



Modeling land cover change dynamic using a hybrid model approach in Qeshm Island, Southern Iran

Amir Tajbakhsh · Azadeh Karimi · Anlu Zhang

Received: 9 June 2019 / Accepted: 31 March 2020 / Published online: 22 April 2020
© Springer Nature Switzerland AG 2020

Abstract Multiple factors including natural and human-induced ones lead to land cover change in the landscape. Therefore, identifying the pattern of land cover change can help inform land-use management and prevent associated issues which can affect the natural resources of the landscape. The aim of this study is to assess land cover change in the Qeshm Island in southern Iran by combining the resulting outputs of multiple modeling methods, cellular automata (CA), Markov chains, and artificial neural networks (ANN) based on land cover maps for the years 1996, 2006, and 2016 that have been extracted from satellite imagery (Landsat 5, 7, and 8). In order to evaluate the accuracy of modeling, the Kappa coefficient was calculated to be 0.8. Then, land cover changes for 2025 were predicted by a hybrid model (CA-Markov-ANN). The results indicate that the classes of built-up areas, vegetation, and mangrove forests have changed more significantly

from 1996 to 2016 compared with other classes. Land cover maps generated in this study showed that built-up areas have grown significantly in recent decades due to the region's growing population and development of ports, commercial, and industrial areas. Due to the climate change, the land area covering vegetation has decreased dramatically. The size of the mangrove forests has increased over the time period of the study (1996–2025). The findings of this study can inform land-use planning decisions by providing them with a comprehensive overview of land cover conditions in the future.

Keywords Land management · Cellular automata · Markov chains · Artificial neural networks · Qeshm Island

Introduction

Land use and land cover change (LULCC) are the most substantial issues resulting from human activities on the Earth (Grigorescu et al. 2019; Li et al. 2016a). It influences the Earth's ecosystems through a wide range of human activities including deforestation, desertification, urban expansion, and agricultural development. LULCC also has an additive effect on global warming and climate change through destroying the natural environment and expanding human-made structures (Cheng et al. 2018; Jagarnath et al. 2019; Nkya et al. 2017). The changes in land cover have increased in recent decades due to population growth, industrialization, and economic development (Hashem and Balakrishnan 2015). LULCC is

A. Tajbakhsh · A. Zhang
College of Land Management, Huazhong Agricultural University,
Wuhan, Hubei Province, China

A. Tajbakhsh
e-mail: tajbakhsh.amir@webmail.hzau.edu.cn

A. Zhang
e-mail: zhanganlu@mail.hzau.edu.cn

A. Karimi (✉)
Department of Environment, Faculty of Natural Resources and
Environment, Ferdowsi University of Mashhad, Mashhad, Iran
e-mail: az-karimi@um.ac.ir

directly or indirectly caused by human activities and, in some cases, it results from natural factors (Osman et al. 2018; Valdez et al. 2019). Climate change and drought are also two factors that can change the land cover type on the Earth. For example, farmers in agrarian areas leave their lands during drought. Climate change can convert many agricultural areas and forests to barren lands (Nkya et al. 2017; Cheng et al. 2018; Jagarnath et al. 2019), forcing rural communities abandon their lands. Human-induced land cover change mainly occurs due to destruction of vegetation, rangelands, agricultural, and forest areas resulting from human activities such as expansion of urban areas, development of industries and ports, desertification, deforestation, and expansion of agricultural lands (Flores-Casas and Ortega-Huerta 2019; Grigorescu et al. 2019).

Remote sensing is one of the most effective ways by which land cover change can be assessed over a specified period of time (Shimizu et al. 2018; Wu et al. 2019). In fact, there are many different types of satellite images in different governmental and non-governmental databases which are available for researchers and decision-makers that have made it easy to study land cover changes in different parts of the world (Lin et al. 2019; Singh et al. 2018). The application of remote sensing data has many advantages, including access to low-cost data of a given area at different temporal scales and also reducing the time required to conduct a study (Jensen 2015). Many studies have used remote sensing for analyzing land cover change (Coppin et al. 2004; Lu et al. 2004; Valdez et al. 2019). For example, this method has been used for modeling land-use changes in urban areas (Guodong et al. 2018; Jagarnath et al. 2019), forest areas (Flores-Casas and Ortega-Huerta 2019), and coastal areas (Singh et al. 2018). It has also been used for identifying changes that have occurred in coastal urban areas (Feng et al. 2018), assessing the extent of deforestation (Wyman and Stein 2010), and examining urban sprawl and urban land-use changes (Bununu 2017; Du et al. 2018; Munroe et al. 2005).

Maps extracted from satellite images can also be used to predict future land cover changes (Singh 1989; Abd El-Kawy et al. 2011). Land change prediction is an effective method to develop various scenarios that provide a fairly clear perspective of the coming-years' situations in different ecosystems (Lin et al. 2019; Singh et al. 2018). This information can inform land use planners and decision-makers by providing them with a comprehensive overview of future land cover

conditions. Different approaches for simulating and predicting LULCC can be categorized into three classes (Kazemzadeh-Zow et al. 2017). The first group of methodologies uses regression or Markov chains to assess the change in land cover types. Because of the simplicity of these models, they are unable to model complex changes in real, complex ecosystems. These simple methods are no longer used as stand-alone techniques for modeling LULCC (Kazemzadeh-Zow et al. 2017). The second group of approaches is defined based on dynamic models such as cellular automata, agent-based models, artificial neural networks, system dynamics, and optimization algorithms such as ant colony optimization (Carvalho et al. 2019; Du et al. 2018; Feng and Tong 2018; Ke et al. 2017; Kolb et al. 2013). Since these methods are developed based on intelligent algorithms, researchers are able to model more complicated phenomena. For example, artificial neural networks, as an optimization algorithm, are able to recognize nonlinear patterns in a complex landscape and quantify the complicated relationships between different land cover types (Kazemzadeh-Zow et al. 2017; Zhai et al. 2020).

In the third group of approaches, the modeling outcomes of multiple methods from other methodologies are integrated (Bununu 2017; Dou et al. 2019), and these have been suggested by multiple studies in order to improve modeling efficiency (Liu et al. 2007; Yang and Li 2007; Qiu and Chen 2008; Wu et al. 2019). Each modeling approach has its own capabilities. When it is integrated for a given case study, it can complement the other approach and reduce the overall limitations of such modeling methodologies. For example, the Markov chain can predict the extent at which land-use changes have occurred. However, it cannot simulate spatial variations within a given area (Yang et al. 2012). Cellular automata is the most widely used model that can be applied independently or in combination with other modeling methods, including Markov chains, logistic regression, and neural network to simulate and predict land use/cover change in the landscape (Kazemzadeh-Zow et al. 2017; Hyandye and Martz 2017; Du et al. 2018; Zhai et al. 2020). The cellular automata, modeling technique has the ability to simulate spatiotemporal properties of complex ecosystems (Li and Yeh 2002; Clancy et al. 2010). Artificial neural network is also used for modeling land-use change due to its ability to model nonlinear relationships between variables in different studies either individually or in combination with other modeling methods (Yang et al. 2008; Pijanowski et al. 2014).

There are many studies that have used a separate method or a combination of two or three of the aforementioned methods to model land cover changes within the landscape. For example, Mitsova et al. (2011) used cellular automata in order to simulate urban growth over open lands in the USA. In another study, ANN multi-layer perceptron was used to model changes which occurred in urban and agricultural lands in the northern part of India (Mozumder and Tripathi 2014). Since different factors can contribute to land cover change, determining those variables responsible for the overall change and modeling them has always been problematic for researchers. Therefore, hybrid models which allow using a combination of methodologies can help simplify the LULCC modeling process. Basse et al. (2014) combined cellular automata and ANN to simulate land cover changes in a European cross-border region (an area between Belgium, Germany, France, and Luxembourg), because of their particular potentials at modeling changes in complex ecosystems. In another study, three methods including: CA, Markov chains and ant colony optimization (ACO) were integrated in order to simulate land cover changes in Beijing, China (Yang et al. 2012). Then, the results were compared with the outputs resulting from the use of each two methods including, CA-Markov and ACO-CA. The key finding of this study indicates that the output resulting from a combination of three models (CA-Markov-ACO) was more accurate than the output generated using each pair of methods. Moreover, the combination of logistic regression, CA, and Markov chains presented a reliable output when used to simulate urban expansion in Tehran, Iran (Jokar et al. 2013). Du et al. (2018) integrated tree-based methods and cellular automata to simulate multiple urban land-use changes in Tokyo, Japan. They found that tree-based methods can effectively generate complicated transition rules to predict more accurate results in combination with cellular automata, compared with usual models. In another study, Feng et al. (2018) modeled coastal changes by incorporating spatial autocorrelation into cellular automata to optimize transition rules and increase the modeling accuracy, and their results showed 3.6% increase in overall accuracy. The combination of Markov chain and cellular automata is a widely used method, applied by Hyandy and Martz (2017) to simulate changes in agricultural areas in Usangu catchment, Tanzania. Using this approach they revealed the changes in land cover classes, particularly from grassland and agricultural lands to urban areas.

Generally, review of different studies shows hybrid models are able to achieve more accurate results in the term of land change simulation.

The objectives of the present study were (1) to detect changes occurred in land cover in the Qeshm Island, Iran, in particular, vegetation cover and mangrove forests between 1996 and 2016, and (2) to predict land cover changes in this region by 2025. At the first Landsat satellite, images were classified using the maximum likelihood algorithm, and different land cover classes were identified in order to achieve these objectives. Second, the amount of change in each class was determined during the defined time period and was determined by comparing the resulting outputs. In the next step, a hybrid model was developed by combining the three cellular automata (CA), Markov chain (MC), and artificial neural networks (ANN) models in order to simulate the status of land cover in 2016 based on 1996 and 2006 data. In order to assess simulation accuracy, the modeling output was compared with the actual land cover map of 2016. Finally, land cover changes were projected for 2025 using the proposed hybrid model in this study based on the CA, MC, and ANN methods.

Methodology

Data types and sources

To be able to examine different satellite images for different time periods, it is better to prepare images taken on the same day in different years. However, due to some technical issues such as unavailability of image, satellite transmissions from the region, and cloud cover issue, it is unlikely to provide images taken on the same day in a given time period. In these cases, data from different sensors are preferable (Lu et al. 2004; Lu et al. 2014; Jensen 2015). In this study, the Landsat 5, 7, and 8 satellite images were used to investigate land cover changes in the Qeshm Island, located in the south of Iran. Each Landsat satellite image covers an area of $185 \times 185 \text{ km}^2$ on the ground. The number of multi-spectral bands in the visible and near infrared spectrum for TM, ETM+, and OLI sensors are 6, 6, and 7 bands, respectively. The multispectral bands of these sensors were used to classify different land-use types. The radiometric resolution of images provided by TM and ETM+ is 8 bits, while this resolution for OLI images is 16 bits. However, the spatial resolution of all three

sensor data is 30×30 m, which indicate each pixel covers 900 square meters area on the ground (Table 1).

Study area

Qeshm is the biggest Island located in the Persian Gulf in the south area of Iran from $55^{\circ}15'38''\text{E}$ to $56^{\circ}16'52''\text{E}$ and from $26^{\circ}32'20''\text{N}$ to $27^{\circ}00'00''\text{N}$. The average altitude is about 10 m above sea level and has an area of approximately 1628 km^2 . Because of steamy climate and limy lands, this area has a poor vegetation coverage, and hence, the substantial extent of the Island has been covered by barren lands or sparse vegetation. Another characteristic of Qeshm natural ecosystem is the presence of mangrove forests which are distributed through the shoreline from the Hormuz Isthmus to the Indian Ocean. Human population residing in the Island are reported to be about 148,000 based on the census information in 2016 (Iranian Statistical Center, 2016). Qeshm has experienced many economic changes as a free commercial zone from 1990, so that this Island has been known to be a major industrial zone for international trade in the south of Iran. On the other hand, extracting petroleum and importing manufacturing products, the traditional economy of this area has changed from agriculture and fishery to a modern industrial economy. Moreover, due to the presence of unique natural landscape and cultural characteristics of Qeshm Island, this region has been a well-known tourism destination for tourism and recreational activities; all of which have resulted in various land cover changes in this area in recent decades (Fig. 1).

Pre-processing of satellite images

Remote sensing images should be preprocessed to eliminate errors and problems before being used in the processing stage (Dalmiya et al. 2019; Shimizu et al. 2018; Yan et al. 2019). One of the related issues is cloud cover that makes examination of land use difficult. In these cases, it is required that images without cloud cover problem are selected, or cloudy parts are removed (Sano et al. 2007; Tolnai et al. 2016). Since the images used in this study were without any cloud cover, there was no need to do further preparation for the images used in this study. Radiometric errors are the other problems that should be corrected in the image preprocessing step (Li et al. 2016b; Paolini et al. 2006). Landsat 7 ETM+ images are usually impacted by failure of the scan line corrector and contain strips as a result of scan-line errors (Ali and Mohammed 2013; Hossain et al. 2015).

In order to fix the strip error, new values were replaced with the values of erroneous pixels based on the interpolation method performed using the Landsat-gap fill tool in the ENVI software (Yin et al. 2017). Geometric correction and atmospheric correction are other pre-processing steps that should be conducted before using a satellite imagery (Li et al. 2015; Rumora et al. 2019). Landsat satellite images are usually geometrically corrected before being provided to users. The steps taken for atmospheric corrections can be different based on the types of processing analysis expected to be performed on the image. Since image classification was conducted based on the maximum likelihood algorithm and the training classes are individually sampled, there is no need for atmospheric corrections (Jensen 2015). However, the dark object algorithm was used in this study to correct the atmospheric images to eliminate

Table 1 Specifications of satellite images used in this study (Source: USGS)

Images	Date	Path/ row	Number of multispectral bands	Radiometric resolution	Spatial resolution of multispectral bands
Landsat 5/TM	17 June 1996	160/41 and 160/42	6	8 bit	30×30 m
Landsat 7/ETM+	21 June 2006	160/41 and 160/42	6	8 bit	30×30 m
Landsat 8 / OLI	24 June 2016	160/41 and 160/42	7	16 bit	30×30 m

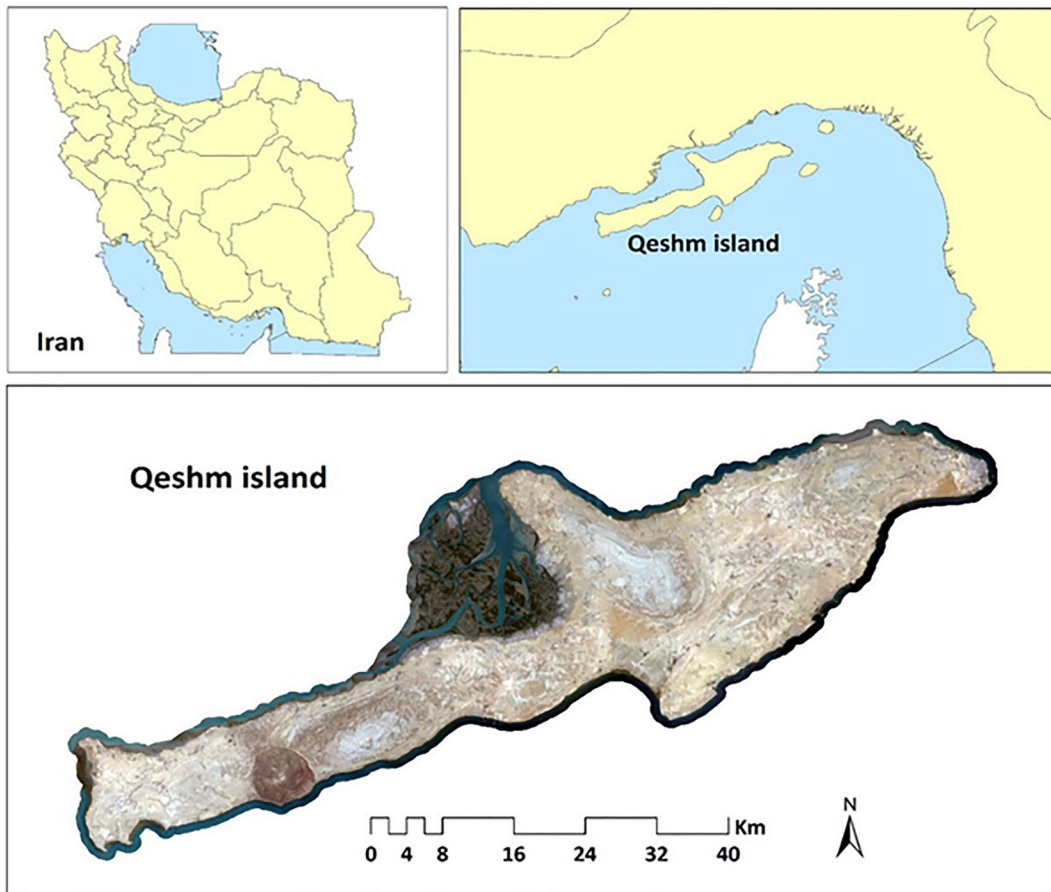


Fig. 1 Location of the study area, Qeshm Island, Iran

the effects of light diffusion from the image in order to correct the effects of the atmospheric dispersion.

Factor maps and variables preparation

The objectives of this study are detection of land cover changes between 1996 and 2016 and prediction of future land cover changes that will occur by 2025 in the Qeshm Island, Iran. To achieve these objectives, we first extracted land cover maps from the Landsat satellite images, and compared them to be able to detect changes that have occurred. In this study, the CA_Markov, ANN hybrid model was used to simulate land cover changes of the study area. The outputs of Markov chain and artificial neural network were used as inputs to the model in order to detect land cover change using the cellular automata method. The initial data required for modeling land changes were the land cover maps and the variables incorporating land changes. For this

purpose, land cover maps related to 1996, 2006, and 2016 extracted from satellite images were used. We also prepared the variables affecting land changes such as altitude, distance from industrial areas, distance from ports, distance from protected areas, distance from roads, distance from built-up, distance from the beach, distance from mangrove forests, distance from rural areas, slope, geology, soil type, vegetation, and distance from rocky lands. To model land cover variations related to two different years, two types of data were generated from the initial data: (1) measuring the quantity of occurred changes and (2) generating maps for potential changes or fit maps. Markov chains were used to generate change values or classes. Possible land-use change in the period from 2006 to 2016 were estimated based on the land-use changes that took place between 1996 and 2006 using Markov chains. To generate potential change maps, the multi-layer perceptron neural network (MLP) algorithm was used. After executing the model,

the output was evaluated by comparing it with actual 2016 land cover. Finally, using the process described, land use/cover changes were projected for the year 2025. Figure 2 shows the overall process of predicting land use/land cover changes.

Image classification

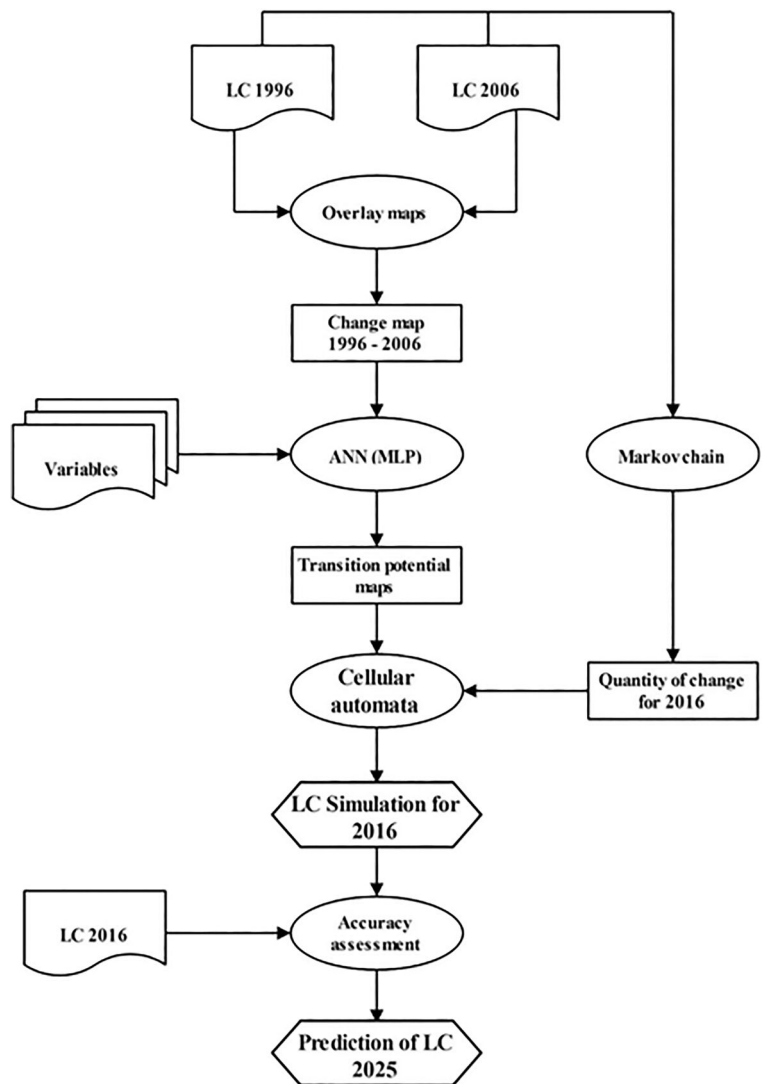
In this study, the maximum likelihood algorithm was used to classify images. This classification is performed based on maximum probability of assigning a pixel to a class in which it is likely to be classified based on information available from the training data. In this method, the probability of each pixel belonging to each pre-defined class is calculated at first and then the class

that has the highest probability is the intended pixel. The assumption of maximum likelihood is that the educational data statistics for each class and in each band are normally distributed. The first step in this classification is to calculate the probability $p(x|w_i)$ which is the probability of assigning a class to a particular pixel. The class is assigned to the desired pixel which has the most likely pixel membership to that class.

$$\hat{p}(x|w_i) = \frac{1}{(2\pi)^{\frac{1}{2}}\hat{\sigma}_i} \exp\left[-\frac{1}{2} \frac{(x-\hat{\mu}_i)^2}{\hat{\sigma}_i^2}\right] \tag{1}$$

In this formula, x is the vector of spectral values, w_i is the spectral class I , and p is the probability of the pixel i

Fig. 2 Steps taken for simulation and prediction of land use/land cover changes



in a particular class. To assign a given pixel to a class, the probability of the pixel to be placed in each class is calculated and then the class that has the most probability is assigned to the given pixel (Jensen 2015).

Change detection

A comparison algorithm was used to identify the changes that have occurred in land use after performing image classification for satellite images used in this study. This is a quantitative method that requires geometric correction of images (geometric matching of images) and their classification outputs. In the next step, two outputs resulting from image classification are compared pixel by pixel, using a matrix identifying changes. Each error in the classified map is also transmitted to the final identification map of changes. Therefore, it is essential that the classified maps used in this method are as accurate as possible. The accuracy in the output map of change identification depends on the accuracy of the classified maps (Jensen 2015).

Cellular automata

The cellular automata model is built based on the interaction of several elements: (1) a lattice space that is a two- or multi-dimensional space; (2) a cell or automation, a discrete variable that represents the network's structural units; (3) situation or cell state that describes the characteristics of the cell that can change according to certain conversion rules; (4) conversion rules, which are mathematical functions that control the change in the status of each cell. The rules of transfer are of two types. For example, there are local and global conversion rules as two types of transfer rules. Local rules show the status of each cell and its neighbors and global rules indicate the general status of a particular land-use in a given time period; and (5) the time, as the cell status changes over time.

The general approach applied in this method is that a cell is a point on a given network space that can occupy a limited number of different situations determined according to a particular transmission law, which can be the result of its interaction with its immediate neighbors in the network (Mitsova et al. 2011). The CA model has useful features which are beneficial for modeling geographic phenomena. The CA modeling output has a spatial characteristic and is generated based on geographic and remote sensing information.

Markov chains

Markov chains are used to derive general conversion rule which specifies the overall rate of change associated with a particular land use compared with other land uses over a given period of time (Mitsova et al. 2011). In this method, the categorized data are compared pixel by pixel for two different times, and accordingly the conversion probability matrix and transformation matrix are extracted. The conversion probability matrix determines the probability of changing each land-use class compared with other classes. The transformation matrix specifies the number of pixels that are expected to be converted to a different class within a given time period from one class to another (Jokar et al. 2013). These rules enable researchers to simulate land-use changes that have occurred in a given area.

Multi-layer perceptron of artificial neural network

The potential change map shows the probability of changing the class of each pixel to another land-use class. In order to generate potential change maps, ANN (multi-layer perceptron function) was used. The neural network calculates the potential change that may occur for each class by connecting modified pixels for a period of time, for example, 1996 to 2006, with variables driving land-use changes.

Results

Generation of historical land cover maps and change detection

Land cover maps extracted from satellite images for 1996, 2006, and 2016 in Qeshm Island are shown in Fig. 3. In these maps, six land-use classes, built-up areas, agricultural landscapes, and vegetation, mangrove forests, water bodies, indigenous lands, and rocky lands were identified and separated. The general changes that occurred in land use/land cover of Qeshm Island in between 1996 and 2006 and 2006–2016 are shown in Fig. 4. The results indicate that the area of mangrove forests has been increasing during the second part of the defined period. The extent of these forests slightly increased about 20 ha from 1996 to 2006 and then increased more significantly between 2006 and 2016 (about 630 ha). Another land use that had an incremental

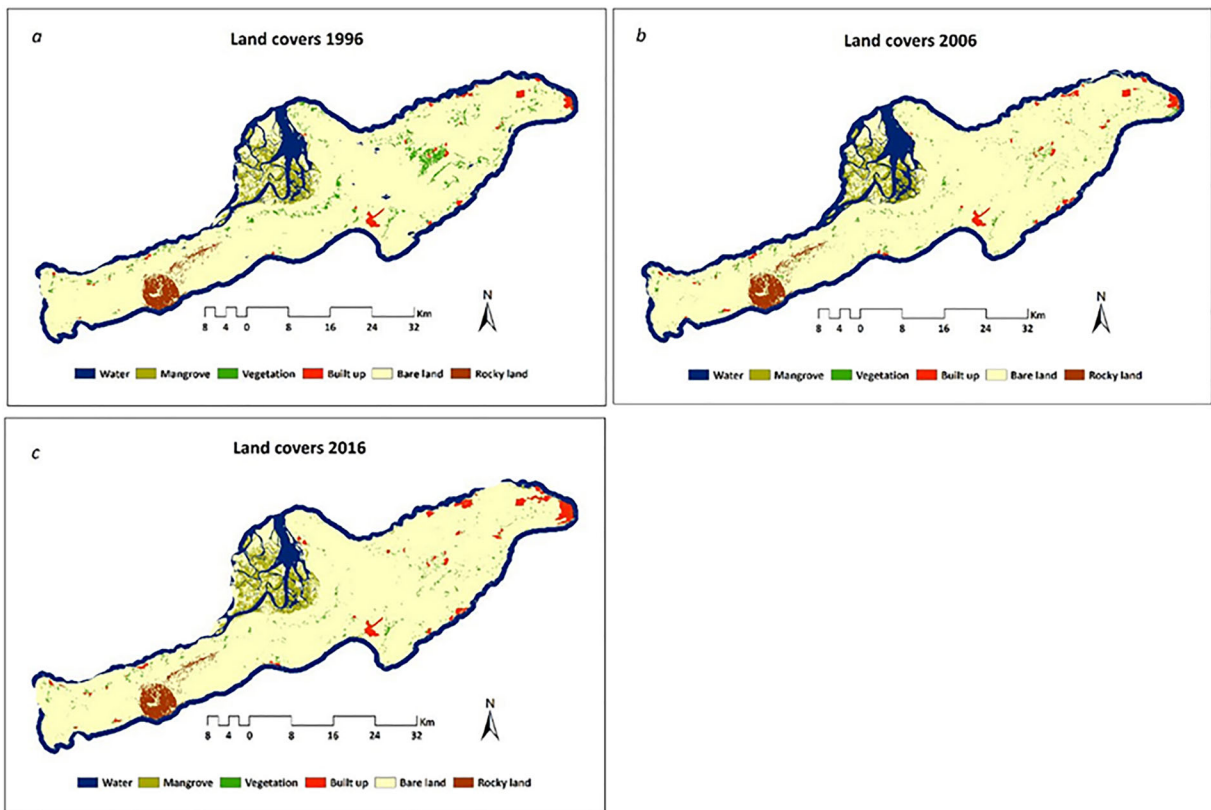


Fig. 3 Land use/cover maps of **a** 1996, **b** 2006, and **c** 2016

trend was the built-up class. Of the examined six classes, vegetation always experienced a declining trend regarding its total extent in the study area, reaching to its minimum area from 5200 ha in 1996 to 2100 ha in 2016. The area of water surface decreased about 4000 ha from 1996 to 2016. Finally, the rocky and mountainous terrain classes remained unchanged during the time period of this study, with occupying almost 3700 ha of the study area.

Quantifying probability of changes by Markov chains

The probability transformation matrix for 2006–2016 is presented in Table 2, as the result of applying the Markov chains method. The numbers in this Table represent the percentage of possible changes from each class to another class in the period from 2006 to 2016.

Generation of transition potential maps

A multi-layer perceptron, as a type of artificial neural network (MLP-ANN) was used to generate transition

potential maps for the study area. In other words, a transition potential map was generated for each land cover class and also for deriving variables which affected land cover change over the specified time period (from 1996 to 2006) using the ANN algorithm. The variables used in this study include sea level altitude, distance from fault, distance from industrial areas, distance from ports, distance from protected areas, distance from roads, distance from built-up, distance from beach, the distance from mangrove forests, distance from rural areas, slope, geology, soil type, vegetation, and distance from rocky lands. Distance-based variables were generated using the distance function, based on the spatial layers generated by relevant organizations using satellite imagery, in the IDRISI software environment. The slope and elevation variables were obtained using a digital elevation model (DEM) generated from ASTER satellite images with resolution of 15 m. For soil and geological variables, associated layers produced by the Geological Organization of Iran were used. Figure 5 shows the potential change map, derived from application of the

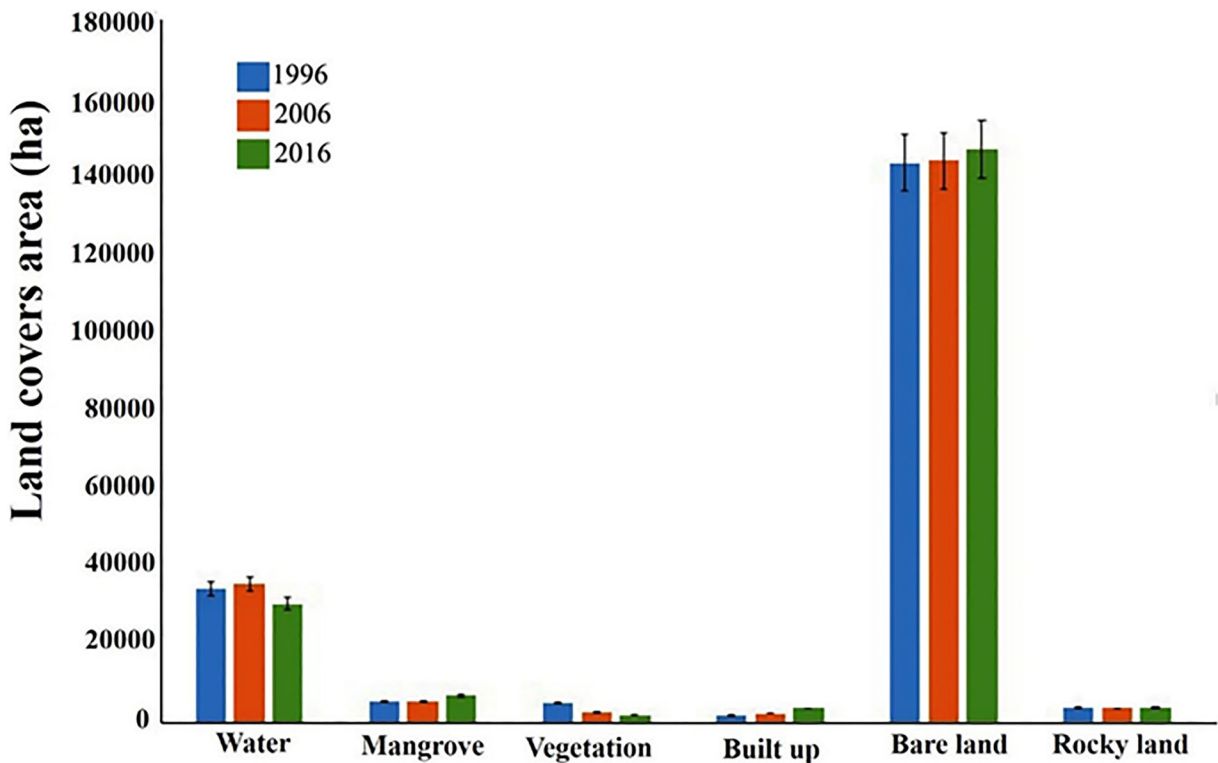


Fig. 4 General changes in land use/cover in 1996 to 2016

neural network algorithm on the above data, for built-in areas, mangrove forests, vegetation, dry lands, and water surface. Since rocky lands had no positive changes, the probability of changing all the pixels in the scope of the study is equal to zero. These potential change maps for different land cover classes were used to simulate overall land-use change from 2006 to 2016. The value score of these maps ranges between 0 and 1 indicating the more each pixel’s value is closer to 1, the more likely it is that it has changed to the desired land cover class.

Simulation of 2016 land use/cover classes

Figure 6 illustrates the simulated map of land cover change from 2006 to 2016. The land cover simulation was conducted based on information obtained from the calibration time period (1996 to 2006). This map was generated based on a combination of the outputs of three modeling approaches used in this study, the Markov chains, the MLP-ANN, and the cellular automata approach. This simulation step was performed to calibrate the combined model and evaluate its accuracy, which

Table 2 The extent of occurred changes for different measured classes using Markov chains for 2016

Land cover type	Water	Mangrove	Vegetation	Built up	Bare land	Rocky land
Water	0.9569	0.0001	0.0006	0.0001	0.0422	0
Mangrove	0.0136	0.9369	0.0008	0	0.0487	0
Vegetation	0.0006	0.0031	0.3	0.0042	0.6922	0
Built up	0.0013	0	0	0.9987	0	0
Bare land	0.0187	0.0023	0.0072	0.0037	0.9681	0
Rocky land	0	0	0.0052	0	0	0.9948

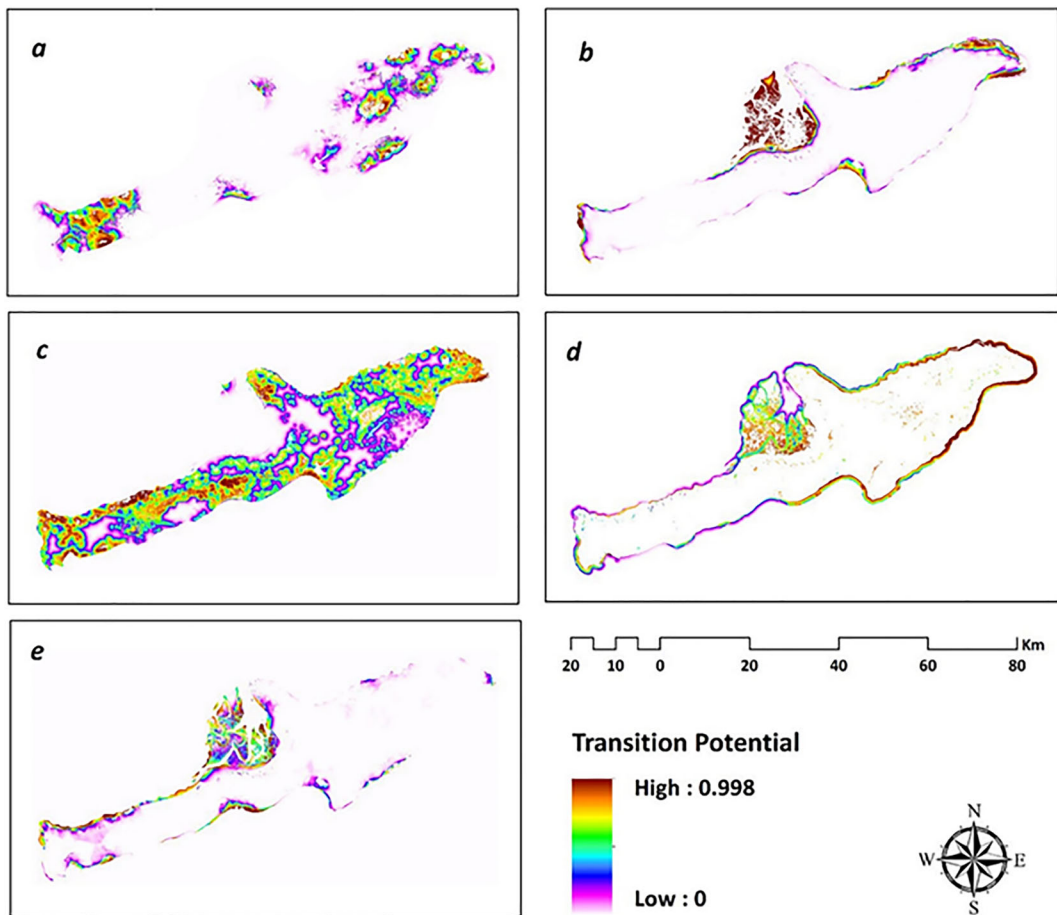


Fig. 5 Transition potential maps (2016): **a** built-up areas, **b** mangrove, **c** vegetation, **d** bare lands, and **e** water surface

was then used to predict land cover change for the future (2025 in this study).

Validation of the model

In order to evaluate the validity of the model, the simulated map was compared with the actual 2016 land-cover map obtained from the Landsat 8 satellite imagery. The Kappa coefficient, which is an indicator used to evaluate the validity of modeling results, was 0.80 for the simulation output. The values of this coefficient for all land-cover classes are shown in Table 3. Examining the extent at which the simulated model correctly predicts the changes for different classes indicates that over all 1602 ha of the changes were correctly simulated. The largest area of change simulated correctly was related to dry lands, 1183 ha, and rocky lands belong to the class for which the smallest area of change was correctly simulated.

Prediction of 2025 land use/cover classes

In this step, based on the experiences and considerations from the simulation stage, we predicted land-use changes for 2025 (Fig. 7). This map indicates the potential changes which may occur for six land-use classes, built-up areas, agricultural landscapes and vegetation, mangrove forests, water surface, dry lands, and rocky lands in 2025.

Quantification of 2025 land use/cover changes

According to the projection results, the built-up area in 2025 will increase about 1100 ha (Table 4). Built-up areas will mainly be expanded to the dry lands (about 1076 ha). The area of mangrove forests will increase by 2025 which also occurs on the dry lands. Considering the expansion of built-up areas and mangroves in bare lands, the extent of this land-cover class will decrease

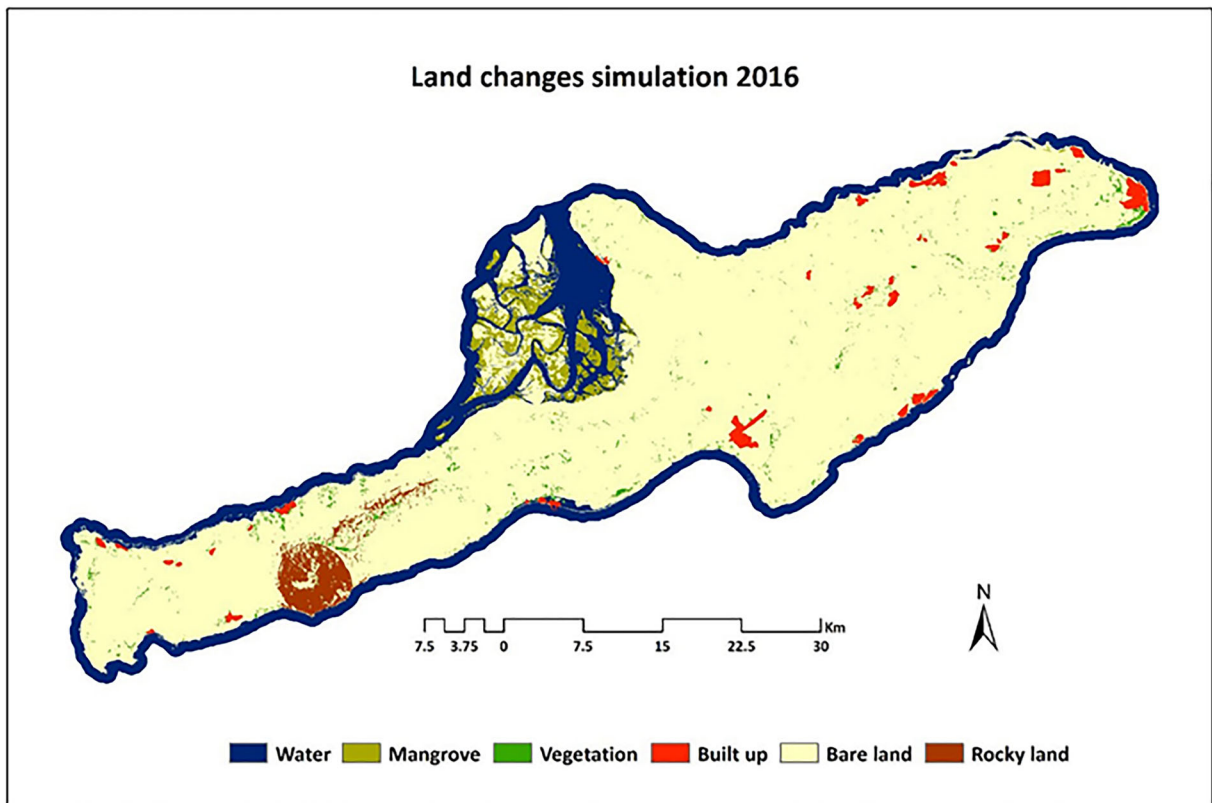


Fig. 6 Simulated land use/cover of 2016

about 2000 ha in 2025. On the other hand, the area of vegetation, non-forest areas, will be reduced due to converting to bare lands. Rocky lands will experience no changes in their extent in 2025 compared with their current area. It is necessary to note that these changes are predicted based on the assumption that current pattern of land-use changes and human activities/development will continue to occur in Qeshm Island.

Table 3 Kappa Index of Agreement indicates the validity of simulated map of land-cover change for 2016

Category	Kappa Index of Agreement	Correct simulated changes (ha)
Water	0.93	62.28
Mangrove	0.73	133.65
Vegetation	0.19	100.26
Built up	0.68	117.99
Bare land	0.76	1183.68
Rocky land	0.99	5.01
Overall Kappa	0.80	1602.86

Discussion

Multiple drivers including socio-economic and biophysical factors have been increasing LULC change (Lambin et al. 2001). This in turn has resulted in many changes in ecosystem processes and functions, and biodiversity across different parts of the world, threatening the pivotal components of natural capital such as vegetation (Behera et al. 2012). In this situation, land use/land cover change modeling is considered to be an inevitable process in order to better comprehend land dynamics (Hyandye and Martz 2017) and predict the future state and spatial distribution of LULC (D. Behera et al. 2012). Among a wide range of methods proposed for predicting land-cover changes (Katana et al. 2013), use of the combined modeling method for simulating land cover changes has always had more substantial outcomes than using any of these methods separately (Bununu 2017; Dou et al. 2019). In this study, the benefits of each of the three CA, ANN, and MC applied methods through using a hybrid model enabled us to model and predict the complex behavior of spatiotemporal phenomena such as land cover changes. Based on

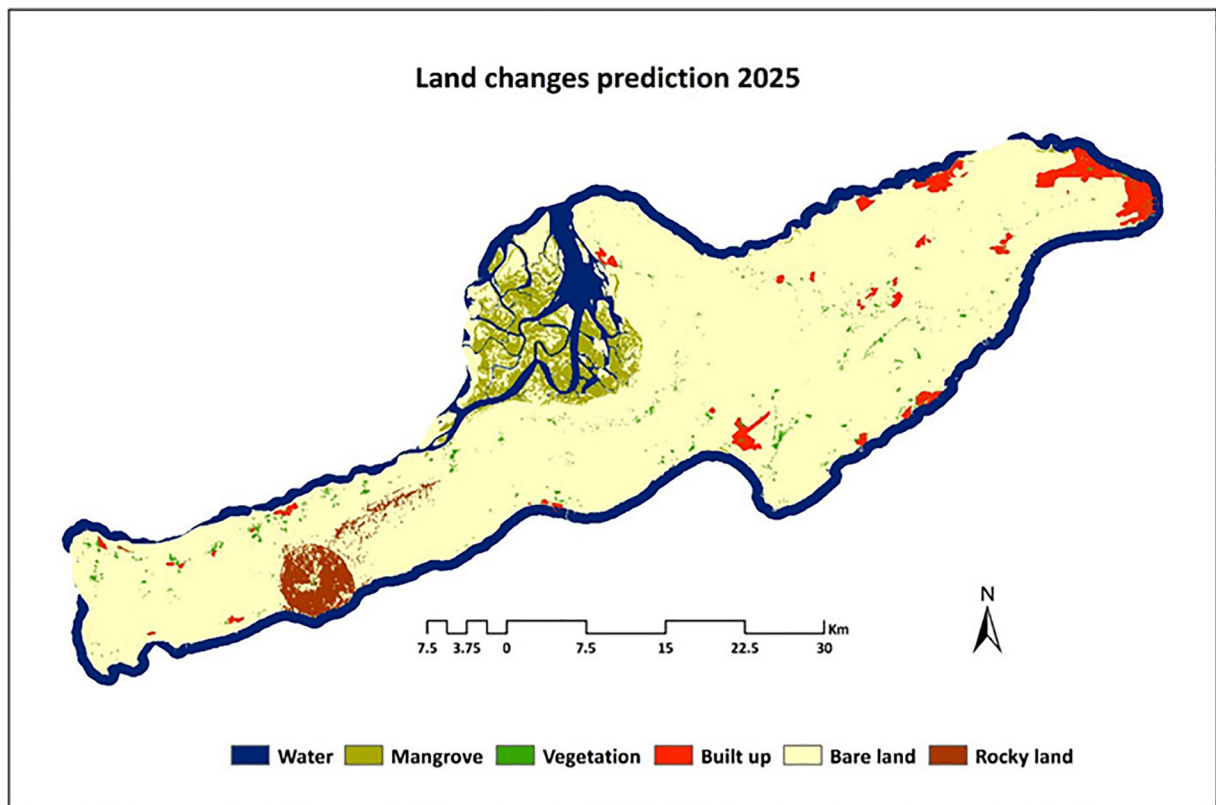


Fig. 7 Predicted land use/cover of 2025

what can be inferred from the results of this study, human population increase and economic development on one hand and climate changes on the other hand are the main factors driving the process of land cover change in the Qeshm Island. As the region's population grows, the development of ports, commercial markets, and industrial areas increase in the region.

As argued by previous studies, land change modeling does not only have the capability for analyzing and predicting spatial and temporal changes occurring

within the landscape but it can also be used as a decision support tool for enabling planners and policy-makers to make more efficient and sustainable decisions (Flores-Casas and Ortega-Huerta 2019; Paegelow et al. 2013). The findings of land change modeling in this study indicate that the extent of built-up areas has expanded significantly in the last two decades. According to Fig. 4, the extent of the built-up areas has approximately doubled from 1996 to 2016, with an increase of about 1700 ha during these years. Further exploration of land

Table 4 Quantification of potential land cover changes in Qeshm Island from 2016 to 2025

Category	Water	Mangrove	Vegetation	Built up	Bare land	Rocky land	Total 2025
Water	30,043	3	0	5	546	0	30,599
Mangrove	273	7052	1	0	1202	0	8529
Vegetation	0	0	983	65	815	0	1865
Built up	23	0	54	3664	1076	0	4818
Bare land	507	38	1017	0	144,771	0	146,334
Rocky land	0	0	0	0	0	3754	3754
Total 2016	30,847	7093	2071	3735	148,412	3754	544,961

cover maps extracted from the Landsat images reveals a significant increase in development of ports and residential patches in the coastal areas of the region, indicating a high growth rate in urbanization and development of economic infrastructure in this area in the future. Our prediction results for the year 2025 also manifest that urban areas and ports will continue to expand, as the region will experience larger built-up patches in 2025.

Global climate change occurring in recent decades has affected land cover in the Qeshm Island similar to other parts of the world (Jagannath et al. 2019). Based on the results of this study, vegetation cover, agricultural lands, gardens, and pastures have decreased dramatically in the last two decades (1996–2016). Examining the land cover maps reveals that the extent of vegetation areas reduced around 3000 ha during these years, most of which has been converted to barren lands. Moreover, other factors including development of industrial and commercial activities, coupled with climate change and water shortages, have led local people to leave their agricultural lands and join industrial, commercial, and service-based activities. Water shortages and decrease in land quality caused by climate variability through the change in rainfall pattern and distribution affect pastoral and agricultural production levels (Nkya et al. 2017). As a result, the land abandonment phenomenon may occur due to several of these natural and social factors including human migration (Flores-Casas and Ortega-Huerta 2019). The combination of all of these factors has played an important role in decreasing the extent of vegetation cover and agricultural areas, and their conversion to barren lands in the study area. As the modeling output generated in this study predicted, vegetation and agriculture areas will continue to decrease in 2025. This finding can help inform land use planners to effectively allocate the land to associated industrial activities in the region in such a way as to protect the remaining vegetation areas. As recommended by previous studies, urban development should be pursued in line with governmental conservation policies and urban planning at the regional level (Zhai et al. 2020).

It has been recognized that tidal forests including mangroves are highly productive ecosystems providing a wide range of ecosystem services and carbon sequestration (Costanza et al. 2014). However, there is a growing evidence revealing that mangrove forests are being converted and diminished across the world (Richards and Friess 2015). Mangrove forests on the shores of Qeshm

Island have also been influenced by climate change and human activities in some parts of the Island. These forests did not experience any sensible change from 1996 to 2006. However, their extent increased noticeably from 2006 to 2016. One reason for this increase could be the implication of environmental protection policies in the Qeshm Island during this time period, which has enabled conservation authorities to safeguard these forests from the impacts of ongoing infrastructure development. According to the prediction model proposed here, it is expected that the mangroves experience further growth in 2025. However, the demand for agricultural expansion and urban coastal development may make mangrove protection challenging in the region (Hauser et al. 2017; Richards and Friess 2015). Although policies and regulations have resulted in stabilization of mangrove forest cover in previous decades, concerns for decreasing the extent of these forests and fragmentation exists due to a growing rate of human disturbance and sea level rise caused by climate change (Nguyen et al. 2013). As stated by previous studies, urban expansion along with associated commercial and industrial developments are complicated phenomena and can be impacted by numerous factors with different levels of uncertainties (Ye et al. 2015). Therefore, the influence of factors such as policies and regulations on the protection of mangrove forests needs to be understood under multiple future scenarios (Hauser et al. 2017).

This study used the capability of these three methods for simulating multiple land covers in a complex system (Memarian et al. 2012; Hyandye and Martz 2017). Examining different studies shows that hybrid models, with the combination of at least two modeling methods, have been widely used when modeling land use/land cover change in recent decades (Bununu 2017; Wu et al. 2019). This is because, these methods have various capabilities and can complement their beneficial aspects when combined together, which can eventually lead to a more efficient simulation of land cover changes for a given region (Du et al. 2018; Zhai et al. 2020). The limitation of using a single modeling approach in the studies conducted in the last two decades has hindered achievement of appropriate results with acceptable accuracy (Mitsova et al. 2011; Kazemzadeh-Zow et al. 2017). By developing various software environments in the recent decade, many studies have attempted to combine different modeling approaches when simulating land cover changes (Yang et al. 2008, 2012;

Mozumder and Tripathi 2014). Among the various methods, the CA modeling method has mostly been used in combination with other methods due to its capability to model the variation of spatiotemporal phenomena, particularly land cover changes (Basse et al. 2014; Ke et al. 2017; Feng and Tong 2018; Feng et al. 2018; Wu et al. 2019). Other methods which have usually been combined with CA include Markov chains, logistic regression, ant colony optimization, agent-based modeling, artificial neural networks, and multi-criteria decision-making (Jokar et al. 2013; Yang et al. 2012; Li et al. 2016a; Zhai et al. 2020). In this study, the combination of CA, ANN, and MC methods did not only facilitate the overall modeling process by separating different parts of simulation but it also allowed us to present more appropriate outputs with a higher level of accuracy (with a Kappa coefficient of 0.8).

Although the proposed model has achieved appropriate simulation performance, the use of satellite images and predictive models, despite their substantial benefits, have some limitations as well. One of the issues that studies with the prediction approach are always faced with is the acceptable level of accuracy (Wu et al. 2019). Particularity, with regard to the prediction of land use and land cover change, the degree of accuracy can vary according to the type of land cover classes (Kazemzadeh-Zow et al. 2017). For example, consider the extent at which the model can correctly predict the change occurred in built-up areas are much higher than other land cover types such as vegetation. In addition, in coastal areas due to tidal variations, maps drawn from medium-resolution satellite images are associated with uncertainty, and hence, the accuracy of the output generated through the image classification of these areas is less than that of non-coastal areas. Moreover, this study did not include urban planning and conservation policies into the modeling process of land-use change simulation, which can be conducted as a future research study (Zhai et al. 2020).

Conclusion

Following the necessity of improved understanding through modeling and predicting land dynamics at the different spatial scales (Geoghegan et al. 2001; Hyandye and Martz 2017), this study attempted to address land-use change phenomenon to better understand the associated causes and consequences, and examine land-use

changes in the future. This study proposed a new framework that integrated three modeling approaches of cellular automata, Markov chains, and artificial neural networks, to simulate land-use changes in Qeshm Island under developing natural and human processes.

The findings of this study can be used to better understand past trends and project scenarios in LULC of the study region (Paegelow et al. 2013). Identifying and predicting land cover change can be used to improve land-use planning and land management of the region by enhancing planners' understanding of the complex pattern of land change in the landscape. In the next step, land-use planning can help with climate change mitigation and adaptation policies in order to achieve more resilient spatial planning (Jagarnath et al. 2019).

The findings of this study reveal how land use/land cover in Qeshm Island will be arranged in 2025 based on the past and present LULC change. Similar to previous studies (e.g., Canute and Lawrence 2017; Hyandye and Martz 2017), historical land-use changes were used as a basis for exploring driving factors contributing to LULC changes and for simulating future LULC changes. Examining the changes which have occurred in the study area from 1996 to 2016, as well as the projected changes for 2025 in particular, highlight the significant increase in the built-up areas and the dramatic decrease in vegetation cover. Urban expansion in the Qeshm Island is caused by population growth on one hand and economic development on the other hand during recent decades. Therefore, built-up areas are expected to increase in the future as predicted by the model. Unlike the built-up, vegetation cover has experienced a dramatic decrease from 1996 to 2016 (a total area of 3000 ha). Although it has mainly been caused by climate change, droughts and water shortages, the role of changing the local economy from agricultural-based activities to commercial developments cannot be ignored. Mangrove forests, located along the coast of the Island, are threatened by both climate change and human activities, which need particular attention of planners and policymakers regarding the effective protection of these unique habitats at local scales. Overall, the simulated 2025 LULC data presented here can be used as critical input for the development of management plans for various uses such as agriculture and potential food production, water balance analysis, urban planning, and conservation planning of protected lands (Hyandye and Martz 2017).

References

- Abd El-Kawy, O. R., Rod, J. K., Ismail, H. A., & Suliman, A. S. (2011). Land use and land cover change detection in the western Nile delta of Egypt using remote sensing data. *Applied Geography, 31*, 483–494.
- Ali, S. M., & Mohammed, M. J. (2013). Gap-filling restoration methods for ETM+ sensor images. *Iraqi Journal of Science, 54*(1), 206–214.
- Basse, R. M., Omrani, H., Charif, O., Gerber, P., & Bodis, K. (2014). Land use changes modelling using advanced methods: Cellular automata and artificial neural networks. The spatial and explicit representation of land cover dynamics at the cross-border region scale. *Applied Geography, 53*, 160–171.
- Behera, M. D., Borate, S. N., Panda, S. N., Behera, P. R., & Roy, P. S. (2012). Modelling and analyzing the watershed dynamics using cellular automata (CA)–Markov model–A geo-information based approach. *Journal of Earth System Science, 121*(4), 1011–1024.
- Bununu, Y. A. (2017). Integration of Markov chain analysis and similarity-weighted instance-based machine learning algorithm (SimWeight) to simulate urban expansion. *International Journal of Urban Sciences, 21*(2), 217–237.
- Canute, H., & Lawrence, M. (2017). A Markovian and cellular automata land-use change predictive model of the Usangu catchment. *International Journal of Remote Sensing, 38*(1), 64–81.
- Carvalho, T. I., Carneiro, M. G., & Oliveira, G. M. B. (2019). Improving cellular automata scheduling through dynamics control. *IJPEDS, 34*(1), 115–141.
- Cheng, M., Jin, J., Zhang, J., Jiang, H., & Wang, R. (2018). Effect of climate change on vegetation phenology of different land-cover types on the Tibetan Plateau. *International Journal of Remote Sensing, 39*(2), 470–487.
- Clancy, D., Tanner, J. E., & McWilliam, S. (2010). Quantifying parameter uncertainty in a coral reef model using Metropolis-coupled Markov chain Monte Carlo. *Ecological Modelling, 221*, 1337–1347.
- Coppin, P., Jonckheere, I., Nackaerts, K., & Muys, B. (2004). Digital change detection methods in ecosystem monitoring. *International Journal of Remote Sensing, 25*(9), 1565–1596.
- Costanza, R., de Groot, R., Sutton, P., van der Ploeg, S., Anderson, S. J., Kubiszewski, I., et al. (2014). Changes in the global value of ecosystem services. *Global Environmental Change, 26*(1), 152e158.
- Dalmiya, C. P., Santhi, N., & Sathyabama, B. (2019). An enhanced back propagation method for change analysis of remote sensing images with adaptive preprocessing. *European Journal of Remote Sensing, 1*–12.
- Dou, Y., Millington, J. D. A., Bicudo Da Silva, R. F., McCord, P., Viña, A., Song, Q., Yu, Q., Wu, W., Batistella, M., Emilio, M. E., & Liu, J. (2019). Land-use changes across distant places: design of a telecoupled agent-based model. *Journal of Land Use Science, 14*(3), 191–209.
- Du, G., JooShin, K., Yuan, L., & Managi, S. (2018). A comparative approach to modelling multiple urban land use changes using tree-based methods and cellular automata: the case of Greater Tokyo Area. *International Journal of Geographical Information Science, 32*(4), 757–782.
- Feng, Y., & Tong, X. (2018). Dynamic land use change simulation using cellular automata with spatially nonstationary transition rules. *GIScience & Remote Sensing, 55*(5), 678–698.
- Feng, Y., Yang, Q., Hong, Z., & Cui, L. (2018). Modelling coastal land use change by incorporating spatial autocorrelation into cellular automata models. *Geocarto International, 33*(5), 470–488.
- Flores-Casas, R., & Ortega-Huerta, M. A. (2019). Modelling land cover changes in the tropical dry forest surrounding the Chamela-Cuixmala biosphere reserve, Mexico. *International Journal of Remote Sensing, 40*(18), 6948–6974.
- Geoghegan, J., Villar, S. C., Klepeis, P., Mendoza, P. M., Ogneva-Himmelberger, Y., Chowdhury, R. R., et al. (2001). Modeling tropical deforestation in the southern Yucatan peninsular region: comparing survey and satellite data. *Agriculture, Ecosystems & Environment, 85*(1), 25–46.
- Grigorescu, I., Kucsicsa, G., Popovici, E. A., Mitrică, B., Mocanu, I., & Dumitrașcu, M. (2019). Modelling land use/cover change to assess future urban sprawl in Romania. *Geocarto International, 1*–19.
- Guodong, D., Kong, J. S., Liang, Y., & Shunsuke, M. (2018). A comparative approach to modelling multiple urban land use changes using tree-based methods and cellular automata: the case of Greater Tokyo Area. *International Journal of Geographical Information Science, 32*(4), 757–782.
- Hashem, N., & Balakrishnan, P. (2015). Change analysis of land use/land cover and modelling urban growth in Greater Doha, Qatar. *Annals of GIS, 21*(3), 233–247.
- Hauser, L. T., Vu, G. N., Nguyen, B. A., Dade, E., Nguyen, H. M., Nguyen, T. T. Q., et al. (2017). Uncovering the spatio-temporal dynamics of land cover change and fragmentation of mangroves in the Ca Mau peninsula, Vietnam using multi-temporal SPOT satellite imagery (2004–2013). *Applied Geography, 86*, 197–207.
- Hossain, M. S., Bujang, J. S., Zakaria, M. H., & Hashim, M. (2015). Assessment of Landsat 7 Scan Line Corrector-off data gap-filling methods for seagrass distribution mapping. *International Journal of Remote Sensing, 36*(4), 1188–1215.
- Hyandye, C., & Martz, L. W. (2017). A Markovian and cellular automata land-use change predictive model of the Usangu Catchment. *International Journal of Remote Sensing, 38*(1), 64–81.
- Iranian Statistical Center. (2016). Population data of Qeshm Island. Retrieved 1.10.2018 from <https://www.amar.org.ir/>
- Jagarnath, M., Thambiran, T., & Gebreslasie, M. (2019). Modelling urban land change processes and patterns for climate change planning in the Durban metropolitan area, South Africa. *Journal of Land Use Science, 14*(1), 81–109.
- Jensen, J. R. (2015). *Introductory digital image processing: a remote sensing perspective* (3rd ed.). Upper Saddle River, NJ: Prentice-Hall.
- Jokar, A. J., Helbich, M., Kainz, W., & Darvishi, A. B. (2013). Integration of logistic regression, Markov chain and cellular automata models to simulate urban expansion. *International Journal of Applied Earth Observation and Geoinformation, 21*, 265–275.
- Katana, S. J. S., Ucakuwun, E. K., & Munyao, T. M. (2013). Detection and prediction of land cover changes in upper Athi River catchment, Kenya: a strategy towards monitoring

- environmental changes. *Greener Journal of Environmental Management and Public Safety*, 2(4), 146–157.
- Kazemzadeh-Zow, A., Zanganeh-Shahraki, S., Salvati, L., & Samani, N. N. (2017). A spatial zoning approach to calibrate and validate urban growth models. *International Journal of Geographical Information Science*, 31(4), 763–782.
- Ke, X., Zheng, W., Zhou, T., & Liu, X. (2017). A CA-based land system change model: LANDSCAPE. *International Journal of Geographical Information Science*, 31(9), 1798–1817.
- Kolb, M., Jean-François Mas, J. F., & Leopoldo Galicia, L. (2013). Evaluating drivers of land-use change and transition potential models in a complex landscape in Southern Mexico. *International Journal of Geographical Information Science*, 27(9), 1804–1827.
- Lambin, E. F., Turner, B. L., Geist, H. J., Agbola, S. B., Angelsen, A., Bruce, J. W., et al. (2001). The causes of land-use and land-cover change: moving beyond the myths. *Global Environmental Change*, 11(4), 261–269.
- Li, X., & Yeh, A. G. O. (2002). Neural-network-based cellular automata for simulating multiple land use changes using GIS. *International Journal of Geographical Information Science*, 16, 323–343.
- Li, S., Peng, M., Wu, C., Feng, X., & Wu, Y. (2015). Optimal selection of GCPs from Global Land Survey 2005 for precision geometric correction of Landsat-8 imagery. *European Journal of Remote Sensing*, 48(1), 303–318.
- Li, J., Oyana, T. J., & Mukwaya, P. I. (2016a). An examination of historical and future land use changes in Uganda using change detection methods and agent-based modelling. *African Geographical Review*, 35(3), 247–271.
- Li, H., Wang, X., Shen, H., Yuan, Q., & Zhang, L. (2016b). An efficient multi-resolution variational Retinex scheme for the radiometric correction of airborne remote sensing images. *International Journal of Remote Sensing*, 37(5), 1154–1172.
- Lin, J., Weihao, W., & W. (2019). Investigating the land use characteristics of urban integration based on remote sensing data: experience from Guangzhou and Foshan. *Geocarto International*, 34(14), 1608–1620.
- Liu, X. P., Li, X., Yeh, A. G. O., & Tao, J. (2007). Discovery of transition rules for geographical cellular automata by using ant colony optimization. *Science China Earth Sciences*, 50, 1578–1588.
- Lu, D., Mausel, P., Brondizio, E., & Moran, E. (2004). Change detection techniques. *International Journal of Remote Sensing*, 25(12), 2365–2407.
- Lu, D., Li, G., & Moran, E. (2014). Current situation and needs of change detection techniques. *IJIDF*, 5(1), 13–38.
- Memarian, H., Balasundram, S. K., Talib, J. B., Sung, C. T. B., Sood, A. M., & Abbaspour, K. (2012). Validation of CA-Markov for simulation of land use and cover change in the Langat Basin, Malaysia. *Journal of Geographic Information System*, 4(6), 542–554.
- Mitsova, D., Shuster, W., & Wang, X. (2011). A cellular automata model of land cover change to integrate urban growth with open space conservation. *Landscape and Urban Planning*, 99(2), 141–153.
- Mozumder, C., & Tripathi, N. K. (2014). Geospatial scenario based modelling of urban and agricultural intrusions in Ramsar wetland Deepor Beel in Northeast India using a multi-layer perceptron neural network. *International Journal of Applied Earth Observation and Geoinformation*, 32, 92–104.
- Munroe, D. K., Croissant, C., & York, A. M. (2005). Land use policy and landscape fragmentation in an urbanizing region: assessing the impact of zoning. *Applied Geography*, 25(2), 121–141.
- Nguyen, H.-H., McAlpine, C., Pullar, D., Johansen, K., & Duke, N. C. (2013). The relationship of spatial-temporal changes in fringe mangrove extent and adjacent land-use: case study of Kien Giang coast, Vietnam. *Ocean & Coastal Management*, 76, 12e22.
- Nkya, S. E., Hagai, M., & Kashaigili, J. J. (2017). Land cover change impacts on beef cattle productivity under changing climate: case of Ilemela and Magu districts, Tanzania. *East African Agricultural and Forestry Journal*, 82(2), 188–200.
- Osman, T., Shaw, D., & Kenawy, E. (2018). An integrated land use change model to simulate and predict the future of greater Cairo metropolitan region. *Journal of Land Use Science*, 13(6), 565–584.
- Paegelow, M., Camacho, M. T., Mas, J. F., Houet, T., & Gilmore, R. (2013). Land change modelling: moving beyond projections. *International Journal of Geographical Information Science*, 27(9), 1691–1695.
- Paolini, L., Grings, F., Sobrino, J. A., Jiménez Muñoz, J. C., & Karszenbaum, H. (2006). Radiometric correction effects in Landsat multi-date/multi-sensor change detection studies. *International Journal of Remote Sensing*, 27(4), 685–704.
- Pijanowski, B. C., Tayyebi, A., Doucette, J., Pekin, B. K., Braun, D., & Plourde, J. (2014). A big data urban growth simulation at a national scale: configuring the GIS and neural network based land transformation model to run in a high performance computing (HPC) environment. *Environmental Modelling and Software*, 51, 250–268.
- Qiu, B. W., & Chen, C. C. (2008). Land use change simulation model based on MCDM and CA and its application. *Acta Geographica Sinica*, 63, 165–174.
- Richards, D. R., & Friess, D. A. (2015). Rates and drivers of mangrove deforestation in Southeast Asia, 2000–2012. *Proceedings of the National Academy of Sciences*, 113(2), 344–349.
- Rumora, L., Miler, M., & Medak, D. (2019). Contemporary comparative assessment of atmospheric correction influence on radiometric indices between Sentinel-2A and Landsat 8 imagery. *Geocarto International*, 1–15.
- Sano, E. E., Ferreira, L. G., Asner, G. P., Steinke, E. T., & E. T. (2007). Spatial and temporal probabilities of obtaining cloud-free Landsat images over the Brazilian tropical savanna. *International Journal of Remote Sensing*, 28(12), 2739–2752.
- Shimizu, K., Ota, T., Mizoue, N., & Yoshida, S. (2018). Assessments of preprocessing methods for Landsat time series images of mountainous forests in the tropics. *Journal of Forest Research*, 23(3), 139–148.
- Singh, A. (1989). Digital change detection techniques using remotely-sensed data. *International Journal of Remote Sensing*, 10(6), 989–1003.
- Singh, S. K., Basommi Laari, P., Mustak, S. K., Srivastava, P. K., & Szabó, S. (2018). Modelling of land use land cover change using earth observation data-sets of tons River Basin, Madhya Pradesh, India. *Geocarto International*, 33(11), 1202–1222.

- Tolnai, M., János György Nagy, J. G., & Bakó, G. (2016). Spatiotemporal distribution of Landsat imagery of Europe using cloud cover-weighted metadata. *Journal of Maps, 12*(5), 1084–1088.
- Valdez, M., Chen, C. F., Chiang, S. H., Chang, K. T., Lin, Y. W., Chen, Y. F., & Yu-Chi Chou, Y. C. (2019). Illegal land use change assessment using GIS and remote sensing to support sustainable land management strategies in Taiwan. *Geocarto International, 34*(2), 133–148.
- Wu, H., Li, Z., Clarke, K. C., Shi, W., Fang, L., Lin, A., & Zhou, J. (2019). Examining the sensitivity of spatial scale in cellular automata Markov chain simulation of land use change. *International Journal of Geographical Information Science, 33*(5), 1040–1061.
- Wyman, M. S., & Stein, T. V. (2010). Modeling social and land-use/land-cover change data to assess drivers of smallholder deforestation in Belize. *Applied Geography, 30*(3), 329–342.
- Yan, Y., Hua, W., Liu, X., Cui, Z., & Diao, D. (2019). Spatial-spectral preprocessing for spectral unmixing. *International Journal of Remote Sensing, 40*(4), 1357–1373.
- Yang, Q. S., & Li, X. (2007). Integration of multi-agent systems with cellular automata for simulating urban land expansion. *Scientia Geographica Sinica, 27*, 542–548.
- Yang, Q., Li, X., & Shi, X. (2008). Cellular automata for simulating land use changes based on support vector machines. *Computational Geosciences, 34*(6), 592–602.
- Yang, X., Zheng, X., & Lv, L. N. A. (2012). Spatio-temporal model of land use change based on ant colony optimization, Markov chain and cellular automata. *Ecological Modelling, 233*, 11–19.
- Ye, Y., Su, Y., Zhang, H. O., Liu, K., & Wu, Q. (2015). Construction of an ecological resistance surface model and its application in urban expansion simulations. *Journal of Geographical Sciences, 25*(2), 211–224.
- Yin, G., Mariethoz, G., Sun, Y., & McCabe, M. F. (2017). A comparison of gap-filling approaches for Landsat-7 satellite data. *International Journal of Remote Sensing, 38*(23), 6653–6679.
- Zhai, Y., Yao, Y., Guan, Q., Liang, X., Li, X., Pan, Y., et al. (2020). Simulating urban land use change by integrating a convolutional neural network with vector-based cellular automata. *International Journal of Geographical Information Science, 1*–25.

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.