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Scenario modeling to predict changes in land use/cover using Land Change Modeler and InVEST model: a case study of Karaj Metropolis, Iran

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Abstract Models for land cover/land use simulation are appropriate and important tools for decision-makers, helping them build future plausible landscape scenarios. Due to the fact that the simulation results of different models may be different, it is sometimes difficult for users to choose a suitable model. Therefore, in this study, an integrated approach is used, combining the data obtained from remote sensing and GIS with Land Change Modeler (LCM) and Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) models to simulate and predict land cover/land use changes for 2028 in Karaj metropolis (Northern Iran as a poor region—in terms of data—which is under intense and rapid urbanization. In this sense, three land cover/land use maps related to the study area were primarily generated using satellite image data for the period 2006, 2011, and 2017. They were used as a basis to define two scenarios: business-as-usual (BAU) scenario and participatory plausible scenario (PPS) for 2028. Afterwards, the necessary input data used in running of both models were prepared and, then, the outputs of the models were interpreted and compared. According to the results, while human-made coverage and low-density grasslands increased by about 74% and 12%, respectively, it was from 2006 to 2017 that agricultural lands, gardens, and high-density grasslands decreased by 42%, 34%, and 7%, respectively. According to the business-as-usual scenario, which was projected using the LCM model, the increase in human-made cover will continue by about 29% by 2028, and the reduction rate of agricultural lands, gardens, and low-dense and dense grasslands will experience decrease by about 20%, 3%, 11%, and 9%, respectively. The participatory plausible scenario for 2028, which was defined using the InVEST model, confirmed the same results, but having different quantities. Accordingly, while human-made cover will increase by about 73%, the reduction rate of agricultural lands, gardens, and low-dense and dense grasslands will decrease by about 41%, 10%, 16%, and 1%, respectively. The output quantities of InVEST scenario model seem to be closer to reality with less uncertainty, because this model estimates the quantity of demand for land and its suitability for different uses, based on the views of different stakeholders, and considers landscape development future policies and plans. In contrast, the LCM model is based solely on trend

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extrapolation from the past to current time and changes in the landscape structure.

Keywords Land use/land cover · Urban expansion · LCM · InVEST · Scenario modeling · Karaj

Introduction

Scenario modeling is a way to visualize future uncertain events that occur in a natural landscape or urban environment (Kindu et al., 2018). Land use/land cover (LULC) change is noticed as one of the most significant environmental issues worldwide because it is driven by the need to provide food and shelter and by the rise in economic development among many other factors (Aksoy et al., 2022). Hence, it is one of the main drivers of disturbances in the natural environment (Sarparast et al., 2020). In this sense, land degradation eventually leads to critical environmental and social problems due to the unprincipled conversion of land for various uses, starting with the modification of the Earth's terrestrial surface (Desta & Fetene, 2020). Moreover, it is worth mentioning that urbanization and industrialization, which can be regarded as the most important factors affecting the land system (Rizvi et al., 2020), have led to the transformation of intact lands into impervious human-made cover and become an increasing trend in both developed and developing worlds in recent decades (Das & Angadi, 2020). Global LULC changes, mainly for more socio-economic development, have raised a wide variety of concerns about ecological unsustainability and its devastating consequences (Homer et al., 2020). Therefore, LULC analysis is a basic necessity for a range of biophysical, ecological, and socio-economic consequences, whose aim is to determine preventive and mitigation strategies of such consequences as a prerequisite for natural resource management (Gupta & Sharma, 2020). In other words, data on LULC changes and their driving forces in the absence of such changes provide a well understanding of the dynamics of LULC changes (Aksoy et al., 2022).

Thanks to the data obtained from remote sensing and satellites and their application in GIS, the LULC evaluation and monitoring have been facilitated in recent years (Romano et al., 2018). Regarding further development of this technology, it has been confirmed that the novel spatio-temporal models are suitable tools in order to understand the dynamics of many natural systems and predict changes in them (Al Kafy et al., 2020; Armenteras et al., 2019).

Significantly, various studies have analyzed the quantity and quality of changes in LULC patterns, using different approaches and techniques, such as artificial neural network (Al Kafy et al., 2020; Islam et al., 2018; Liu et al., 2020; Xu et al., 2019), logistic regression (Adnan et al., 2020; Siddiqui et al., 2018), Markov chain (Al Kafy et al., 2020; Levrel et al., 2017; Silva et al., 2020; Sun et al., 2018), cellular automata (CA) (Karimi Firozjaei et al., 2019; Mansour et al., 2020; Munthali et al., 2020), SLEUTH (Chaudhuri & Clarke, 2019; Clarke & Johnson, 2020; Liu et al., 2017) and CLUE-S (Jiang et al., 2017; Waiyasusri et al., 2016). In this sense, the Land Change Modeler (LCM) model has been widely used (Areendran et al., 2017; Ayele et al., 2019; Reddy et al., 2017) but, on the contrary, limited studies have analyzed and predicted land use change using the recently introduced Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) Scenario Generator model.

Anand et al. (2018), Islam et al. (2018), Armenteras et al. (2019), and Silva et al. (2020), in their studies, have predicted the future LULC trend using the LCM model. They also selected the following variables: distance from roads, distance from water bodies, distance from urban areas, population, slope, and digital elevation model (DEM) as important parameters in LULC changes. In another study, Mohammadyari et al. (2021a) simulated LULC changes in the region of Behbahan using the LCM model. The used variables included DEM; slope; distance from residential area, agricultural areas, and roads; and the probability map of evidence. Based on the literature review, the variables used for modeling were selected according to the availability of data, their relative importance, and their corresponding impact on the changes in LULC. Kramer correlation coefficient was also used to determine the correlation between independent variables and dependent variables. On the other hand, regarding studies performed by Zarandian et al. (2017) and Fadaei et al. (2020), LULC forecasting has been done with the participation of stakeholders using InVEST Scenario Generator model. In all of these studies, model inputs included the amount of LULC variation, transfer probabilities, LULC preferences or weights from stakeholder perspectives, and physical factors which aimed at determining land suitability, i.e., the slope, DEM, soil type, distance to roads and markets, and rainfall distribution.

The LCM tool in the IDRISI TerrSet software is manually used to analyze LULC spatial patterns and predict changes (Gupta & Sharma, 2020). The basic principle in using this model is to evaluate the trend of change from one land use to another under the influence of factors such as roads, slope, aspects, and type of soil and, finally, to predict the changes in LULC pattern based on the trend of previous changes.

The InVEST modeling tool was designed to devise informed resolves about natural resource management (Sharp et al., 2015). This model was also developed by the Natural Capital Project (www.naturalcapitalproject.org), jointly with Stanford University, World Wide Fund for Nature (WWF), and The Nature Conservancy (TNC) (Liu et al., 2017). Furthermore, its purpose was to create coordination between socio-economic forces and environmental conservation objectives (Bai et al., 2011). It is worth mentioning that InVEST is an open-source tool to map, quantify, and value ecosystem services (Guerry et al., 2012). Regarding the output analysis from InVEST, information can be provided to policy-makers weighing the tradeoffs in ecosystem services, biodiversity conservation, and other land use objectives.

The InVEST Scenario Generator tool offers a relatively simple method in order to generate participatory scenarios based on user-defined principles of where land changes can occur and also the possible extent of these changes (Yan et al., 2018). Given that, most ecosystem studies and assessments require the generation of future layers of LULC data to predict environmental impacts. In this regard, it is worth mentioning that this tool can be of great help. It is well known that scenario design, used to predict LULC changes, is complex due to the need to combine multiple economic, social, and ecological factors. In addition, preparing an LULC map for future planning is often a problem due to the lack of explicitly spatial data. The innovative approach of the InVEST Scenario Generator model is to combine different variables, such as land suitability for development types, and environmental factors with stakeholder inputs on some specific factors like land demand and the likelihoods for land use transition. Regarding data combination, the tool produces simple maps of the possible future that make it possible to visualize the future of the LULC under an explicit spatial method.

The present study aims at analyzing the LULC changes in Karaj metropolis from 2006 to 2028 based on the change trend analysis from the past to current situation and, then, creating a visual representation of future LULC scenarios. It should be mentioned that the year 2028 will be the last year of the seventh national socio-economic development plan in Iran (Program & Budget Organization of Iran, 2022). Regarding the implementation of this plan, it is expected that extensive changes will occur in Iranian metropolises, including Karaj (study area), which can be associated with environmental consequences. Therefore, this year was chosen to predict changes in LULC.

During the past decades, the metropolis of Karaj has been dominated by green covers. But, nowadays, due to urbanization, natural resources have been severely degraded. The intensification of LULC changes in the region reduces ecosystem services in the region. Moreover, the studied area is one of the most important metropolises of Iran, which has rapidly faced the phenomenon of urban expansion. Hence, the preparation of LULC maps in this area has become one of the priorities of urban planners. In this regard, using different methods to prepare LULC maps is an effective strategy in order to help LULC policies. From this point of view, the evaluation of LULC changes in Karaj metropolis was considered as one of the important issues for Iranian researchers.

Significantly, herein, the prediction of future LULC changes has been carried out using two different ordinary and more advanced scenario-making models which are respectively called LCM and InVEST Scenario Generator models. Subsequently, the result outputs of both models were compared. Accordingly, this study uses an integrated approach that combines remote sensing and GIS data with LULC models to simulate and predict LULC changes for the year 2028 in Karaj metropolis, a place that is considered as a poor data region whose ecological structure is changing rapidly due to intensive urban development. Considering this study area, there is a great demand for the conversion of natural land into human-made infrastructures. Therefore, any unprincipled change in LULC management can lead to conflicts between different land beneficiaries, including agriculture and industry on the one hand and organizations in charge of environmental protection on the other. To reduce such conflicts and prevent adverse environmental and developmental tradeoffs, scenario modeling to predict future LULC changes can be a principled solution leading to an increase in the understanding of different stakeholders about the future of the land and, ultimately, improving LULC policy and planning. Since the various stakeholders in our study area are interested in understanding future changes in the LULC structure, there exists a suitable case to use the scenario modeling approach to project LULC. In this regard, the InVEST scenario generating model is a novel and up-to-date model that provides the possibility of considering the opinions of all stakeholders in the form of future LULC scenario. While visualizing the future scenario in the form of a map, it puts in front of them a clear picture of the future of the land. This can be a basis used to adjust the quantity of demand for change in LULC, thus leading to reduce conflict and strengthen synergies between different users and, ultimately, improving the management of land in the study area with better and more informed decisions of land allocations to various human uses.

Study landscape

The studied landscape (Fig. 1) has an area of 117,520 ha and is located in 35° 46′–36° 09′ N, 50° 46′–51° 21′ E, east of Alborz Province, which is one of the most important industrial hubs of Iran. Furthermore, Karaj metropolis, with a population of approximately 2 million people, is the capital of Alborz Province and is located downstream and south of the study landscape. Additionally, it has a vital role in the country's economy and is the closest city to Tehran, the capital of Iran (Eslamlou & Mirmoghtadaee, 2017). The climate of Karaj is cold and semi-arid according to the Köppen classification method (Ghobadi et al., 2018). Much of the drinking water used in the capital is also supplied by the Karaj River, which originates in the northern upstream areas of the study landscape, passing through the city of Karaj. Therefore, any destructive changes in the natural features of Karaj can directly affect the capital in terms of water pollution. Karaj is under pressure from unbridled urban development, expansion of settlements, and factories that directly affect the ecological structure of the city. Accordingly, such severe physical development has led to various environmental crises such as air pollution, loss of vegetation, reduced water quality, and generally, reduced quality of life (Mohammadyari et al., 2020).

Methods

This research methodologically included three main steps.

Step 1: generate LULC maps using satellite imagery

Three LULC maps of the study area for the periods of 2006, 2011, and 2017 were generated and analyzed using satellite image data. In this sense, satellite images of Landsat 5 from Thematic Mapper (TM) sensor for 2006 and 2011 and Landsat 8 from Operational Land Imager (OLI) sensor for 2017 were downloaded (from the USGS website) (https://www.usgs.gov/). The selected satellite images (the pixels of which were 30 m × 30 m) were as cloud-free as possible. The necessary initial processing was performed with atmospheric and geometric corrections in ENVI software. Thus, 10 LULC classes were separated in the study landscape: human-made areas (including rural settlements, urban areas, industrial land, and mining land), agricultural lands, garden, water bodies, low-dense grassland, dense grassland, barren, rocky mountains, urban green space, and rivers. The supervised classification method (Silva et al., 2020) with support vector machine (SVM) algorithm (Heydari & Mountrakis, 2019; Karimi et al., 2019) was used for LULC classification. According to a study performed by Khatami et al. (2016), the SVM model is the most efficient tool for LULC classification because of its ability to minimize classification errors. Therefore, it was preferably applied to the parametric classification model, i.e., the maximum likelihood estimation classifier (Khatami et al., 2016; Rana & Suryanarayana, 2020). Moreover, the image classification efficiency was checked out using the kappa index (Silva et al., 2020).

These raster LULC maps will be used in the next steps as one of the main inputs to run both the LCM and InVEST Scenario Generator models. Although the outputs of the two models depend on the same raster map, due to the different computational natures of the two models, the predicted results are expected to be different. This is because the LCM model predicts the LULC with a retrospective approach based solely on the extrapolation of past trends to the current. This is while there is a need for prospective scenarios based on the real needs and demands of different stakeholders for land conversion. Significantly, it is a process

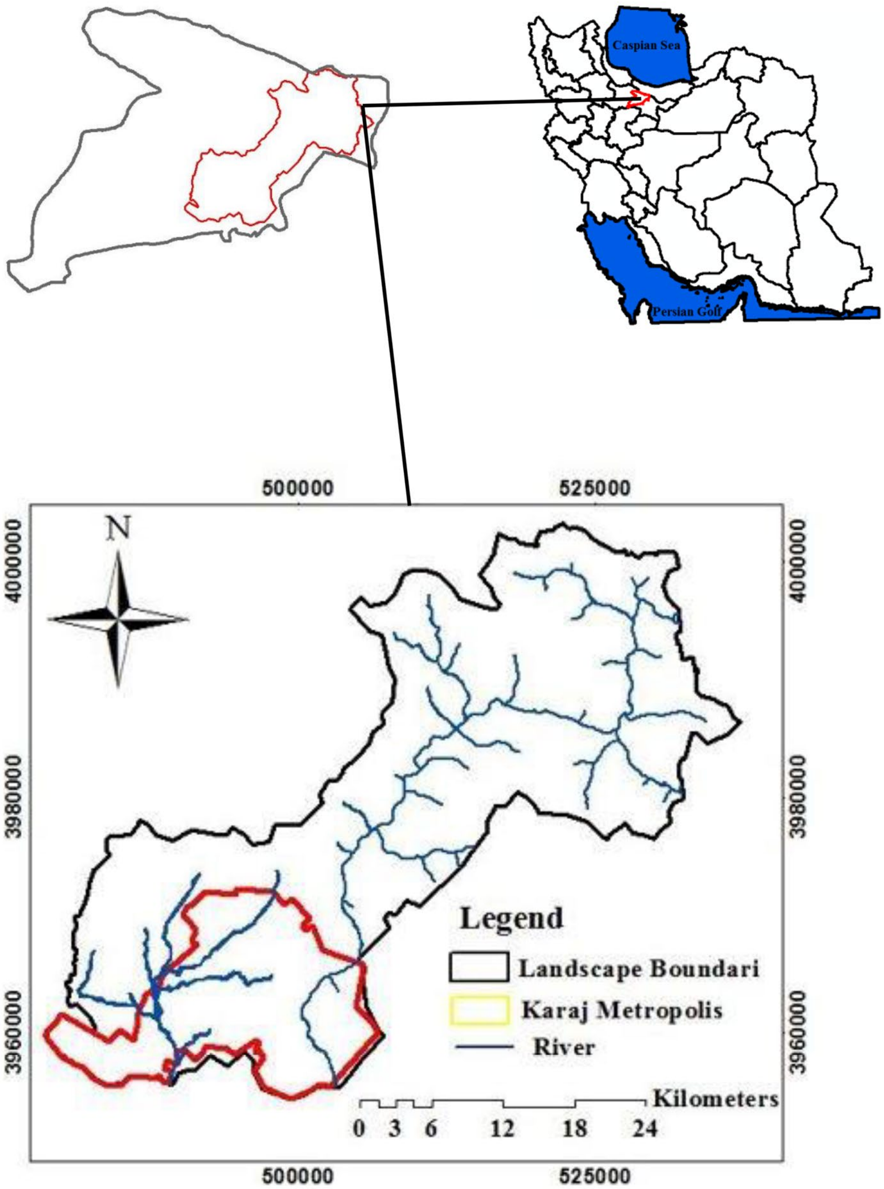

Fig. 1 Location of the study area

designed to operate the InVEST Scenario Generator model. Therefore, the results were compared using the implementation of both models.

Step 2: scenario modeling using LCM

Analysis of changes in LULC

LCM tool was used, based on artificial neural network (ANN) and Markov chain (Eastman, 2009) analysis. The change analysis (CA) tool in the LCM model was used to identify class changes that occurred in 2006, 2011, and 2017. This tool evaluates transitions between LULC classes for the selected period, and as such, it was used to quantify historical change rates in area units and terms of the transition probability of LULC classes for 2006–2017. The classified images from 2006, 2011, and 2017 with the transition probabilities calculated by CA were used as input data in the multilayer perceptron (MLP) model to simulate the business-as-usual (BAU) scenario for 2028. Dynamic modeling in LCM includes three prediction steps of transition potential, modeling (evaluation of the ANN), and validation.

Prediction of transition potential

The MLP was used based on an ANN analysis approach to predict the LULC transition potentials. To implement the MLP model, the factors controlling the LULC changes were considered as independent variables and the LULC images were considered as dependent variables (Silva et al., 2020). Primarily, the changes in LULC in the metropolitan area of Karaj in 2006 and 2011 were analyzed. Afterwards, transition classes were defined to simulate LULC in 2017 and 2028. The prediction model (for 2017) was used to determine whether the predicted LULC map is satisfactory, as compared to the actual prepared map using satellite images (observed).

MLP was trained with four sub-models (agriculture to human-made; garden to human-made; low-dense grassland to human-made; dense grassland to human-made) and also various effective factors, including distances from human-made constructions, agriculture, garden, low-dense grassland, dense grassland, barren, rocky mountains, urban green space, river, road, DEM, slope, and evidence likelihood. These variables were selected for testing based on land cover changes and literature in the study area.

Three variables of DEM, slope, and evidence likelihood were selected as static, and other variables were selected as dynamic. Euclidean distance analysis in ArcGIS 10.3 software was used to prepare distance maps. All the above variables are quantitative. Moreover, regarding the use of the qualitative variable of land cover, a transfer map from all other LULCs to human-made cover and a transfer map from human-made cover to all other LULCs were generated. Afterwards, considering the use of the evidence likelihood tool and the land cover map of the first year (2006) as the input of the model, the quality variable of evidence likelihood was prepared through the variable transformation utility module of the LCM model (Eastman, 2009). In this sense, thirteen driver variables are shown in Fig. 2.

Based on Cramer's *V*, the acceptance or rejection of the driver variable is judged (Gupta & Sharma, 2020; Silva et al., 2020). A high Cramer's *V* value (more than 0.15) is considered applicable, while those with values of 0.4 and superior are treated as appropriate for transitions. The accuracy of the run model depends on the repetition of the explanatory and transfer variables considered. In this regard, according to studies of Islam et al. (2018) and Silva et al. (2020), several experiments were performed to predict the land cover to achieve greater accuracy or equal to 80%.

Prediction of LULC future changes with the Markov chain method

Markov chain model which was also available in LCM was applied to simulate future LULC changes. The Markov chain estimates transition probabilities and combinations of remote sensing data to simulate LULC changes. Transition potential layers of LULC classes, which are created using MLP, are used as inputs in the Markov chain model to forecast future LULC changes based on transition probabilities. The transition probability matrix is created from the Markov chain analysis in the LCM model (Gupta & Sharma, 2020).

Regarding an MLP accuracy higher than 80%, it can be said that the learning algorithm has well simulated the transfer potential maps. Therefore, after achieving such precision, MLP was used to acquire the transition probability matrix from 2006 to 2011 in order to simulate the year 2017 and also maps from 2006 to 2017 were used to predict the year 2028.

Validation of LULC prediction

The kappa coefficient does not give us useful information due to its incapability to distinguish between the quantification and place wrong (Pontius, 2000, 2002). Therefore, to verify the accuracy of the classification, the kappa indices (K standard, K no, and K location) were calculated. In addition to kappa indices, the error hits, false alarms, and misses were calculated to distinguish the appropriate LULC prediction map in IDRISI VALIDATE module (Eastman, 2009). After successful confirmation, the simulation was used to predict the LULC of the Karaj metropolis for the year 2028.

Step 3: scenario modeling using InVEST

In this study, the InVEST Scenario Generator tool (Sharp et al., 2015) was also used to model future plausible changes in LULC. This tool prepares a relatively simple way to produce multiple scenarios based on land suitability and depending on the aim of the

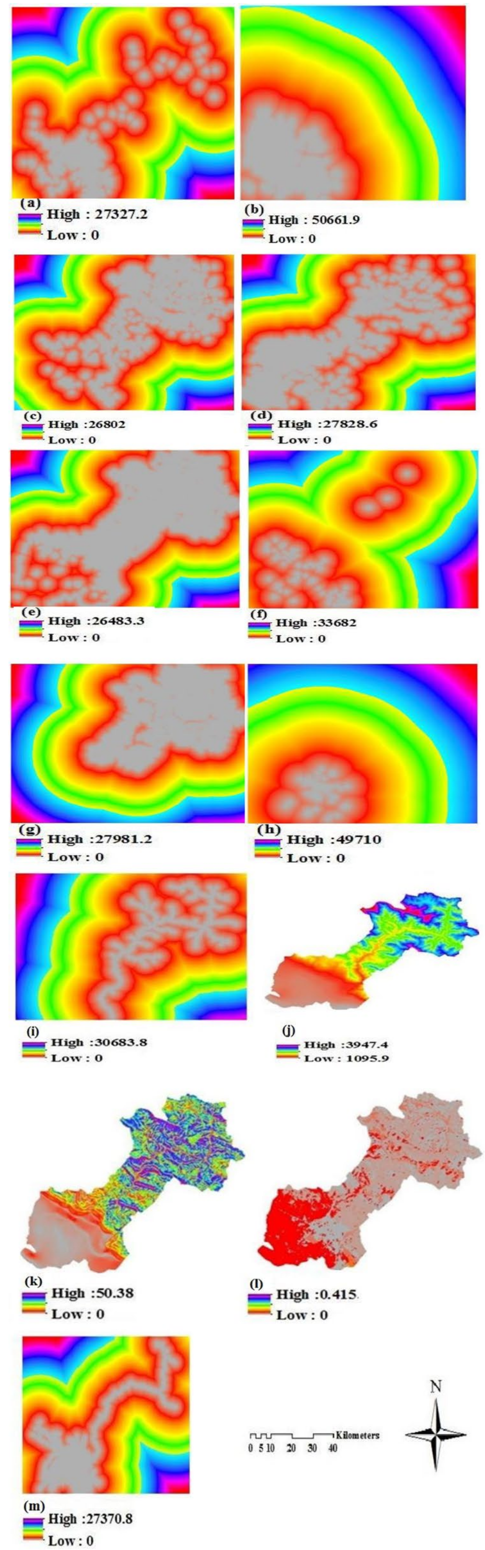

Fig. 2 Driver variables used in this study. **a** Distances from human-made cover. **b** Distances from agricultural lands. **c** Distances from garden. **d** Distances from low-dense grassland. **e** Distances from dense grassland. **f** Distances from barren. **g** Distances from rocky mountains. **h** Distances from urban green space. **k** Distances from river. **l**; DEM. **m** Slope. **n** Evidence likelihood. **o** Distances from road

user. It works on the principle that changes on land occur in regions that are rather fit for a given use. The scenario generator uses a compound of overlay analysis and multi-criterion evaluation methods and directly uses expert knowledge to map alternative futures. The InVEST Scenario Generator is designed to work with data from stakeholders/experts ordinary in a participatory workshop setting. The required principal inputs to run the model are (A) the transition likelihood, (B) the physical and environmental factors that influence changes, and (C) the quantity of forecast change under a given scenario.

Quantitative change in LULC

The quantitative change is indirectly determined by the demand for land for different uses and is estimated by the user and consultation with stakeholders. The tool turns all appropriate pixels in a raster map in order of compatibility until this aim is met for the cover or until all the available pixels are converted (Sharp et al., 2015).

Transition possibility

The possibility that a given parcel is converted from one LULC type to another (transition possibility) is determined by the stakeholders. For example, they may consider the likelihood of grassland being converted to agricultural land, assigning a value of 8 on a scale from 0 to 10.

The scenario generator needs that the stakeholders rank the LULC types to assign weight. In other words, the importance of different land use/cover classes (such as forest, rangeland, settlement, farm, etc.) should be ranked from the perspective of different stakeholders. This is because in the process of simulating future land changes when different uses compete for a single parcel (or a pixel in the raster map), the one that weighs the most wins.

Priority ranking the cover types is complex, and an optional feature is provided which utilizes a pairwise comparison matrix (Table 1) in an analytic hierarchy process (AHP) (Saaty, 1977).

According to Table 1, the matrix was scored based on the results of a consultative workshop with the presence of representatives from various stakeholders, including residents, farmers, urban planners, environmental protection experts, etc., in the study area and also the priorities that they give to each LULC (Table 2). For example, rivers are given extreme importance against agricultural lands with moderate importance because water consumption is more important than cultivation. When the matrix is complete, the InVEST model, using this scoring matrix, compares different uses in pairs in a hierarchical analytical framework and, finally, will weigh each cover.

Factors

There is a wide variety of physical and environmental factors (e.g., elevation, slope, aspect, and soil types) that affect land cover's potential for change. The tool allows the user to cater these factors and their connection with land suitability. The impact of these factors differs regarding each goal. Therefore, the user can enter more than one factor for each of the cover types and use one factor to multiple cover types. Moreover, the tool uses relative weights to incorporate these factors and determine the areas which are most appropriate for some LULC classes (Sharp et al., 2015).

The user provides the raster layers for each of the factors and determines the pixel suitability based on the value ranging from 0 (unsuitable) to 10 (extremely suitable). The effects or all factors are then combined based on the weights defined by the user. According to the number of uses, the land potential layers are provided. Pixels with values closer to 10 come first (Sharp et al., 2015).

Herein, two types of human-made and agricultural LULC classes were considered as the most important drivers of human development that play a significant role in future changes in the natural cover of the study landscape. Furthermore, elevation and slope were considered as the most effective physio-environmental factors which affect the expansion of the human-made and agricultural land uses. The conditions related to the variable of land capability for the development of human-made and agricultural lands and also how to weigh the environmental factors of altitude and slope are listed in Table 3. According to the existing regulations and the authors' knowledge of the study area, lands with an elevation of more than 1800 m above sea level and a slope of more than 15% are not suitable for human-made infrastructures. Moreover, due to the mountainous nature of the study area, while increasing elevation and slope, land suitability for agriculture decreases.

Proximity suitability

Pixels close to an LULC type may be more likely to be converted to that cover type. For instance, parcels close to agriculture, if appropriate, may be most likely converted first. To exert the effect of proximity, the distance of each cell to the cover under analyses is computed to diminish the maximum distance entered

Table 1 Score based on a 9-point Saaty scale

Score	Saaty scales	Description
1	Equal importance	2 land uses contribute equally to the objective
2	Weak or slight	
3	Moderate importance	Experience and judgment slightly favor 1 land use over another
4	Moderate plus	
5	Strong importance	Experience and judgment strongly favor 1 land use over another
6	Strong plus	
7	Very strong importance	As land use is favored very strongly over another, its dominance is demonstrated in practice
8	Very very strong	Extreme importance
9	Extreme importance	The evidence favoring 1 land use over another is of the highest possible order of affirmation

Table 2 Priority matrix of uses relative to each other in the study area

Human-made	LULC type	LULC code	Green space	Rocky outcrop	Barren	Dense grassland	Low-dense grassland	Water body	Garden	Agriculture	River
1	Human-made	1									
2	Agriculture	5/8	1								
3	Garden	8/5	8/6	1							
4	Water body	8/6	8/4	8/7	1						
5	Low-dense grassland	8/5	8/6	8/7	8/9	1					
6	Dense grassland	9/5	9/6	9/7	1	9/8	1				
7	Barren	4/8	4/6	3/8	2/9	4/8	4/9	1			
8	Rocky mountains	3/8	3/6	3/9	2/9	2/7	2/8	1	1		
9	Urban green space	6/8	5/6	5/8	6/8	4/7	4/8	7/3	7/5	1	
10	River	9/5	9/3	9/6	9/8	9/7	9/8	9/2	9/3	9/6	1

by the user. The cells closest to the cover are given the value of 100 while those farther than the maximum distance are given the value of 1. Considering this tool, the maximum effect of the proximity factor of 30% is defined.

In the present study, according to the evidences found in the study area, the maximum effective proximity distance for agricultural and garden uses is 5000 m, while that for human settlements and roads is 2000 m and 300 m, respectively.

Constraints

Constraints (e.g., protected area) are rare parameters that prevent human-induced LULC change. In this sense, the user can define how affective the existing constraints are. An access value of 0 refers to the fact that the constraint has full effect and no conversion can take a location within the boundary of the constraint, while a value of 1 refers to the fact that the constraint does not have any specific effect.

In this study, due to the establishment of the Central Alborz Protected Area within the boundary of the region, this area was considered as an obstacle to the conversion of land uses and cover within the protected boundary. This means that, in the LULC map scenario created by the model, no changes will structurally occur within the boundaries of the protected area.

Computing process

The last stage in this method is to transform the pixels (land allocation). The InVEST Scenario Generator applies LULC transition by transforming the suitable pixels into an array, processing each pixel and, finally, transforming them based on their suitability values. Beginning from the cover type with the highest priority, the % change is considered as an aim and the transformed pixels start from the highest suitability. After each cover is processed, the transformed pixels are masked, so that they would not be available for conversion again. Where more pixels of the same suitability are available, the tool accidentally chooses the available pixels from the first encountered group (region). Table 4 summarizes the input data required to run the model (Sharp et al., 2015).

Figure 3 compares both approaches applied in the study area.

Table 3 Environmental factors affecting the distribution of human uses in future probable situations

Developing LULC type	LULC code	Effective environmental factors		Capability (0–100)	Factor weight (0–1)
Human-made	1	Elevation (m)	≥ 1200	95	0.8
			1200–1800	40	
			≥ 1800	0	
		Slope (%)	≤ 8	100	0.9
			8–15	50	
			≥ 15	0	
Agriculture	2	Slope (%)	≥ 15	100	0.5
			15–30	50	
			≥ 30	20	

Results and discussion

Changes in land cover from 2006 to 2017

The three LULC classification maps were prepared using Landsat satellite data to analyze changes in 2006, 2011, and 2017, as shown in Fig. 4a–c. Figure 4d also shows the LULC forecast map (produced by MLP) for 2017. The classification adequately corresponded to the study landscape with kappa indexes of 0.92, 0.94, and 0.95 in the images, which are considered excellent.

Based on these results, the changes in LULC classes are as follows: human-made cover (from 8343.18 to 14,478.66 ha), low-dense grassland (from 20,254.23 to 22,586.96 ha), rocky mountains (from 21,189 to 24,393.78 ha), and urban green space (from 780.57 to 802.42 ha). Therefore, these classes have increased from the baseline (2006) to the current period (2017). The rest of the LULC classes experienced reduction during this period as follows: agricultural lands (from 11,181.42 to 6511.86 ha), garden (from 10,674.99 to 7036.67 ha), dense grasslands (from 43,221.87 to 40,167.09 ha), and barren (from 578.97 to 227.43 ha). The highest increase and decrease were observed in human-made (6135.48 ha) and agricultural (4669.56 ha) classes, respectively (Table 5). Thus, over an 11-year period, the three classes of human-made cover, low-dense grasslands, and rocky mountains have undergone increasing trends. Barren lands and green space decreased during the first period (2006–2016) and increased during the second one (2011–2017). Agricultural lands, gardens, and dense grasslands have been continuously declining over time. Moreover,

Table 4 Required data to run the InVEST Scenario Generator model in the study area

Input data	Description
LULC map in the existing situation (current LULC)	A map with Raster format and numeric codes for categorizing the types of LULC for each cell
Cover table/transitional land use	In dbf and CSV formats, containing transition likelihoods (change), priority (weight) of each land use, percentage of land use change, and neighborhood distance
Table of factors for land capability	In dbf and CSV formats, containing the name of the factors, the cover/land use affected, the effective distance of each factor, the suitability value in the range of 0 (unsuitable) to 100 (very suitable), and the weight of the factor
Priority matrix (weight) factors	The weight of the factors is calculated using a multi-criterion analysis approach using a binary comparison process under the hierarchical analysis process
Constraint layer	A polygon (vector) layer that represents parts of a landscape that is protected or has barriers to land use change

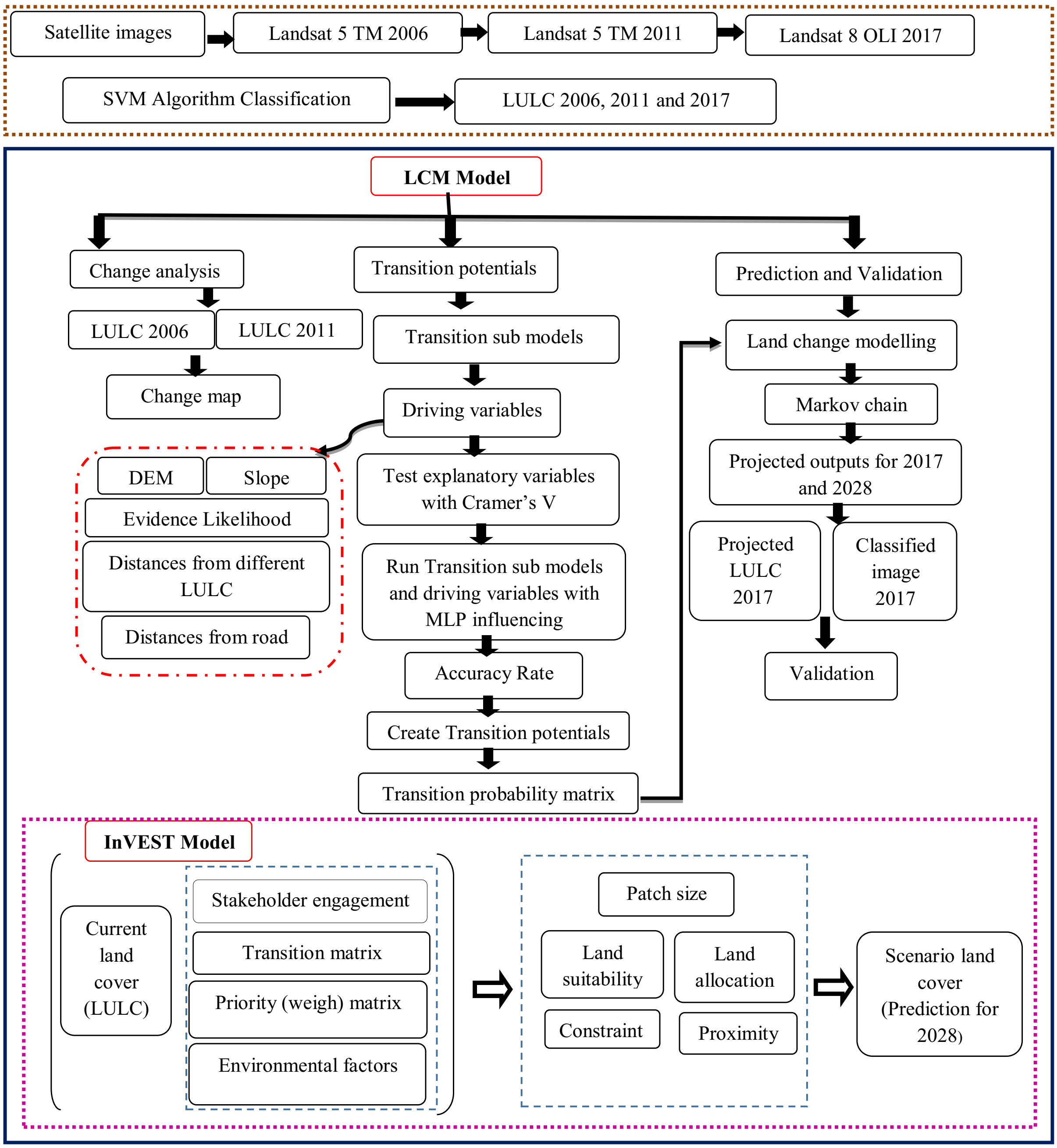

Fig. 3 Methodology flowchart

occupied areas of human settlements have almost doubled. In general, it can be concluded that, during this period, agricultural lands and grasslands have been gradually replaced by human settlements, and dense grasslands with low-dense and barren or rocky lands without vegetation.

Results of LCM model under BAU scenario

Regarding the year 2028, explanatory variables required for the LULC modeling for Karaj City were gained by Cramer's *V* test (Table 6). The selected variables had a correlation coefficient of more than 0.15.

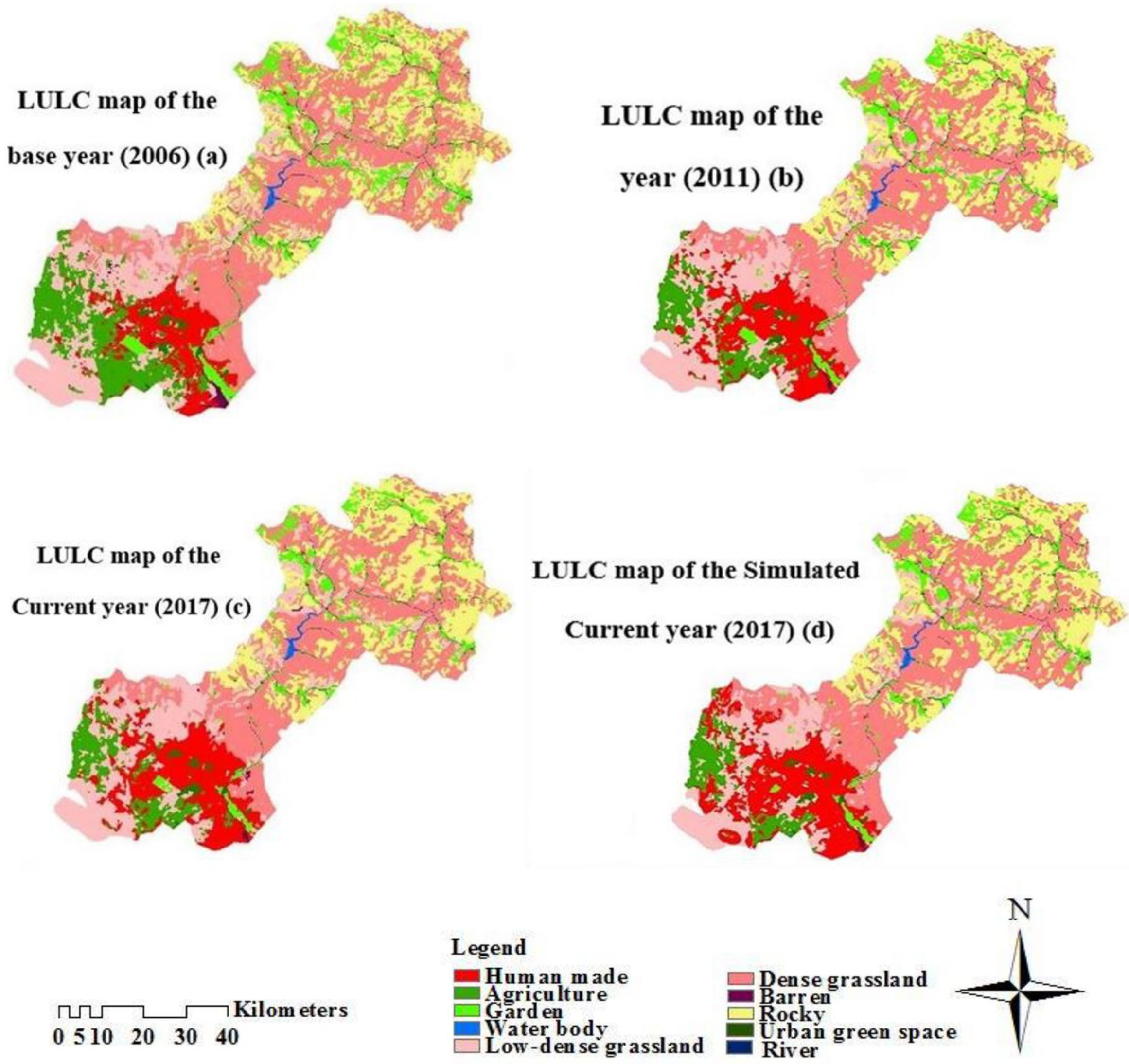

Fig. 4 LULC changes over time. **a** LULC map of the base year (2006). **b** LULC map of the year (2011). **c** LULC map of the current year (2017). **d** Simulated LULC map using MLP for 2017

According to the results of Cramer's *V*, the explanatory variables considered in the modeling were distanced from human-made areas, agricultural lands, garden, dense grassland, rocky mountains, road, DEM, and evidence likelihood.

Regarding the dynamic modeling of LULC, the best training result was obtained based on the MLP model from the repetition of the explanatory variables with the transitions of interest and had an accuracy rate equal to 81% after 10,000 repetitions. Table 7 shows the LULC transition probability matrix of 2006 and 2017. The results of the oblique display the percentages of durability, while the other results correspond to the rates of change from one LULC category to another.

A comparison of the classified map (observed in real world based on Landsat image) for 2017 and the predicted map (produced using the LCM model) for 2017 are shown in Table 8.

The results showed that the lands covered by human-made cover, garden, and dense grassland in the predicted

Table 5 A comparison of LULC changing trends in the base (2006), 2011, and current (2017) years

LULC type	Area (ha)			Converted area (ha)		Trend
	2017	2011	2006	Decreased	Increased	
Human-made	14,478.66	12,941.73	8343.18	–	6135.48	↑
Agriculture	6511.86	6845.76	11,181.42	4669.56	–	↓
Garden	7036.67	8885.24	10,674.99	3638.32	–	↓
Water body	326.97	323.27	305.55	–	21.42	↑
Low-dense grassland	22,584.96	21,916.26	20,254.23	–	2330.72	↑
Dense grassland	40,167.09	40,821.21	43,221.87	3054.78	–	↓
Barren	227.43	132.3	578.97	351.54	–	↓
Rocky mountains	24,393.78	23,984.03	21,189.06	–	3204.72	↑
Urban green space	802.42	680.04	780.57	–	21.85	↑
River	990.36	990.36	990.36	–	–	↔

model were overestimated. The occupied area of the river class is not changed on both maps. Other classes showed less coverage than the classified map. According to Pontius et al. (2008), the obtained results are consistently compatible with each other despite the estimated difference between the two classified and predicted maps (Table 9). The ratio of hit pixels to total modified pixels indicates the acceptable results of the model in predicting LULC change, which was 22%. Results between 1 and 59% are satisfactory results in LULC modeling. Figure 5 shows the changing regions for each of the classes analyzed in the observed and predicted images for 2017.

Figure 6a shows the LULC prediction for 2028. The expected behavior of the LULC and the projected trend of the occupied areas for the Karaj metropolis in 2028 are similar to 2017. The water body, barren, dense grassland, rocky mountain, and urban green space classes in 2028 show the same situation in 2017. Moreover, the increasing trend of human-made coverage will continue. Conversely, classes covered by agriculture, garden, and low-dense grassland will decrease, as compared to 2017. Most of these incremental and decreasing changes will occur in the center and west of the Karaj metropolis, which is located in the southern part of the study landscape. In the north and west downstream of the area, an increase by the human-made class and a change from the agricultural to the human-made class were observed for 2028. Furthermore, in the central region, the agricultural and garden classes decreased and were replaced by the human-made class. In the southwest and southeast area, the results showed a decrease in the low-dense and dense grasslands.

Table 6 Results for Cramer's *V* test for the explanatory variables

Explanatory variables	Cramer's *V*
Distance from human-made	0.216
Distance from agriculture	0.297
Distance from garden	0.25
Distance from low-dense grassland	0.09
Distance from dense grassland	0.228
Distance from barren	0.098
Distance from rocky outcrop	0.326
Distance from green space	0.142
Distance from river	0.084
Distances from road	0.255
DEM	0.277
Slope	0.009
Evidence likelihood	0.519

Results of the InVEST model under participatory plausible scenario

Herein, the quantitative change was estimated based on the comparison of changes in different LULC classes between the previous period (baseline–2006) and the existing one (current–2017). Afterwards, as inspired by previous changes and the received feedback from various stakeholders through a consultative workshop on priorities and possibilities for change in different land use quantities, the following storylines were defined for future changes. The definition of this storylines, as shown in Table 10, was done in such a way to be most consistent with the study landscape. It is not possible to definitely predict changes in natural variables,

Table 7 Matrix of the transition probability of land cover categories for 2006 and 2017 in the study area (number of pixels, no unit)

2006	2017									
	Human-made	**Agriculture**	**Garden**	**Water body**	**Low-dense grassland**	**Dense grassland**	**Barren**	**Rocky outcrop**	**Green space**	**River**
Human-made	160,873	0	0	0	0	0	0	0	0	0
Agriculture	1621	70,740	0	0	0	0	0	0	0	0
Garden	202	0	77,497	0	0	0	0	0	0	0
Water body	0	0	0	3632	0	0	0	0	0	0
Low-dense grassland	2963	0	0	0	247,980	0	0	0	0	0
Dense grassland	450	0	0	0	0	445,897	0	0	0	0
Barren	0	0	0	0	0	0	2528	0	0	0
Rocky outcrop	0	0	0	0	0	0	0	271,041	0	0
Green space	0	0	0	0	0	0	0	0	8905	0
River	0	0	0	0	0	0	0	0	0	10,681

Table 8 Comparison between the classified and estimated images for 2017

LULC type	**Area (ha)**	
	Classified 2017	**Predicted 2017**
Human-made	14,478.66	16,707.22
Agriculture	6511.86	5535.27
Garden	7036.67	8666.44
Water body	326.97	323.37
Low-dense grassland	22,584.96	19,900.05
Dense grassland	40,167.09	40,595.76
Barren	227.43	132.1
Rocky mountains	24,393.78	23,989.86
Urban green space	802.42	679.77
River	990.36	990.36

including LULC. However, decision-makers also need to look to the future to evaluate land management policies. In this study, a participatory scenario–generating approach was used to hypothetically analyze the future of land change. Therefore, although this estimate is not a definitive prediction, it will be close to reality in terms of the real views of stakeholders. This approach reflects a kind of possible future and can help ensure that future planning is not based solely on speculation. In other words, this model captures expert knowledge and makes an attempt at representing plausible land cover change as realistically as possible, but does not predict the certain future LULC.

The output of the InVEST model (Fig. 6b) shows the visual structure of the landscape in 2028. As can be seen in this figure, low-dense grasslands and human-made areas will have the highest levels of LULC in the metropolis of Karaj in 2028. The water body and river classes in 2028 presented the same occupied area as in 2017. Likewise,

Table 9 Assessing the accuracy of the modeled map for 2017

Parameters	Values
Kappa indices (%)	
K standard	0.8
K no	0.89
K location	0.89
Errors (pixel values)	
Hits	48,071
False alarms	101,343
Misses	60,030

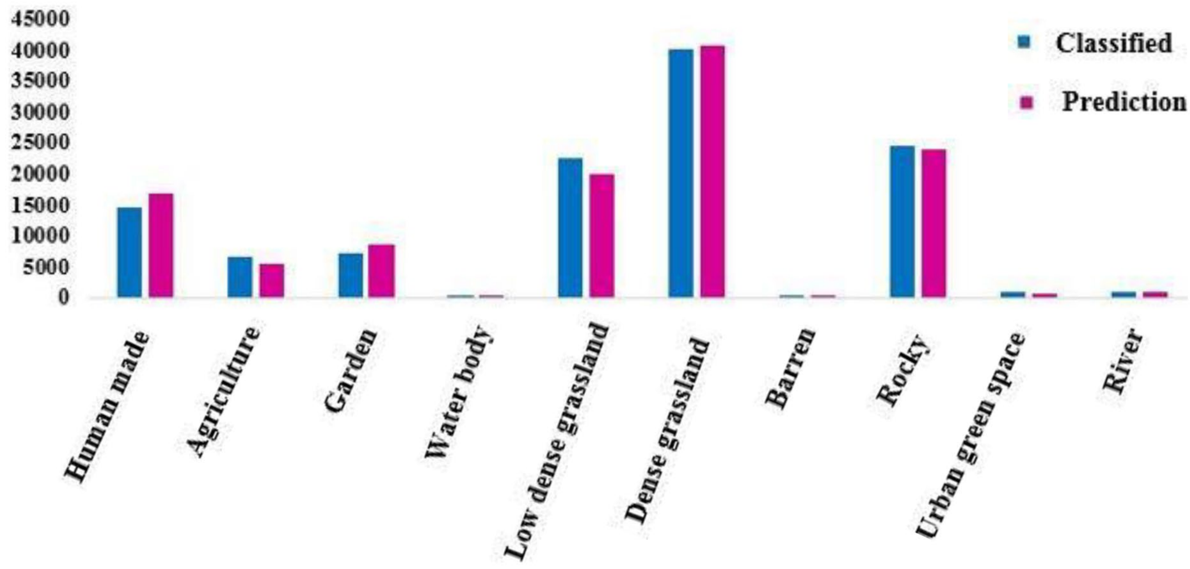

Fig. 5 Classified and predicted land cover for the analyzed classes for 2017 (hectares)

the trend of changes in the classes of human-made cover (from 14,478.66 to 25,199.83 ha), urban green space (from 801.36 to 823.64 ha), and rocky mountains (from 24,393.78 to 24,395.85 ha) is increasing, whereas the trend of agricultural lands (from 6511.86 to 3840.27 ha), garden (from 7036.67 to 6316.63 ha), low-dense grassland (from 22,584.96 to 18,966.41 ha), dense grassland (from 40,167.09 to 36,614.47 ha), and barren (from 227.43 to 47.19 ha) has been decreasing during 2017–2028. The most significant positive change (3%) was found for green space, mainly in the upstream area. The most significant negative change (79%) was found for barren.

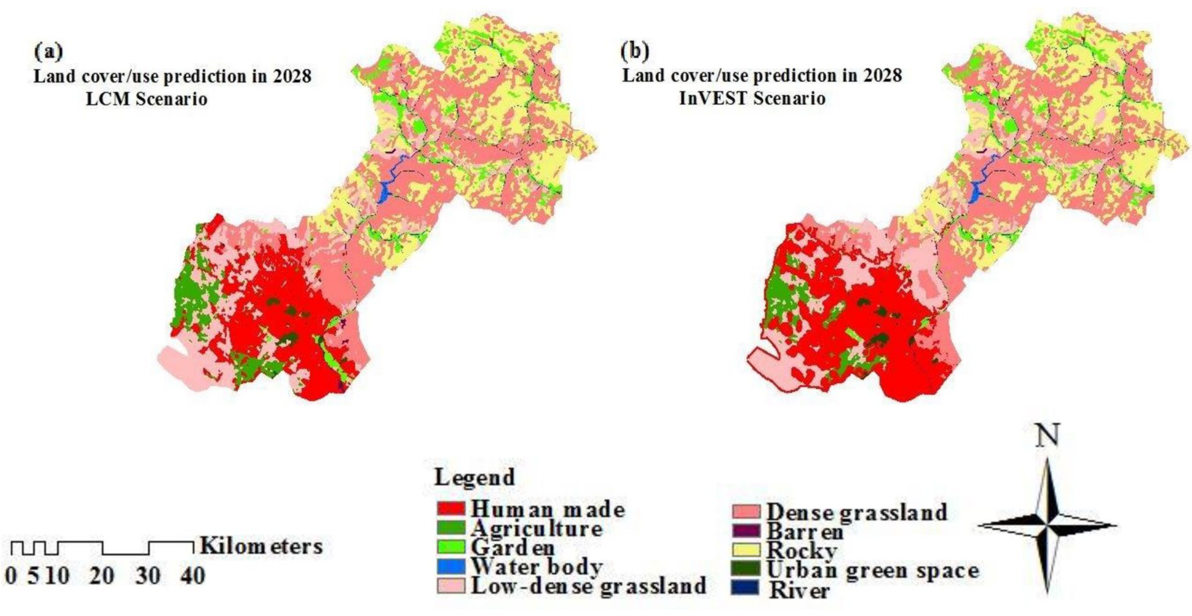

Fig. 6 Land cover prediction for 2028. **a** LCM scenario. **b** InVEST scenario

Table 10 Possible/plausible future

InVEST software scenario
Significant increase of the human-made cover with a growth rate of 74%
Relatively high decrease of the agriculture at a negative rate of 42%
Relatively high decrease of the garden at a negative rate of 59%
Relative increase of the low-dense grassland with a growth rate of 14%
A relative decrease of the dense grassland by a rate of 7%
Decrease of the barren by a negative rate of 60%
Mild increase of the green space with a growth rate of 3%

Comparison of LCM and InVEST scenarios in predicting LULC changes

A comparison between the simulation results of the two models in terms of areas occupied by different LULC classes in 2028 and the 2017-classified map is shown in Table 11. Accordingly, two trends of change are clearly evident in the scenarios. In the LCM scenario, human-made cover and rocky cover will primarily increase and, then, low-dense and dense grasslands, agricultural lands, and garden will reduce in the future. Moreover, according to the InVEST scenario, human-made cover, green space, and rocky cover will initially increase and, then, agricultural lands, gardens, low and dense grasslands, and barren lands will decrease.

Figure 7 illustrates a change in LULC classes in 2006, 2011, and 2017 and also the forecasted scenarios for 2028. During the study period (2006–2028), the river class did not show significant changes. The human-made class developed with the loss of agricultural land and low-dense grassland. Moreover, the areas occupied by agricultural lands and gardens (for 2028) reduced by 5981.57 ha and 3840.7 ha in the LCM BAU scenario and by 7341.15 ha and 4358.36 ha in the InVEST PPS, respectively.

The change from agricultural land to man-made land in the period 2006–2017 was equivalent to 1978.97. These changes for the period 2017–2018 will be 1458.90 ha and 2672.82 ha, respectively, under the LCM and InVEST scenarios. In addition, during the period 2017–2028 and under the LCM scenario, the conversion rate of lands covered by garden, low-dense grasslands, and dense grasslands to human-made cover will be 181.80 ha, 2666.70 ha, and 405 ha, respectively. The changes under the InVEST scenario are 658.80 ha, 6766.83 ha, and 438.48 ha, respectively. The area covered by agricultural farms

Table 11 Comparison between the classified and estimated images for 2017

LULC type	Area (ha)		
	Classified 2017	LCM BAU scenario	Possible InVEST scenario
Human-made	14,478.66	18,729.64	25,199.83
Agriculture	6511.86	5199.85	3840.27
Garden	7036.67	6834.29	6316.63
Water body	326.97	326.97	325.65
Low-dense grassland	22,584.96	20,197.93	18,966.41
Dense grassland	40,167.09	39,810.59	36,614.47
Barren	227.43	227.43	47.19
Rocky mountains	24,393.78	24,401.78	24,395.85
Urban green space	802.42	801.36	823.64
River	990.36	990.36	990.36

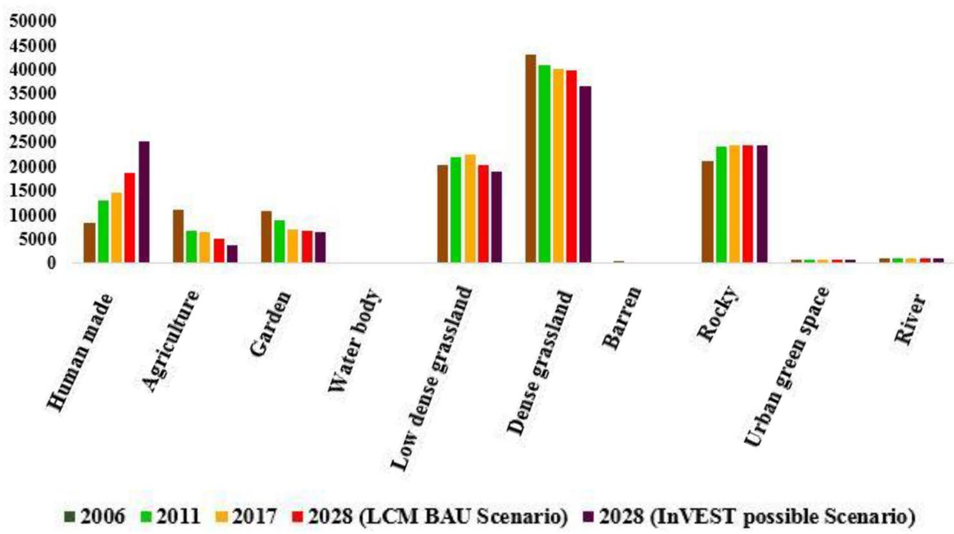

Fig. 7 Areas occupied by the land cover classes in the Karaj metropolis in 2006, 2011, 2017, and 2028 (hectares)

will experience reduction from 6511.86 to 5199.85 ha and 3840.27 ha, respectively, under the two scenarios of LCM and InVEST, which means 20 to 40% reduction of agricultural land over the next 11 years. Furthermore, the area of garden lands will decrease by 202.38 ha and 720 ha in the LCM and InVEST scenarios, respectively.

According to both scenarios, the development of human-made areas will continue to increase in the future. Thus, regarding the LCM scenario, human-made areas will increase by 29%, as compared to 2017 from 14,478.66 to 18,729.64 ha. Moreover, considering the InVEST scenario, this amount increases by 74% from 14,478.66 to 25,199.73 ha.

The existence of such a difference in the percentages estimated by the two models can be due to the difference in the inputs of the models. Moreover, as mentioned earlier, the LCM model is based on the past trend of changes in LULC while the InVEST model considers the future expectations of the beneficiaries in addition to the past trends. Accordingly, it can be concluded that in the current situation, in addition to the continuation of the past trend, the demand for land conversion into human-made lands has also increased sharply.

As witnessed, the occupied LULC area made by humans shows an increasing trend during the period 2006–2028, which may possibly be due to the population increase because of increasing demand for construction, considering the fact that Karaj is close to the capital city Tehran. Moreover, the area occupied by agriculture shows a decreasing trend during the period 2006–2028, mainly because of the expansion of the human-made class. Due to the uncontrolled development of human-made structures, agricultural lands are usually the first available areas for land use conversion and settlement construction and are in favorable conditions in terms of environmental parameters such as slope, height, and proximity to road. The LCM scenario predicts that, by 2028, the area covered by agriculture will be only 5199.85 ha (4% of the landscape). Likewise, regarding the InVEST scenario, it is predicted that the area covered by agriculture will be 3840.27 ha (3% of the landscape).

In this study, we used two different tools, LCM and InVEST, to generate and project the future LULC data layer of the Karaj study landscape in Northern Iran. According to the outputs of both models, urban development is the main factor in LULC change that is commensurate with the results of Zarandian et al. (2017), Zhang et al. (2017), Anand et al. (2018), Armenteras et al. (2019), Silva et al. (2020), Fadaei et al. (2020), González-García et al. (2020), Nie et al. (2020), and Mohammadyari et al. (2021a). Our investigations show that a significant part of agricultural lands has been replaced by developing urban infrastructures particularly alongside the Karaj River and steep slopes in the north and east of the city area. As compared to the present study, Zhang et al. (2017) and Mohammadyari et al. (2021a) also reached a similar conclusion on the reduction of agricultural land as a result of urban expansion. Additionally, rapid population growth due to the increasing migration as a result of the proximity to the capital city Tehran, industrialization, and urgent need for more human settlement construction have been the key drivers of significant changes in LULC during recent decades. Significantly, they will continue to drive more LULC transformations in the next decade. Pourkhabbaz et al. (2015), Li et al. (2016), You et al. (2017), Mansour et al. (2020), Fadaei et al. (2020), and Mohammadyari et al. (2021b) also stated that one of the reasons for the expansion of urbanization is population growth, which is consistent with the results of this study. It is worth mentioning that this unplanned loading process of human-made infrastructure development leads to a wide variety of challenges for both environmental and city planners. Accordingly, there is an urgent need to use tools and models that can visualize the future of the landscape.

Advantages and limitations of InVEST and LCM models

The present study shows that although the use of each of these two models has its own advantages and limitations, the simultaneous use of both models can lead to more complete results. While older models such as LCM are based on the method of extrapolating the changing trend from the past to the present, the InVEST Scenario Generator model focuses on predicting the future scenario landscape using data collected with the participation of various stakeholders. Hence, the LCM model seems to be a retrospective tool while the InVEST model is a futuristic tool. It is on this basis that the combined use of both models enabled us to first calculate the rate of changes of different LULC classes from the past to the present using the LCM model and, then, to use the results as a basis for defining a scenario storyline for the future with stakeholder participation and visualizing the future plausible LULC using the InVEST Scenario Generator.

To the best of our knowledge, no study has been reported comparing the best model for the LULC change between the two models (LCM model and InVEST Scenario Generator). Islam et al. (2018), Xu et al. (2019), Silva et al. (2020), Liu et al. (2020), Nurwanda and Honjo (2020), Mohamed and Worku (2020), Babbar et al. (2020), and Mohammadyari et al. (2021a) pointed to the efficiency of the LCM model in modeling the LULC change. On the other hand, Zarandian et al. (2017) and Fadaei et al. (2020) have stated that the results of the InVEST Scenario Generator are acceptable and have high accuracy for LULC change modeling. Due to the fact that LULC changes lead to changes in ecosystem services, preparing an LULC map with high accuracy leads to more accurate results, better decisions, and more certainty. Therefore, in this manuscript, an LULC change was modeled with two widely used models and, then, the advantages and limitations of each model was pointed out. Finally, for future research, we introduced the superior model according to the results. Regarding the comparison between the future LULC maps using both models, it is worth mentioning that the variables used as inputs in the LCM model are adapted from changes that have taken place in LULC from the past to the present and can be used only to generate a BAU scenario for the future. But, the InVEST Scenario Generator tool enables a user to look at the landscape with a change-oriented perspective by asking the following questions: What can experience change? To what does it change? Thus, users can think through different possible situations in order to produce different future plausible scenarios including a BAU scenario. Considering the study landscape, the results of running both models indicated that the total estimations of changes in the water body, rocky mountains, and river were almost equivalent. The class area of human-made and urban green space estimated by the InVEST model was higher than that estimated by the LCM model.

On the contrary, the class area of agriculture, garden, low-dense grassland, dense grassland, and barren estimated by the InVEST model was somewhat lower than that estimated by the LCM model. However, the typical result of both models was that urbanization is expanding rapidly and farmlands and gardens are decreasing and being replaced by built-up covers. Moreover, both dense and low-dense grasslands as the most critical ecological structure are decreasing during recent decades which means unsustainable land allocation and management. Regarding the estimated quantities, the output of the InVEST scenario model seems to be closer to reality with less uncertainty, because this model has taken into account the quantities of land demand for different uses based on the views of different stakeholders and considering the future policies and plans of landscape development. Moreover, applying the InVEST Scenario Generator tool enabled us to include a larger number of environmental and social factors in the modeling process including a constraint polygon layer to prevent changes within the protected area. Significantly, this feature is not available in previous models. Therefore, in LULC studies using the InVEST tool, conservational scenarios can also be defined.

Generating LULC change scenarios using the InVEST model has some specific advantages, i.e., accuracy. The InVEST Scenario Generator tool creates spatial data from stakeholder input. This focus enabled us to create storylines of future change that best fit our study needs. Furthermore, this feature enables users to create storylines of future LULC changes that are largely consistent with the conditions of their study area and stakeholder demands for LULC changes. It is worth mentioning that one of the main limitations of classical overlay mapping and previous modeling approaches such as LCM is the difficulty in incorporating value judgments such as stakeholder preferences. The InVEST model has solved this problem by combining GIS with a multi-criterion evaluation which makes it easier to incorporate expert knowledge into such analysis. Therefore, the produced scenarios using this model can be acceptably accurate and the visual predicted LULC maps can be closer to reality. However, there are some limitations and simplifications to use the InVEST model. This model presumes that a cover type is either growing or relenting, but not both. Indeed, change takes place in both directions; but, for simplicity, only one direction is presumed. Moreover, this tool presumes a single-step transition from the beginning land cover to the scenario land cover. Indeed, these changes can be stepwise with several patterns at each step. Moreover, the tool needs a challenging translation of all stakeholder descriptive inputs to quantitative matrix, tables, or GIS maps which requires more technical expertise, as compared to the simpler models such as LCM.

Conclusion

The most obvious results that can be summarized as a summary of the findings of this study are as follows: During the period under review, the largest increase and decrease occurred in human-made land uses and natural covers of the study landscape, respectively. This means that over a decade, a large part of agricultural land and grasslands has been gradually replaced by human-made settlements and infrastructure. Unfortunately, the prediction of changes by each LCM and InVEST model showed that the decreasing trend of natural covers and the increasing trend of human-made structures will continue until 2028. Obviously, the continuation of such a process can lead to the deterioration of the ecological infrastructure of the study area and reduce its environmental quality. Although both models predicted the general trend of future changes similarly, the amount of changes was different in the LULC classes. In other words, the estimated increase in human-made land use and the decrease in agricultural, grassland, and garden covers by the InVEST model were much higher than the values estimated by the LCM model. Given that the InVEST model takes into account stakeholder preferences in addition to the trend of landscape structural changes from the past to the present, such a result indicates the intense demand of stakeholders to convert natural covers to human-made land uses.

Overall, the results of applying the proposed models showed that using the InVEST model to predict the future of LULC can achieve a more realistic result because this model allows the incorporation and integration of descriptive and preferential opinions of different stakeholders in addition to explicit spatial data from remote sensing. Accordingly, another important advantage of this model is that it provides the ability to define multiple scenarios (for example, natural cover protection of the landscape) to be applied in future land use planning. However, such a feature does not exist in conventional classic models such as LCM.

In general, regarding future-related studies, in order to increase the efficiency and accuracy of the LCM model, other drivers such as population dynamics, per capita income, land market supply, and demand patterns should be included in the modeling process. In addition, considering the benefits of modeling the LULC changes with the InVEST model, it is suggested that this method be used in future studies if data and conditions are available.

The results and outputs of this study can provide the necessary input data for future studies, especially about the environmental status of the study area. Considering the destructive trend of the natural land cover classes in the study area, research on the effects and consequences of such changes on the process of providing various ecosystem services is highly recommended. Finally, the method introduced in this research for LULC modeling can be used in different geographical areas and at different scales from urban ecosystems to watersheds. Likewise, the results of this study can be an essential guide for governors and local planners to manage the spatial and temporal directions of urban development and their future consequences. On the other hand, it can be a good guide for researchers to choose the right method, aiming at modeling the LULC change.

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Author contribution A.Z. and F.M.: conception and design, data collection, methodology, modeling and mapping, validation, and writing and preparation of original draft; A.Z.: formal analysis and resources; M.M.M. and J.S.V.: methodology, validation, and writing and preparation of original draft. All authors read and approved the final manuscript.

Availability of data and materials The datasets used or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate Not applicable.

Consent for publication Not applicable.

Competing interests The authors declare no competing interests.

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