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A Belief-Desire-Intention Agent-based procedure for urban land growth simulation. A case study of Tehran Metropolitan Region, Iran

Saeed BEHZADI[1,*], Kiana MEMARIMOGHADAM[1]

[1] Faculty of Civil Engineering, Shahid Rajaee Teacher Training University, Lavizan, Tehran, Iran
* *Corresponding author*: behzadi.saeed@gmail.com

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Abstract

Urbanization, growth of urban areas, is a process that has been growing rapidly during the last two decades. This phenomenon affects aerobiological, economical, industrial, ecological processes, social control, and the family. Hence, the prediction of the urban area extent has an important role in the future decision of the municipality. Multi-Agent System (MAS) is a proper tool for simulation and modeling process, which has been used for solving different types of spatial and non-spatial problems. In this article, we use MAS for urban simulation in the rural area around Tehran, which is the most populated and the fastest-growing city of Iran. In this paper, the behavior of three groups of agents: environmentalist, industrialist, and resident are simulated. These three groups are the dominant and influential population in the formation of urban texture. In this research, the behavior of these three groups of agents is specified, according to a series of map layers, such as slope, aspect, soil type, distance of urban areas, roads, and so on. The Belief-Desire-Intention (BDI) architecture of agents is used for the simulation, which is defined based on some variables, functions, and coefficients. The simulation is carried out based on two different interaction scenarios: Rational and Nash-Equilibria. The future urban area is predicted by a combination of MAS and spatial urban area. To evaluate the proposed model, the comparison of the predicted area is made at different times and scenarios. The results of implementation in different scenarios show that the residents of the study area follow the Nash-Equilibria interaction with Kappa Coefficient accuracy of 0.8104.

Keywords: *multi-agent systems, interaction, landscape metrics, Tehran metropolitan area*

Rezumat. Asupra unei proceduri de simulare a extinderii terenurilor urbane pe baza credinței – dorinței – intenției. Studiu de caz: Regiunea Metropolitană Teheran, Iran

Urbanizarea, extinderea ariilor urbane, a avut o dinamică rapidă în ultimele două decenii. Fenomenul afectează procesele aerobiologice, economice, industriale, ecologice, controlul social și familia. Astfel, anticiparea extinderii zonei urbane are rol semnificativ în deciziile municipalității. Sistemul Multi-Agent (MAS) este un instrument bun pentru simularea și modelarea procesului, fiind folosit pentru rezolvarea unor problem spațiale și non-spațiale diverse. În acest articol, MAS este utilizat pentru simularea dinamicii urbane în aria rurală din jurul Teheranului – cel mai mare și dinamic oraș al Iranului. În lucrare se simulează comportamentul a trei grupuri de agenți (ecologist, industrial și rezidențial), aceste grupuri influențând dominnt populația în formarea texturii urbane. Cercetarea urmărește comportamentul acestor grupuri de agenți prin straturi tematice precum panta, aspectul, tipul de sol, distanța la zonele urbane, drumurile etc. Arhitectura agenților credință-dorință-intenție (BDI) este utilizată pentru simulare, aceasta fiind definită pe baza unor variabile, funcții și coeficienți. Simularea se desfășoară pe baza a două scenarii de interacțiune diferite. Viitoarea suprafață urbană este prevăzută prin combinația între MAS și spațiul deținut de oraș. Pentru a evalua modelul propus, compararea zonei previzionate se face pentru momente și prin scenarii diverse. Rezultatele implementării în diferite scenarii arată că rezidenții urmează interacțiunea Nash-Equilibria, coeficientul Kappa fiind de 0,8104.

Cuvinte-cheie: *sisteme multi-agent, interacțiune, parametrii ai peiasajului, aria metropolitană Teheran*

Introduction

Land is the main resource for nearly all people. Land use change is the main theme of global environmental change research (Liu et al., 2014). Land use change is done naturally or man-made. The latter is done for different purposes. The impacts of human activities on the natural environment are becoming more and more pronounced (Szu-Hua Wang, Shu-Li Huang, & William W. Budd, 2012). Land use changes have dramatic effects on aerobiological (García-Mozo, Oteros, & Galán, 2016), economical (Wang, Chen, Shao, Zhang, & Cao, 2012), industrial (Tonini, Hamelin, & Astrup, 2016), ecological processes (Kovács-Hostyánszki et al., 2017), and social control (Wang, He, & Lin, 2018; Weathers et al., 2016).

Urbanization represents a type of land use changes happening in urban land and its surrounding. Worldwide, countries are becoming increasingly urbanized and within a few years, more than 50% of the world population will reside in urban areas (Gül, Gezer, & Kane, 2006).

Urbanization has significant effects on climate, soil, water resources, and grasslands (Valbuena, Bregt, McAlpine, Verburg, & Seabrook, 2010). As the urbanization has noticeable effects on a variety of factors, it represents an important phenomenon. That is why a large area of studies pays attention to this problem, and a great number of researches were done in the field of urbanization (Taleai, 2007). As a result, different models were proposed for urbanization.

Cellular Automata (CA) is a common model used for land use planning, particularly in urbanization (Gong, Yuan, Fan, & Stott, 2015; Rimal, Zhang, Keshtkar, Wang, & Lin, 2017; Wu 2010). In these models, the process of urbanization is defined based on some rules for cells. For example, Berling-Wolff and Wu developed CA to simulate the urban growth of Phoenix, which is in four different types of urban growth - spontaneous, diffusive, organic and road-influenced distinguished (Berling-Wolff & Wu, 2004).

Urbanization is a complex issue and cannot be analyzed with some preliminary rules. On the other side, the urban area's texture is not similar and uniform, so the regular structure of CA cannot be the right tool for solving urbanization problems. For solving the first problem, they often combine CA models with artificial algorithms such as Fuzzy Logic, neural network, Makov chain and so on. (Qiang & Lam, 2015). For instance, in Maria and Gleriani's research, CA simulation was introduced on urban land use change, in which Neural Network has been used to modify the simulation model. Then the model was tested in a medium-sized town (Maria & Gleriani, 2005). The second problem is one of the CA model's weaknesses. Using cells with different dimensions, cells with smaller dimensions and topology relations are recommended as a solution for this issue (Behzadi & Alesheikh, 2014), but, occasionally, the complexity and irregularity of the urban areas are very high and require researchers to look for other methods of simulation (Aburas, Ho, Ramli, & Ash'aari, 2016; Chopard, 2018). Consequently, these shortages made CA ineffective for urban simulation.

MAS is more flexible than CA models (Behzadi & Alesheikh, 2013b). These models do not have any restrictions on the physical structure. The study area is definable for MAS models with any shape and texture. On the other side, this model supports learning capabilities, logical rules, optimization, autonomous, etc. in addition to its common reactive rules. These specifications have recommended the appropriate use of these models for complicated problems (Abar, Theodoropoulos, Lemarinier, & O'Hare, 2017; Michel, Ferber, & Drogoul, 2018; Ringler, Keles, & Fichtner, 2016). In MAS, agents are used to present a group of people and organizations with the same behavior. This means that they act as specific groups in urbanization (A. Ligtenberg, Wachowicz, M., Bregt, AK., Beulens, A., Kettenis, DL, 2004; Guangjin Tian et al., 2016). As a result, the combination of all organizations (agents) decides for the present and future of the urban land. Ligtenberg's research (A. Ligtenberg, Wachowicz, M., Bregt, AK., Beulens, A., Kettenis, DL, 2004) and Tian's study (G. Tian, Ouyang, Quan & Wu, 2011) are samples of using MAS in land use modeling and simulation. In Ligtenberg's study, multi-agent systems are used to simulate land use changes. For the simulation, some multi-decision makers are used in spatial planning to generate spatial scenarios. Tian and his colleagues developed an agent-based model of urban growth for the Phoenix metropolitan region of the United States. In this paper, they simulated the behavior of different groups, such as regional authorities, real estate developers, residents, and environmentalists in the urbanization. The main difference between the current research and previous studies refers to the fact that in this paper special architecture of agent-based models (Belief-Desire-Intention architecture) has been used, which is high in proportion to human behaviors. For this reason, the predicted behaviors by agents are far closer to reality.

In the present paper, a BDI agent-based model is proposed for urban simulation. The simulation of the urban area is done based on different scenarios, among different groups of agents with distinctive behaviors. The following section approaches the study area. In the next section, the conceptual framework of the model is introduced. Then, the model is implemented for simulation. Next, the evaluation of the model is made in the 6th section. Finally, the conclusion is discussed in the last section.

Study area and data

Tehran metropolitan area is the most populated and the fastest-growing city in Iran. It is located in the center of Iran, being characterized by a temperate climate.

During the last decade, Tehran exemplifies urbanization with an underground and overland network from the center and industrial area to the surrounding in west open space. During recent years, Tehran has been changing as the fastest-growing city in Iran, with a population growth rate of 1.84% between 2000 and 2010. More than 90% of the population growth was due to immigration from other cities. Because of physical and geographical barriers in north, east, and south of the city, Tehran is prone to development from the west area. That is the reason for using the west part of Tehran in this Research. The geographical location of the study area is 35° 41′ to 35° 46′ N latitude and 51° 05′ to 51° 18′ E longitude (Fig. 1).

Table 1: Statistical data for the study area

	Year 2000	Year 2010
Number of urban parcels	2442	2618
Urban area	50.98 km²	65.86 km²
Population	> 17000	> 33000

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Required data such as slope, aspect, soil type, urban land, agricultural land, water resource, major road, railway, service area are collected from Tehran's official website (www.tehran.ir). The statistical data for the study area are shown in Table 1.

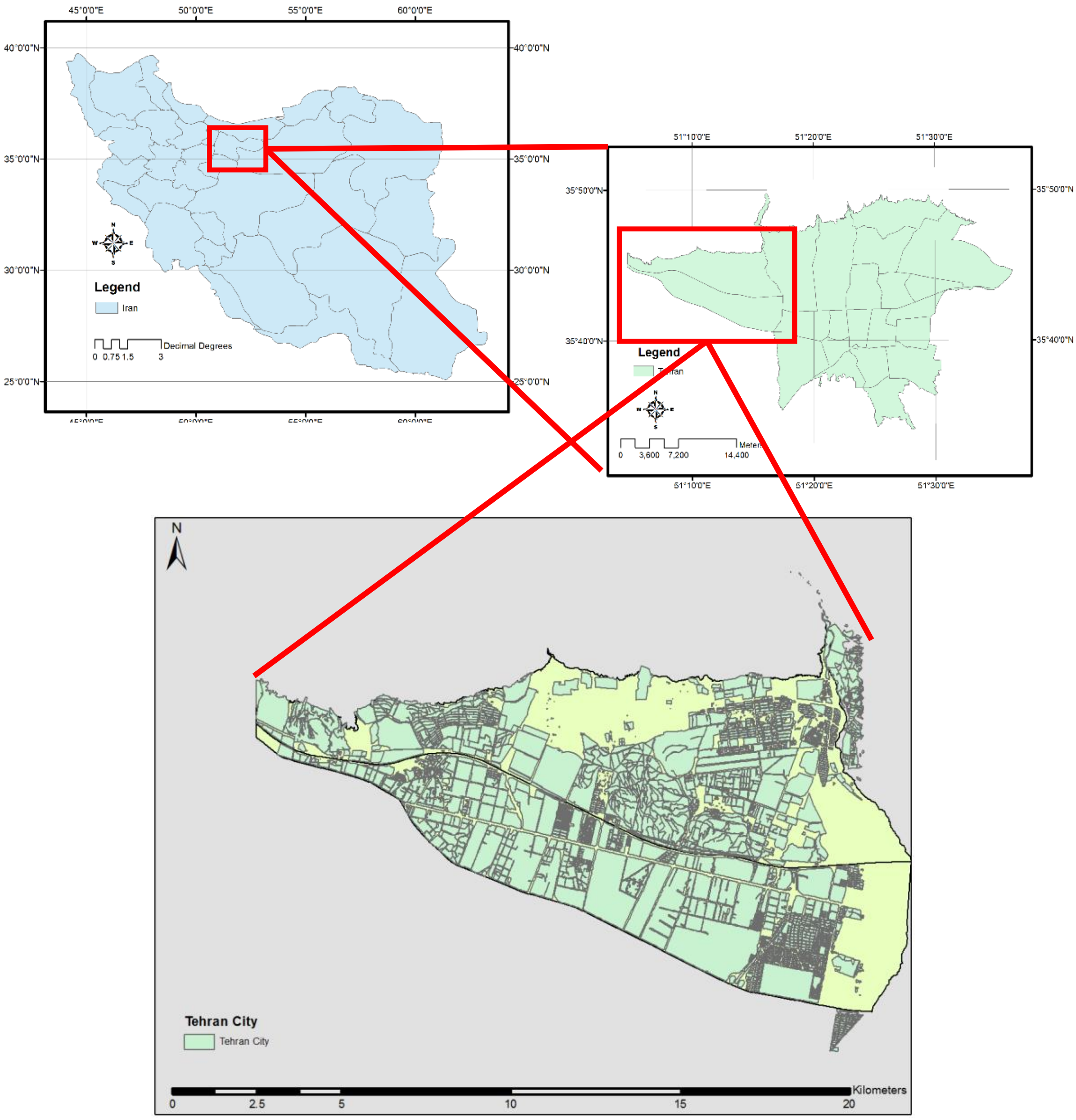

Fig. 1: Case study area (West of Tehran City)

Methodology

A multi-agent system (MAS) is a system composed of multiple interacting agents to solve problems that are difficult or impossible for a monolithic system to solve (Behzadi & Alesheikh, 2013a). In such a framework, an agent is a computer system that is situated in some environment and that is capable of autonomous action in the environment to meet its design objectives (Tweedale et al., 2007; Weiss, 1999; M. a. J. Wooldridge, N. R., 1995; M. J. Wooldridge, 2002). Based on this definition of agents, four classes of architectures were introduced, namely logic-based, reactive, hybrid, and belief-desire-intention (BDI) architectures. The latter has received more attention from scientists than the other ones, due to the implementation of intentional stance, which has been built after the philosophical work of Bratman (Bratman, 1987) and Dennet (Dennett, 1988; Brison, 1989). In BDI architecture, each agent believes the environment, desires what it wants to be true in the environment, and intends to do an action based on its belief and desire (A. Ligtenberg, Beulens, A., Kettenis, D., Bregt, A. K., & Wachowicz, M. , 2009; A. Ligtenberg, Wachowicz, M., Bregt, AK., Beulens, A., Kettenis, DL, 2004). Belief refers to the current state of the environment. Hence, belief is considered by perceiving the spatial and attributive information of the land use map. For example, the type of the land, area, and distance to roads are considered as elements of belief. The objectives of the agent are considered as the desire. For example, environmental protection and industrial development are considered as the desire of the model. Intentions are considered as changes in the environment. The agents make their belief by observing the environment; they make their intentions by adjusting specific weights to their belief. The result displays their desire obtained by implementing the intention on the belief (Relation 1) (Hall, Guo, Davis, & Cegielski, 2005).

$$F(des) = F(bel) \times F(int) \qquad (1)$$

In this article, the agents are considered as a group of individuals with the same behavior. Our model presents three groups of agents with different behavior: environmentalists, industrialists, and residents. Environment, water resources, and soil type for farming are the main factors for the agents from the environmentalist group. So, these parameters are with the highest priorities in the agent's behavior. The economic issues completely affect the behavior of the agents in the industrialist group. Being in the adjacency of the urban area and of the main roads are two fundamental characteristics of the behavior of the industrialist group. The behavior of resident agents is determined by their location and mobility. Adjacency to urban areas and communication networks (railroad and main road) are the highest priorities for resident agents.

The interaction among agents is done based on the payoff table. If we have two agents and T_1, T_2 are two tasks that agents can do, the payoff table is shown as:

		Agent$_1$: T_1	Agent$_1$: T_2
Agent$_2$	T_1	P^1_{T1T1}, P^2_{T1T1}	P^1_{T1T2}, P^2_{T1T2}
	T_2	P^1_{T2T1}, P^2_{T2T1}	P^1_{T2T2}, P^2_{T2T2}

The upper-right value shows the desire values obtain by Agent$_1$, and the lower-left value shows the desire values obtain by Agent$_2$. The interaction is done based on one of the two strategies: *Rational* and *Nash-Equilibria* (Uhrmacher & Weyns, 2009). In the Rational interaction, each agent computes the minimum profit of each intention based on the other agent's intentions, and then it selects the intention of which profit has maximum value among these minimum values. In the Nash-Equilibria interaction, two strategies were followed by agents: 1) under the assumption that agent *i* selects the intention *1*, agent *j* can do no better than the selection of intention *2*, and 2) under the assumption that agent *j* selects the intention *2*, agent *i* can do no better than the selection of intention *1*.

Then, four common landscape metrics (Seto, Fragkias, & Schneider, 2007) are used to evaluate implementation results (McGarigal & Marks, 1995): 1) NP: the total number of urban patches in the area. 2) ED: the total length of all urban patch edge segments per square kilometers. 3) MPS: mean urban patch size. 4) AWMPFD: averages of the fractal dimensions of all patches by weighting larger land cover patches (Equation 2) (G. Tian et al., 2011).

$$AWMPFD = \sum_{i=1}^{n} \frac{2\ln 0.25P_i}{\ln(a_i)}\left(\frac{a_i}{A}\right) \qquad (2),$$

where P_i is the perimeter of patch i, a_i is the area of patch i, n is the number of land patches, and A is the total landscape area.

Figure 2 shows the conceptual model of the MAS for the urban development issue. As in this figure, three groups of agents (environmentalist, industrialist, and resident) are inside the model. These agents build their beliefs based on observations of the environment. Then, a set of actions is determined based on their desires. Finally, each agent does its best action on the environment based on its interactions.

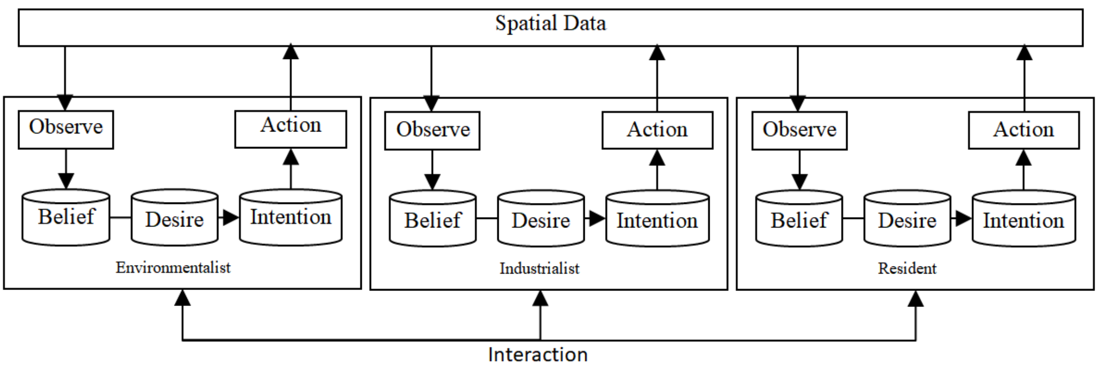

Fig. 2: The conceptual MAS framework for land use processes

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Model implementation

Each parcel represents a small patch of the land with some attributes, such as soil type, topology. The proposed model takes some variables into account, which can affect the land use: neighborhood of urban land, neighborhood of agricultural land, distance to urban land, distance to agricultural land, distance to water resource, distance to major roads, distance to railways, distance to open space, distance to service area. All these variables are considered as the belief of the agent.

In this study, the land use conversion function is defined as:

$$LUC = \sum_{i=1}^{12} \alpha_i Y_i \qquad (3),$$

where Y_i represents the deriving factors, and α_i are corresponding coefficients. The α_i values were obtained by agents through land-use data. Table 2 presents the description of each variable.

Table 2. Description of the variables

Main Variables	Sub Variables	Description
Y_1	$0.5X_1^2 + 4X_1$	slope
Y_2	$0.2\ln(X_2)$	aspect
Y_3	$4X_3^3 + 3X_3^2 + X_3$	soil type
Y_4	X_4	neighborhood of urban land
Y_5	X_5	neighborhood of agricultural land
Y_6	X_6	distance to urban land
Y_7	X_7	distance to agricultural land
Y_8	X_8	distance to water resource
Y_9	X_9	distance to major road
Y_{10}	X_{10}	distance to railway
Y_{11}	X_{11}	distance to open space
Y_{12}	X_{12}	distance to service area

The behavior of agents significantly affects the land-use conversion value, which is represented in the model by changing the coefficients of these factors. The coefficient domains of the variable are represented in Table 3 for each group of agents.

These values are obtained by expertise, based on the importance of each main variable for the specific group. For example, "neighborhood of agricultural land" is the same for the three agent groups (industrialist, environmentalist and resident). Therefore, the range of coefficients of variation associated with the "neighborhood of agricultural land" is assumed to be uniform for these three groups of agents. For environmentalists, "distance to agricultural land" is twice as important as to the other two agents, so its average range of coefficients is more than the other two agents.

Table 3. The coefficient domains of the variable (for each group of agents)

Coefficient domains	Environmentalist	Industrialist	Resident
α_1	[0.10 - 0.15]	[0.0 – 0.10]	[0.0 - 0.5]
α_2	[0.05 - 0.10]	[0.0 - 0.10]	[0.0 - 0.5]
α_3	[0.15 - 0.20]	[0.0 - 0.10]	[0.0 - 0.5]
α_4	[0.0 - 0.5]	[0.10 - 0.15]	[0.5 - 0.10]
α_5	[0.0 - 0.5]	[0.0 - 0.5]	[0.0 - 0.5]
α_6	[0.0 - 0.5]	[0.15 - 0.20]	[0.15 - 0.20]
α_7	[0.5 - 0.10]	[0.0 - 0.5]	[0.0 - 0.5]
α_8	[0.15 - 0.20]	[0.5 - 0.10]	[0.10 - 0.15]
α_9	[0.10 - 0.15]	[0.20 - 0.25]	[0.15 - 0.20]
α_{10}	[0.0 - 0.5]	[0.0 - 0.5]	[0.15 - 0.20]
α_{11}	[0.5 - 0.10]	[0.5 - 0.10]	[0.0 - 0.5]
α_{12}	[0.5 - 0.10]	[0.5 - 0.10]	[0.15 - 0.20]

The coefficient domains directly depend on the behavior of each agent. The land-use type of each patch is considered based on the land-use conversion function's value. The land-use type of each patch is obtained as:

$$\begin{cases} \text{If } 0 \le \text{land use conversion} < \text{T} & \text{'Urban'} \\ \text{If } \text{T} < \text{land use conversion} \le 1 & \text{'Agriculture'} \end{cases} \qquad (4)$$

The threshold T is obtained based on the land use data and the interaction among agents. The desire function of each group of agents is obtained as:

$$Desire = \min\left(\sum_{i=1}^{patch\ Number} (LUC_i - LUC^T)^2\right) \qquad (5),$$

where LUC_i is the land-use conversion proposed by the agent for parcel i, and LUC^T is the land-use conversion obtained from the interaction.

Equation 5 shows that the desire of the agent depends on the coefficient value, as well as threshold T. These two sets are the main unknown variables of this problem. The main goal is to find the appropriate values for these two categories of unknown elements, so that the predicted value by agents in 2010 should be the most similar to the actual one.

For each value of the threshold, each agent proposes a set of values for α_i to minimize the desire function. The T value is selected as the best threshold to minimize all agents' desires. As a result, the interaction among agents can obtain the best coefficients for each agent.

Model simulation

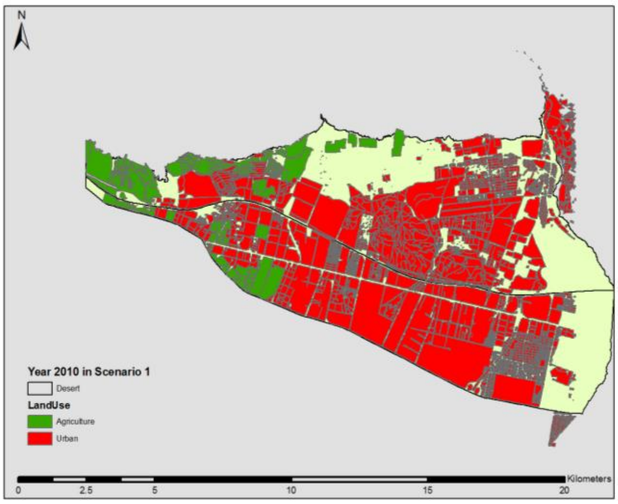
In this paper, two scenarios are designed for simulation analysis. In both scenarios, three agents handle the problem. They compute different values of coefficients for different threshold values to obtain an acceptable desire.

The interaction among agents adjusts the threshold value for obtaining acceptable coefficient values. Once the values are obtained, each agent uses the Equation 3 to find the land use of each patch. The final land use of each patch is obtained based on the combination of three agents' suggestions.

In Scenario 1, the rationality is the interaction strategy. Three defined agents interact based on this strategy. Figure 3 shows the result of the agents' action on the land use map in the years 2010 and 2020 in Scenario 1. Table 4 shows the coefficient of variables suggested by three groups of agents.

Table 4 The coefficient of variables suggested by three groups of agents (Scenario 1)

Coefficient domains	Environmentalist	Industrialist	Resident
α_1	0.10	0.06	0.04
α_2	0.07	0.06	0.04
α_3	0.19	0.06	0.01
α_4	0.02	0.11	0.10
α_5	0.04	0.03	0.02
α_6	0.04	0.16	0.15
α_7	0.07	0.04	0.01
α_8	0.20	0.08	0.12
α_9	0.15	0.21	0.15
α_{10}	0.01	0.03	0.17
α_{11}	0.06	0.08	0.01
α_{12}	0.05	0.08	0.18



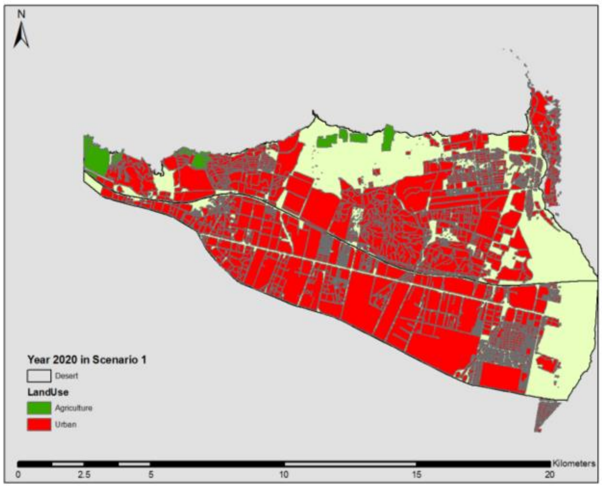
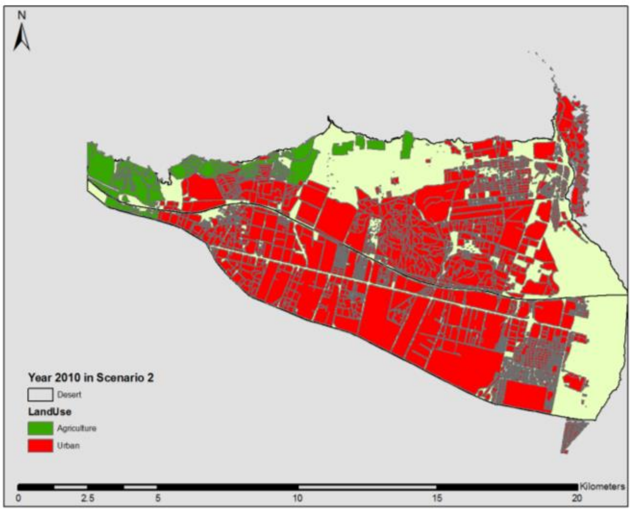


Fig. 3: The result of the agents' action on the land use map in the years 2010 and 2020 in Scenario 1

In Scenario 2, the Nash-Equilibria strategy is used for interaction. Figure 4 shows the result of the agents' action on the land use map in the years 2010 and 2020 in Scenario 2. Table 5 shows the coefficient of variables suggested by three groups of agents.

Table 5 The coefficient of variables suggested by three groups of agents (Scenario 2)

Coefficient domains	Environmentalist	Industrialist	Resident
α_1	0.12	0.03	0.02
α_2	0.10	0.04	0.03
α_3	0.17	0.02	0.01
α_4	0.02	0.15	0.04
α_5	0.03	0.03	0.01
α_6	0.03	0.19	0.20
α_7	0.05	0.03	0.01
α_8	0.18	0.08	0.15
α_9	0.14	0.22	0.18
α_{10}	0.01	0.05	0.18
α_{11}	0.09	0.06	0.01
α_{12}	0.06	0.10	0.15



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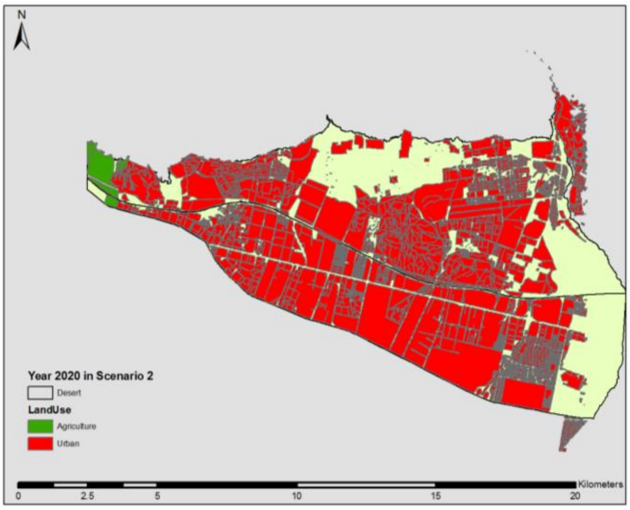


Fig. 4: The result of the agents' action on the land use map in the years 2010 and 2020 in Scenario 2

Model evaluation

Before simulating the two scenarios, the projected result is evaluated with the empirical land use map for 2010, using the Kappa coefficient (Congalton & Green, 1999):

$$Kappa = \frac{P_0 - P_C}{1 - P_C} \qquad (6),$$

where P_0 represents the correct percent for the model output, and Pc is the expected percent correct just due to chance.

The Kappa coefficient is computed based on the settings of Scenario 1 (*Rational interaction*), and Scenario 2 (*Nash-Equilibria interaction*). The values of Kappa were 0.7881 and 0.8104 respectively. The model is then simulated to project the land use maps for 2010 and 2020, following the two scenarios.

In 2000, the urban land accounted for 69% of the total area.

Scenario 1 projected that the urban land would reach 86% in 2010, and 96% in 2020 (Fig. 3).

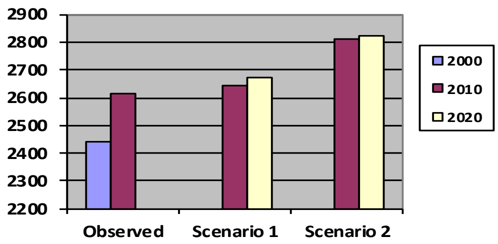
In Scenario 2, urban land would reach 90% in 2010, and 98% in 2020 of the total area (Fig. 4). The urban growth in Scenario 2 is faster than the other one because the industrialist and resident agents have more flexibility with the environmentalist agent in interaction.

To compare the simulated results in detail, four criteria of landscape metrics are used. These factors are used to quantify the urbanization in the west of the city.

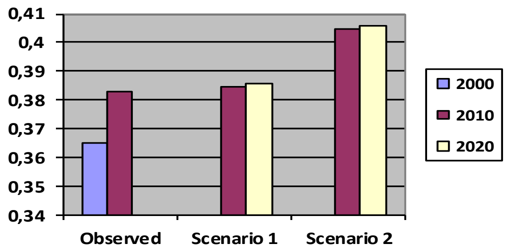
From the simulation results (Fig. 5), the values of NP, ED, and MPS for the two scenarios improve dramatically from 2000 to 2010.

The increase of NP value shows the urban growth. The increase of MPS value shows the emergence of the new small urban areas that we have expected in 2020. The increase of ED value shows the dispersion of the urban patches.

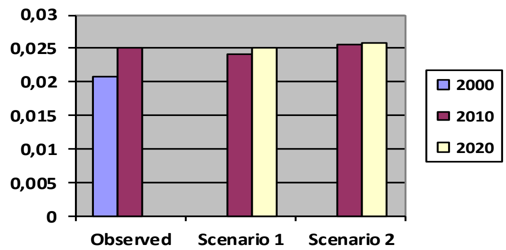
Firstly, from 2000 to 2010, the value of AWMPFD goes down and then (from 2010 to 2020) it goes up in both Scenario 1 and Scenario 2. In both scenarios, the AWMPFD values go down at first. This fact shows the regularity of patch shapes from 2000 to 2010. However, the values of AWMPFD for both scenarios decline dramatically from 2010 to 2020. This second dynamics shows that the shapes of patches are made irregularly.



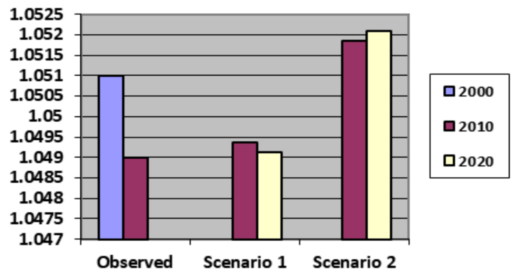
a) number of urban patches (NP)



b) urban edge density (ED)



c) mean urban patch size (MPS)



d) area weighted mean patch fractal dimension (AWMPFD)

Fig. 5: Results of prediction among the two different scenarios for 2000, 2010, and 2020

Conclusion

Nowadays, the use of simulation has made it easier for decision-makers to predict the behavior of the environment. As a result, they make better decisions. In this study, one of the main issues of Tehran city management was investigated. Since MAS represents a model that can simulate human behavior better, it was used for identifying people's behavior in the city. The flexibility of this model and its adaptation to the complexity of the urban context were other reasons for using it instead of previous models, such as CA. In this study, three types of agents (environmentalist, industrialist, and resident) were identified as the main decision-makers. The behavior of these agents was modeled as a series of formulas. These agents were simulated based on two scenarios of *Rational* and *Nash-Equilibria* interactions. The implementation results show that residents have Nash-Equilibria interaction behavior, and this has 81% similarity to Nash-Equilibria behavior interaction. This result has been reached from comparing the obtained maps of Nash-Equilibria interaction and the reality in 2010. The paper evaluates four criteria of landscape metrics to assess the quality of the results. The results show that the surface of urban land in the study area has grown significantly in 2020. This reflects urban growth in the region.

The values in the MPS diagram show that the probability of creating settlements in this area is very low and somehow impossible and the city of Tehran will have only the urban development in the mentioned area. The values in the ED diagram indicate that there is a possibility of urban land use scattering in the area, which reflects the behavior of urban development in the area. The results obtained from the AWMPFD diagram show that the growth behavior of the western area of Tehran is completely irregular.

In summing up the results of this section, it can be said that urban development behavior in this area is carried out without the supervision of the relevant organizations, and this development is carried out by the residents of the city sporadically. The lack of a definite structure in this development is one of the prominent characteristics that can be mentioned. The present study was based on data available in 2000 and 2010. The large time difference between the data can be one of the weaknesses of this study, which is inevitable due to the ten years of data updating from the municipality. The existence of more data certainly had a significant impact on improving the results, but in the present study, ground observations at present can confirm the model's accuracy, as the Kappa Coefficient indicates this.

In this article, the urban simulation is done by MAS. However, the main groups of decision-makers (environmentalists, industrialists, and residents) are introduced here. To simulate the urbanization completely, the other miner groups of agents are needed to be defined in the model. The behavior of the new groups must be defined based on the coefficients domain. Moreover, twelve essential variables of urbanization are discussed in the present paper. However, considering the other variables will make the model more realistic.

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