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ABSTRACT

The agent-based modelling (ABM) is commonly used to simulate urban land growth. A key challenge of ABM for the simulation of urban land-use dynamics in support of sustainable urban management is to understand and model how human individuals make and develop their location decisions that then shape urban land-use patterns. To investigate this issue, we focus on modelling the agent learning process in residential location decision-making process, to represent individuals' personal and interpersonal experience learning during their decision-making. We have constructed an extended reinforcement learning model to represent the human agents' learning when they make location decisions. Consequently, we propose and have developed a new agent-based procedure for residential land growth simulation that incorporates an agent learning model, an agent decision-making model, a land use conversion model, and the impacts of urban land zoning and the developers' desires. The proposed procedure was first tested by using hypothetical data. Then the model was used for a simulation of the urban residential land growth in the city of Nanjing, China. By validating the model against empirical data, the results showed that adding agent learning model contributed to the representation of the agent's adaptive location decision-making and the improvement of the model's simulation power to a certain extent. The agent-based procedure with the agent learning model embedded is applicable to studying the formulation of urban development policies and testing the responses of individuals to these policies.

1. Introduction

The process of urban land growth is one that has shaped, and continues to impact, both human society and nature in an irreversible way. According to Nobel laureate Joseph Stiglitz in 2001, both understanding the urban transition and improving information technology will be the two key factors that will affect human progress in the twenty-first century (Seto & Fragkias, 2005). In China, where urbanization is still one of the major means to boost economy, the complexity of the urban growth, the incoordination between population urbanization and land urbanization, combined with the lack of comprehensive urban land use planning, has increased the pressure on planners and caused disorder in urban land management, threatening the region's sustainability. A survey of the seventeen cities in eastern China showed that, from 1990 to 2010, < 70% of urban growth was consistent with urban land use plan in most cities with the lowest only 40.6% (Li et al., 2015). The difference between urban land growth and what is described in the premier urban land use plan is indicative of the change of urban development drivers from macro-control to mixed macro-micro in China. Meanwhile, the World Bank's report on “Mind, Society and Behaviour” (Worldbank, 2015) also explicitly acknowledges the importance of capturing the most advanced understanding of how humans think and how context shapes thinking for the design and implementation of policies. Both of them highlight an urgent need for deeply understanding and modelling human location behavior to support the urban growth simulation modelling as a tool of urban land use planning.

In a growing volume of literature, agent-based modelling (ABM)

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approaches have been applied to construct models and have made achievements for the simulation of urban land-use change (Clarke, 2014; O'Sullivan, Millington, Perry, & Wainwright, 2012). It is due to the fact that ABMs allow researchers to explore the relationships between micro-level individual decision-making and the emergent macro-level phenomena (Batty, Crooks, See, & Heppenstall, 2012; Li & Liu, 2008; Matthews, Gilbert, Roach, Polhill, & Gotts, 2007; Miller, Hunt, Abraham, & Salvini, 2004; Sun & Müller, 2013; Verburg, 2006). A number of studies have demonstrated that the appropriate inclusion of human decision-making in agent-based geo-simulation models is of fundamental importance (Filatova, Verburg, Parker, & Stannard, 2013; Groeneveld et al., 2017; Le, Seidl, & Scholz, 2012; Müller et al., 2013; Parker, Hessl, & Davis, 2008; Schlüter et al., 2017). However, comprehensive descriptions of the human decision-making process have not been a focal point of scholarly research on agent-based land use change modelling until relatively recently (Müller et al., 2013). Particularly, as a typical social interaction within human system, learning processes, as parts of or precursors to decision making, of real world decision makers have been poorly represented (An, 2012; Bousquet & Le Page, 2004; Groeneveld et al., 2017).

Aiming to construct a sound human decision-making model, we intend to construct an agent learning model and include it into an agent's decision-making model in ABMs for residential land growth simulation. Given learning is inherently crucial for understanding the adaptation of human agents' decision-making, there has been some work endeavouring to model agent's learning in ABMs for ecological and geographical simulations (e.g. An, 2012; Bennett & Tang, 2006; Bone & Dragicevic, 2010a, 2010b; Bone, Dragicevic, & White, 2011; Grimm et al., 2010; Le et al., 2012; Li et al., 2015; Morales, Fortin, Frair, & Merrill, 2005; Müller et al., 2013; Tang & Bennett, 2010). Particularly, in the update of ODD protocol, which was proposed as a standard protocol for describing agent-based models, Grimm et al. (2010) added two design concepts including basic principles and learning. Furthermore, Müller et al. (2013) extended the content of agent's learning in the ODD + D protocol which is an extension of ODD protocol. However, answering how individuals change their location decisions over time as a consequence of learning still has major shortcomings (Bousquet & Le Page, 2004; Le et al., 2012; Li et al., 2015).

First, although modelling agent's learning can play an important role in fostering understanding of the dynamics of agent's location decision-making (An, 2012; Bennett & Tang, 2006; Bone et al., 2011; Le et al., 2012; Li et al., 2015; Tang & Bennett, 2010), a systematic approach for analyzing and incorporating learning mechanisms in land-use systems that guides the modelling of land-use change is lacking. The learning behavior within human system, which is focused more in social, economic, and psychosocial studies, has not been fully explored in the context of geo-simulation (Filatova et al., 2013; Li et al., 2015; Meyfroidt, 2013). Furthermore, how agents learn from their past decisions regarding the landscape is more often studied rather than how agents learn from one another (recent work including Bone & Dragicevic, 2010a, 2010b, Bone et al., 2011). Second, in most of the ABMs for geo-simulation which consider agent's learning, collective learning, which has been nourished by machine learning algorithms (e.g. Bennett & Tang, 2006; Bone et al., 2011; Bone & Dragicevic, 2010a, 2010b; Bousquet & Le Page, 2004; Tang, 2008), is often simulated to a much higher degree than individual-level learning in the coupled human-environmental system. Relatively few models for geo-simulation (such as Bennett & Tang, 2006, Morales et al., 2005, Bone & Dragicevic, 2010a, 2010b, Bone et al., 2011) explicitly incorporate agent's learning mechanism at the individual-level in ABMs for geo-simulation. Modelling agent's learning on the population level simplifies things, whereas neglecting details at the individual level comes at with the risk that learning process details at this level may indeed matter, which could lead to flawed predictions (Brenner, 2006). Third, the application of explicitly spatial learning models to modelling adaptations in an agent's decision-making in real-world ecological and geographical systems is still in its initial stage (An, 2012; Tang & Bennett, 2010). In related studies, agents compare and imitate land-use practices, residential location practices and products (usually a few discrete choices) or adopt an innovation adopted by their neighbors or peers to reduce risk and obtain a higher reward or benefit (e.g. Benenson, Hatna, & Or, 2009; Benenson, Omer, & Hatna, 2002; Caillault et al., 2013; Chen, Li, Wang, & Liu, 2012; Dung, Vinh, Tuan, & Bousquet, 2005; Gotts & Polhill, 2009; Le et al., 2012; Manson, 2006; Monticino, Acevedo, Callicott, Cogdill, & Lindquist, 2007; Sun & Müller, 2013). In most of these models, agent learning is discussed and modelled implicitly in the agent's decision-making models. Computational approaches for individual-level agent's learning are infrequent in ABMs for geo-simulation, which may be partly due to that relatively few land-change models actively consider theories of human behavior (Groeneveld et al., 2017; Irwin & Geoghegan, 2001; Manson, 2006). Researchers consider that modelling an agent's learning explicitly and at various levels will contribute to the model's quality and an increase in confidence for the model's users to simulate spatial phenomena by using ABM (An, 2012; Claessens, Schoorl, Verburg, Geraedts, & Veldkamp, 2009; Le et al., 2012; Li et al., 2015; Meyfroidt, 2013).

Therefore, we intend to construct an individual-level learning model to represent both the interpersonal and intrapersonal learning process at individual level and include it into an agent's decision-making model and an ABM for residential land growth simulation. We assume that agent-based residential land growth models intend to model residents' behavior as realistically as possible, in order to support deep understanding of urban development and people-oriented urban land use planning. As a consequence, our model is based on research in psychology because psychologists have established most of the actual knowledge about human learning. As Brenner (2006) mentioned that, since 1950s, psychologist have concentrated on the processes of cognitive learning, meaning that the concept of reinforcement learning, in which self-experience learning is emphasized, was transferred to interactions and observation. Whereas, cognitive learning processes in the form of equations are relatively rare given its complexity (Brenner, 2006). Thus, we intend to extend reinforcement learning (RL) model so that not only agent's learning from personal experience, but also agent's learning from one another can be depicted. We opted to extend a computational RL algorithm by Roth and Erev (1995), which has been extensively studied and successfully used in the field of economics (see review by Brenner (2006)) as they utilize a similar essential process to develop strategy decision-making by obtaining and utilizing knowledge. Then, we define a hybrid utility function by combining the agent's learning result with a land utility function, which is used in agent's location decision-making model. Consequently, we propose an agent-based procedure for residential land growth simulation by incorporating a hybrid utility function, a discrete location choice model and a land use conversion model. The proposed agent-based procedure was tested by application in a residential land growth simulation in our study area, and the experiment results were analyzed and discussed followed by a discussion of issues for future research.

2. Methods

The framework shown in Fig. 1, with reference to the framework proposed by Li et al. (2015), illustrates our procedure for residential land growth simulation. A household agent (HA) in this study is defined as an entity with a desire to locate or relocate the place of residence. An HA has his own attributes, learning ability and preference to the biophysical environment (see Section 2.1 for detailed description). Land is the object of human action, and it provides the material environment to support HAs' behaviors. Land is represented as pixels which have their own attributes and states. Change in land use occurs as a result of change in the states of the pixels, which is not only directly associated with the HAs' location behavior, but also influenced by urban land use plans and policies and the developers' desire. We define a land unit that

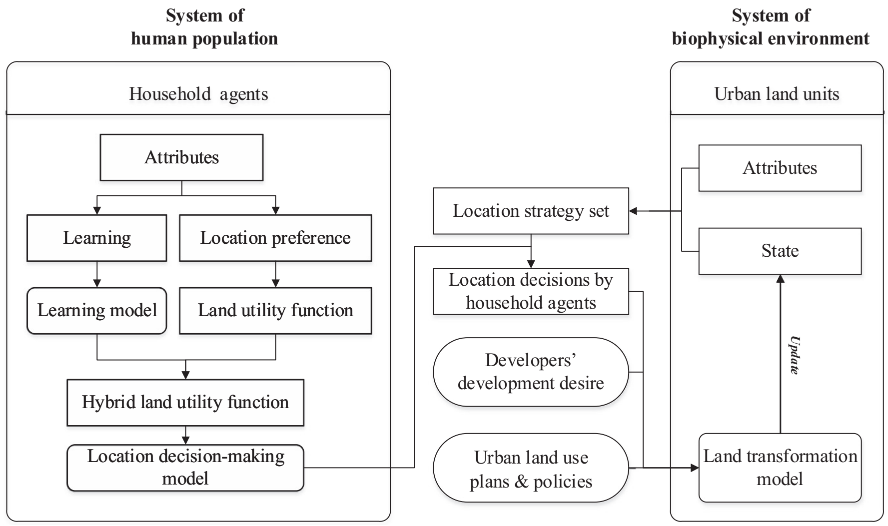


Fig. 1. The model framework.

is convertible at a certain scale as a location strategy for a household agent, when that agent makes location decision. The location strategies with similar attributes (such as similar accessibility, similar environmental quality, or similar distance to a CBD, etc.) or with the same level land utility value are defined as the like-location-strategies. The initial location strategy set is composed of all the convertible land units.

Three sequential sub-models are constructed to simulate three key sub processes in the HA-land interaction. They include *the agent learning sub-model*, *the agent decision-making sub-model*, *and the land use conversion sub-model*. In the procedure, *the agent learning sub-model* represents the process by which agents obtain knowledge from the past-experiences (both personal and interpersonal) within the human system for their location decision-making before they finally settle down. *The agent decision-making sub-model* indicates the process of agents' location selection by taking into account the agent's learning result, as well as the agents' preference for environmental conditions. *The land use conversion sub-model* aims to link the results of the agents' location decision and land-use type change, which accounts for the feedback of the biophysical environment on the individuals' behavior. These models are linked and processed in a sequential, nested, and systematic manner to demonstrate the essential process of human-induced alterations of the urban land system.

In the process of model running, the estimated number of household agents enters the modelling landscape and searches through the available pixels at each time step which is set to one year in the study. Each household agent finds a pixel that satisfies their requirements about housing location. Then, the land use type of the pixels selected by the household agents is converted or not based upon urban land use plans and the developers' development desire. Once the pixels selected by the HAs are marked for conversion, the household agents settle down and the states of the pixels are updated accordingly. The model then runs until all household agents settle in appropriate pixels.

2.1. The household agents and their decision-making

We define Eq. (1) to demonstrate how HAs make residential location decisions by using both their knowledge about the biophysical environment and prior experiences from the human system.

$$HA_{decision} = f\ (HA_{attributes}, HA_{locationPref}, HA_{learning}) \quad (1)$$

HAs' ability to make decision and to learn, and their location preference differ from one another due to their varied characteristics, thus, we define $HA_{attributes}$ to represent HAs' major characteristics which can be used to categorize HAs when needed. $HA_{attributes}$ contains a set of variables that present a household agent's characteristics. We define the household agents with similar attributes, such as similar family income, education level, or family structure as like-agents. We assume like-agents show similar preference to the environment conditions. Furthermore, like-agents are more likely to learn from each other when making location decisions.

We define $HA_{locationPref}$ as a land utility function that represents HAs' location preferences to the biophysical environment. Both a set of variables and a vector of preference coefficients are included in $HA_{locationPref}$. Accessibility, the conditions of environmental amenities, the public facilities (e.g. distance to CBD, distance to major medical institutions) and neighborhood educational resources are included in the land utility function, which are the major factors influencing HAs' location decision according to the China Real Estate Chamber of Commerce (2009) and Li et al. (2015).

Moreover, a learning function, $HA_{learning}$ is utilized to capture how HAs learn to develop their location decisions through the experiences learning among household agents. On the one hand, psychologist has concentrated on the impact of social interaction and observation on learning since 1950s, in which the basic argument was that people do not only learn from their own experience but also from the experience of others (Brenner, 2006). On the other hand, according to the results of an investigation on house purchase behavior in Beijing, Guangzhou and Tianjin in 2009 by the China Real Estate Chamber of Commerce (2009) and Li et al. (2015), 75.9% of the house purchasers paid close attention to the estimates of available housing by Internet users as current homeowners. Both of them indicated that household agents refer to experience learning when making residential location decisions.

2.2. The model of agent learning

We employ and extend RL algorithm for depicting how HAs develop their location decision by interpersonal and intrapersonal learning. RL studies place focus on the impact of personal past-experiences on human decision-making, and the general consensus is that actions followed by good or bad outcomes have their tendency to be reselected altered accordingly – in other words an action may be repeated more frequently based upon positive outcomes and less frequently based upon negative outcomes (Sutton & Barto, 1998). On the one hand, RL algorithms have been discussed and validated to be suitable for modelling individual-level learning mechanism in geo-simulation (Bone & Dragicevic, 2010b; Tang, 2008). On the other hand, as psychologist have concentrated on the impact of social interaction and observation on learning since 1950s (Brenner, 2006), we argue that the basic idea that social interaction and observation impact learning can be incorporated by extending the RL algorithm. Hence, we extend RL model for depicting both the interpersonal experiences exchange and personal past-experiences learning. In the extended RL model, we assign a new computational equation to the payoff function and extend the to-be-reinforced location strategy set for simulating the HAs' learning in their location decision-making.

2.2.1. The Roth-Erev reinforcement learning algorithm

In the Roth-Erev RL algorithm (Roth & Erev, 1995), if an agent selects the *i*th strategy from the strategy set $\{a_1, a_2, \ldots, a_n\}$ at time $t-1$ and receives a payoff of $r(t)$, then the propensity to select strategy i by the agent at time t is updated by Eq. (2).

$$q^t(a_i) = \phi * q^{t-1}(a_i) + (1-\delta) * I(a_i, y) * r(t-1) \tag{2}$$

where $q^t(a_i)$ represent the propensity to select strategy a_i for an agent at time t, $\phi \in [0,1]$ is a forgetting parameter (or defined as recency parameter) which is used to reduce the importance of past experience gradually over time. $\delta \in [0,1]$ is an experimentation parameter which represents the influence of an unselected strategy. When its value exceeds 0, the influence of past experience is extended to those unselected strategies through learning function. The function $I(a_i, y)$ equals one if $a_i = y$ holds and equals zero otherwise, in which y is the strategy that other agents select. The payoff $r(t)$ is obtained by an agent if he chooses strategy a_i at time t.

2.2.2. An extended reinforcement learning algorithm

We extend the RL model by refining the payoff function $R_i^j(t)$ and extending the to-be-reinforced location strategy set. In the applications of RL models in economics research, the reward calculated by a utility function usually results in the enhancement of confidence in the selected strategy. Similarly, for the HA's location decision-making, we argue that when location strategy j (i.e. land unit j) is selected by an HA, the expected return by the like-agents from selecting its neighbors will be increased due to the similarity in the characteristics of neighbour pixels according to the first law of geography (Tobler, 1970). In this study, we assume that the reward when location strategy j is selected by an HA increases as the number of newly-selected location strategies increase in its neighborhood. Thus, the payoff function $R_i^j(t)$ is defined as the proportion of the number of newly-selected location strategies in the land-unit$_j$'s neighborhood represented by $n_{selected}(j)$ and the total number of available land units in the land-unit$_j$'s neighborhood depicted by N_{nei}, and it can be calculated by using Eq. (3). In the experiment conducted in our study area, the neighborhood scale is defined as a 21 pixels by 21 pixels window centered on land unit j with a pixel size of 50 m, which is a neighborhood of approximately 1 km by 1 km. In order to represent the randomness of HAs' location decisions and to avoid the status that it is hard for some newly-added location strategies to be selected and reinforced, $R_i^j(t)$ is set to be one-tenth of $1/N_{nei}$ when $n_{selected}(j)$ is equal to 0.

$$R_i^j(t) = (n_{selected}(j)/N_{nei}) * 100 \tag{3}$$

Furthermore, when a land unit is selected by an HA at iteration $t-1$, the to-be-reinforced location strategy set for the like-agents at iteration t is extended to its neighbors and like-location-strategies. We assume that the propensities for the like-agents to select its neighbors or the like-location-strategies will be increased, when a location strategy is selected by an HA. Here, all the selected location strategies by like-agents (including itself) at iteration $t-1$ are simplified to be equally treated by the HAs who tend to make decisions at iteration t. That is, personal experiences and the experiences of all like-agents about location decision are assumed to equally affect the HAs' location decision-making in the next iteration.

We define an attractiveness index (AI) for each location strategy to represent an HA's learning result, which changes in the iterations until a final decision is reached. When a land unit is selected by an HA at iteration $t-1$, its neighbors and like-location-strategies will be marked at iteration t whose AI values to like-agents will be increased. There are two cases for the calculation of AI value at each iteration: one is when location strategy j is selected by HA$_i$ at iteration $t-1$ and the other is when location strategy j is not selected by HA$_i$. In the first case, $A_i^j(t)$ value is defined as Eq. (4).

$$A_i^j(t) = \phi * A_i^j(t-1) + (1-\delta) * R_i^j(t) \tag{4}$$

where the meaning of ϕ and δ is the same as those defined in Eq. (2); the payoff function $R_i^j(t)$ represents the reward when HA$_i$ selects location strategy j at time t.

In the second case, when location strategy j is not selected by HA$_i$, the AI value of a location strategy is defined as Eq. (5).

$$A_i^j(t) = \phi^* A_i^j(t-1) + \frac{\delta * R_i^j(t)}{N_i(t) - 1} \tag{5}$$

where $N_i(t)$ is the number of location strategies available to HA$_i$ at time t.

We assume that all the location strategies show a similar attraction to the like-agents at the beginning of each time step, since HAs have no experiences at iteration $t = 0$. The initial AI value of location strategy j for HA$_i$ is calculated by Eq. (6).

$$A_i^j(0) = \frac{\kappa * \left(\sum_{i=1}^{M} R_i^j(0) \big/ M \right)}{n} \tag{6}$$

where n is the number of location strategies; M is the number of a certain type of household agent; κ is an initial strength parameter for HA$_i$; and $R_i^j(0)$ is the initial reward when HA$_i$ selects land unit j at iteration $t = 0$, we set its value as 1.

2.3. The model of agent decision-making with embedded agent learning

2.3.1. The traditional land utility function

In this study, we utilized a traditional land utility function to depict HAs' preference to the environment conditions, in which accessibility, the conditions of environmental amenities, the public facilities (e.g. distance to CBD, distance to major medical institutions) and neighborhood educational resources are considered according to an investigation by the China Real Estate Chamber of Commerce (2009) and Li et al. (2015). The investigation by the China Real Estate Chamber of Commerce (2009) indicated that residents in the cities of eastern China show the importance of accessibility, neighborhood education quality, environment quality and house price. Due to the difficulty of data acquisition, house price factor is not included directly in this study. To a certain extent, the house price factor can be represented by accessibility, the conditions of environmental amenities, neighborhood educational resources and the public facilities.

2.3.2. The hybrid land utility function

We define a hybrid land utility function by combining the traditional land utility and the agent's learning result about location decision, which is used for HAs to make location decisions. The hybrid land utility value of a land unit for an HA is calculated as a weighted linear combination by using Eq. (7) for summing up the HA's learning result and the preference to the environment factors.

$$U_i^j(t) = \alpha * \sum_{k=1}^{m} \omega_k * X_k + \beta * A_i^j(t) + \varepsilon_i^j, \sum_{k=1}^{m} \omega_k = 1, \alpha + \beta = 1 \tag{7}$$

where $U_i^j(t)$ is the hybrid land utility value of land unit j for HAi at time t; j indexes a specific land unit; i indexes a household agent; α is the weight of an HA's preference for the biophysical environment conditions, β is the weight of an HA's learning result; k indexes a specific variable X_k which represents an environment factor, and the value of variable X_k has been normalized to [0, 100]; m is the amount of variable X, and ω_k is the preference coefficient of X_k. [X_1, …X_4] delineates accessibility, the conditions of environmental amenities, the public facilities and neighborhood educational resources respectively in the following experiments. The uncertainty term ε_i^j is created by a random number generator and accounts for the uncertainties inherent in the HAs' decision-making.

2.3.3. The selection probability

The selection probability, which is the probability of a land unit to be selected by an HA, is calculated by using a discrete location choice model as given in Eq. (8):

$$P_i^j(t) = \left. exp(U_i^j(t)) \middle/ \sum_{j=1}^{n} exp(U_i^j(t)) \right., \sum_{j=1}^{n} P_i^j(t) = 1 \tag{8}$$

where $P_i^j(t)$ is the probability that agent i chooses land unit j; $U_i^j(t)$ is the hybrid utility value of the given land unit j, as perceived by the ith HA; and n is the total number of available land units.

The land conversion probability can be calculated and updated using a total probability formula (Eq. (9)), when we consider the HAs' location decisions alone:

$$P^j(t) = \left. \sum_{i=1}^{m} P_i^j(t) * P_i(t) \middle/ M \right. \tag{9}$$

where $P^j(t)$ is the land conversion probability of land unit j with the impact of location decisions of M HAs in one category; $P_i(t)$ is the probability of HA_i being involved in the land use decision. The value of $P_i(t)$ is set to be 1 because all the agents were assumed to participate in the location decision-making in this study.

2.4. The land use conversion model

2.4.1. Impact of urban land zoning and housing developers' desire

Land use conversions are influenced by various socio-economic plans and housing developers' desire. Urban land zoning is one of the prominent spatial plans for urban land use in China. It is the representation of the intentions and plans of local government for urban development. A variable $S \in \{0, 0.5, 1\}$ is defined to represent whether an available land unit is located in the planned urban development zone or not. S is set to 1 when the available land units are located in the planned urban development zone; S is set to 0 when the available land units are located in the strictly protected areas where development is restricted; otherwise, S is set to 0.5.

Additionally, new urban land formation is a direct consequence of housing developers' land development behavior, which is characterized by pursuing maximum profit and results in land use conversion directly. For purpose of simplification, we assume that developers intend to develop the land units close to the urban area and in the neighborhood of existing resident communities which are highly valued by the homeowners, as they can take full advantage of the existing ancillary facility (such as schools, public transportation, new sub-CBD etc.) as well as the predecessors' experience to reduce investment risk. Accordingly, we define a variable $D^j(t)$ to represent the housing developers' preference for the pre-existing beneficial status. $D^j(t)$ is represented by the percentage of residential land units in a fixed neighborhood of a convertible land unit, a window of 21 pixel by 21 pixel centered on land unit j with a pixel size of 50 m is used to calculate $D^j(t)$ in this study, which is a neighborhood of approximately 1 km by 1 km. $D^j(t)$ is set a value of one tenth of the reciprocal of the number of land units in the fixed neighborhood, when no residential land exists in the neighborhood.

2.4.2. Calculation of final land use conversion probability

We employ a multi-probability model to calculate the synthetic land conversion probability (Eq. (10)) considering the HAs' location decision, the impact of urban land zoning and the housing developers' desire:

$$T^j(t) = K^j(t) * P^j(t) * D^j(t) * S \tag{10}$$

where $K^j(t) \in [0,1]$ is the constraint of land use conversion, and its value is set to be 1 in this study; $T^j(t)$ is the final conversion probability of land unit j to residential land.

A vector can be formed with calculation of $T^j(t)$ for all available land units. We used a conditional stochastic model to determine whether a land unit is converted or not (Eq. (11)).

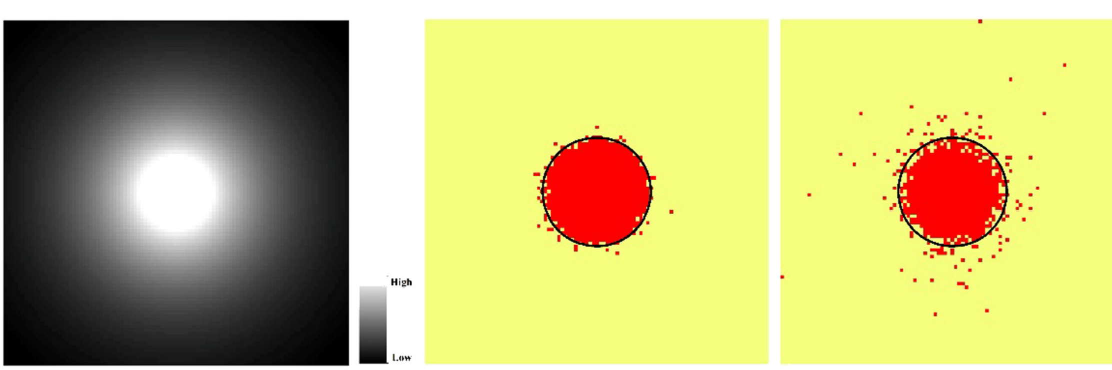
$$transform_j^{rz} = \begin{Bmatrix} true & if \quad q \le T_{jrz} \\ false & otherwise \end{Bmatrix} \tag{11}$$

where, $q \in [0,1]$ is a random number; T_{jrz} = max ($T^j(t)$); $transform_j^{rz}$ represents whether land unit j will be converted to residential land or not.

3. Model implementation and analysis of the results

3.1. Experiment with hypothetical data

We tested the proposed model by applying it to hypothetical data. We designed a scenario with a 101 pixels by 101 pixels artificial study area with the highest traditional land utility value (i.e. agent's learning result was not included) covering 798 pixels at the center of the study area (Fig. 2(a)). The traditional land utility values decreased linearly from the center to all directions. In the experiment, all pixels in the experiment area had the possibility of being converted. We allowed 800 household agents to make location decisions in the study area. HAs' decision-making with reference to traditional land utility values and with reference to our hybrid land utility values were simulated



a b c

Fig. 2. The procedure's application experiment with hypothetical data.
a Suitability value distribution; b simulation result without agent's learning model; c simulation result involving reinforcement learning model.

separately. At the beginning of the simulation, the household agents were randomly seeded with respect to location. At each iteration, parts of the HAs could be located, and those who could not settle down would enter the next iteration. The simulation was terminated when all the HAs were located.

In the simulation results, most of the newly-converted residential land units were those with relatively high traditional land utility value in both Fig. 2(b) and (c). 95% and 85% of the newly-converted residential land units were located in the area with highest traditional land utility value in Fig. 2(b) (traditional land utility values were used) and Fig. 2(c) (hybrid land utility values were used) respectively. The simulation result in Fig. 2(c) shows a little more dispersal around the high land utility value than in Fig. 2(b). On the one hand, the results indicated that both of the models could reflect the HAs' location decision-making process which is characterized by pursuing most suitable locations or locations with high utility value. On the other hand, in Fig. 2(c), the household agents were not all located in the spots with highest land utility value and some were dispersed around the area with highest utility value. It indicated that HAs' location decision-making is affected by the learning process. It conforms to the understanding that HAs often select the locations with relatively high land utility value rather than the optimal ones given that HAs possess limited computational resources and information on which to base decisions (Simon, 1997).

3.2. Application in the Nanjing residential land growth simulation

3.2.1. Study area and data

We applied the proposed model to the simulation of residential land growth in Nanjing, China during 2001–2007 to test the model. The city of Nanjing (Fig. 3) is located in the lower Yangtze River drainage basin (31°14′–32°17′N, 118°21′–119°14′E), and it is one of the important commercial and industrial cities in eastern China. The level of urbanization is above 80% with over 8.2 million permanent residents in 2014. Urban land use increased almost 14 times during 1949–2007, and urban land mainly extended in the North East and South West portions of the city along the Yangtze River (Li, Li, Liu, Liang, & Chen, 2007).

A region with an area of 600 km^2 located to the south of the Yangtze River was selected as the experiment area, as this is a region where much surrounding farmland has been developed and substantial changes to the landscape have occurred. The residential land distribution map of 2001 was used for the simulation of residential land growth during 2001–2007. We represented the study area using pixels with a resolution of 50 m. There are 239,384 pixels in the study area totally, in which 127,879 pixels are convertible considering the land use in 2001 and the urban land zoning. The distribution maps of the environment factors scores are shown in Fig. 4. The weights of the environment factors were computed using the analytic hierarchy process (AHP) method (Satty, 1980) and the entropy-weight method (He & Shang, 2017; Hou & Huang, 2010). The weight vector $\{W_a, W_e, W_p, W_{ed}\}$ is set as {0.2423, 0.2132, 0.2831, 0.2615} which represents the weight of accessibility, the weight of conditions of environmental amenities, the weight of public facilities, and the weight of neighborhood educational resources.

The number of HA participating in the simulation was set as 39,620, approximating the residential land growth scale (39,620 pixels) spanning 2001–2007. Given that young people were the principal migrants in the study area during the simulation period, no demographic categories were defined in the experiment for purpose of simplification. At each time step (one year), about 6603 household agents entered the simulation landscape. They were randomly seeded with respect to location and searched for pixels to settle down. The iterations were terminated when all the entering household agents were able to settle down in appropriate pixels.

We estimate the initial values of the model parameters by referencing the application of RL model in economic simulations, and we ran our model and then modify the initial values for these parameters. Ultimately, for this application, values of ϕ, δ and κ were set to 0.9, 0.4 and 1.0 respectively, which are the best fit values for residential land growth simulation in the study area.

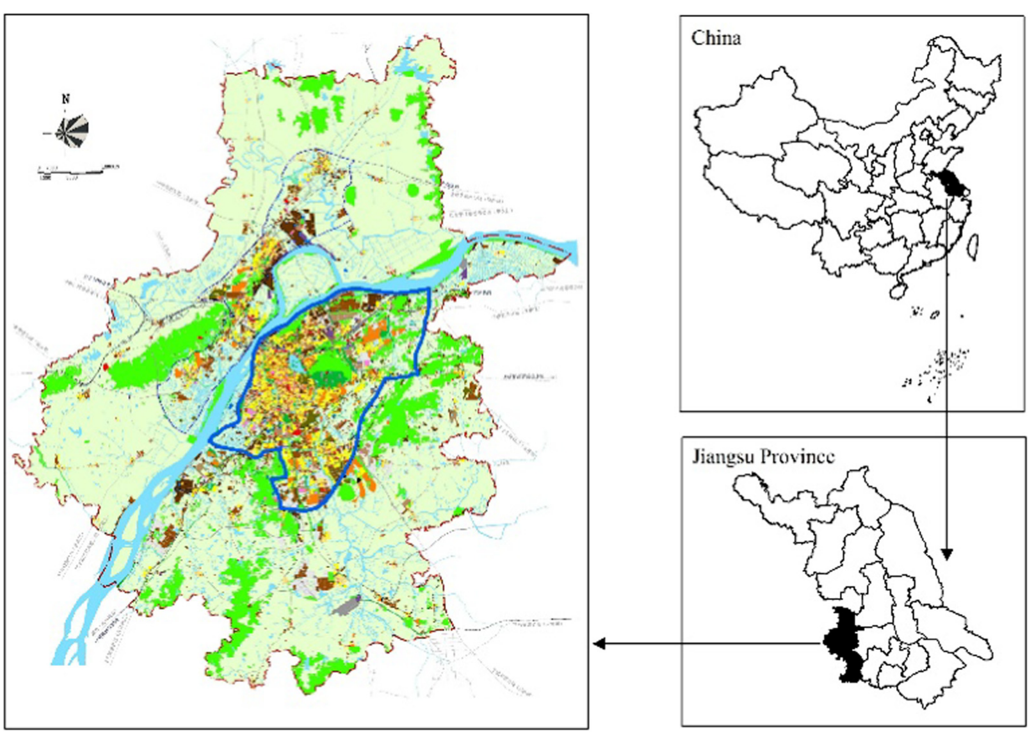
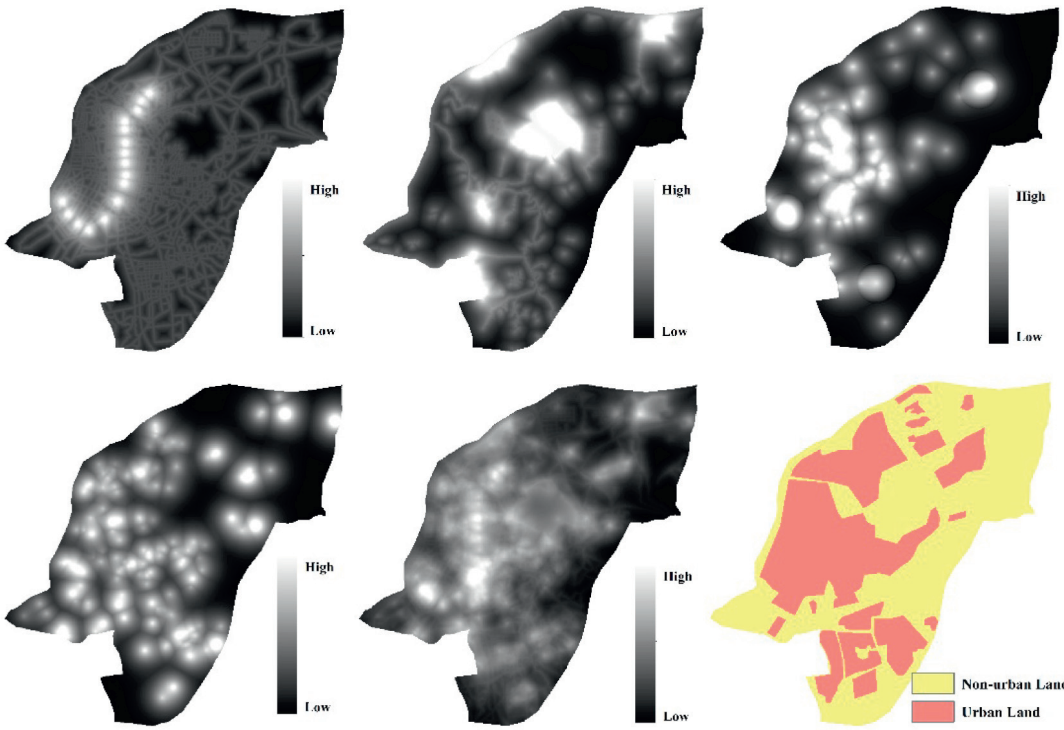


Fig. 3. Location of study area.
(a) Accessibility; (b) environmental amenity; (c) public facilities (considering CBD and hospital); (d) neighborhood education resources; (e) suitability value distribution; (f) urban land zoning.



(a) Accessibility; (b) environmental amenity; (c) public facilities (considering CBD and hospital); (d) neighborhood education resources; (e) suitability value distribution; (f) urban land zoning

Fig. 4. Assessment of the environmental conditions in the study area.

3.2.2. Experiment results and analysis

Two residential land growth simulation experiments were implemented in the study area. In the experiment 1, the land utility values were calculated by using accessibility factor only. In the experiment 2, accessibility, conditions of environmental amenities, public facilities, and neighborhood educational resources were considered in the land utility function.

(1) Experiment 1

In the experiment 1, results of a site-specific accuracy assessment reveal an accuracy of 44.33% for the simulation with embedded extended RL model, and 40.70% for the simulation without it. The site-specific assessment of the simulation results showed that the integration of the extended RL model is helpful for improving the predictive power of an ABM for residential land growth simulation. To evaluate the model performance further, the predicted pixels were categorized into perfect match, close match, and poor match with reference to the study by Dahal and Chow (2014). The perfect match category includes converted pixels in the predicted map that spatially agree with the developed area in the reference map. The close match indicates the converted pixels in the predicted map that are adjacent to or within a distance of 300 m from the developed pixels in the observed map. Any predicted pixels beyond this distance from the developed pixels in the reference map were categorized into the poor match group. A distance of 300 m is used in the study, given that 300 m $*$ 300 m is the normal residential land size that a land developer can get through *bid invitation, auction and listing system* in urban land transfer in Nanjing, China. The results showed that 86.63% of the predicted units in simulation experiment with the extended RL learning model embedded fell within a distance of 300 m from the developed sites in the reference data while 79.98% in the simulation experiment without it. It indicated that the including learning model affects HAs' location decision-making simulation, which contribute to the improvement of the model's simulation power.

(2) Experiment 2

Because of the stochasticity of our agent-based model, the two models (i.e. the model with learning model embedded and the model without learning model) were run one hundred times. Results of a site-specific accuracy assessment reveal an accuracy ranging from 69.9% to 70.4% for the simulations with embedded extended RL model and a range of 68.4% to 68.7% for the simulations without it. The site-specific assessment of the simulation results showed that the integration of the extended RL model is helpful for improving the predictive power of an ABM for residential land growth simulation. In the one hundred simulations, 85.8% of the convertible pixels have a conversion probability over 80%, while 90.2% of the convertible pixels have a conversion probability over 50% for the simulation results with the learning model embedded. The pixels with low conversion probability located at the edge of the simulated converted pixels.

A simulation result with 70.4% overall accuracy by using our procedure is analyzed in the study. The predicted residential land units were categorized into perfect match, close match, and poor match, and a spatial agreement map was created (Fig. 6). The results showed that > 90.4% of the converted pixels in the simulation fell within a distance of 300 m from the developed sites in the reference data (i.e. < 9.6% fell in the "poor match" category). Thus, we consider that the model performs adequately despite the fact that it has not a comparatively high overall accuracy.

To examine whether the model correctly predicted direction trends, we evaluated the spatial accuracy directionally in the eight principal compass directions (shown in Table 1). According to the statistics of newly developed pixels in the reference map and simulation results shown in Fig. 8 and Table 1, the residential land distribution maps of

Table 1
The spatial accuracy assessment in the eight principal compass directions of the model outputs.

Orientation	Perfect matched simulated pixels in Fig. 5.b	Newly-developed pixels in reference map	Accuracy for Fig. 5.b
E	2863	5765	49.66%
NE	3223	7793	41.36%
N	576	746	77.21%
NW	466	568	82.04%
W	384	568	67.61%
SW	3383	4616	73.29%
S	6277	11,249	55.80%
SE	3501	8315	42.10%

2007 showed a pattern of residential land expansion extending approximately along the Yangtze River (that is extending to both the East-Northeast and the South-Southwest) and from the existing urban areas to the South during 2001–2007. The accuracy of the spatial distributions also showed a relatively higher accuracy in these major urban expansion directions: East, Southwest, and Southeast in the simulation experiment with an embedded extended RL model as shown in Fig. 5(b) during 2001–2007. The directional statistics of the simulation results indicated that the simulated residential land growth pattern was in accordance with the actual residential land growth pattern in the study area.

According to the error distribution map (Fig. 7), 24.1% of the over-estimated error pixels were located in the south western area of the study area, while 51.6% of the under-estimated error pixels were located in the southern part of the study area. The over-estimated pixels are in the Hexi area, which is an early-developed new urban sub-CBD with relatively mature ancillary facilities (such as subway, elementary and middle schools, parks, etc.), thus showing higher attraction to the individuals when they make location or relocation decisions. In the meanwhile, the under-estimated zone is in Dongshan town, where a newly urban sub-CBD is planned. The local government intends to develop Dongshan town and has proposed preferential policies to the developers for investing in and developing the area. Thus, some land pixels had been converted to residential land at the end of simulation period. However, this area showed less attraction to the individuals due to lack of ancillary facility and the infrastructure still being under construction.

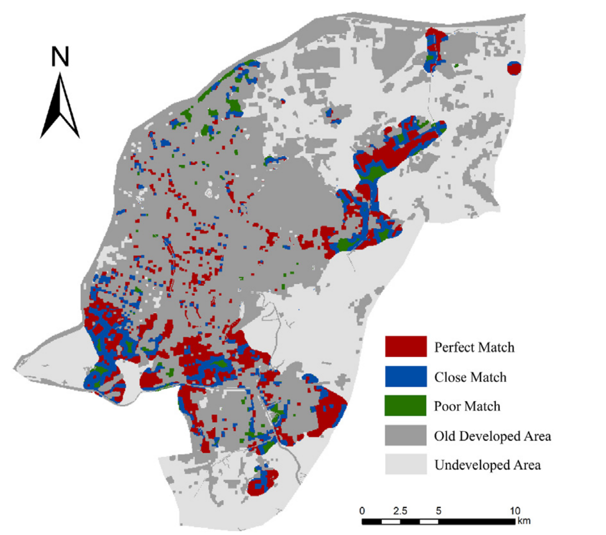
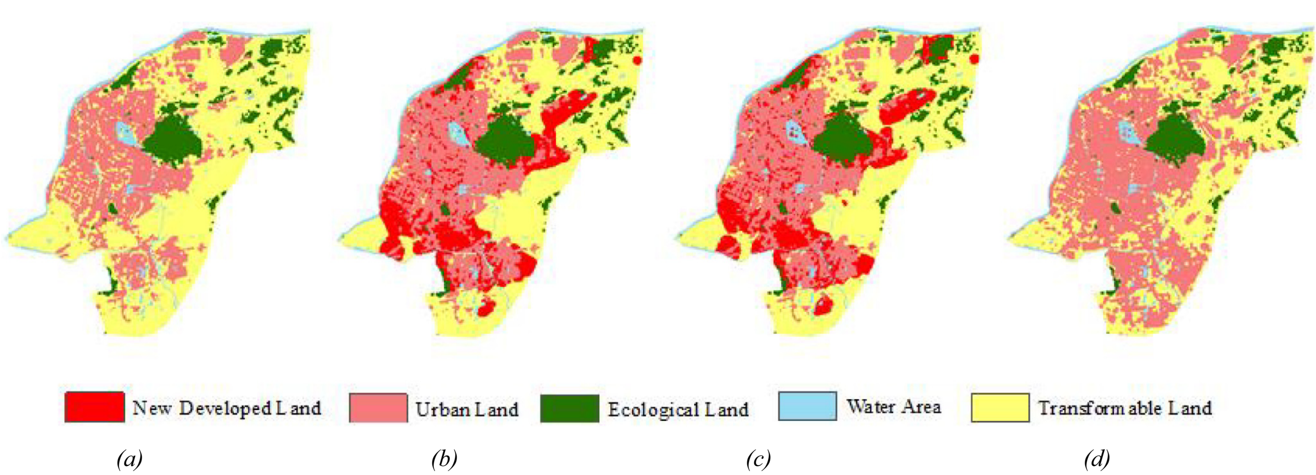


Fig. 6. Spatial agreement map of developed areas for residential land with the simulation outputs.

4. Discussion

4.1. Including a learning model contributes to both ABMs for residential land growth simulation and aiding in human-oriented urban planning

In this study, we focused on agent learning modelling and its integration into the agent decision-making model, a pilot application in residential land growth simulation in the study area was implemented for testing our model. Our model supports the initiative in the ODD protocol (Grimm et al., 2010) and its extension ODD + D protocol (Müller et al., 2013) that learning should be included in the design of agent-based models, which were proposed as standard protocols for describing agent-based models and has been tested by modellers within ecology. We argue that including a learning model into individual's decision-making model is helpful for modelling agent's location decision-making more comprehensively, for in which how agents learn from past-experiences (both personal and interpersonal) to develop their location decisions is taken into account. The implementation of simulation experiments in the study area has provided reliable simulation results, which supports our argument that to model agent learning advances the literature (Bennett & Tang, 2006; Gotts & Polhill, 2009; Le



(a) Land use map of the study area in 2001; (b) simulation map of model with reinforcement learning model embedded for 2007; (c) simulation map of model without learning model for 2007; (d) reference map for 2007.

Fig. 5. Residential land growth simulation of the study area.

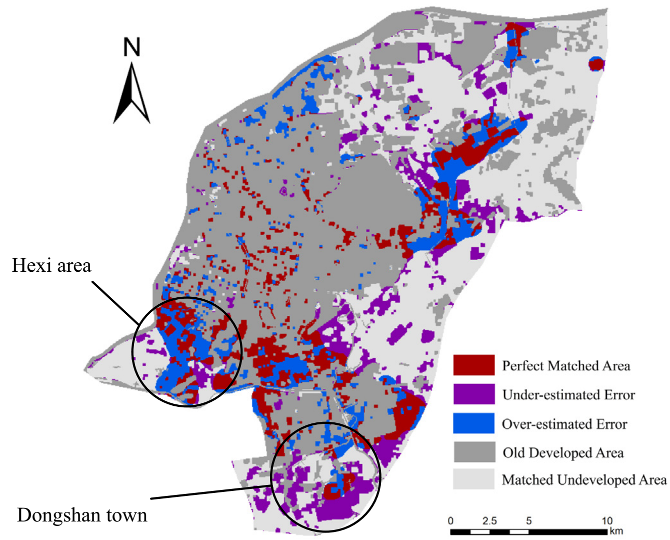


Fig. 7. Error distribution map for residential land growth simulation in the study area.

et al., 2012; Manson, 2006).

Our procedure will aid in a better understanding of micro-mechanism of urban growth and forming human-centered urban plans, in which individual learning is employed as independent part of agent cognition about their surroundings (including the environment and other individuals). The results of applying our procedure can show the changes in both urban patterns and processes and individuals' location decisions. Our procedure is applicable to scenario simulations of urban growth, which could provide references for human-centered urban planning. It can also be applied to analyzing the potential responses of urban residents to series of urban land use drafts, as well as the uncertainties of urban futures. Our procedure can provide decision-makers a more fundamental understanding of the interaction process between individuals' location decisions and urban residential land dynamics. As a result, they can aid to make more proactive urban land use plans.

4.2. The extended reinforcement learning model can be used for modelling agent learning in an ABM for geo-simulation

We proposed an extended reinforcement learning model by assigning a new computational equation to the payoff function and extending the to-be-reinforced location strategy set for simulating the HAs' learning in their location decision-making. The to-be-reinforced location strategy set is extended to the like-location-strategies and the neighbors of the land units that are selected by HAs. This conforms to the urban individual's characteristics and actual learning processes when they make location decisions, that is not only the personal experience but also the social interaction and observation impact their decision, which is appropriate for modelling learning behavior at the individual level (Bone & Dragicevic, 2010a, 2010b; Tang, 2008).

Moreover, we assign new computational equation to the payoff function based on the assumption that the expected return by the like-agents from selecting the neighbors of land unit *j* and the like-location-strategies, when it is selected by an HA, will be increased due to the similarity among neighbouring pixels according to the first law of geography (Tobler, 1970). This is an extension of the basic idea of reinforcement learning model in terms of spatial context, that is successful experiences and their spatial neighbors will be put into practice much more than other experiences. This holds even more so under conditions of high uncertainty about differences in the outcomes from choices and the high-level of need satisfaction, which is the current reality of the individuals' housing decisions in Chinese cities during China's transition from a government-oriented to a more market-oriented economic system.

4.3. The individual-level learning model we proposed is a modest step towards depicting the systematic human's learning process

As human learning behavior is a complicated process and different learning processes take place in different situations (Brenner, 2006; Duffy, 2006), comparison and improvement of agent learning models, and even integrating multiple learning algorithms would contribute to the plausibility of an ABM for residential land growth prediction. Our individual-level learning model covers two fundamental types of learning mechanism – interpersonal learning and intrapersonal learning

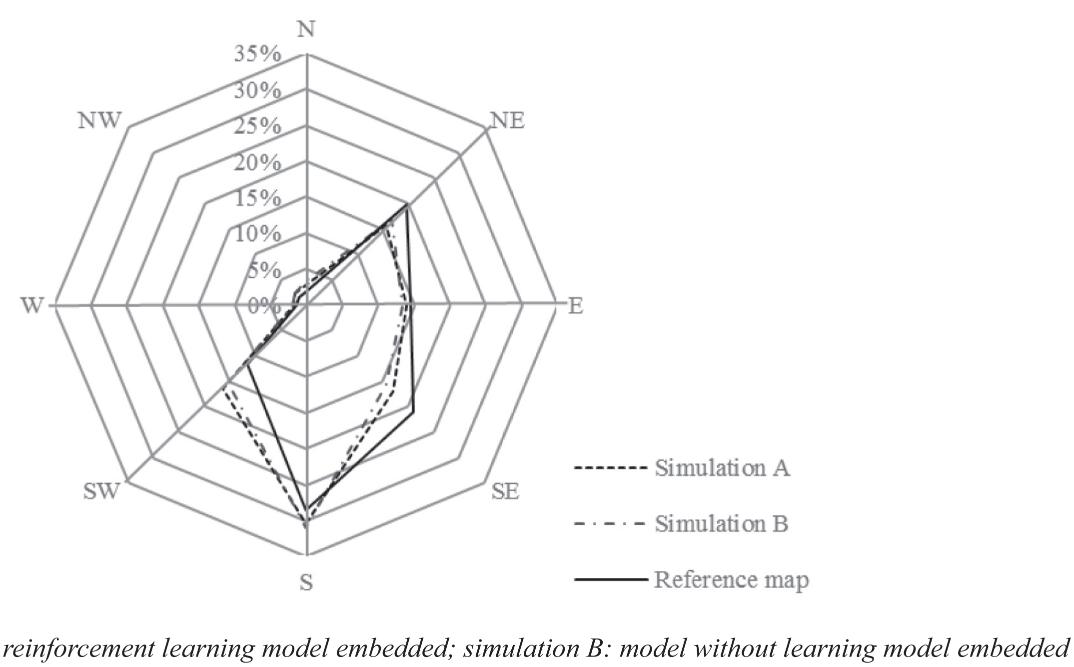


Fig. 8. Directions trends analysis of newly-developed residential pixels distribution in simulation results and reference map.

in the residents' location decision process. Furthermore, multi-stages learning process should be further modelled that includes result-oriented learning, rule-oriented learning and goal-oriented learning according to Piaget's cognition development theory and the opinions about the agent learning in complex urban system (Filatova et al., 2013; Le et al., 2012; Scholz, Gallati, Le, & Seidl, 2011; Smajgl, 2007). The result-oriented learning means that an agent learns by observing the decision results of one another, which has been focused and modelled in our study. We assumed that no great changes happened to the household agent's location decision program considering that the housing and land use policies remained stable in the study area during the simulation period. The rule-oriented learning over a relatively long period leads to reframing the agent's behavioral program. The rule-oriented learning should be modelled further regarding the procedure's general applicability. Moreover, human agents can fundamentally cope with critical environmental transitions by changing their goal system and action programs (Le et al., 2012). This means that the agent's behavior goal can change over numerous human-environment interactions, which should be modelled and integrated into the agent decision-making simulation as goal-oriented learning when needed.

5. Conclusion

This paper outlines a new agent-based procedure with agent learning modelled and embedded for geo-simulation. We have constructed an extended reinforcement learning model to depict both intrapersonal and interpersonal past-experiences learning in the individuals' decision making and decision developing processes. This extended reinforcement learning model makes a significant attempt at representing individual-level agent learning explicitly, modelling it independently and then integrating it into an ABM for geo-simulation. The application experiment results showed that, it contributed to the improvement of the model's simulation power and modelling agent's adaptive decision-making process to a certain extent. The agent-based procedure with the agent learning model embedded is applicable to studying the formulation of human-oriented urban land use plans and testing the responses of individuals to these plans, as well as to scenario simulations of urban land use change. Similarly, the model is also a valuable tool for housing developers to explore, allocate, and manage profitable sites for future development.

The proposed procedure can benefit from further refinements. Modelling multi-stages agent's learning processes, comparison or combination of learning algorithms, as well as definition of a social network as a scope for agent's learning and experiences exchange would enhance the procedure's representational power and the predictive power of ABMs for geo-simulation. Similarly, the simplified assumption in terms of homogenous learning ability of household agents would be addressed by categorizing the household agents to improve the plausibility of the simulation.

Acknowledgments

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References

An, L. (2012). Modeling human decisions in coupled human and natural systems: Review of agent-based models. *Ecological Modelling, 229*(24), 25–36. https://doi.org/10.1016/j.ecolmodel.2011.07.010.

Batty, M., Crooks, A. T., See, L. M., & Heppenstall, A. J. (2012). Perspectives on agent-based models and geographical systems. In A. J. Heppenstall, A. T. Crooks, L. M. See, & M. Batty (Eds.). *Agent-based models of geographical systems* (pp. 1–15). Dordrecht: Springer. https://doi.org/10.1007/978-90-481-8927-4_1.

Benenson, I., Hatna, E., & Or, E. (2009). From Schelling to spatially explicit modeling of urban ethnic and economic residential dynamics. *Sociological Methods & Research, 37*(4), 463–497. https://doi.org/10.1177/0049124109334792.

Benenson, I., Omer, I., & Hatna, E. (2002). Entity-based modeling of urban residential dynamics: The case of Yaffo, Tel Aviv. *Environment and Planning. B, Planning & Design, 29*, 491–512. https://doi.org/10.1068/b1287.

Bennett, D. A., & Tang, W. (2006). Modelling adaptive, spatially aware, and mobile agents: Elk migration in Yellowstone. *International Journal of Geographical Information Science, 20*(9), 1039–1066. https://doi.org/10.1080/13658810600830806.

Bone, C., & Dragicevic, S. (2010a). Incorporating spatio-temporal knowledge in an intelligent agent model for natural resource management. *Landscape and Urban Planning, 96*(2), 123–133. https://doi.org/10.1016/j.landurbplan.2010.03.002.

Bone, C., & Dragicevic, S. (2010b). Simulation and validation of a reinforcement learning agent-based model for multi-stakeholder forest management. *Computers, Environment and Urban Systems, 34*, 162–174. https://doi.org/10.1016/j.compenvurbsys.2009.10.001.

Bone, C., Dragicevic, S., & White, R. (2011). Modeling-in-the-middle: Bridging the gap between agent-based modeling and multi-objective decision making for land use change. *International Journal of Geographical Information Science, 25*(5), 717–737. https://doi.org/10.1080/13658816.2010.495076.

Bousquet, F., & Le Page, C. (2004). Multi-agent simulations and ecosystem management: A review. *Ecological Modeling, 176*(3–4), 313–332. https://doi.org/10.1016/j.ecolmodel.2004.01.011.

Brenner, T. (2006). Agent learning representation: Advice on modelling economic learning. *Handbook of computational economics*. *2. Handbook of computational economics* (pp. 895–947). . https://doi.org/10.1016/S1574-0021(05)02018-6.

Caillault, S., Mialhe, F., Vannier, C., Delmotte, S., Kedowide, C., Amblard, F., ... Houet, T. (2013). Influence of incentive networks on landscape changes: A simple agent-based simulation approach. *Environmental Modelling & Software, 45*, 64–73. https://doi.org/10.1016/j.envsoft.2012.11.003.

Chen, Y. M., Li, X., Wang, S. J., & Liu, X. (2012). Defining agents' behaviour based on urban economic theory to simulate complex urban residential dynamics. *International Journal of Geographical Information Science, 26*(7), 1155–1172. https://doi.org/10.1080/13658816.2011.626780.

China Real Estate Chamber of Commerce (2009). Report of house purchasing behavior in China—The case of Beijng, Tianjing and Guangzhou. Retrieved from http://www.chinahouse.info/html/ZGBDCZZ/2009-8/31/09_56_00_891.html, Accessed date: 31 August 2009.

Claessens, L., Schoorl, J. M., Verburg, P. H., Geraedts, L., & Veldkamp, A. (2009). Modelling interactions and feedback mechanisms between land use change and landscape processes. *Agriculture, Ecosystems and Environment, 129*, 157–170. https://doi.org/10.1016/j.agee.2008.08.008.

Clarke, K. (2014). Cellular automata and agent-based models. In M. M. Fischer, & P. Nijkamp (Eds.). *Handbook of regional science*. Berlin Heidelberg: Springer-Verlag.

Dahal, K. R., & Chow, T. E. (2014). An agent-integrated irregular automata model of urban land-use dynamics. *International Journal of Geographical Information Science, 28*(11), 2281–2303. https://doi.org/10.1080/13658816.2014.917646.

Duffy, J. (2006). Agent-based models and human subject experiments. *Handbook of computational economics*. *2. Handbook of computational economics* (pp. 949–1011). . https://doi.org/10.1016/S1574-0021(05)02019-8.

Dung, L. C., Vinh, N. N. G., Tuan, L. A., & Bousquet, F. (2005). Economic differentiation of rice and shrimp farming systems and riskiness: A case of Bac Lieu, Mekong Delta, Vietnam. In F. Bousquet, (Ed.). *Companion modeling and multi-agent systems for integrated natural resource management in Asia* (pp. 211–235). Metro Manila: International Rice Research Institute.

Filatova, T., Verburg, P. H., Parker, D. C., & Stannard, C. A. (2013). Spatial agent-based models for socio-ecological systems: Challenges and prospects. *Environmental Modelling & Software, 45*, 1–7. https://doi.org/10.1016/j.envsoft.2013.03.017.

Gotts, N. M., & Polhill, J. G. (2009). When and how to imitate your neighbours: Lessons from and for FEARLUS. *Journal of Artificial Societies and Social Simulation, 12*. Retrieved from http://jasss.soc.surrey.ac.uk/12/13/12.html.

Grimm, V., Berger, U., DeAangelis, D. L., Polhill, J. G., Giske, J., & Railsback, S. F. (2010). The ODD protocol: A review and first update. *Ecological Modelling, 221*(23), 2760–2768. https://doi.org/10.1016/j.ecolmodel.2010.08.019.

Groeneveld, J., Müller, B., Buchmann, C. M., Dressler, G., Guo, C., Hase, N., ... Liebelt, V. (2017). Theoretical foundations of human decision-making in agent-based land use models—A review. *Environmental Modelling & Software, 87*, 39–48. https://doi.org/10.1016/j.envsoft.2016.10.008.

He, J., & Shang, P. (2017). Comparison of transfer entropy methods for financial time series. *Physica A: Statistical Mechanics and its Applications, 482*. https://doi.org/10.1016/j.physa.2017.04.089.

Hou, G. L., & Huang, Z. F. (2010). Evaluation on tourism community participation level based on AHP method with entropy weight. *Geographical Research, 29*(10), 1802–1813 (in Chinese).

Irwin, E. G., & Geoghegan, J. (2001). Theory, data, methods: Developing spatially explicit economic models of land use change. *Agriculture, Ecosystems & Environment, 85*(1), 7–24. https://doi.org/10.1016/S0167-8809(01)00200-6.

Le, Q. B., Seidl, R., & Scholz, R. W. (2012). Feedback loops and types of adaptation in the modelling of land-use decisions in an agent-based simulation. *Environmental Modelling & Software, 27–28*, 83–96. https://doi.org/10.1016/j.envsoft.2011.09.002.

Li, F. X., Li, M. C., Liu, Y. X., Liang, J., & Chen, Z. J. (2007). Urban growth in Nanjing since 1949. *Journal of Natural Resources, 22*(4), 524–535. https://doi.org/10.11849/zrzyxb.2007.04.004.

Li, X., & Liu, X. (2008). Embedding sustainable development strategies in agent-based models for use as a planning tool. *International Journal of Geographical Information Science, 22*(1), 21–45. https://doi.org/10.1080/13658810701228686.

Li, F. X., Liang, J., Clarke, K. C., Li, M., Liu, Y. X., & Huang, Q. (2015). Urban land growth in eastern China: A general analytical framework based on the role of urban micro-agents' adaptive behavior. *Regional Environmental Change, 15*(4), 695–707. https://doi.org/10.1007/s10113-014-0665-1.

Manson, S. M. (2006). Bounded rationality in agent-based models: Experiments with evolutionary programs. *International Journal of Geographical Information Science, 20*, 991–1012. https://doi.org/10.1080/13658810600830566.

Matthews, R. B., Gilbert, N. G., Roach, A., Polhill, J. G., & Gotts, N. M. (2007). Agent-based land-use models: A review of application. *Landscape Ecology, 22*, 1447–1459. https://doi.org/10.1007/s10980-007-9135-1.

Meyfroidt, P. (2013). Environmental cognitions, land change, and social-ecological feedbacks: An overview. *Journal of Land Use Science, 8*(3), 341–367. https://doi.org/10.1080/1747423X.2012.667452.

Miller, E., Hunt, J. D., Abraham, J. E., & Salvini, P. A. (2004). Microsimulating urban systems. *Computers, Environment and Urban Systems, 28*, 9–44. https://doi.org/10.1016/S0198-9715(02)00044-3.

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*(5), 656–663. https://doi.org/10.1016/j.envsoft.2005.12.017.

Morales, J. M., Fortin, D., Frair, J. L., & Merrill, E. H. (2005). Adaptive models for large herbivore movements in heterogeneous landscapes. *Landscape Ecology, 20*(3), 301–316. https://doi.org/10.1007/s10980-005-0061-9.

Müller, B., Bohn, F., Dreßler, G., Groeneveld, J., Klassert, C., Martin, R., ... Schwarz, N. (2013). Describing human decisions in agent-based models–ODD + D, an extension of the ODD protocol. *Environmental Modelling & Software, 48*, 37–48. https://doi.org/10.1016/j.envsoft.2013.06.003.

O'Sullivan, D., Millington, J., Perry, G., & Wainwright, J. (2012). Agent-based models—Because they're worth it? In A. J. Heppenstall, (Ed.). *Agent-based models of geographical systems* (pp. 109–123). Dordrecht: Springer.

Parker, D. C., Hessl, A., & Davis, S. C. (2008). Complexity, land-use modeling, and the human dimension: Fundamental challenges for mapping unknown outcome spaces. *Geoforum, 39*(2), 789–804. https://doi.org/10.1016/j.geoforum.2007.05.005.

Roth, A. E., & Erev, I. (1995). Learning in extensive form games: Experimental data and simple dynamic models in the intermediate run. *Games and Economic Behavior, 28*, 294–309. https://doi.org/10.1016/S0899-8256(05)80020-X.

Satty, T. L. (1980). *The analytic hierarchy process: Planning, priority setting, resource allocation.* New York: McGraw-Hill.

Schlüter, M., Baeza, A., Dressler, G., Frank, K., Groeneveld, J., Jager, W., ... Schwarz, N. (2017). A framework for mapping and comparing behavioural theories in models of social-ecological systems. *Ecological Economics, 131*, 21–35. https://doi.org/10.1016/j.ecolecon.2016.08.008.

Scholz, R. W., Gallati, J., Le, Q. B., & Seidl, R. (2011). Integrated systems modeling of complex human-environment systems. In R. W. Scholz (Ed.). *Environmental literacy in science and society: From knowledge to decisions*. Cambridge, UK: Cambridge University Press.

Seto, K. C., & Fragkias, M. (2005). Quantifying spatiotemporal patterns of urban land-use change in four cities of China with time series landscape metrics. *Landscape Ecology, 20*(7), 871–888. https://doi.org/10.1007/s10980-005-5238-8.

Simon, H. A. (1997). Behavioral economics and bounded rationality. In H. A. Simon (Ed.). *Models of bounded rationality* (pp. 267–298). Cambridge, MA: MIT Press.

Smajgl, A. (2007). Modelling evolving rules for the use of common-pool resources in an agent-based model. *Interdisciplinary Description of Complex Systems, 5*, 56–80. Retrieved from http://indecs.eu/2007/indecs2007-pp56-80.pdf.

Sun, Z., & Müller, D. (2013). A framework for modeling payments for ecosystem services with agent-based models, Bayesian belief networks and opinion dynamics models. *Environmental Modelling & Software, 45*, 15–28. https://doi.org/10.1016/j.envsoft.2012.06.007.

Sutton, R. S., & Barto, A. G. (1998). *Reinforcement learning: An introduction.* MIT press.

Tang, W. (2008). Simulating complex adaptive geographic systems: A geographically aware intelligent agent approach. *Cartography and Geographic Information Science, 35*(4), 239–263. https://doi.org/10.1559/152304008786140551.

Tang, W., & Bennett, D. A. (2010). Agent-based modeling of animal movement: A review. *Geography Compass, 4*(7), 682–700. https://doi.org/10.1111/j.1749-8198.2010.00337.x.

Tobler, W. (1970). A computer movie simulating urban growth in the Detroit region. *Economic Geography, 46*(Supplement), 234–240. https://doi.org/10.2307/143141.

Verburg, P. H. (2006). Simulating feedbacks in land use and land cover change model. *Landscape Ecology, 21*, 1171–1183. https://doi.org/10.1007/s10980-006-0029-4.

World Bank (2015). *World development report 2015: Mind, society and behavior.* Washington, DC: World Bank.