



# Comparison of three hybrid models to simulate land use changes: a case study in Qeshm Island, Iran

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**Abstract** Land use change simulation is an important issue for its role in predicting future trends and providing implications for sustainable land management. Hybrid models have become a recognized strategy to inform decision-makers, but further attempts are needed to warrant the reliability of their projected results. In view of this, three hybrid models, including the cellular automata-Markov chain-artificial neural network, cellular automata-Markov chain-logistic regression, and Markov chain-artificial neural network, were applied to simulate land use change on the largest island in Iran, Qeshm Island. The Figure of Merit (FOM) was used to measure the modeling accuracy of the simulations, with the FOMs for the three models 6.7, 5.1, and 4.5, respectively. Consequently, the cellular automata-Markov chain-artificial neural network most precisely simulates land use change on Qeshm Island and is, thus, used to simulate land use change until 2026. The simulation shows that the incremental trend of the built-up class will continue in the coming years. Meanwhile, the areas of valuable ecosystems, such as mangroves, tend

to decrease. Despite the protection plans for mangroves, these areas require more attention and conservation planning. This study demonstrates a referential example to select the proper land use models for informing planning and management in similar coastal zones.

**Keywords** Land use/cover change · Hybrid models · Qeshm Island · Persian Gulf

## Introduction

Land use/cover change (LUCC) simulation can help obtain a better understanding and more realistic prediction of future developments (Olmedo et al. 2015; Newman et al. 2016) and create better plans for solving environmental problems. Models used to predict LUCC are considered useful tools for environmental and geoscience research (Varga et al. 2019; Mustafa 2020). LUCC maps are applicable to environmental decisions and support planning for sustainable development

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(Yirsaw et al. 2017). These maps not only help reduce the unwanted effects of anthropogenic activities on natural resources but also provide an integral resource for studies on land resources management (Yang et al. 2012). Today, LUCC is considered one of the most important environmental concerns of the international community (Rimal et al. 2018). Accordingly, predicting the future of LUCC is a current and widespread necessity, wherein experts must rely upon simulation models (Ghosh et al. 2017).

Although LUCC prediction models have been used for decades, advances in geospatial technologies and increased computing power in the GIS environment have led to the recent development of a wide range of LUCC models encompassing various processes, analyses, and research questions (Verburg et al. 2004). Indeed, different types of LUCC prediction models have been introduced that differ in structure and application. To simulate LUCC, GIS-based mathematical models, such as cellular automata (CA) (Aburas et al. 2016), can be used as well as statistical techniques, such as Markov chain (MC), logistic regression (LR), machine learning, and data mining algorithms, including artificial neural networks (ANNs) and support vector machines (SVMs) (Shafizadeh-Moghadam et al. 2017). Among these models, the CA model is the most well-known (Aburas et al. 2016; Li et al. 2017; Liu et al. 2017), as it can simulate macro-phenomena (e.g., land use change) considering the interactions of micro-phenomena (i.e., cell state change) through a top-down approach (Xu et al. 2019).

Each LUCC simulation model has its strengths and weaknesses and can be used alone or in combination with other models. For example, the MC approach can predict the extent of land use change but cannot simulate changes in spatial distribution (Ghosh et al. 2017). The CA model is a powerful calculating technique that can alone be used to simulate the spatial variability of an ecosystem (Kamusoko et al. 2009). Yet, its combination with the MC model (CA-MC) provides a more accurate simulation of the temporal and spatial patterns of land use change (Sang et al. 2011; Ghosh et al. 2017). Therefore, to achieve more precise results, hybrid models designed by integrating two or more individual parts or models are often proposed by researchers. Thus, to gain a better and more accurate understanding of the relationship between the factors affecting LUCC and the related processes, complex LUCC spatial models have been developed and are used nowadays (Verburg et al. 2004).

Despite the numerous applications of LUCC simulation models in recent years, there has yet to be a consensus developed about them; thus, the strengths and weaknesses of these methods require further discussion (De Rosa et al. 2016). Though many simulation studies of LUCC combine cellular automata (CA) with standard models, such as MC, LR, and ANN, to obtain more accurate results from the modeling process (Hamdy et al. 2016; Ghosh et al. 2017), a comparison of the models has not been sufficiently conducted. For instance, Yan et al. (2019), Karimi et al. (2018), Chu et al. (2018), and Yirsaw et al. (2017) used a CA-Markov model to predict LUCC changes in different areas by combining the CA-Markov model with ANN and LR to obtain better results in the prediction process. However, the use of these methods in an integrated manner and with the same data, with the primary purpose of comparing the accuracy of each, has not been sufficiently addressed; this gap in comparing LUCC modeling methods with similar data has also been mentioned in the literature (Sun and Robinson 2018). Moreover, applying several LUCC models on the same data and comparing the results can help explain the advantages of each model for various applications.

To obtain better comparisons and make more informed decisions regarding the selection of a LUCC model type, we focus on this gap in the LUCC model comparison. Here, emphasis is placed on a comparative study of hybrid models with similar data; this comparative evaluation was performed first to compare the accuracy and validity of the models and, then, to propose the optimum model for modeling LUCC changes in the region.

Qeshm Island is the largest island in the Persian Gulf (Ebrahimi-Sirizi and Riyahi-Bakhtiyari 2013; Kokabi et al. 2016). Because of its diverse landscape, ecological richness, and unique environment, Qeshm Island is recognized as a tourist attraction in southern Iran (Mirza et al. 2019). Among the island's tourist attractions are reef colonies, the widest mangrove forests in Iran, and historical sites (Yazdi and Dabiri 2018), making Qeshm Island one of the most visited areas of Iran and even of the Middle East. Moreover, due to Qeshm Island's unique environment, the UNESCO designated it as the first geopark in the Middle East in 2006 (Pourahmad et al. 2018). Simultaneously, because of its strategic location and the establishment of active ports, Qeshm Island was established as part of the Qeshm Free Trade Zone in the early 1990s and has since

played an important role in the Iranian economy. However, the remarkable economic development of Qeshm Island and the growth of urbanization in coastal areas have threatened the region's valuable environment. Specifically, the research objectives of this study are to compare three commonly used hybrid models (namely, cellular automata-Markov chain-artificial neural network (CA-MC-ANN), Markov chain-artificial neural network (MC-ANN), and cellular automata-Markov chain-logistic regression (CA-MC-LR)) and to inform strategies in environmental conservation for this region and propose the most accurate model for LUCC modeling.

## Methodology

### Study area

The study area is Qeshm Island in the eastern part of the Persian Gulf, adjacent and proximate to the Strait of Hormuz (Fig. 1). It is the largest island in the Persian Gulf under the jurisdiction of the Islamic Republic of Iran and is located at 55° 14' 58" E and 56° 17' 27" E and 27° 00' 00" N and 26° 32' 04" N. Its area is 1491 km<sup>2</sup>, about 2.5 times that of Bahrain (the second largest island in the Persian Gulf). Its length is approximately 115 km and its width 35 km in the widest part and 10 km in the narrowest part. The annual average temperature of Qeshm Island is approximately 26 °C, and the maximum and minimum daily average temperatures are 34 and 18.5 °C in July and January, respectively. While the annual precipitation of the Island is less than the average of the country, and the climate of the region is classified as warm and dry (Bwh) according to the Köppen classification, the air humidity is high, and the average maximum and minimum relative humidities are 86.5 and 44.4, respectively. According to the 2016 census, the island's total population is approximately 150,000. The mean annual temperature and average annual precipitation are shown in Table 1. The island's location is also shown in Fig. 1.

### Data preparation

Landsat data are an indispensable source of satellite imagery for LUCC studies because of their high temporal, spatial, and spectral resolution (Shafizadeh-Moghadam et al. 2017). Here, Landsat data for 2002,

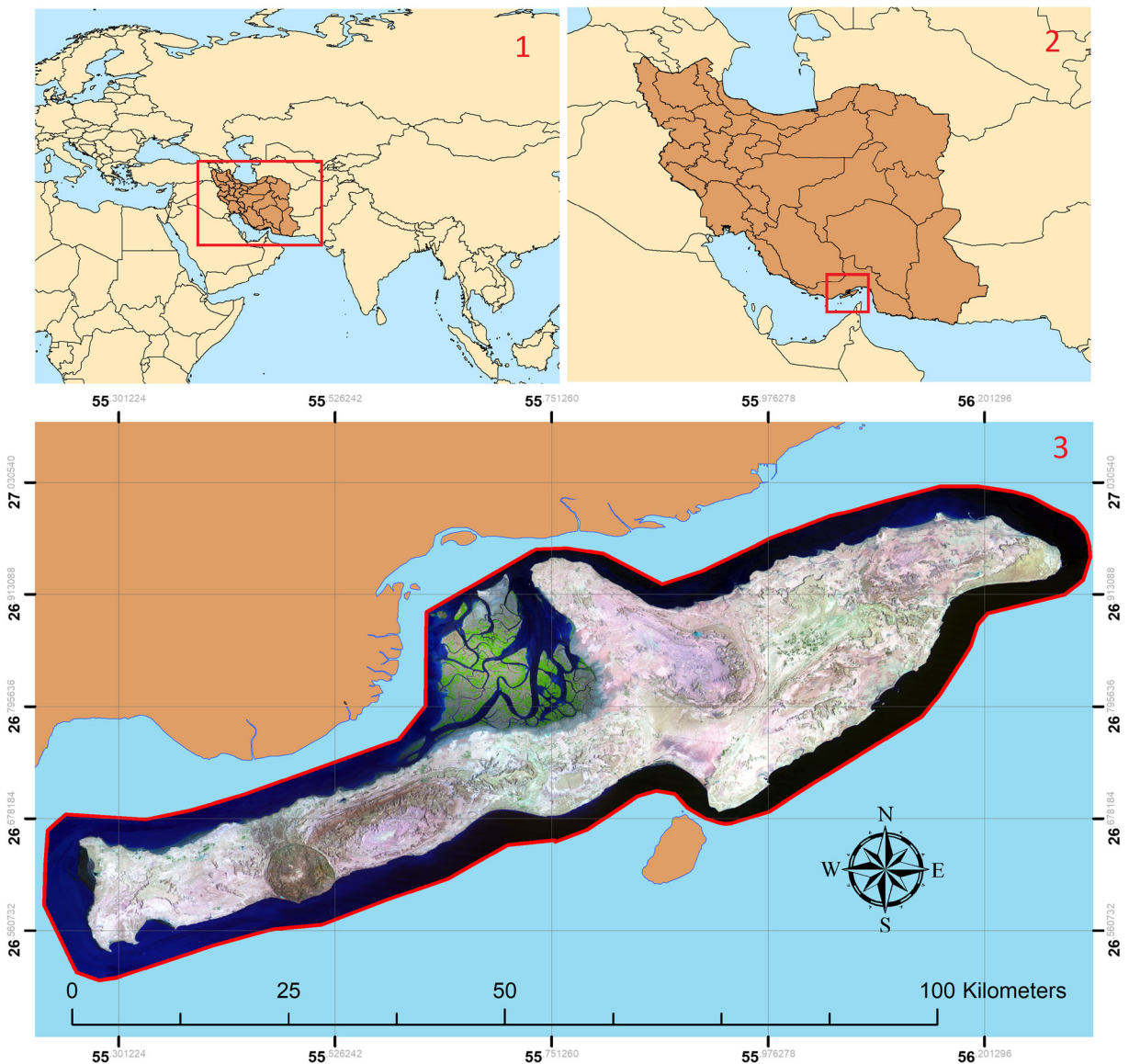
2008, and 2014 were used to produce LUCC maps as the inputs for the model (Table 2). Since Qeshm Island is located between two Landsat scenes, two scenes were used for each year as described below. In data selection, cloud-free images with temporal closeness were selected from the USGS Landsat level-2 archives. To produce LUCC maps, topographic maps and Google Earth were also used as complementary data.

Land use/cover maps were generated from the Landsat images in 6 classes, including built-up, agriculture, dense vegetation, mangrove, water body, and barren land. To produce these maps, the on-screen digitizing method was used for the two classes of built-up and agriculture, and the supervised classification method (maximum likelihood) was used for the other 4 classes. In the pre-processing phase, all layers of the Landsat images were combined by the Layer Stacking command. Then, we performed mosaicking to join the two Landsat scenes. Atmospheric and radiometric adjustments were performed in the next step. The study area was specified on the image and was clipped from other parts of the image that were not needed in the last part of the pre-processing phase. It is worth noting that since Landsat level-1 images were used, no geometric corrections were applied to the images. In the classification step, a 1:25000 scale topographic map, Google Earth software, and field data were used to prepare training points to identify the 4 classes mentioned before. In this step, we masked the area related to the built-up and agriculture classes we identified before through the on-screen digitizing. Finally, we jointed all 6 classes in the GIS environment and generated the land use maps for 4 years. An error matrix was created to assess the accuracy of the maps. The corresponding results are shown in Table 3.

### Models description

#### *Cellular automata (CA)*

CA is a well-known and common modeling technique that is defined in raster space and is used today to simulate many natural and anthropogenic phenomena (Hu et al. 2018; Shadman-Roodposhti et al. 2019). In CA, space is defined as a raster grid, with each unit considered as a cell. The automated cell model is based on the interaction of the following five components: (1) the grid space, also known as the lattice, and the cell that forms it; (2) the state of the cell, which shows the



**Fig. 1** Location of the case study

properties and modes of each cell; (3) transition rules that control changes in cell states; (4) time, by which the state of all cells is controlled and simultaneously updated; and (5) the neighborhood, by which cells change in status because of the mutual interactions between

target cells and their neighbors which are also under the influence of transition rules (Keshtkar and Voigt 2016). Transition rules include global rules and local rules. Here, the MC model is used to derive transition rules and the multi-layer perceptron artificial neural

**Table 1** Mean annual temperature and average annual precipitation of Qeshm Island

	January	February	March	April	May	June	July	August	September	October	November	December
Avg. Temperature (°C)	18.5	19.7	23.1	26.4	30.1	32.7	34	33.6	32.4	29.9	24.6	20
Precipitation/rainfall (mm)	42	36	15	7	2	0	0	0	0	2	11	25

**Table 2** Date, path, and row of Landsat satellite images

No.	Satellite	Date	Row	Path
1	Landsat7	05-25-2002	041	<b>172</b>
2	Landsat7	05-09-2002	042	
3	Landsat5	05-17-2008	041	
4	Landsat5	05-17-2008	042	
5	Landsat8	05-18-2014	041	
6	Landsat8	05-18-2014	042	

network (MLP-ANN) and LR algorithms to derive local rules. In the modeling process, the cells of this network are simultaneously updated at discrete times according to global and local rules. In this method, the value of each new cell at the output of the modeling process is determined by a set of variables, including the values of the neighboring cells and of the cell itself. The automated cell model can be obtained from Eq. (1) (Sang et al. 2011; Shadman-Roodposhti et al. 2019):

$$S_{(t, t+1)} = f(S_{(t)}, N) \tag{1}$$

where  $S$  is a finite set independent of cell states,  $N$  is the cell ground,  $t$  and  $t + 1$  are different times, and  $f$  represents the transition rules of cell states in local space.

*Markov chain (MC)*

The Markov model is commonly used to predict geographic features without any secondary effect and has become an important predictor in geographic research (Xu et al. 2019). The MC expresses quantitative changes in land use from one period to another and uses these changes as a basis or variable for mapping future changes. This is done by developing a transfer probability matrix of land use changes from time 1 to time 2 to be used as a basis for mapping future time periods. Based on the conditional probability of the Bayes formula, land use change prediction in the Markov model is computed using Eq. (2) (Sang et al. 2011):

$$S_{(t+1)} = \mathbf{P}_{(ij)} * S_{(t)} \tag{2}$$

where  $S(t)$  and  $S(t+1)$  are the states of the system at times  $t$  and  $t + 1$  and  $\mathbf{P}(ij)$  is the transfer probability matrix in a state that is calculated by Eq. (3) (Sang et al. 2011).

$$\mathbf{P}_{ij} = \begin{bmatrix} p_{11} & p_{12} & \dots & p_{1n} \\ p_{21} & p_{22} & \dots & p_{2n} \\ \dots & \dots & \dots & \dots \\ p_{n1} & p_{n2} & \dots & p_{nn} \end{bmatrix} \left[ \begin{array}{l} 0 \leq \mathbf{P}_{ij} < 1 \text{ and } \sum_{j=1}^N \mathbf{P}_{ij} = 1, (i, j = 1, 2, \dots, n) \end{array} \right] \tag{3}$$

The MC is considered as an effective tool for modeling land use changes and provides indices to determine the direction and extent of land use change (Benito et al. 2010; Eastman 2015).

*Multi-layer perceptron artificial neural network (MLP-ANN)*

An MLP-ANN is used to calculate the transition potential of land use as well as the position of transferred cells in this study. An MLP is actually a supervised model that uses single- or multi-layer perceptron to estimate the intrinsic relationships of inputs and outputs in a model (Yuan et al. 2009). The ANN consists of a network of interconnected processing units that has been simulated by modeling the network of neurons in the human brain. Neural networks have a nonlinear structure and function as a sophisticated mathematical tool in modeling the conversion of a system’s inputs to users’ desired outputs. The MLP approach, which uses back-propagation (BP) learning algorithms, is one of the most widely used neural network models (Kazemzadeh-Zow et al. 2017). Typically, an MLP network consists of one input layer, one or more hidden layers, and, finally, an output layer (Eastman 2015), which are used for data entry, data analysis, and model output, respectively (Hu and Weng 2009). Here, the input layer includes the land use changes in previous periods and the criteria that influence these changes over the study period; the

**Table 3** Overall accuracy for the land use maps

Year	Error count	Sample count	Overall accuracy %	User’s accuracy %	Producer’s accuracy %	K-standard
2002	32	300	89.33	90.35	89.33	0.87
2008	33	300	89.00	89.72	89.00	0.86
2014	27	300	91.00	90.18	91.33	0.89

hidden layer is used to identify the relationships between the changed pixels and the criteria used; the output layer is determined based on a transition potential map (TPM). See the Manual of IDRISI TerrSet Software for further details on MLP (Eastman 2015).

### Logistic regression (LR)

LR is a multivariate technique that considers different physical parameters to estimate probability percentages. This statistical method takes binary and scalar values as independent variables and allows the use of qualitative and discontinuous variables in the processes. The advantage of LR modeling over other multivariate statistical techniques is that this method can be used for variables that are not fully continuous or are otherwise qualitative. This model has been widely used in various fields, including epidemiology, ecology, environmental monitoring, weather forecasting, and LUCC (Silva et al. 2019). The main point in LR is that the dependent variable is a two-state variable and can only take the value of 1, indicating the occurrence of an event, and 0, indicating the non-occurrence of an event. LR uses the maximum likelihood estimation method to find the best set of parameters to run the model. In LR, we can predict the probability of the occurrence of event  $Y = 1$  by Eq. (4) (Arsanjani et al. 2013):

$$P(Y = 1|x) = \frac{\exp(\sum BX)}{1 + \exp(\sum BX)} \quad (4)$$

where  $P$  is the probability of the dependent variable,  $X$  represents the independent variable, and  $B$  represents the estimated parameters. To linearize the above model and remove the boundary of 1.0 for the main dependent variable, which is the probability of occurrence, the following equation is used to transform Eq. (4) (Arsanjani et al. 2013):

$$\text{Logit}_{(P)} = \ln \left[ \frac{P}{(1-P)} \right] = B_0 + B_1X_1 + B_2X_2 + \dots + B_NX_N + \varepsilon \quad (5)$$

### Model configuration

Here, different combinations of techniques and models are used to model land use changes. The hybrid models used are as follows: (1) CA-MC-ANN, (2) CA-MC-LR, and (3) the ANN-MC, which is otherwise known as the

Land Change Modeler (LCM). Generally, a number of elements for modeling land changes are needed, including land cover maps, factors affecting land change, the change interval, numerical estimation of changes in the simulation or prediction period, and, finally, maps of transition potentials. Land cover maps and variables were extracted using baseline data (satellite images, etc.), and the time intervals of changes were also determined according to the study objectives. The Markov technique was used to estimate the numerical changes in the simulation period for all three hybrid models. Neural network and LR methods were used separately to prepare the transition potential maps (TPMs). Each of these methods provides a TPM to predict each of the land use classes during the simulation period. After obtaining the above elements, modeling of the change can commence. For example, in the first hybrid model, the neural network output (TPMs) and the MC (the estimated change rate for each class of land use) were added as inputs to the CA model. The CA model simulates the LUCC over a defined period. In the second hybrid model, the outputs of Markov and LR models were added as inputs to the CA model, and land changes were simulated. Finally, in the third hybrid model, Markov and neural network techniques were used as LCM components and inputs to simulate changes. To evaluate the accuracy of each model in simulating the changes, the simulation results of all three hybrid models were compared with the observed land cover map in 2014 using the Pontius and Millones' method, known as the 3D method. From this comparison, the most accurate modeling method was determined. Finally, to predict changes until 2026, the hybrid model that performs best in the simulation phase was used. The overall framework of the study is shown in Fig. 2.

### Validation of land change modeling

The validity and accuracy of the modeling results were evaluated for each of the three methods used in this study by comparing the modeling simulation results of 2014 with the observed map of the same year. The final results produced in the simulation process were compared with the observed map, and the simulation accuracy was calculated separately for all three methods. To describe the difference between the simulated and observed maps, the method proposed by Pontius and Millones was used, also known as the 3D method. This technique has been used recently in many similar

studies (Yao et al. 2017; Tajbakhsh et al. 2018; Kourosh Niya et al. 2019, Varga et al. 2019). The method measures the agreement and disagreement between the simulated and observed maps via the calculation of quantification and allocation errors, which quantify the accuracy of the modeling process. Quantity disagreement is the number of pixels of a land use class in a simulated map in disagreement with the number of pixels in the observed map, ranging from 0 to 100% (Pontius and Millones 2011), and allocation disagreement has been defined as the difference between observed and simulated maps in the spatial allocation of classes (Pickard et al. 2017). The Figure of Merit (FOM) index is known as the index of the ultimate accuracy of each modeling method and is calculated as shown in Eq. (6):

$$\text{FOM} = B / (A + B + C + D) \quad (6)$$

where  $A$  is the amount of actual change that is simulated as persistence,  $B$  represents the correct simulated area,  $C$  is the area that is simulated as change but in the wrong class, and, finally,  $D$  is the persistence area that is simulated as change (Pontius and Millones 2011; Olmedo et al. 2015).

## Results

### Land use/cover change (LUCC)

An analysis of LUCC over the period 2002–2014 reveals that land use changes are coordinated with the expansion of the built-up class; an increasing demand for construction and, thus, the expansion of this class reduces the area allocated to other classes. For example, in 2002, the area assigned to the built-up class was 5400 ha, which then reached 8215 ha in 2014, an increase of 52%. Among the six land use classes, the built-up class is the only class that increased in both study periods (2002–2008 and 2008–2014). Simultaneously, the barren land class is the only class that declined in both periods. Of the other four classes, the agriculture, dense vegetation, and water classes first decreased and then increased, and the mangrove class first increased and then decreased. The amount and trend of changes over time are shown in Table 4.

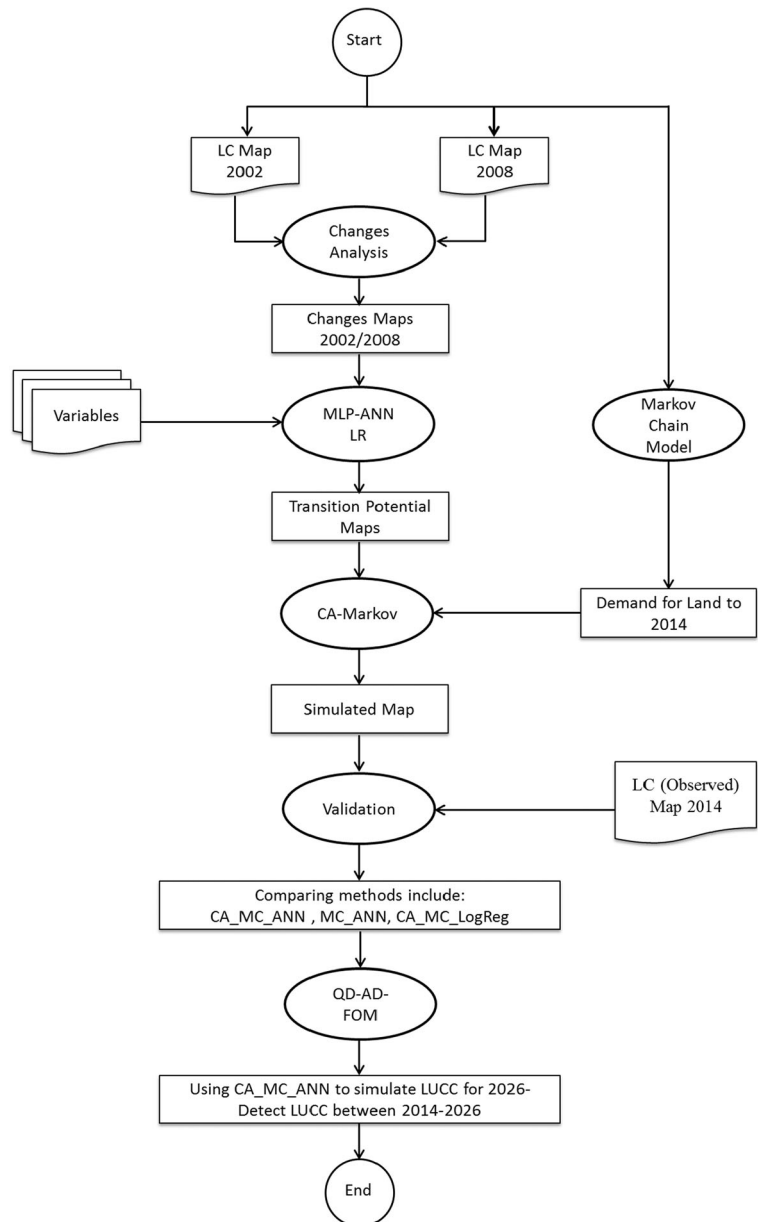
### Analyzing transition potential maps (TPMs)

ANN and LR methods were used to generate the TPMs. These methods generate the TPMs for each type of land use by relating the change map and the variables affecting the land change during the calibration period. As these methods use a different logic in modeling and producing TPMs, their outputs are likewise different. The relative operating characteristic (ROC) method was used to evaluate and compare the efficiency of these techniques. ROC can sufficiently evaluate the accuracy of a model that predicts the location of changes in a land use class. This is done by comparing a correspondence or potential map showing the probability of a land use class per pixel with a Boolean map indicating the actual location of the pixels belonging to that class (Pontius and Schneider 2001). Here, the potential or correspondence maps are the ANN and LR output maps. The Boolean map also shows the location of land use changes during the simulation period. This method uses the area under the curve (AUC) index to evaluate correspondence maps or TPMs. An AUC value of 1 indicates a perfect spatial agreement between the Boolean map of each class and their correspondence maps. An AUC value of 0.5 and lower indicates that if there is an agreement between the two maps, this compatibility is accidental. Figures 3 and 4 show the TPMs derived from ANN and LR, respectively. The AUC values are shown as diagrams in Fig. 5 for the TPMs of these two methods. These values were greater than 0.78 in both methods and for the potential maps of all land uses. The comparison of the two methods shows that the TPMs produced by ANN (except or the vegetation map) were in higher spatial agreement with the transition Boolean map than were the LR correspondence maps during the simulation period. This demonstrates the superior performance of the ANN in producing TPMs to simulate land changes.

### Land change simulation

This study aimed to model LUCC in Qeshm Island, Iran, and to compare three hybrid models, including CA-MC-ANN, CA-MC-LR, and MC-ANN (i.e., LCM). To calibrate these models, the LUCC map and variables from the period during 2002–2008 were used to prepare the simulated maps of 2014. The land cover maps of 2014 were then simulated using the three considered models (as shown in Fig. 6).

Fig. 2 Study flowchart









To evaluate the accuracy of the simulated maps, the outputs of all three methods were compared with the observed land cover maps of the same year (2014). The land use classes for which the most changes were associated are the built-up and barren land use classes; from 2008 to 2014, approximately 2000 ha were added to the built-up class, and approximately 3000 ha removed from the barren land class (Table 5). In general, the results show that modeling of land changes using the CA-MC-ANN hybrid model is more accurate than that of the other two models. The area of the correct

simulated changes was calculated 611 ha in the CA-MC-ANN model, compared to 455 ha for the LCM and 396 ha for the CA-MC-LR model. Additionally, separate comparisons of the state of each land use show that the three models have different results for each type of land use. For example, in the CA-MC-ANN and CA-MC-LR models, the largest correctly simulated area is related to barren land, but in the LCM, the prediction of the growth of the built-up class is more accurate than that of the other land use classes.



**Table 4** The amount and trend of changes over the three time periods (unit: hectare)

Land use classes	2002	2008	2014	Trend of changes
Agriculture	4462	4440	4676	
Barren land	139534	139354	136061	
Built-up	5400	6026	8215	
Dense veg.	842	580	1425	
Mangrove	6823	7529	6620	
Water	91836	90968	91900	

Validation of land change simulation

The validation results are presented in Table 6. As shown in the table, more than 96% of the area studied by all three methods was simulated correctly to be persistent, including areas that have remained stable and had no change in the observed and simulated maps. No change in a majority of the study area has also been reported in a study by Tajbakhsh et al. (2018). According to Table 6, the percentage of the correctly simulated area, marked in the table with the letter B, and the FOM index, as the ultimate determinant of accuracy herein, were found to be higher in the results of the CA-MC-ANN model than in those of the two other models; the FOM index was 6.7, 5.1, and 4.5 for the CA-MC-ANN, LCM, and CA-MC-LR models, respectively. Therefore, the CA-MC-ANN hybrid model has a higher ability to model and simulate land changes in Qeshm Island than the other two models. Figure 7 shows each of the effective factors in the FOM index.

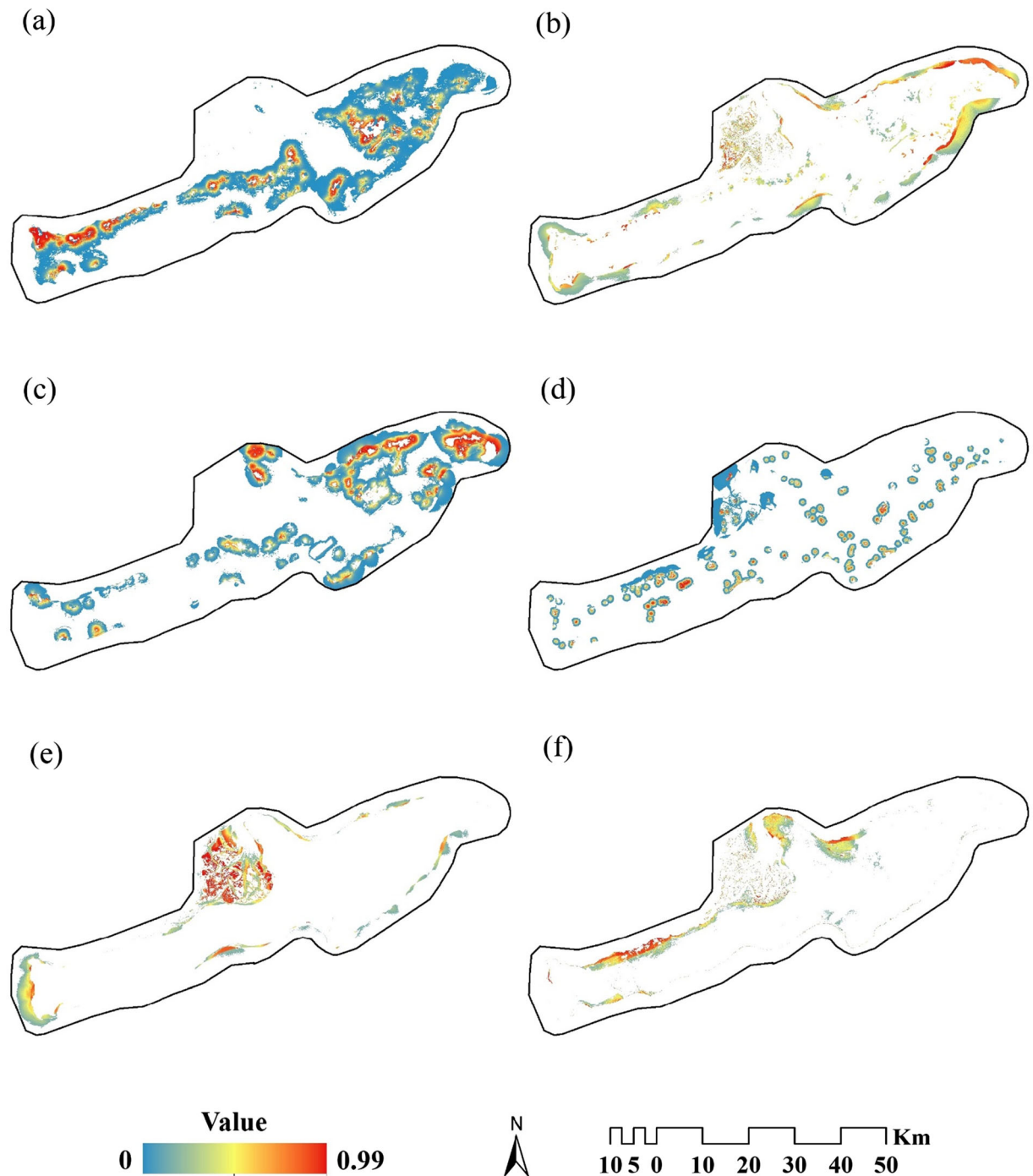
Prediction of land use/cover change (LUCC) in 2026

Because the CA-MC-ANN model was found to perform better than the other two models in modeling and simulating land changes in Qeshm Island, it was used to provide a simulated map illustrating the LUCC in Qeshm Island for the year 2026 (shown in Fig. 8). This map was compared with the 2014 map to reveal the extent of the changes in land use. The results of this

comparison are provided in Table 7 and Fig. 9. As with the changing trends from 2002 to 2008, the barren land use class is associated with the largest area of land lost compared with the other classes, providing the land that other classes acquired. Unlike the barren land class, the built-up and agriculture classes show a continuing increasing trend; this can be attributed to the region’s development process and concurrent expanding demand for building and agriculture. Although a similar trend to that of the built-up and agricultural classes is evident in the dense vegetation class, as shown in Table 7, the uncertainty is high in the modeling results of the dense vegetation class. This may be attributed to the dense vegetation class’ dependence on precipitation and the fact that most of the plants in this class are therophytes. This is also true for the water class, which is affected by the tide phenomenon. Significant in Table 7 is the decline in the mangrove class in 2026 compared with 2014. Although the area of the mangrove class increased between 2002 and 2008, it declined between 2008 and 2014 and then, according to the CA-MC-ANN simulation map, was again predicted to decrease by 2026.

Discussion

To study land use changes in Qeshm Island from 2002 to 2014, images from the Landsat satellite series from 2002 to 2014 were used. After analyzing the images, land use maps were obtained for these years. Investigations show



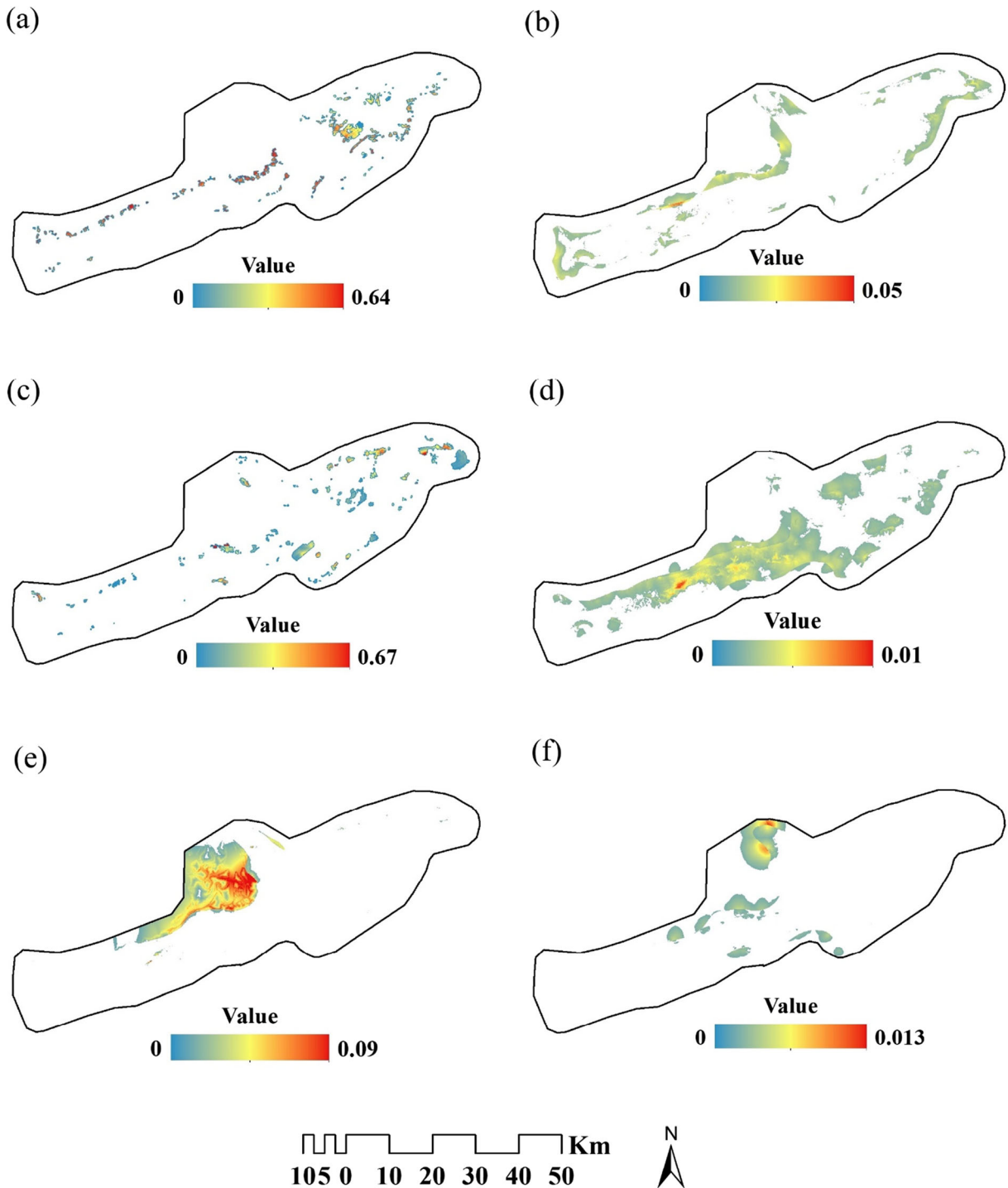
**Fig. 3** TPMS' MLP-ANN: **a** agriculture, **b** bare-land, **c** built-up, **d** dense vegetation, **e** mangrove, **f** water body

that the process of land use change has occurred rapidly on Qeshm Island. During this time period, the area associated with agricultural and built-up land use classes increased dramatically, with the largest decrease (in terms of area) related to the barren land use class. The

simultaneous decline in the area of barren land and the increasing trend of built-up land can be attributed to significant economic changes and recent developments on Qeshm Island. The transformation of Qeshm Island into a strategic and economic hub for both the country

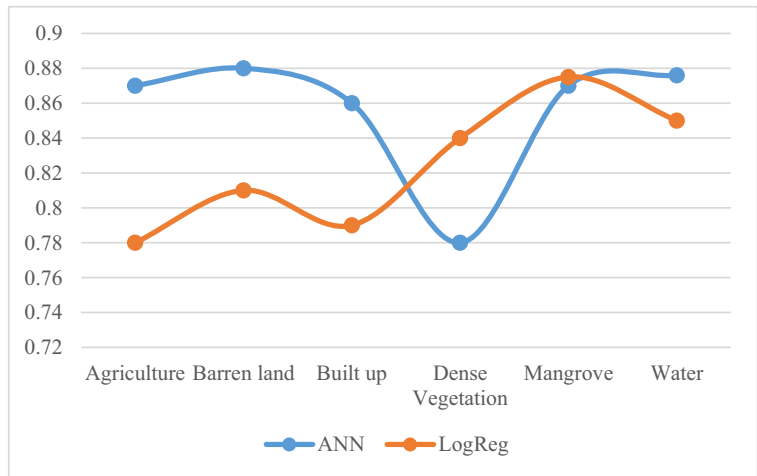
and the region has led to an increase in population in the region, wherein the population of Qeshm has increased from approximately 80,000 in 2002 to approximately

148,000 in 2014 (Iran’s Population and Housing Census, 2016). This population growth has led to widespread land use changes, especially involving the



**Fig. 4** TPMs’ logistic regression: **a** agriculture, **b** bare land, **c** built-up, **d** dense vegetation, **e** mangrove, **f** water body

**Fig. 5** Comparison of TPMs, using area under the curve (AUC)



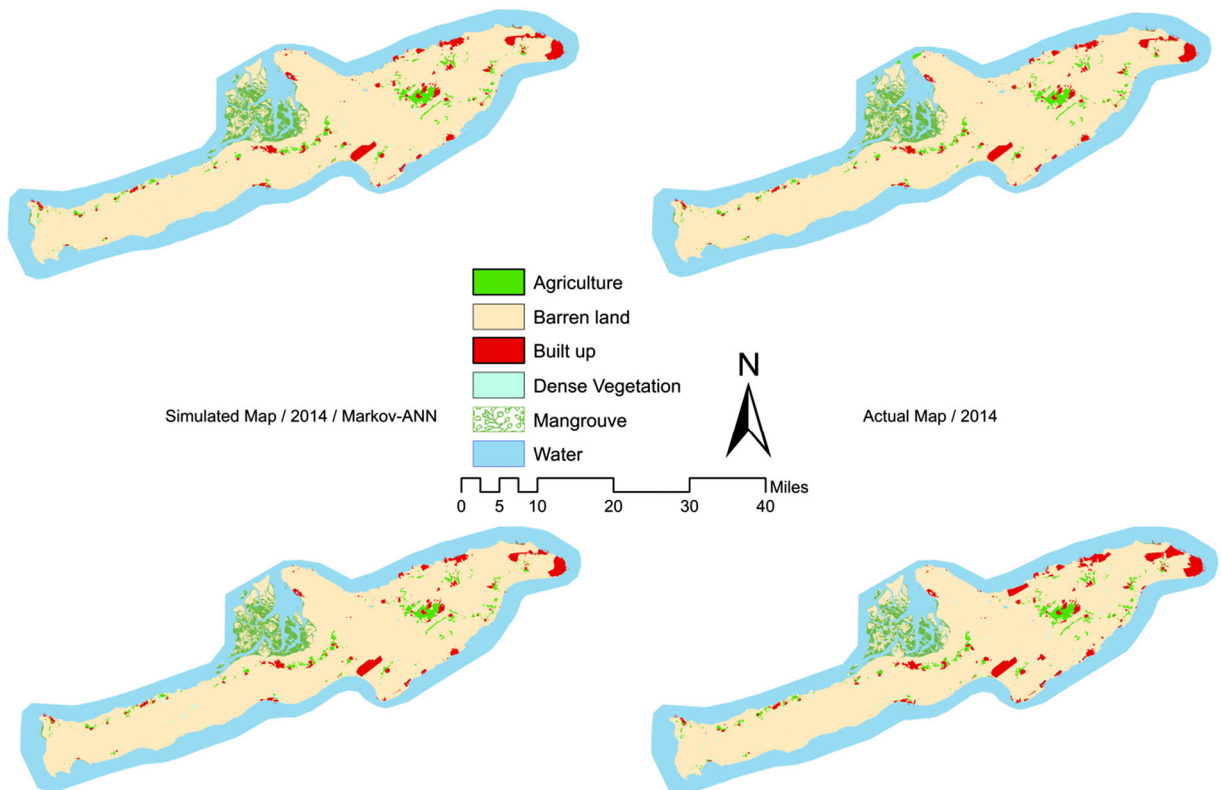
conversion of natural lands to man-made ones. Additionally, as listed on Qeshm Island’s Free Area Organization website, the large number of tourists, who visit the island every day, intensifies this conversion.

The accuracy of the obtained maps (from 2002, 2008, to 2014) was evaluated using the overall accuracy and

kappa coefficient (Alilou et al. 2018). The evaluation results showed that the overall accuracy of land use maps was 89.33 for 2002, 89.00 for 2008, and 90.00 for 2014. The kappa coefficient for these years was 0.87, 0.86, and 0.89, respectively. The overall accuracy and kappa coefficients obtained in this study showed that the

Simulated Map / 2014 / CA-Markov-ANN

Simulated Map / 2014 / CA-Markov-Logistic Regression



**Fig. 6** Actual and simulated maps of 2014 using three models

**Table 5** Comparison between results of the modeling and real map of 2014

Land use/cover classes	Land covers area (hectare)				Correct predicted changes through modeling methods (hectare)			Observed change of 2014
	Land 2014	CA-MC-ANN	MC-ANN (LCM)	CA-MC-LR	CA-MC-ANN	MC-ANN (LCM)	CA-MC-LR	
Agriculture	4676	4415	4277	4488	40	5	0	235
Barren land	136,296	138,930	139,941	140,075	177	144	221	- 3293
Built-up	8216	6648	6044	6030	134	185	0	2189
Dense vegetation	1425	828	537	179	83	16	0	845
Mangrove	6620	8205	8205	8230	114	39	126	- 909
Water body	91,664	89,871	89,893	89,894	63	66	49	931
Total area	248,897	248,897	248,897	248,897	611	455	396	-

images are of high accuracy and could even be higher than the standard and what was reported in other similar studies. For example, the kappa coefficient was reported as 0.76 by Mitsova et al. (2011), 0.67 by Hyandy and Martz (2017), and 0.85 by Memarian et al. (2012). Therefore, the overall results indicate that the maps obtained herein have high accuracy and precision. It can, thus, be concluded that Landsat satellite imagery can be used to monitor land use changes with acceptable accuracy.

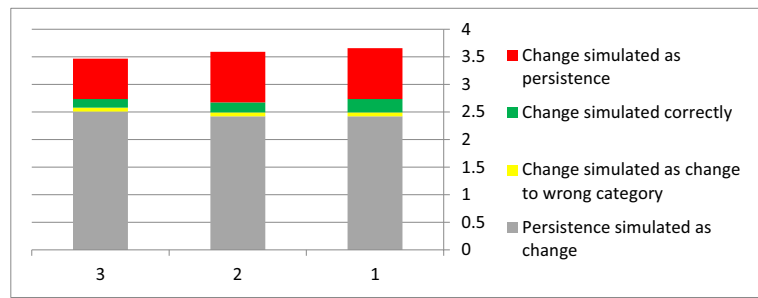
To model and predict future changes in the study area, the performance and accuracy of three hybrid models (CA-MC-ANN, CA-MC-LR, and ANN-MC (i.e., LCM)) were compared. Based on this comparison, the best model was then selected and used to model future changes in the study area. Thus, the LUCC map

of 2014 was first simulated using the aforementioned three methods and past maps from 2002 to 2008. To evaluate the accuracy of the simulated maps of 2014, the outputs of all three methods were compared with the observed map of 2014. The quality of the simulated LUCC by each of the methods is then evaluated using transfer matrix features, a validation method, and the quality of the LUCC transfer correspondence maps. Therefore, it is necessary to first consider the requirements for the creation of an appropriate transfer matrix; then, this matrix can be used for future predictions considering the initial state and the possibility of change (Koomen et al. 2007). Here, the validity of the models' results was investigated using the Pontius and Millones' method, i.e., the 3D method. This is one of the most useful and highly accurate methods that has been used to

**Table 6** Agreement and disagreement components in the three used methods for modeling

Component	Factor name	Agreement/disagreement	CA-MC-ANN Proportion (%)	MC-ANN	CA-MC-LR
Persistence simulated correctly	---	Agreement	96.3433	96.4059	96.5314
Persistence simulated as change	D	Disagreement	2.4244	2.4244	2.5089
Change simulated as change to wrong category	C	Disagreement	0.0671	0.0671	0.0702
Change simulated correctly	B	Agreement	0.245	0.1824	0.1575
Change simulated as persistence	A	Disagreement	0.9202	0.9202	0.732
Total			100	100	100
Simulated change			2.7365	2.6739	2.7366
Observed change			0.3121	0.2495	0.9597
Allocation disagreement			1.72	1.23	1.15
Quantity disagreement			1.69	2.1	2.17
FOM			6.7	5.1	4.5

**Fig. 7** Graphs of agreement and disagreement components: (1) CA-ANN, (2) LCM, (3) CA-Markov-LR

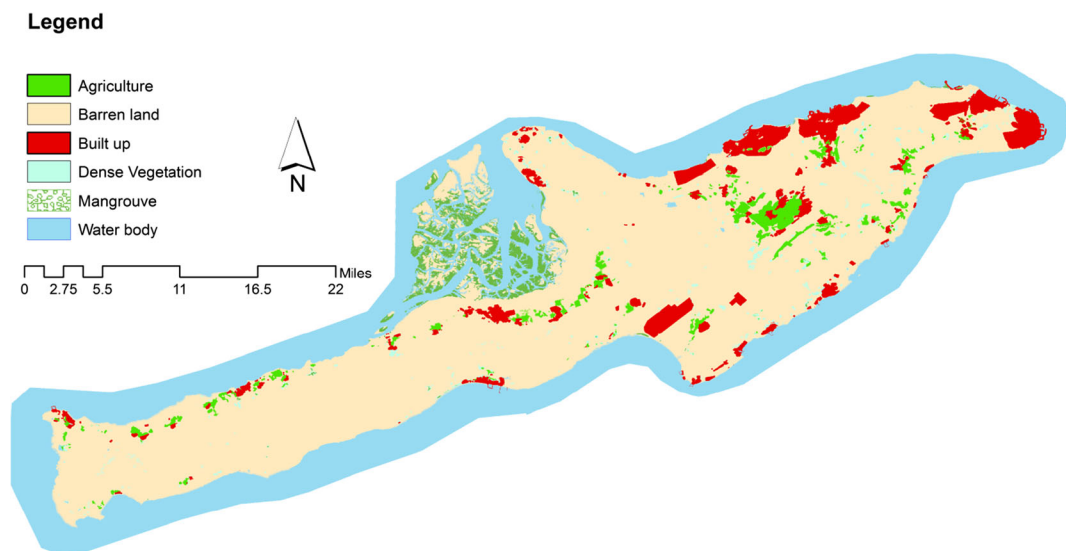


compare and verify the accuracy of land simulation models in many studies. The results of our study, with regard to the use of the Pontius and Millones’ method, are in good agreement with studies on the robustness of this method’s application to verifying the accuracy of simulation models. For example, Kourosch Niya et al. (2019) investigated the validity of different models using the Pontius and Millones’ method and the FOM index in the Qeshm Island. They stated that the Pontius and Millones’ method was highly capable in verifying the accuracy of the simulated model and that the majority of the study area was predicted correctly by this method. Tajbakhsh et al. (2018) used the Pontius and Millones’ method to evaluate the accuracy of two types of land use change modeling techniques and resultantly posited that this method can suitably verify the accuracy of the models and obtain good results with regard to land use simulation. Varga et al. (2019) verified the accuracy of the CA-Markov model using this method; as a result, the accuracy of the model was

sufficiently verified, and the CA algorithm was found to be more error-prone than the Markov algorithm.

Comparisons of the results of the methods used in this study show that the area of the correctly simulated changes and the results of the land use change in each model were different. Considering the FOM index and the agreement/disagreement values obtained from these three methods, it can be concluded that the CA-MC-ANN hybrid model is more accurate than the other two models and more capable of modeling future changes. According to the results (Table 6), the values of agreement that show the change simulated correctly are higher in the CA-MC-ANN method than in the other two methods. Additionally, the FOM value, which shows the accuracy of the model, is higher in the CA-MC-ANN than in the other two methods.

Similar studies investigated the validity of different models using the Pontius and Millones’ method and the mentioned factors. By examining agreement and disagreement values for the CA-Markov model, Hyandye



**Fig. 8** Predicted map of 2026—using integration of CA-Markov-ANN

**Table 7** Comparison of the area of each land use class between 2014 and 2026 (unit: hectare)

Class name	2014	2026	Gains	Losses	Net change
Agriculture	4676	5120	836	-392	444
Barren land	136,296	130,813	2074	-7557	-5483
Built-up	8216	12,119	3903	0	3903
Dense veg.	1425	2402	1592	-615	977
Mangrove	6620	5394	666	-1892	-1226
Water	91,664	93,049	2736	-1351	1385
Total	248,897	248,897	11,807	-11,807	0

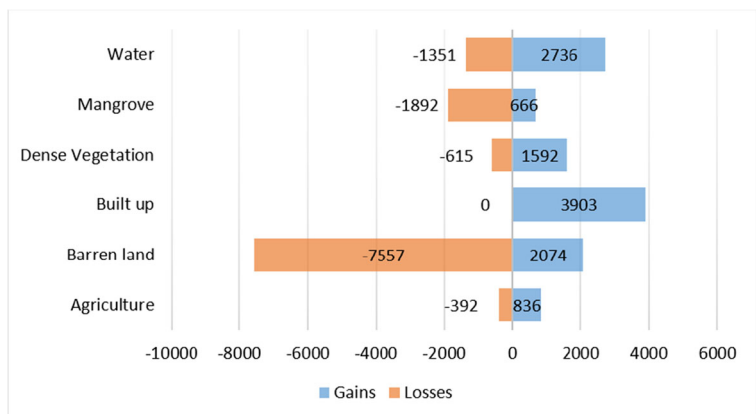
and Martz (2017) concluded that the quantity agreement is larger than the allocation agreement. They attributed this to the calibration process, which results in the creation of a simulation model that ultimately increases the model’s performance in determining the correct values of quantity compared with that of allocation. Similar results have been reported in the studies of Memarian et al. (2012) in Malaysia, where high values of quantity/allocation disagreement and low values of FOM were found, showing that the CA-Markov model alone is not suitable for simulating and expressing LUCC dynamics.

Although some studies have been performed to compare different LUCC modeling methods, few studies have compared models proposed by different studies with similar data. This was an important gap that served as one of the main objectives of this study. Xu et al. (2019) investigated and simulated urban land use changes in the southern city of Auckland in New Zealand using the CA-MC-ANN model. The validation results showed that the combination of the ANN with the CA-MC model is more capable of simulating land use changes than conventional models, such as the

Analytical Hierarchy Process (AHP) and LR-CA-MC. Tajbakhsh et al. (2018) used MC in combination with Fuzzy-AHP and ANN-MLP to simulate land use maps in the urban watershed of Birjand, Iran and compared these models. Simulation and validation results showed the superior performance of MLP-ANN compared with Fuzzy-AHP; FOM values for the MLP-ANN and Fuzzy-AHP were 5.69 and 5.18, respectively. Another similar study by Mustafa et al. (2018) compared CA-SVMs and CA-LR methods to investigate LUCC changes. The combination of CA with both SVM and LR models was highly capable in investigating land use changes and analyzing controlling factors. By examining the validity of the two models, the performance of CA-SVMs was found to be better than that of CA-LR.

By careful examination of the validity and reliability of the models used in this study, the CA-MC-ANN method was found to be the most accurate; the LUCC map for 2026 in the study area was then simulated with the CA-MC-ANN method. The simulated map indicates that, as before, the barren land class lost most of its area to other land use classes, particularly the built-up and the agriculture classes. The results also showed that the

**Fig. 9** Gains and losses between 2014 and 2026 (hectares) for each land use class



mangrove class decreased, as seen in the previous period (from 2008 to 2014). The decreased area of this valuable ecosystem can seriously damage the environmental value of the area. Direct factors, such as deforestation, and indirect factors, such as sea pollution caused by marine transportation, have caused damage to the ecosystem. On the other hand, conservation programs led by national and international organizations have been effective in preserving this valuable ecosystem. Studies have been conducted to investigate the areas of mangrove forests and their threatening factors. For example, Khorani et al. (2015) investigated mangrove forests using satellite imagery from 1984 to 2009 and reported a variable trend over the period; it was shown that anthropogenic factors have contributed to the decline of mangrove forests in the area, while the decline in precipitation in recent years has also contributed to the decline of mangrove forests in the area (Khorani et al. 2015). In another similar study, Mafi-Gholami et al. (2019) investigated the relationship between drought and mangrove forests and found that the area of mangrove forests was significantly associated with decreases in annual precipitation and the subsequent drought in the area. Additionally, Etemadi et al. (2018) examined the changing pattern of land use in the Mangrove forest located in the coastal region in southern Iran over 14 years (from 2000 to 2014) and predicted future losses and gains in land type uses up until the year 2026. They noted that an obvious change had not been observed in the mangrove area and that the relative sea-level rise had acted as the predominant influencing factor of converting mangrove forest area to water area. In a similar study conducted by Bihamta Toosi et al. (2019), the results of the change detection showed an increase in total mangrove areas but a decrease in mangrove forests near the coastal areas, mainly because of significant human activities over the past two decades.

Much of the LUCC over the past two decades has been due to the establishment of the Qeshm Free Trade Organization. As a result of the transformation of Qeshm Island into a free trade zone and its subsequent development, increased economic and commercial activity, and increases in industrial activities and national and international investments, the land use/cover on Qeshm Island has undergone extensive changes. These dramatic developments have led to an increase in the population of the region. According to statistics from the National Statistical Center of Iran, the region's population has nearly doubled in the past two decades: the population

of Qeshm City in 1996, 2006, and 2016 was 73,000, 105,000, and 149,000, respectively. This rapid population growth has led to the conversion of barren land to built-up and agricultural land uses. The growing population also raises concerns for the future with regard to environmental sustainability and will play an important role in future LUCC developments. Additionally, natural parameters, such as the decreased precipitation mentioned in the study of Mafi-Gholami et al. (2017), have affected LUCC in the study area and, if climate change intensifies, may have more negative environmental impacts in the future. Therefore, to preserve valuable environmental resources and create a sustainable development on the Qeshm Island, it is important to maintain a proper balance between the region's environmental health and its developments. This balance can be achieved through sufficient management plans and efforts, such as environmental impact assessment of projects, the participation of local residents in conservation projects, development of land reclamation plans, assessment of the ecological potential of the area, determination and estimation of carrying capacity, and land use planning. Additionally, national and international organizations should contribute to the planning and conservation of mangrove habitats in the study area.

## Conclusions

Here, the performance and accuracy of three hybrid methods for modeling land use change were investigated in an application to Qeshm Island, the largest Persian Gulf island; these methods are the CA-MC-ANN, the CA-MC-LR, and the ANN-MC (otherwise known as the LCM). The performance and validity of the models were evaluated using optimum methods and different factors. The overall results indicate that the combination of CA-MC with the ANN portrays LUCC dynamic changes with higher accuracy compared with the other two methods. Therefore, using the CA-MCC-ANN method, future land use changes in the study area were predicted for the year 2026. Although this serves as a case study conducted in Qeshm Island, Iran, the hybrid models used in this study and the performance evaluation of the models can be applied in other areas.

Spatial and temporal surveys of land use changes in the study area show that the level of agriculture and built-up land use classes increased dramatically from 2002 to 2014, while the land use type with the largest decrease



was associated with the barren land class. The economic and industrial development in recent decades and investments have been the most important anthropogenic factors of land use change in the study area; such factors have played an important role in the increasing demand for the expansion of the agriculture and built-up land use classes to take advantage of the opportunities and resources available in the region. This trend is expected to continue in the future, where there is an expected increase in the conversion of barren land use to anthropogenic uses. Regarding changes in land use classes, an important point to consider is the reduction of the mangrove class by 2026, which is predicted to decrease in a similar manner as in the 2008–2014 period. Although there are plans to protect this ecosystem, the predicted continuing decrease in the area of this valuable ecosystem raises concerns; national and international conservation programs should, thus, continue with a greater emphasis on preventing the destruction of mangrove forests.

Although the combination of CA-MC with ANN simulated LUCC with acceptable accuracy and relative superiority among other methods in the study area, further studies are needed in the field of land use change modeling to better understand the performance and capabilities of this method. It is strongly recommended that the method used in this study be applied to other regions, especially coastal regions with climates that are both similar and different to that considered in the present study. This would not only allow further assessment of the validity and usefulness of the model but also assist in identifying the tools needed for the planning and management of various areas and ecosystems.

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#### Compliance with ethical standards

**Conflict of interest** The authors declare that they have no conflict of interest.

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