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The cover image shows a sea glacier ice that melts away.

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Contents

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Residential development simulation based on learning by agent-based model

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Abstract

Increasing population and desire for urbanization increase housing demand in urban areas and ultimately induce growth and development of residential land-uses that result in urban sprawl. This paper simulates these sprawls of residential land-use in Qazvin city based on learning method by agent-based model. For this purpose, a model with the ability to learn from agents has been developed, in which families as agents can interact with each other and learn based on previous decisions. The model makes it possible to simulate residential land-use conversion based on the agent-based structure over the ten years by applying both demographic changes and household relocation desirability. The multiplication of the average level of land occupation by each family and the number of inserted new families indicates the potential magnitude of land-use changes. Also, results show the priority of residential development locations partially in the northeast regions and a small part of the south of Qazvin. These developments are expected to move towards the east in ten years.

Keywords

Agent-based model (ABM); Agent learning; Residential development; Qazvin.

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1. Introduction

Residential location simulation is at the forefront of social science's grand challenges (Pagliara et al., 2010). One of the main drivers of urban dynamics is the household's residential location, affecting Jobs, economic growth, societal order, spatial division, and transportation. Also, other land use types like commercial ones could affect transportation choice and vice versa (Saffarzadeh et al., 2021). Still, one of the exciting issues for urban planners is understanding and modeling residential location choice behavior (Schirmer et al., 2013). Alonso, in 1964, was the first researcher who developed the idea of bid-rent, which was applied to suburban locations. He examines a monocentric city with work opportunities in that households decide where to live by optimizing a utility function based on their spending on goods, the land size, and distance to the city center (Alonso, 1964). Although, the origins of residential location modeling can be traced back to Von Thunen's pioneering work, which has used a land market function through a single market in an agricultural area to demonstrate the impact of transportation costs on the activity locations (von Thünen, 1966).

These interactions in land-use and travel behaviors have been in focus since 2000. The ALBATROSS system developed a model that (a) derived rules representing selective initiative from memory activity data. (B) incorporate all aspects of the main activity patterns. Moreover, (c) could be embedded in an environment that supports a set of reporting, performance evaluation, scenario generation, and evaluation tools. From theories of heuristic customer preference in decision making in dynamic settings, the activity model is the foundation of travel behaviors (Arentze et al., 2000). They presented a simulation learning model based on the transport system. This activity model is the basis of travel behaviors from consumer choice heuristic theories in decision-making within complex environments.

Some other models try to simulate the location choice of users based on their utility function. For this purpose, Waddell (2002) developed the urban simulate model, named UrbanSim, which was used in urban areas. UrbanSim differs from other urban planning models in several remarkable features (Waddell, 2002). The first significant difference in design is that it represents a dynamic disequilibrium procedure and shows adjustment processes that operate at different rates, in contrast to the cross-sectional approach. Various accommodation selection models are readily available in UrbanSim (Waddell, 2011). Traditionally, the UrbanSim location-allocation model uses Monte Carlo and Logit simulations. Benenson et al. related the entity-based modeling used to interpret the different decision-makers' behavior in the urban residential dynamic model (Benenson et al., 2002). Further, in 2003, Hunt proposed an approach to spatial simulation of the economic system called PECAS. PECAS expresses the Production, Exchange, and Consumption Allocation System. It has been used to develop a land-use forecasting model in Edmonton, Canada. PECAS has two components. One is the space developing module, which shows developers' actions in giving space for activity locations including new development, destruction, and redevelopment that occur from one point to another. The other is the module on locating activities; this model shows how they are located in the space provided and how they interact (Hunt, 2003). Also, Bousquet and Le. Page stated that the systematic approach combines the learning mechanisms in land use with modeling systems of low user changes (Bousquet & le Page, 2004).

In 2005, ABM was introduced as a novel technique for modeling systems made up of autonomous, interacting agents and simulation. ABM can significantly impact how companies utilize computers to aid decision-making (Macal & North, 2005). The ABMs can model agent behavior in the stock market and supply chains, modeling the intricacies of human behavior and interaction, and many more applications are among them (Macal & North, 2006). Moreover, the ABM can model people's decision-making and their interactions. These factors create social and financial activities with environmental decision-making and dynamic equations (Matthews et al., 2007).

These researches linking land-use changes and urban development Continued to present some complex and agent concept models. In this regard, Valbuena et al. have assessed two main conflicts in the Land Use/Cover Change (LUCC) study. The body of LUCC is a complex process, including stakeholders at different socio-space levels. They presented a conceptual framework to analyze and evaluate regional LUCC processes. In the second step, the conceptual framework combined different concepts, including agent, model trajectory, and probable decision-making processes (Valbuena et al., 2010). Tuscany could be mentioned as a testbed concerning landscapes changes (Zullo et al., 2015). Also, Micheal Iocono et al. presented a Markov chain model of land use change (Iacono et al., 2015). Bert et al. developed the ABM to simulate the structural changes and land use in the agricultural systems due to environmental and social changes. This model was described as a standard protocol (ODD) (Bert et al., 2011). After, in 2013, Muller et al. developed the agent learning model's content using the ODD+D protocol, which is an extended form of the ODD protocol (Müller et al., 2013). In this regard, San and Muller showed that the ABM allows the researchers to predict the relationships between the individual decision-making at low levels and the significant phenomena arising from them (Sun & Müller, 2013). In continuation of their work, Murray-Rust et al. presented a new ABM framework called Aporia, which reduces the complexity and difficulty of constructing land-use models. The Aporia was designed based on previous conceptual developments and the provision of ecosystem services to generate complex models from sub-component (Murray-Rust et al., 2014).

Actually, an ABM technique is being used to create models in the field of urban land-use-change simulation in an increasing volume (Huang et al., 2014). It supported the development of agent-based decision-making models and the protocols or architectures, facilitating human decision-making modeling in different chances (Azari et al., 2013). Lilibeth et al. developed an ABM to simulate land-use patterns changes due to global environmental changes. The ABM uses three categories: 1) farmer types based on a cluster analysis of socioeconomic attributes; 2) agricultural appropriateness based on regression investigation of historical land-use maps and biophysical features, and 3) future movements in the economic and climatic environments based on the International Board on Climate Change (Acosta et al., 2014). Rolf Moeckel presented a study to create an integrated transportation and land-use model, considering transportation users' satisfaction. The study considered several factors to produce more realistic results, including the cost of dwelling, travel time to work, and transportation budget constraints (Moeckel, 2017).

Following this concept, Beck et al. suggested a two-stage model based on micro executive (spatial) data to allow planners to identify the places with a destruction potential due to the land's value and predict appropriate policies instead of reacting to a specific situation. Therefore, a logistic model was introduced at first. In the second stage, a land-use model was developed to execute the random samples to identify the place capable of rehabilitation over the coming years (Beck et al., 2017). Almost in a period, Zagaria et al. have developed an ABM via collaboration with farmers and local society experts to provide a primary tool for vision generation research. They have developed a model based on agent, land-use change, and ecosystem services based on a dynamic evaluation of land-use change and ecosystem services (Zagaria et al., 2017). As the cellular automata technique has some similarities with the agent-based concept, Campos et al. used a cellular automata-based model to analyze land-use change simulation in a peripheral urban area before and after the construction (Campos et al., 2018). Furthermore, Polhill identified the required improvements of ABM in the industry. Over the past decade, the behavior of ABM has been changing from general indexes of the systems to applied ones, which increases the users' potential perception of the ABM output. However, empirical ABM is not a permanent solution because it requires factors such as calculations, more data sources, and limiting the programs to the fields in which the data is accompanied by appropriate environmental models (Polhill et al., 2019).

Choosing a place to live and changing the residential locations in the urban lifecycle reveal how urban development evolves. Thus, for clearing the detailed attributes, Household size, income, and social class or ethnic background influence the decision-making household's choice of the alternatives in the choice sets (Schirmer et al., 2013, 2014). Thanks to the ABM's potential to reflect an individual's decision-making mechanism and versatility from the bottom up. Agent-based land-conversion studies examine the residence evolution based on the household's preferences and interactions. In such studies, it is assumed that households choose the residential location with the highest level of desirability for their family based on a set of utility factors, so they are more likely to choose points that are better aligned with family criteria.

Besides, Li et al. created a reinforcement learning model to demonstrate human agents' learning during local decision making. As a result, they suggested a new agent-based approach to simulate the growth of residential lands, including a learning agent model, a decision-making agent model, and a land-use change model, and evaluated the effects of urban zoning and the demands of developers (Li et al., 2019). Lie et al. presented the Land-use Simulation and Decision-Support system (LandSDS) for integrating system dynamics (SD) model, agent-based model (ABM), cellular automata (CA) model, and Geographic Information System (GIS) to model the Beijing urban expansion (Liu et al., 2020). Chen et al. used the theory of thinly traded land markets to find out the land use patterns. They found out that increases in transportation costs and the number of in-migrants cause to decrease the intensity and persistence of scattered development (Chen et al., 2021).

In this study, the aspect of learning models used in combination with ABM. This paper extends and enhances Li's study's performance, as it discusses the process of changing with more details and develops residential land-use simulations in Qazvin. The paper attempts to provide an innovative method to increase the accuracy of the prediction model and simulation results that could be closer to reality. In this regard, this study outlines to simulate the process of family residential selection by ABM. So, households are defined as agents who can learn and make decisions based on what they have learned. The study also considered the opportunity of interactions between households defined in the form of agents for more realistic simulation. Subsequently, household as agents choose their locations based on what they have learned and interacted with them. Thus, this paper scrutinizes the possibility of changing existing households' location, finding accommodations for new families, describing both interactions within families and land-use, and finally, simulating residential land-use development on lands without specified land use based on the frequency of demand generated for housing in Qazvin during ten years.

2. Methodology

The presented model simulates residence choice for the added population and investigates residential location changes in each period. This procedure framework is shown in Figure 1, which simulates urban development based on the Li et al. study as the 4-processing model (Li et al., 2019). In this simulation process, household agents seek to select or change their locations.

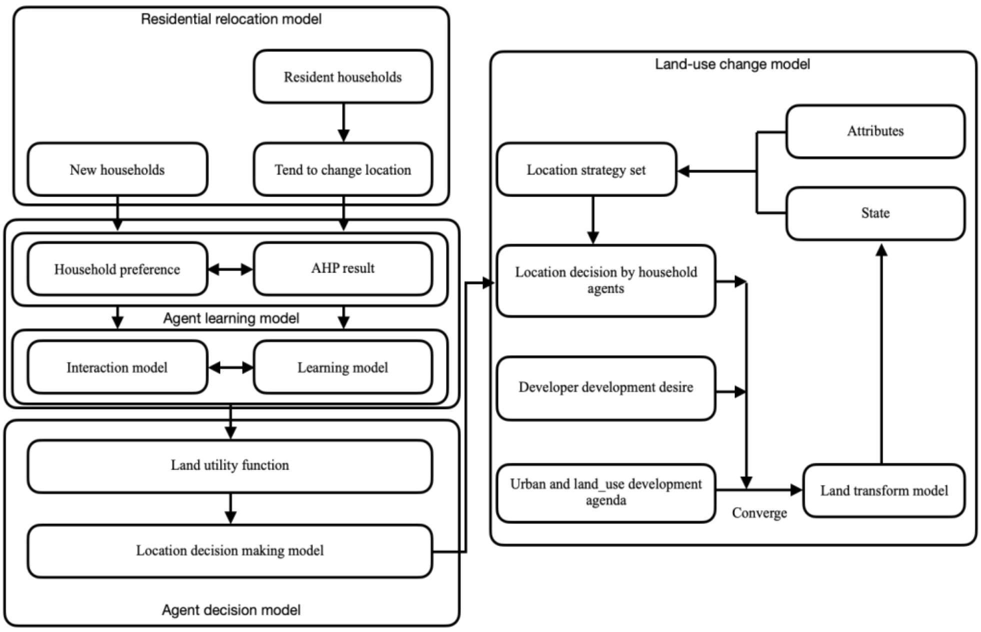


Fig.1 Proposed urban development

Each agent has unique features and a learning capability in choosing their preferences. The tendency to change the place of residence varies for different households, part of which is related to the family's unique characteristics, and the other part is related to the type of property (rent or ownership) of the family's residence.

Land units are considered to be cells with unique characteristics. Changes in land-use developments are based on existing households' preferences in changing their residence location—new households choose the residential location considering development, urban policies, and land-use change feasibility. The size of the land units intended for development should be such that it is possible to simulate the model and convert it into real-scale blocks. So, the study measured the dimensions of each cell as 25*25 meters, and each of them includes the unique features of that position on a real scale. Factors that reflect accessibility (such as ease of access to business and service centers, and environmental quality) are considered for each cell. Finally, the desirability of the cells is determined based on the factors considered. By considering the household decision processes, four sub-models have been developed to simulate the procedure of family interaction and land-use, including the agent learning model, the agent decision-making model, the land-use change model, and the residential relocation model.

3. The model

3.1 How households make decisions

The decision model of household agents, to change the residence place, is based on the four parameters of household learning; household characteristics, the desirability of the cell's position for households; and the parameter of the probability of relocation for the residence household. Equation 1 shows how households make decisions.

$$HA_{decision} = P_{location-change} * f(HA_{attributes}, HA_{locationpref}, HA_{learning}) \tag{1}$$

In equation 1,

- $HA_{learning}$ indicates households' ability to make decisions based on previous experience and learning; it shows how households decide to relocate;
- $HA_{attributes}$ shows desirability factors for households in choosing residence location and their importance for each family. Household desirability factors include a set of factors that result from social interactions and their effects on learning;
- $HA_{locationpref}$ is a function that reflects the utility of each of the existing cells for different households based on the environmental factors of each cell;
- $P_{change-location}$ reflects a household's desire to change their place of residence.

The amount intended for this parameter is considered equal to one for the added households, and the value of this parameter for households that are tenants is higher than for owner-occupied households, and the amount is determined based on the rate of change of residence for each area.

3.2 Agent learning model

To calculate household preferences for different situations, each of the household's cells' attractiveness index should be defined. The attractiveness index is determined based on changes in each iteration, and its value is set equal to the initial value when the final decision is made for each year.

In each iteration of the land-use conversion process, cells are selected as modified cells subject to change. Cells that have been selected as changeable cells in previous steps will increase their attractiveness in the current step.
To calculate the attractiveness index for different types of cells, they are divided into two categories: cells that have been modified in the previous step and cells that have not been modified in the previous step.
The attractiveness index is calculated based on equation 2 for the cells that have been modified in the previous step:

$$A_i^j(t) = (\phi * A_i^j(t-1) + (1-\delta) * R_i^j(t)) * P_{new-location}^j \tag{2}$$

The defined values of ϕ and δ in this equation are numbers in the range [0.1], respectively, representing the parameter to reduce the importance of previous experiences over time and the experience parameter that reflects the selected cells' effect. $A_i^j(t-1)$ also indicates the attractiveness index in the previous step. The $P_{i,new-location}^j$ indicates the appropriateness of the newly selected location for the household to change the place of residence. This parameter is calculated based on equation 5.
The calculation of the attractiveness index of cells that have not been modified in the previous step is done using equation 3.

$$A_i^j(t) = (\phi * A_i^j(t-1) + \frac{\delta * R_i^j(t)}{N_{(t)} - 1}) * P_{new-location}^J \tag{3}$$

$N_i(t)$ indicates the number of available residence locations for the household HA_i at time t.
In the initial step, it was assumed that all situations had equal attractiveness for different households. Therefore, the attractiveness index's value in the initial step $(t=0)$, when household agents have no experience, is calculated from equation 4:

$$A_i^j(0) = \frac{k * (\sum_{i=1}^{M} R_i^j(0)/M)}{n} * P_{new-location}^j \tag{4}$$

In this regard, $N_i(t)$ is defined earlier, and M represents the number of households. $R_i^j(0)$ is the value of the reward function for the family i to select cell j at the initial time $(t=0)$, which is equal to one.
The parameter $P_{i,new-location}^j$ is defined as probability, which indicates the degree to which the family i tends to live near its former place of residence. The parameter is defined based on equation 5.
Each household's residence zone and the distance from the center of that zone to the center of other zones

$$P_{i,new-location}^j = \alpha_z (1 - \frac{dist(zone_i^{settled\_location}, zone_i^{new\_location})}{Max\{dist(zone_i^{settled\_location})\}})^{\beta_z} \tag{5}$$

are determined. Given that each household's location is considered as a cell. Therefore, the zone of each cell must be specified. The value of this parameter is considered equal to 1 for new families. The amount considered means that one area is not preferred over other areas for new families.
$dist(zone_i^{settled\_location}, zone_i^{new\_location})$ parameter indicates the distance between the center of the household i residence zone and the center of the selected zone for the household i. the $Max\{dist(zone_i^{settled\_location})\}$ parameter indicates the maximum distance from the center of the household i residence zone to the center of the other zones. The parameters α_z and β_z are used to calibrate the model, in which case α_z can take a value between zero to one.
The reward function for calculating the attractiveness index of cells by different households for cell j is equal to the ratio of the number of land units in the neighborhood of cell j, which were previously selected as subject to change to all neighboring cell j. Each cell's neighborhood count is 41*41 squares, with the j cell centered at 25*25 meters. Therefore, the maximum distance between the center of neighboring cells and the center of

cell j is 500 meters. If the number of the neighbors modified to land-use change for a cell is equal to zero, the value of this reward function is considered equal to one-tenth of the number of neighbors in that cell. Equation 6 shows how the reward function is calculated.

$$R_i^j(t) = (n_{selected}(j)/N_{nei}) * 100 \tag{6}$$

3.3 Agent decision model

This part includes two subsections, land utility function and selection probability.

Land utility function

The model's utility function is calculated based on the agents' learning ability and the agents' observation in previous steps. In this function, the utility of each cell for each household is calculated. This function is calculated using the number of cell desirability factors and the value of their importance for different households. Equation 7 shows how to calculate the utility of land j for the family i at time t.

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

In Equation 7, α is the weight of household preferences for environmental conditions, and β is the weight of household learning outcomes. ε_i^j is related to the uncertainty in household decisions that are generated randomly. Parameter X represents the utility matrix for each cell, the values that have been normalized for the cells. The utility factors that have been used in this study include cell vicinity, environmental conditions, public transportation facilities, and proximity to educational resources. ω Matrix is the coefficient of utility for different households, equal to one for each household and k represents each utility factor.

Land selection probability

The probability of cell j selection is calculated by different households using the logit function. Equation 8 shows how to calculate.

$$P_i^j(t) = \frac{exp(U_i^j(t))}{\sum_{j=1}^{n} exp(U_i^j(t))}, \sum_{j=1}^{n} P_i^j(t) = 1 \tag{8}$$

In equation 8, P_i^j indicates the probability of selecting cell j by households i and n indicates the number of cells present. Cell selection probability is calculated by averaging the probability of choosing that cell by different households. Equation 9 shows the probability of cell j land-use conversion.

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

M represents the number of households in each class. $P_i(t)$ indicates the probability of each agent participating in the decision to change land-use of each cell. Since all agents are assumed to be involved in the decision, this parameter's value is considered equal to one.

3.4 Land-use change model

As land-use changes should be modeled in each period, the S parameter is used to examine the changes in cells. This parameter can take one of the values $\{0,0.5,1\}$. A value of zero is considered for cells that cannot be developed, and for cells located within the development agenda, this parameter is considered to be 1, otherwise equal to 0.5.

Given that the process of urban development takes place by builders and builders tend to invest in areas where the relative cost of construction and development is minimized, it is assumed that the previously developed areas have a higher utility for investors. Therefore, $D^j(t)$, which indicates the investment desirability for cell j in step t, is determined using the percentage of the number of residential neighbors in that cell. Thus, the investment desirability equals the number of residential neighbors in the cell neighborhood (a square with a 1 km^2). If there are no residential units in the cell neighborhood, this desirability value is considered one-tenth of the inverse number of neighbors in that cell.

Equation 10 is used to calculate the probability of changing the use of cell j.

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

In Equation 10, $T^j(t)$ indicates the probability of changing the use of cell j in step t and $K^j(t)$ indicates a constraint of land use conversion. Cells are arranged in descending order according to the probability of utility change.

In the change of each cell usage, if the value of the parameter $rand$ (a number in the form of randomness, used to create the nature of the randomness) is less than the probability of change of use for cell j, this cell is subject to change of use. Equation 11 illustrates this point.

$$transform_j^{rz} = \begin{cases} true & if\ rand(0, \max\{T_{jrz}\}) \leq T_{jrz} \\ False & otherwise \end{cases} \tag{11}$$

In the land-use change process, it is assumed that every year the M_y household must be located in M_y cells; that means one cell per household; which motivates to change the land use of those cells each year. To achieve this goal, the process iterates until 99% of the cells that need to be changed that year and had the highest value of T^j in stage t are part of the cell with the highest T^j values in stage $t+1$. Equation 12 illustrates this issue.

$$different(\{max(T^J(t), size = M_y)\}, \{max(T^J(t+1), size = M_y)\}) = 1\% \tag{12}$$

Equation 12 indicates that the repetition process stops when only 0.01 of the M_y cells selected at step t, which have the highest T^j values, differ from those at step $t+1$.

After obtaining the condition expressed in equation 12, the M_y cells with the highest T^j value change their land-use in that year, and the households settle on the most desirable cells.

Therefore, these new households in that year are considered families living in the coming years, and in the following years, they can change their residential location. The cells in which these households are located are known as residential cells.

After identifying the cells that make the change, the families living in each cell must be identified. The criterion for selecting families to live in each cell is the cell's desirability for that family. Therefore, the family is selected to live in a cell if Equation 13 is proven.

$$p_i^j(t) \geq p_{i'}^j(t), \forall i' \in HouseholdAgents \tag{13}$$

Since these families include two sections of new families and families which are looking for relocation, the relocated families must be taken not to exceed the maximum number of replaced families, in which case new families will be used to accommodate each situation.

The presented model in this study, unlike previous studies, has little dependence on initial selection. In the previous models, if a cell is selected as a cell subject to change in the first step, in the next steps, that cell and its neighbors have a very high chance of changing the land-use in the future steps. In other words, cells have a chance of changing their use, which they or their neighbors have chosen in step $t = 1$ as cells subject to land-use change, indicating a strong dependence of the final answer on the initial stage. Due to the random nature of the initial state, it is possible to have a different answer. In the method presented, each year, the process is repeated from the beginning, and the initial step's effect on the final answer is reduced.

3.5 Residential relocation model

Some households are selected and apply for a change of residence in the residence change model in each period. Therefore, their current residential cell will be emptied (the cell does not change its use), and other families can occupy that cell. Applicant families will also be relocated and added to families created by population growth.

The probability of residential relocation for families is based on the length of stay in a cell. Accordingly, the probability of a family living in a cell inversely related to the length of stay increases. The relocation tendency increases with the family's stay time. Equation 14 shows the likelihood of a change of residence.

$$P_{location\_change} = 1 - \alpha_r t_{resident}^{-\beta_r} \tag{14}$$

In this regard, α_r and β_r are the calibration coefficients for the model. In this case, α_r can take a value between zero and one. This value is set to one for new families.

4. Results

The simulation process of the model presented in this study is based on data from the city of Qazvin in 2016. The generated model is used to investigate the process of urban residential growth in Qazvin. The trend and structure of the model are shown in Figure 2.

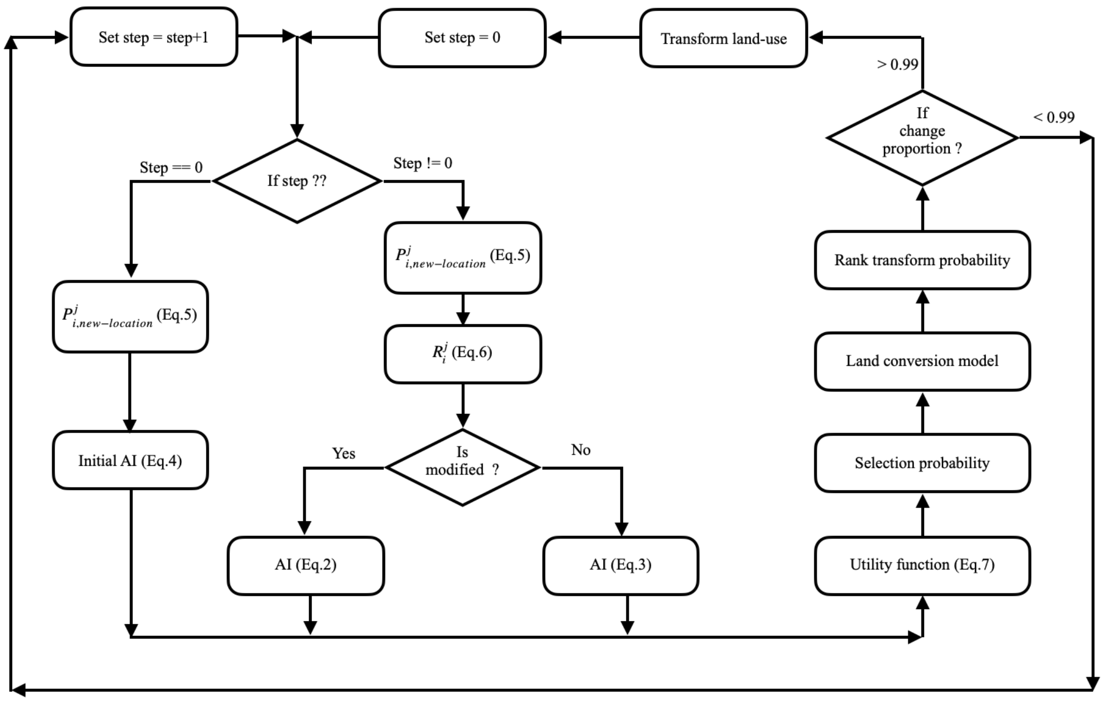


Fig.2 Trend and structure of the proposed model

Qazvin, a currently developing city in Iran, has a population of 161,532 households with a yearly growth rate of 1.17 households in 2016. It also covers about 11 square kilometers of urban land use, making up approximately 46 percent of the city's non-barren land. Fig.3 shows a sample map of Qazvin. As shown in Figure 3, land uses are divided into residential, non-residential, and barren.

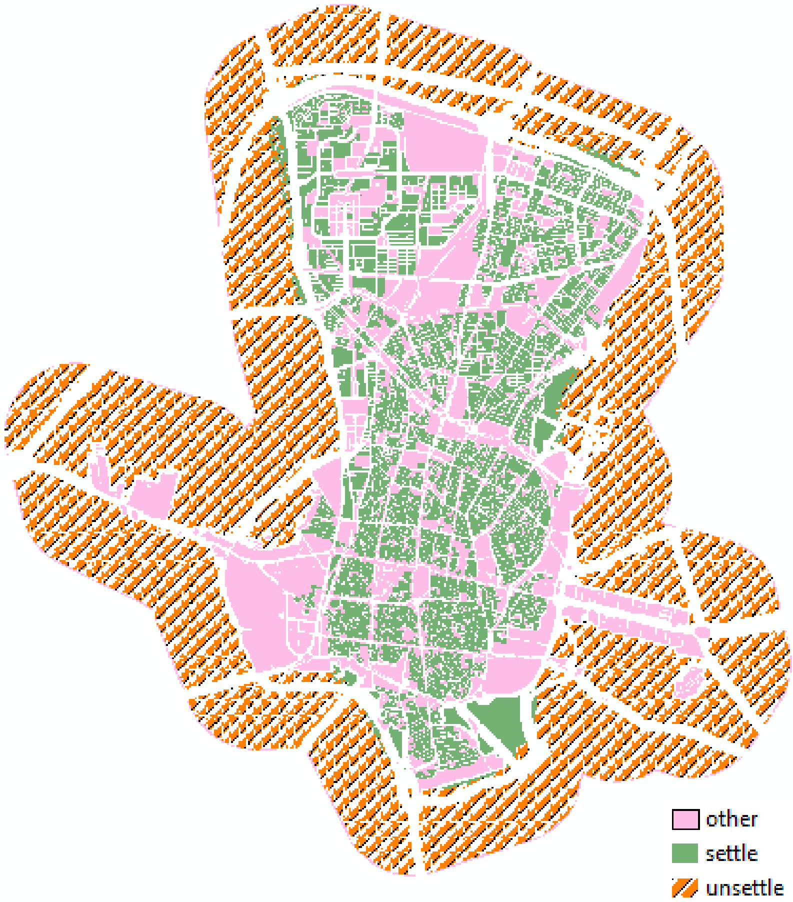


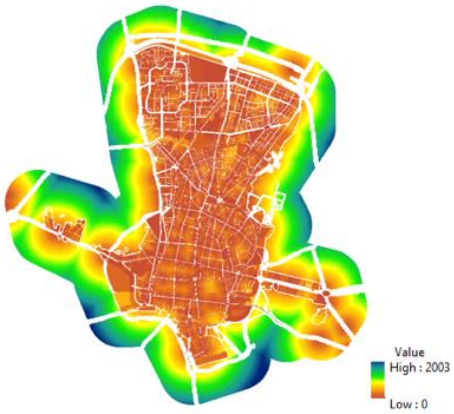
Fig.3 Qazvin land-use map

Fig.4 shows a raster map of Qazvin. This illustration shows the worth of accessibility factors, environmental amenities, access to public transportation, and educational facilities in Qazvin's map. The factors considered are quantitative (e.g., distance). For example, to calculate the factor of access to public transport for each cell, the distance from the nearest bus station to that cell is considered.

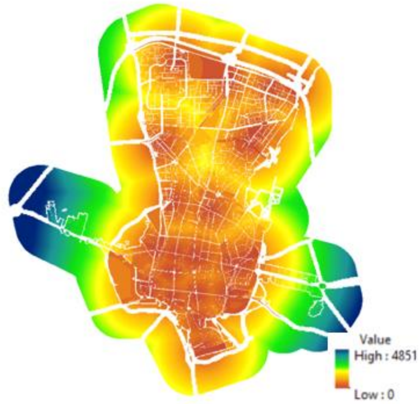
Cell dimensions are considered 25×25 m. In the raster map as shown in Figure 4, points surrounding the red areas have a higher worth. The points most adjacent to blue dots indicate lower desirability for each examined factor. For each considered factor, the distance parameter is admitted, the lower values of each parameter designate a higher utility. For example, the value of the environmental facility parameter for each cell intimates the distance from the most proximal recreational land-use.

In this study, the land-uses map of Qazvin city is converted to 25 x 25 cells using ArcGIS software, and four utility factors are calculated for each cell. Each cell's results are used as the input of written code in Python to execute the agent base model.

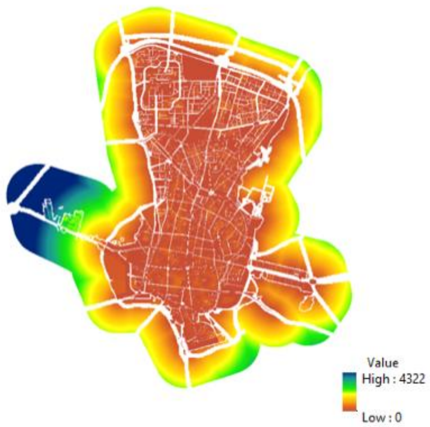
The model is based on the average annual household growth rate of 1.17 percent (based on the statistics of 2016). Consequently, the number of cells that change their use each year is similar to 1.17% of households living in Qazvin in the same year, reflecting the number of residential areas added to accommodate families added for the next year.



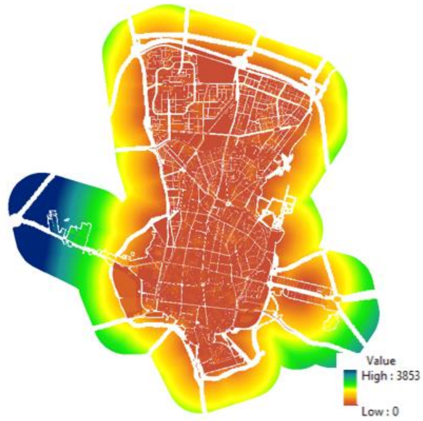
(a) Vicinity



(b) Public transportation vicinity



(c) Proximity to educational facilities



(d) Proximity to environmental amenities

Fig.4 Qazvin desirability factor heat map

Also, the coefficient values for different households have been obtained by performing a survey from different city traffic zones. Since the values of the desirability coefficients fluctuate for different households and it is impossible to take statistics from the whole society, at least 2% of the households living in each traffic zone must be presented in the sampled households of that zone. The selected population's statistical sample is based on the normalized values of coefficients for the statistics' utility parameters. The mean and variance of the sample parameters have been used to generalize a statistical sample for the target population. The coefficients of importance are artificially constructed for each household based on a normal distribution.

The preference coefficients for each household are multiplied by the importance coefficients acquired by the performed method using the expert's opinions. The sum of the interest coefficients for each household should be equivalent to one. The resulting coefficients are used as model input.

In this study, each factor's importance compared to other factors was determined, and a pairwise comparison matrix was created. The pairwise comparison matrix has been collected for the four criteria based on the opinions of 40 experts, and finally, the weighted matrix has been calculated. The coefficients' results from the AHP method indicate the values of 0.272, 0.460, 0.180, and 0.88 for accessibility factors, access to public transport and environmental amenities, and educational conditions.

According to the study's values, the initial values for parameters ϕ, δ, and k are 0.4, 0.9, and 1, respectively, according to the Li et all. study's values (Li et al., 2019).

The values of α_z and β_z are to be equal to 1 and 2, respectively, to calculate the attractiveness index.

In the model used in Qazvin city, the values of α_r, β_r for the relocation and resident change model for the resident population equal to 0.5, 1 have been admitted. Based on the study's objectives, no distinction has been made between the resident change of tenants or owners, and the relevant values have been used cumulatively.

In the residential relocation model, the residence's maximum change value equals 20% of the resident population. Therefore, if the applicant's population is more than 20% of the population to switch their place of residence, they will be selected from the applicant's population as a random group with the maximum condition for changing their residence.

The simulating results of the learning ABM for Qazvin city are shown in Figure 6. Figure 6 shows how residential have developed over ten years based on the base year of 2016.

The green dots in the raster map manifests residential land-use in the base year, the gray dots are for non-residential uses in the base year, and the light gray betokens barren areas. The development of residential areas in Qazvin city is shown in the raster map. It shows that the small southern parts of the city, then the northwest and east parts are developed.

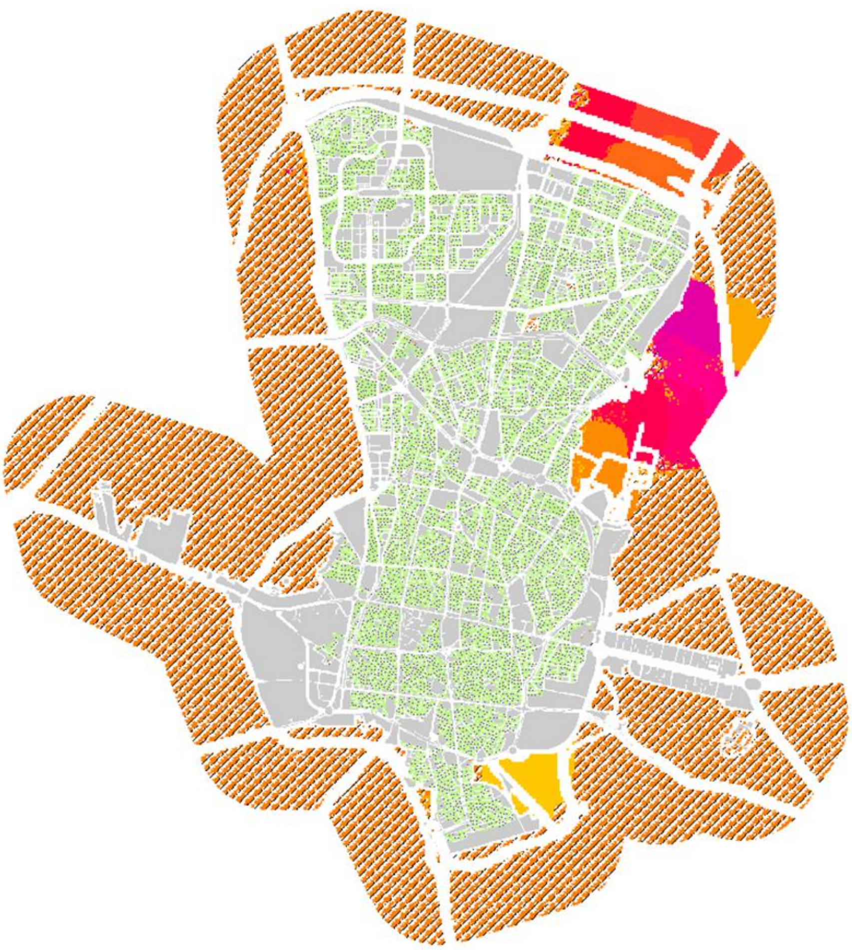


Fig.5 The results of the implementation of the simulation process of the basic agent learning model for Qazvin city

As we can find out from satellite images and compare them with the model predictions, it is clean and clear that the ABM works prodigiously for the past three years. As is showed in Figure 6, the trend of developments was close to the prediction results. In Figure 7, two profiles of Qazvin in two years, 2016 and 2020, are shown. The red arrows added to these figures to show the changes that have taken place in these two screens during these times. As could be seen based on Fig.6 and Fig.7, results show the trend of development and priority of residential development in Qazvin are in northeast and a small part of the south. The east and northeast of Qazvin developed over these ten years, and no residential development has occurred in the southwest.

(a) 2016 (b) 2020

Fig.6 Qazvin Esri satellite map changes; (a) 2016 and (b) 2020

5. Conclusion

This study was done to simulate the residential land-use development in Qazvin city in Iran based on household's desirability and interaction. In this regard, the paper provided an excellent platform for predicting changes and residential land-use development progress. It simulated the relocation for resident households and the choice of residence for new households. The presented model simulated the behavior and association between agents by learning methods and the tendency of agents to anticipate the process of urban development.

Further, the study was able to accurate the previous methods' deficiencies and provided a more realistic appraisal of residential lands' evolution by presenting a new method and reducing the nature of the initial selection randomness that significantly impacted the final results.

Besides, considering the preferences of resident households, their defined agents helping in residence location assisted to predict urban development more realistically. Also, the developed parameter (tendency to change the residence of households) could be generalized to different classes of households for more reliable forecasting.

The model insinuated that urban development transpired in a small part of the south in the initial year. In the second and third years, some sectors of eastern Qazvin developed. In the fourth to seventh years, the northeastern parts of Qazvin changed their residential land-uses. Finally, the inclination of urban development in the eighth to tenth years bent to the east.

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Image Sources

Fig.1 to Fig.6: Authors;

Fig.3: Tehran Municipality.

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