residents. In the beginning of running this expansion model, we allocate the agents with a spatio-temporal criterion to obtain a better simulation. The preliminary result shows that multi-agent model has some advantages in simulating urban sprawl phenomenon.

Key Words: MAS; Simulation; Urban Sprawl; Land use; GTA

1. INTRODUCTION

Urban sprawl is one of the most important topics in urban studies. Simulation is regarded as an essential way to study sprawl phenomenon, and modeling urban system is helpful to understand the mechanisms of urban evolution, examine existing urban theories, and provide planning support in growth management. Involving complex processes, urban systems are usually difficult to be simulated well by traditional 'top-down' models. Some 'bottom-up' approaches, such as cellular automata (CA), and agent-based model (ABM), are adopted to the simulation (Couclelis, 1997; Torrence, 2006). CA models are focused on landscapes and transitions, and there are some obvious limitations when facing the behaviors and decisions of individuals, such as residents, firms, employers, developers, planners, etc., which play important roles in urban dynamics. The limitations can be overcome by introducing Multi-agent Systems (MAS), which focus on human actions.

MAS has been widely employed to represent individual decision-making in social science research (Gilbert, 1995), and then it is applied to land use and urban modeling (Parker et al., 2002; Bousquet and Le Page, 2004). In urban modeling, MAS is introduced to micro-simulate land use, combined with environment, transport, and other economic models to build complicated urban systems, such as UrbanSim (Waddell et al., 2003), ILUTE (Miller et al., 2004), PUMA (Ettema et al., 2005), ILUMASS (Wagner and Wegener, 2007). These models are very data demanding and specifying realistic agent diversity and behavior is challenging (Verburg, 2006). There is no doubt, however, micro-simulation improves the reliability and accuracy of urban simulation models.

MAS can be used to simulate individuals in a human system interacting with environment to understand urban sprawl (Li, 2005; Monticino et al., 2007; Kou et al., 2008). Various development scenarios based on modeling multi-actor decision-making are explicated for municipal policy makers

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to analyze in a spatial planning process (Li, 2005; Ligmann-Zielinska and Jankowski, 2007). As population growth is the main engines of change in urban sprawl (Torrens, 2006), it is important to model residential dynamic. New residents, including immigrants, have strong demands for their living places. There are many papers about residential preference and choice location (e.g., Benenson, 1998; Otter, 2001; Semboloni, 2005; Brown and Robinson, 2006; Filatova et al., 2007; Li and Liu, 2008). While for existing residents, especially these who live in suburb area, not like new residents with strong living space demanding, they are likely to protest some development proposals when they are actively involved in urban planning. In fact public participation has a big influence when government making the final decision in urban planning especially in developed countries (Fagence, 1977; Innes and Booher, 2000; Monticino et al., 2006).

In the paper, we divide residents into two parts, new and existing residents, interacting with developer, government agents, and nature system to understand urban sprawl phenomenon. So there are mainly two components in the simulation. One is an agent-based model that describes the decision-making of the key individuals in urban system. The other is the environment over which individuals make decisions. The rest of the paper is structured as follows. Information about data is given in section 2. Section 3 explains the methodology in detail. Section 4 describes the spatio-temporal criterion of agents allocation, and discusses the simulation results. Conclusion is given in section 5.

2. STUDY AREA AND DATA DESCRIPTION

This study area is the Greater Toronto Area (GTA), being located in southern Ontario, Canada, and covers an area of approximately 7,125 km^2. It includes the city of Toronto and four regional municipalities: York, Peel, Halton and Durham (Wikipedia, 2009). There has been a rapid urban sprawl and change of land use in GTA over the past few decades, mainly due to the increasing population to 5,555912 in 2006 census, while the Toronto Census Metropolitan Area (CMA), which is 17% smaller in land area than the GTA planning area, had a population of only 3,733,085 in 1986 census (Wikipedia, 2009).

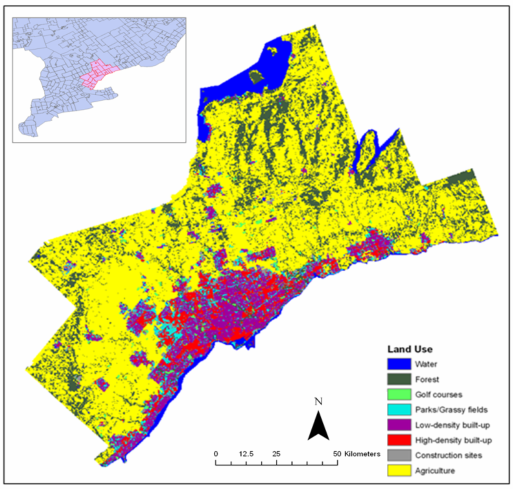


Fig.1. Study area and land use classification in 1985.

Landuse maps of the GTA were derived from classification of three Landsat TM images from 1985 1995, and 2005 respectively. The major types of land cover include: water, forest, golf courses, parks/pasture, low-density built-up areas (LDB), high-density built-up areas (HDB), construction and agriculture (Furberg and Ban, 2008), see Fig. 1. In our simulation, LDB, HDB and construction sites were combined into urban land area, while golf courses and parks/grassy fields were combined into green land for simplification. It is assumed that the land use maps are error-free. Other spatial data are also collected including the maps of transportation network, DEM data, and the distribution of public facilities.

3. METHODOLOGY

The simplified model we present here was developed with three types of agents, i.e. residents (new and existing), developers, and government, who exist on a heterogeneous two dimensional environment.

3.1. Environment

We represent geographic space with a two dimensional square lattice (grid). The results presented below all take place on a 1380 by 1380 lattice and each cell is interpreted as 100 by 100 meters, after resampling original classification maps. Each cell on the landscape has several exogenous characteristics: land use type, nature quality, terrain. Land use type is one of the most important factors in the simulation. Agents have different decision behaviors related to different land use types. People prefer to live in a location close to nature. Here we calculate it with two indicators: the percentage of green land and forest in the neighborhood, and the proximity to water (Li and Liu, 2008). Terrain here mainly refers to elevation. Although some residents like to live in a place with slightly above average elevation to have better views, area with low slope is more welcome because it could save developer construction costs.

Besides, each cell has the attributes of accessibility and public services. Accessibility can be viewed as the ability to access one place. Usually, a place can be accessed by streets, highways, and railways. So we compute Euclidean distances from each cell to all three transportation networks and sum them to get the final accessibility. It is also quite understandable that the sites would be more attractive if they are near communal facilities, such as parks, hospitals, schools, and commercial centers of course.

3.2. Multi-agent model

The model consists of three classes of agents: residents, developers and government. There are two kinds of residents: new residents and existing residents. At the beginning, new residents seek for their living places. Developer agents receive their requests, considering the profits as well, and then send a development proposal to government and existing residents who live near the development area. Government will make the final decision after considering the existing residents’ protest. Before the next iteration, the land use type changes and this will influence the next new residents’ choices. See Fig. 2.

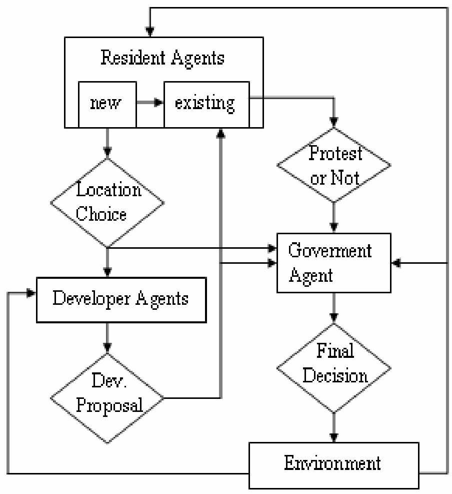


Fig.2. Model decision and information flow.

3.2.1. Resident agents

For new residents, a utility function is defined to evaluate a potential living place. The utility function of location (i,j) for resident agent can be presented as follows:

$P_{NR} = k_A E_A + k_{NQ} E_{NQ} + k_F E_F + \varepsilon$, where E_A, E_{NQ}, E_F are the factors of accessibility, natural quality, and other facilities. The parameters of k_A, k_{NQ}, k_F are the preferences of residential location behavior for each factor, and ε is random term.

For existing residents, they decide whether to protest the proposed development near their home. It's not a simple process. They will evaluate the consequence of a proposed development on their home value. Perceived environmental effect of land use change and many other aspects will be also considered. Here we simplify the model and suppose people don't like their neighborhood to be developed because people intend to live in a low density zone (Rand et al., 2002). Existing residents' protest can be calculated by counting existing residents around the proposed place with a 3×3 window. We count the number of existing residents around the proposed place (i,j) as N_{ij} within a 3×3 window. Then existing residents' protest can be calculated as: $P_{ER} = N_{ij}^{-1}$.

3.2.2. Developer agents

Urban developers always aim at much more profit from the market. However some detailed data, such as housing price, development cost and etc, is hard to obtain. Many developers actually tend to select the areas with existing residents because of lower developing risk for their investment. So the developing probability for developer agent can be simply calculated by counting the density of already developed cells in the neighborhood of a 5×5 window. Elevation is also considered by developers (Watson, 2006). Then we get the development probability from developer agent's view:

$P_{DEV} = \frac{N_{ij}}{5 \times 5} E_T$, where N_{ij} is the number of already developed cells; E_T is the inverse of altitude change rate at each cell.

3.2.3. Government agent

Government agent will decide whether an application for land development is approved or not, according to a number of factors. Firstly, some types of land use are forbidden to transfer, such as water. In our model, urban area can not be changed either for simplification. Here we define the constraint as the function F_{CON}. Secondly, approval probability is also related to master plan. Here we can't get plan maps, but we can calculate the percentage of each land use type that translate into developed urban area with two given classified images from 1985 and 1995 respectively. We use this transition probability as initial approval probability for government and define it as P_{ACCEPT}. So government's decision is presented as: $P_{GOV} = P_{ACCEPT} F_{CON}$. Besides, government should consider the existing residents who live near the potential development area. Demand of new residents and proposal of developers are also considered by government agent. As the final decision-making institute in the model, Government will decide whether to approve or deny the development proposal. Therefore, the probability of a location to be chosen can be expressed as: $P = k_{NR} P_{NR} + k_{ER} P_{ER} + k_{DEV} P_{DEV} + k_{GOV} P_{GOV}$.

4. RESULTS AND DISCUSSION

First of all, determine the total number of new resident agents according to the actual amount of urban sprawl in 1985-2005. It's assumed that each new urbanized cell accommodates on a resident agent, and one agent represents a number of residents. We have population data from Statistics Canada, Censuses, and urban area data by counting urbanized cells from classifications of 1985 and 2005 Landsat images. According to a modified Tietenberg model (Yeh and Li, 1998), optimized land consumption for each period (5 years) is calculated. Same weights are used in each equation for simplification since there is no prior knowledge. The simulation result shows that Toronto area is under simulated while York area is over simulated too much. Then we modify the allocation and consider GTA regions separately when assigning agents. See table 1. The final simulation result is shown in Fig. 3.

Table 1. Land consumption for different regions in different periods.

	Population growth				Land consumption (cell number)			
	85-90	90-95	95-00	00-05	85-90	90-95	95-00	00-05
Toronto	83,050	109,650	96,073	21,787	1431	1872	1656	387
Halton	41,751	26,739	35,354	64,027	2250	1440	1899	3447
Peel	140,629	119,728	136,422	170,457	4995	4257	4851	6057
York	154,379	87,464	136,809	163,458	6633	3762	5886	7029
Durham	82,891	49,546	48,285	54,357	3177	1899	1845	2079

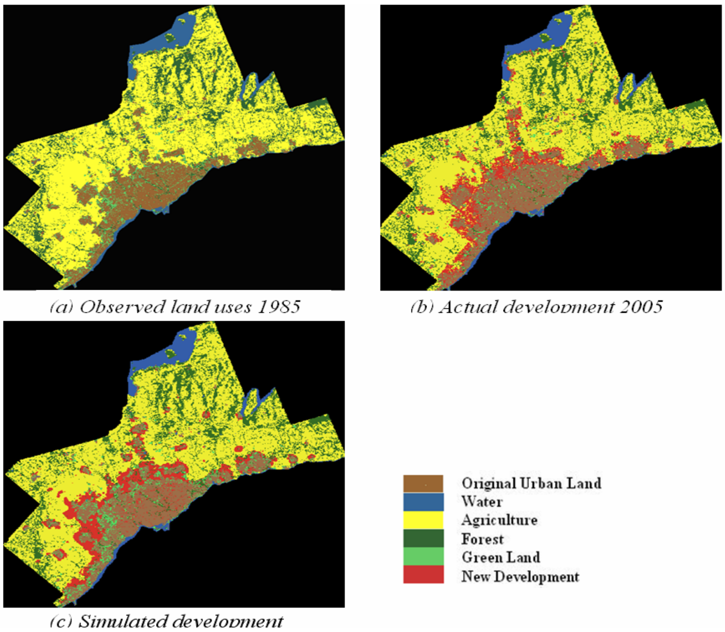


Fig.3. Urban growth simulation from year 1985 to 2005. Simulated development is also 2005.

In urban studies, the reality can not be reproduced in a laboratory, at least in the most cases (Semboloni, 2004). However, we can still evaluate the model in contrast with actual development. Cell-by-cell comparison is used here to evaluate the simulation against the landuse classification from 2005. For error matrix calculation, the land use classification is reduced to just two classes of developed area and undeveloped area. The total accuracy is 91.4%. More information is shown in Fig.4.

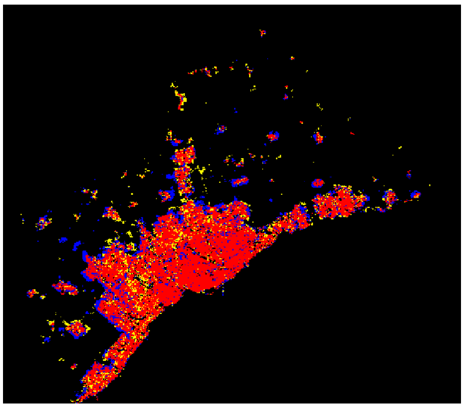
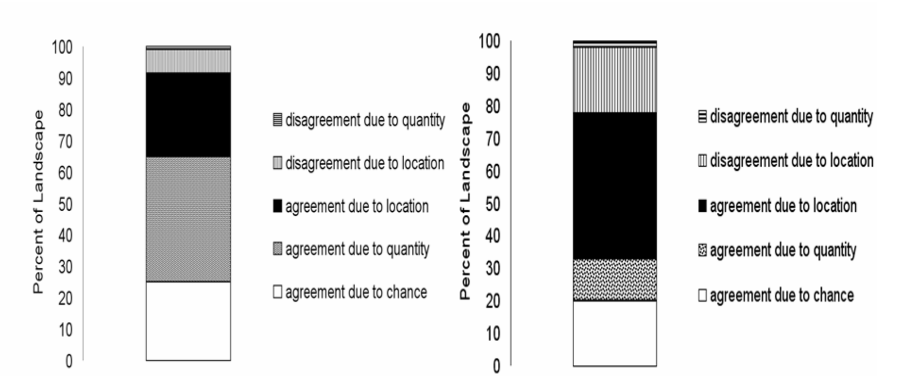


Fig.4. Comparison between simulated and actual urban area in 2005. Red areas are urban in both simulated and actual maps, while yellow areas are under simulated, which means they are urban areas in actual map but not appear in our simulated map, and blue areas are over simulated.

Then we compare maps with the quantity and location of cells in each class (Pontius and Millones, 2008). Quantity disagreement and location disagreement for map comparison is adopted to evaluation the simulation result according to PontiusMatrix1.xls instead of kappa coefficients. There are only two categories in Fig.9 (a), developed area and undeveloped area, and the agreement is quite high. However if we calculate five categories: urban area, water, agriculture, forest and green land, agreement is not so good. See Fig.9 (b). That's partly because: (1) Our assumption is not correct, actually existing urban area and water area still change; (2) We didn't consider the changes among agriculture, forest, and greed land in our model.



(a) (b)

Fig.5. Disagreement due to quantity and location.

Because there's a lack of detailed social and economic data, it's difficult to define agents' properties and divide them into more accurate types. Besides, preference of each type of agents needs to be modified. More agents will be added in the future, such as firm, because we can't ignore residents' employments, when considering residential location choice.

5. CONCLUSION

As a 'bottom-up' approach, MAS provides a useful tool for simulating and analyzing urban systems. It can simulate individuals in human society and represent the complex interactions between individuals and environment which influence and shape urban morphology. Using GTA as a study area, we simulate the urban land use change from 1985 to 2005. Three main classes of agents are defined in the model: resident agents, developer agents and government agent. Different types of agents interact with each other and affect the environment in the whole simulation process. Meanwhile, changes of environment will also dynamically affect the behaviors of agents. In order to get a better result, we use a spatio-temporal criterion to allocate agents. Compared with actual urban growth based on satellite data, the simulated result shows multi-agent model is effective in simulating urban sprawl phenomenon with approximately 90% agreement of developed and undeveloped areas between the simulation result and the landuse map from 2005.

Reference

Benenson, I., 1998. Multiagent simulations of residential dynamics in the city. Computers, Environment and Urban Systems, 22 (1): 25-42.

Bousquet, F. and Le Page, C., 2004. Multi-agent simulations and ecosystem management: a review. Ecol. Modelling 176:313-332.

Brown, D.G. and Robinson, D.T., 2006. Effects of heterogeneity in residential preferences on an agent-based model of urban sprawl. Ecology and Society 11 (1), 46.

Couclelis, H., 1997. From cellular automata to urban models: new principles for model development and implementation. Environment and Planning B 24, 165-174.

Ettema, D., de Jong, K., Timmermans, H., Bakema, A., 2005. PUMA multi agent modelling of urban systems. In: 45th Congress of the European Regional Science Association, Vrije Universiteit Amsterdam.

Fagence, M., 1977. Citizen participation in planning. Oxford, UK: Pergamon.

Filatova, T., Parker, D.C., and van der Veen, A., 2007. Agent-Based Land Markets: Heterogeneous Agents, Land Prices and Urban Land Use Change. Proceedings of the 4th Conference of the European Social Simulation Association (ESSA'07), Toulouse, France.

Furberg, D. and Ban, Y., 2008. Satellite Monitoring of Urban Sprawl and Assessing the Impact of Land Cover Changes in the Greater Toronto Area. The International Archives of The Photogrammetry, Remote Sensing and Spatial Information Sciences, ISPRS Congress Beijing 2008. WG VIII/1: Human Settlements and Impact Analysis, 131-136.

Gilbert, N., Conte, R., 1995. Artificial Societies: The Computer Simulation of Social Life. UCL Press.

Innes, J.E. and Booher, D.E., 2000. Public Participation in Planning: New Strategies for the 21st Century. Institute of Urban & Regional Development. IURD Working Paper Series. Paper WP-2000-07.

Kou, X., Yang, L., Cai, L., 2008. Artificial Urban Planning: Application of MAS in Urban Planning Education. 2008 International Symposium on Computational Intelligence and Design, 349-353.

Li, A., 2005. Exploring Complexity in a Human-Environment System: An Agent-Based Spatial Model for Multidisciplinary and Multiscale Integration. Annals of the Association of American Geographers, 95 (1).

Li, X. and Liu, X., 2008. Embedding sustainable development strategies in agent-based models for use as a planning tool. International Journal of Geographical Information Science, Vol. 22, No. 1, January 2008, 21-45.

Ligmann-Zielinska, A., Jankowski, P., 2007. Agent-based models as laboratories for spatially explicit planning policies. Environment and Planning B: Planning and Design 34, 316-335.

Miller, J.E., Hunt, D.J, Abraham, J.E., and Salvini, P.A., 2004. Microsimulating urban systems. Computers, Environment and Urban Systems 28:9-44.

Monticino, M., Acevedo, M., Callicott, B., Cogdill, T., Lindquist, C., 2007. Coupled human and natural systems: A multi-agent-based approach. Environmental Modelling & Software 22, 656-663.

Otter, H.S., van der Veen, A., Vriend, H.J., 2001. ABLOoM: Location behavior, spatial patterns, and agent-based modelling. Journal of Artificial Societiesand Social Simulation, 4 (4), published online.

Parker, D.C., Manson, S.M., Janssen, M.A., Hoffmann, M.J. and Deadman, P., 2002. Multi-agent systems for the simulation of land-use and land-cover change: a review. Annals of the Association of American Geographers 93 (2):316-340.

Pontius Jr., R.G. and Millones, M., 2008. Problems and solutions for kappa-based indices of agreement. Studying, Modeling and Sense Making of Planet Earth, Mytilene, Greece.

Semboloni, F., 2005. Multi-agents simulation of urban dynamic. Proceedings of XII CUPUM. Ed. London.

Torrens, P.M., 2006. Simulating Sprawl. Annals of the Association of American Geographers, 96 (2), 248-275.

Verburg, P.H., 2006. Simulating feedbacks in land use and land cover change models. Landscape Ecology, 21: 1171-1183.

Waddell, P., Borning, A., Noth, M., Freier, N., Becke, M., and Ulfarsson, G., 2003. Microsimulation of Urban Development and Location Choices: Design and Implementation of UrbanSim, Networks and Spatial Economics, vol. 3, no. 1, pp. 43-67.

Wagner, P. and Wegener, M., 2007. Urban Land Use, Transport and Environment Models. DISP, 2007, 170, 3, 45-56.

Watson, B., 2006. Modeling land use with urban simulation. In SIGGRAPH ’06: ACM SIGGRAPH 2006 Courses, pages 185-251, New York, NY, USA. ACM Press.

Wikipedia, 2009. “Greater Toronto Area.” Accessed 1 March 2009: http://en.wikipedia.org/wiki/Greater_Toronto_Area.

Yeh, A.G.O. and Li, X., 1998. Sustainable land development model for rapid growth areas using GIS. International Journal of Geographical Information Science, 12 (2), 169-189.