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Case Study

Strategies for monitoring environmental changes: monitoring and predicting land-use land-cover (LULC) change (Case study: South Pars special economic zone, Iran)

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ABSTRACT

Background and objective: In recent years, the importance of modeling and predicting land-use/land-cover (LULC) changes for regional planning and environmental management has grown significantly. This study aims to discover and predict LULC changes in the South Pars' special economic zone over a 20-year period.

Materials and methods: In this study, geographic information system (GIS) and a remote sensing technique (RS) were used to classify satellite imagery and the land change modeler (LCM) for monitoring LULC changes. The CA-Markov model was also used to predict LULC changes. The input data of our model were satellite images from TM sensor (Thematic Mapper) for 1998, and 2008 and OLI sensor (Operation Land Imager) for 2018, and this led us to predict LULC changes for 2028.

Results and conclusion: Monitoring the results indicated that the area of the built-up areas was increased by 21.2533 km^2 (0.81%) during this period, and the largest reduction area was related to the Bare land with 15,298 KM^2 (-1.174%). prediction of LULC changes for 2028 revealed that the area of the Built-up areas is doubled and its area will reach 48.65 KM^2 (56%). Water bodies and bare land areas will decrease by 113.13 km^2 (-19%) to 165.96 km^2 (-12%) respectively. Vegetation cover will increase to 23.24 km^2 (65%). These results showed that the study area is susceptible to changes due to environmental and human factors that should be considered in urban and environmental planning.

1. Introduction

Increasing population growth, increasing pressure on natural areas, and inappropriate exploitation and alteration of land use (LU) have degraded the ecosystem (Lu & Weng, 2007). In general, climate change and technological and economic factors are the most important determinants of LU change at different spatial and temporal scales (Eric et al., 2007; Teodoro Carlón Allende et al.,

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2021; Jamali et al., 2021).

Inappropriate use of land, pollution, degradation of natural resources, etc. are known as disturbing factors of environmental balance around the world (Singh et al., 2012; Carvalho et al., 2014). So it can be stated that land cover (LC) and its changes are important variables that have significant impacts on the environment and environmental processes (Foody, 2000). In the meantime, beaches are highly important and have been used extensively by humans. Therefore, it can be said that these areas have been affected by human changes throughout history and will continue to do so in the future. Because coastal areas have the potential for development due to their natural, industrial resources, access to development activities, and aesthetic value, these factors lead to changes in LU patterns in these areas (Lo & Gunasiri, 2014).

South Pars Special Economic Zone off the coast of Asaluyeh is one of the areas in which less than 10 years of extensive industrial investment have been made. The establishment of this area of Asaluyeh has not only attracted a large population of people from the region and surrounding provinces (Fars, Hormozgan, etc.) but also caused migration from all over the country to rural and urban areas around the region because of its wide scope of operation and the need for a large number of human resources. Therefore, about 30,000 people are working in the area at present. Population migration, investment, and the advent of petrochemicals have not only accelerated the process of industrialization and technological advancement in the region but has also provided an evolving field of environmental and LU developments (Azizpour & Ghasemi, 2011)..

In other words, the petrochemical industry is recognized as an important source of production for the needs of the domestic industry and has a special potential and place in the national economy of the country Therefore, it is necessary to study the environmental impacts of these industries (Narimisa et. al., 2013; Bhatt & Khanal, 2010). Therefore, environmental impact assessment is one of the acceptable approaches to achieving sustainable development goals, and as a planning tool, it can identify potential environmental impacts that occur after the implementation of petrochemical projects and provide reasonable options for choosing to delete and reduce them (Pandey, 2015; Klir & Yuan, 1995).

Therefore, to mitigate these effects and achieve proper land development, understanding how LULC changes affect natural resources and the environment enables planners to design strategies to mitigate the adverse effects of future LULC changes (Alansi et al., 2009). Therefore, awareness of LULC changes and developments over a while is very important to planners and managers, so, it is necessary to use change detection methods to identify changes over time (Lu et al., 2004). MacLeod and Congalton (1998) stated that four aspects of change detection should be considered when monitoring natural resources: identifying changes occurring, identifying the nature of change, assessing the extent of regional change, and evaluating the spatial pattern of changes. In this regard, remote sensing (RS) images can effectively record LULC changes and provide an excellent source of data, with up-to-date information on these changes that can be extracted, analyzed, and simulated (Bajracharyan et al., 2020; Pradhan et al., 2008; Singh et al., 2018).

Therefore, RS is widely used in the detection and monitoring of LULC at various scales (Hua, 2017; Olokeogun et al., 2014; Vishwakarma et al., 2016; Mishra et al., 2016). There are many models for predicting LC changes including equation-based models (Shamsi, 2010), statistical models (Hyandye, 2015), evolutionary models (Aitkenhead & Aalders, 2009), Cellular models (Singh et al., 2015), Markov models (Yang et al., 2012), hybrid models (Subedi et al., 2013) and specialized system models (Stefanov et al., 2001). The most common methods in LULC are cell-based and agent-based models or a combination of the two (Berger, 2001; Hartkamp et al., 1999; An et al., 2005; Breuer et al., 2006).

The CA-Markov model is a combination of the cellular automata (CA) model and the Markov chain model. The CA-MARKOV model is highly efficient as a suitable method for simulating spatial variations in a complex system (He et al., 2014). The Markov chain model was developed by a Russian mathematician named Andrei A. Markov in 1970. This model was first used by Burnham to model LC changes (Mishra and Rai, 2016; Amini et al., 2016). Markov chains are random processes (Halmy et al., 2015; Subedi et al., 2013) and its matrix shows variations between different classes of LC (Koomen & Borsboom-van Beurden, 2011) and It is often used in modeling and simulating LULC changes (Halmy et al., 2015; Mishra & Rai, 2016; Amini et al., 2016).

The CA was introduced in 1940 by Ulam. CA consists of a grid or plaid space. The basic principle of CA is that it can explain the change of each cell according to its current state and changes in the neighboring cells (Koomen & Borsboom-van Beurden, 2011). CA is a dynamic model that shows changes based on the concept of proximity and indicates the probability that one class will convert to another (Eastman, 2003).

Combining the CA-Markov model results in dynamic spatial and temporal modeling and better simulation of changes (Sang et al., 2011; Yang et al., 2014). In the CA-MARKOV model, change in one region is characterized by a set of transition probabilities from one situation to another over a period of time, and these probabilities can be used to predict future LU changes (Wu et al., 2010).

Sobhani et al. (2021) simulated a future LULC map for 2050 using the Markov chain-cellular automata model and monitored LULC changes with Landsat imagery in the Jajrud and Tangeh Vashi, Iran. In this study, it was predicted that by 2050, that built-up areas will have the top increasing trend and high-density pasture will decrease because of the heavy dependency and immediate vicinity of Jajrud to Tehran, the largest city and the capital of Iran. In Tangeh Vashi, bare land expansion will have the top increasing trend, whereas the volume of high-density pasture will have the top decreasing trend. Ghorbani Kalkhajeh and Jamali (2019) in an article entitled "Analysis and predicting the trend of land use/cover changes using neural network and systematic points statistical analysis (SPSA)" used Landsat 5 and Landsat 8 images, multilayer perceptron (MLP) neural network and systematic points to evaluate and predict the trend of LULC Changes. According to the results, during the 30 years, 10.6% of agricultural lands were destroyed and urban areas increased by 23.4%.

Das and Angadi (2021) evaluated the LULC change dynamics of the Barrackpore Subdivision area, India using remote sensing data (Multi-temporal Landsat images) and utilized the urban growth. They applied the maximum likelihood classifier (MLC) method to generate the LULC maps. Their analysis revealed that vegetation cover, agricultural/cropland, wetland, and water bodies decreased while the area under built-up and fallow lands increased. Wang et al. (2021) used Landsat images and applied supervised classification to extract LULC then simulated the land use situation. They evaluated LULC change with the logistic regression-cellular automata-Markov chain (LR-CA-Markov). The results showed that the built-up land area grew rapidly and found the economy was the major factor influencing the change in LULC. They predicted that LULC would change dramatically over the next 30 years (probably due to urban sprawl).

There is a gap in research on the direct impact of human and natural factors on environmental changes at a regional scale. There is a need to protect urban and natural environments to prevent natural disasters and unplanned population growth (Jamali et al., 2022; Mojarad et al., 2021). This study is unique in addressing this gap by studying environmental changes such as LULC change detection.

In this study, Land Change Modeler was used to analyze LULC changes during the period and the CA-Markov model was used to predict future LULC changes in the South Pars region to monitor LU management practices and assess its future impacts. This study is based on the hypothesis that the development of petrochemical industries leads to drastic changes in LULC and environmental degradation.

This study had four primary objectives: 1) to monitor and assess environmental changes (LULC), 2) to evaluate the increase of construction effects without a land-use plan, 3) to reduce pollution, destruction of natural resources, and prevent the shoreline from advancing according to the predicted changes in the intended classes, and (4) to identify management priorities at a regional scale.

In previous studies and research, the models used in the present study have not been used, so it is expected that the results of this study will be the basis for better decisions for land resource management and environmental impact assessment in the study area.

2. Material and Methods

South Pars Special Economic Zone was established in 1998 to use oil and gas in the South Pars Basin and to operate in the field of oil, gas, and petrochemicals. The area is located in the Persian Gulf, 300 kilometers east of Bushehr Port and 570 kilometers west of Bandar Abbas and is about 100 kilometers from the South Pars Gas Basin located in the middle of the Persian Gulf (Qatar's North Dome Basin).

The study area is located in Bushehr Province of Iran between longitude 52° 4″ 52° 47″ East to latitude 27° 21″ 27° 50″ North Fig. 1. It is bounded on the north by the Zagros Mountains, on the south by the Persian Gulf, on the west by the Shirino village, and on the east by the Chah Mubarak village and its approximate area is 14,000 hectares (Hatami et al., 2013).

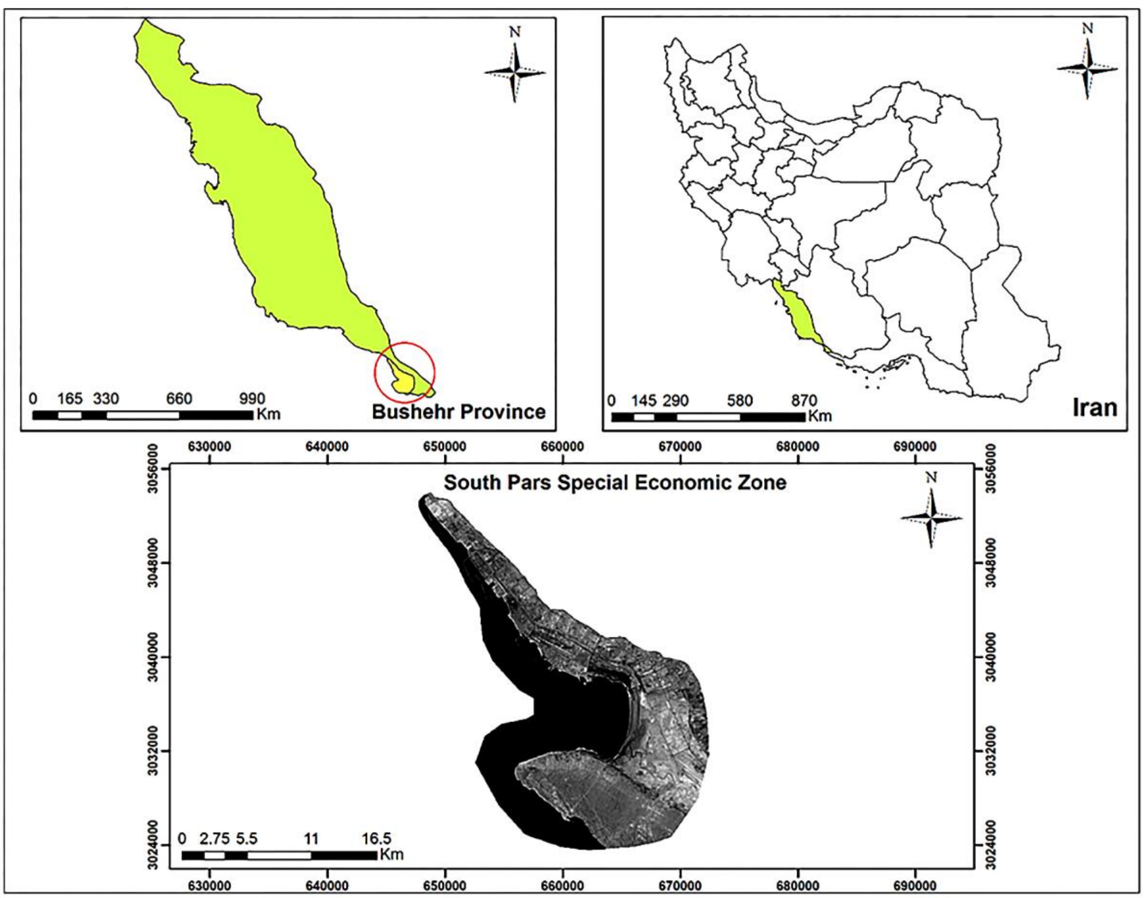

Fig. 1- Schematic diagram of the study area (for illustrative purposes only, the image here is from the Landsat 8 OLI data of 2018).

2.1. Data collection and research methods

Fig. 2 shows the framework of the change predicting process. The research steps include data preparation, classification results of the three desired periods, and the final stage of using the CA-Markov model to predict LULC changes for 2028.

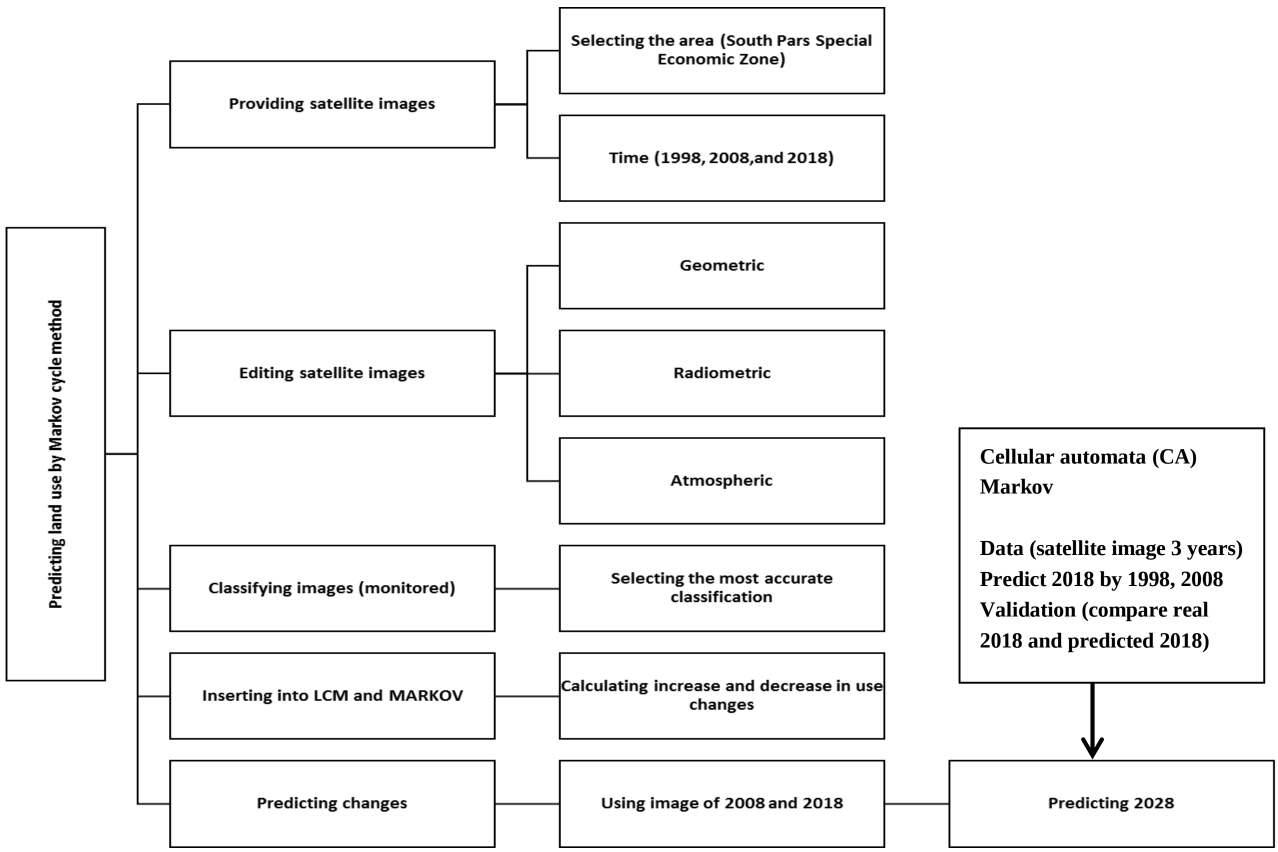

Fig. 2 - Research process flow diagram

2.2. Data Acquisition and Processing

In this study, coastline and LC changes were analyzed using time series satellite imagery from the US Geological Survey (USGS) website. (https:// landsat.gsfc.nasa.gov/landsat-surface-reflectance-factsheet-available-from-usgs).

Landsat satellite images are from the years 1998 Thematic Mapper (TM), 2008 Thematic Mapper (TM), and 2018 Operational Land Imager (OLI) related to July, April, and August respectively. All images were selected in the seasons with 0% cloud cover. Then in the pre-processing step, geometric, atmospheric, and radiometric corrections were performed to improve image quality.

Scepan et al. (1999) stated that to show more precisely the LC, the best band composition for Landsat satellites are bands 3-5-4, 2-3-4, and 1-2-3 in red, green, and blue respectively. Band 5 Landsat is sensitive to changes in water content, soil, and vegetation, as well as variations between different vegetation types. In the present study, false composite color (FCC) was used to enhance classification accuracy using bands 2, 3, and 4 for 1998 and 2008 and bands 3, 4, and 5 for 2018.

Four groups of LC were identified according to the available maps and images, conditions, and properties of the study area for classification using the maximum likelihood algorithm, which includes: Built-up areas, Bare land, Vegetated areas, and Water bodies (see Table 1).

The maximum likelihood algorithm is one of the most common methods of supervised classification in remote sensing data (Richards & Richards, 1999). Accuracy assessments were performed for 1998, 2008, and 2018 images to determine the quality of the information provided from the data. The classification accuracy for each image was evaluated using the error matrix and kappa coefficient.

Table 1- Descriptions of classes adopted

Land Cover	Description	Colour Assigned
Built-up areas	This class includes continuous and discontinuous urban fabric, industrial, commercial,	Violet
Bare land	Sand plains, unpaved roads, excavation site, are considered as bare lands.	Yellow
Vegetated areas	This comprises green urban areas, non-irrigated arable land, irrigated land, scrubs and forest cover,	Green
Water bodies	Permanent open water, lakes, ponds and reservoirs, coastal lagoons	Blue

2.3. LULC Change Modeling

2.3.1. Land Change Modeler (LCM)

Land Change Modeler (LCM) is an integrated software environment for analyzing and predicting LULC and validating the results (Eastman, 2014). The LCM examines LULC changes between two different times, calculates the changes, and displays the results with different charts and maps. One of the benefits of this model is a more accurate prediction in a short period, especially for sustainable LC (Roy et al., 2014).

Using the LCM, one can gain a basic understanding of the elements of the LU system and the factors needed to plan and execute the strategy. It is also possible to predict LC under different management scenarios and possible future changes (Jamali et al., 2018; Ahmed & Ahmed, 2012; Costanza & Ruth, 1998;). In this study, LCM model is used to analyze LULC changes and modeling.

2.4. Markov Chain Model Analysis

In this study, the LCM is used to monitor LULC changes and the CA-Markov model is used to model and predict LULC changes for 2028. Most change detection methods compare one data (image) with another data (image) on two different dates. In this study, LULC maps produced between1998-2008, and 2008-2018 were selected as inputs to the LCM model to analyse regional changes. Reductions and increases in each LULC[1], Net change, unchanged areas[2], and transfer from one LULC to another LU[3] in different LULC classes were assessed by the LCM. Then, the Markov chain model was used to predict LULC changes for the study area.

[1] Gain and Losses

[2] Persistence

[3] Transition

It predicts based on the changes in images over a period of time and the likelihood of what cell will become a cell in the future. Markov's chain ability is that it can calculate the probability that one class will be transformed into another.

3. Results and discussion

3.1. Image classification accuracy assessment

In the present study, according to the available data, 20 years is considered to detect and predict LULC changes in the study area. As described, four classes were identified, including built-up area, vegetation, bare land, and water bodies. Kappa coefficients for the classification accuracy for 1998, 2008, and 2018 were 95.91%, 96.29%, and 98.31%, respectively. Liang and Weng (2010) reported a minimum kappa coefficient of 85% for evaluating classification accuracy.

The overall accuracy of classification was obtained at over 90% in all images, indicating satisfactory classification accuracy and an acceptable level of agreement. Shao et al. (2001) indicated the classification accuracy of their study on Landsat images between 77.6 to 89.2%. The LC pattern in the South Pars region of Assaluyeh is presented in Fig. 3 for 1998, 2008, and 2018. According to this model, the land development in the study area is very significant due to the creation of petrochemical industries and employment.

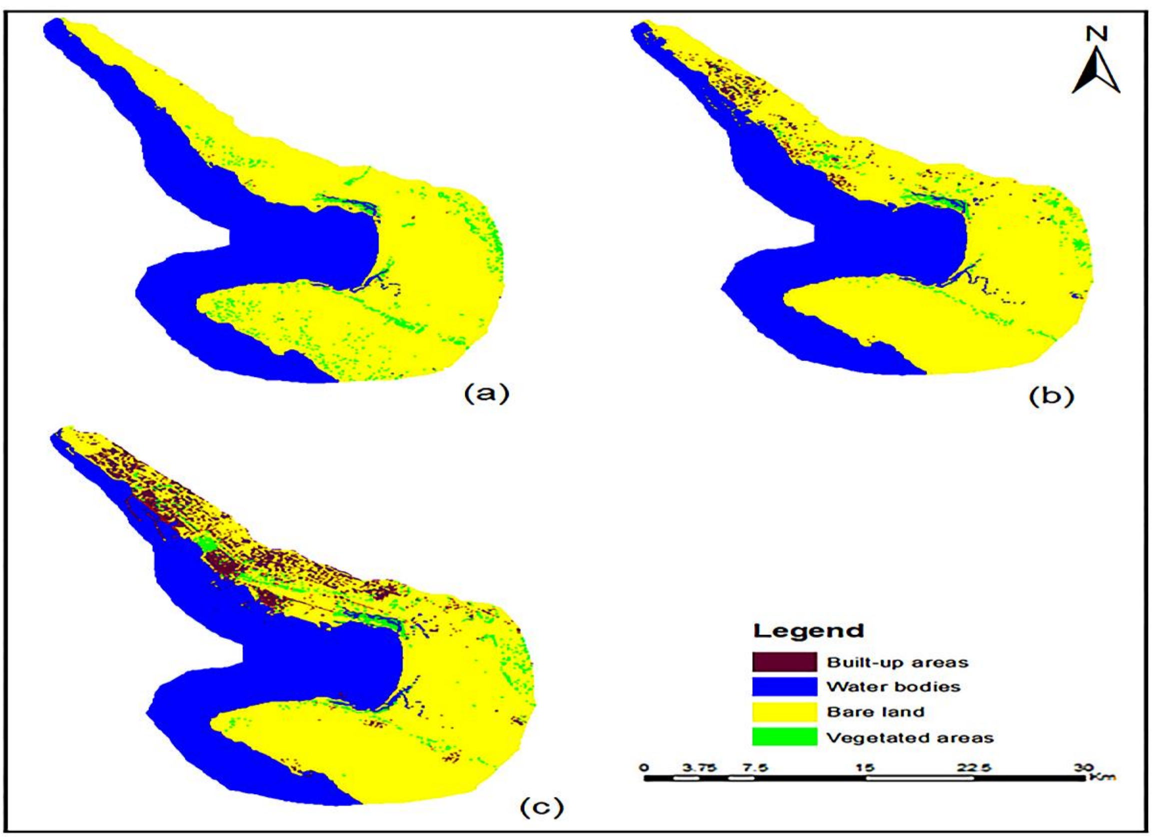

Fig. 3 - LULC pattern by year in Pars Special Economic Zone (a) 1998; (b) 2008; (c) 2018

Table 2 and Fig. 4 show the area of each class for 1998, 2008 and 2018. The results of the classification show that the area of built-up from 0.0657 km^2 in 1998 has increased to 21.319 km^2 in 2018. While the area of the bare land has decreased from 201.914 km^2 to 186.616 km^2.

The area of water bodies also decreased during the whole period from 141.564 km^2 to 134.811 km^2. But vegetation in the area has been different, with the area declining from 1998 to 2008, reaching from 7.447 km^2 to 5.002 km^2 and then since 2008, changes in this class have been increasing so that the area in 2018 has reached 8.244 Km^2.

Table 2 - LULC in 1998, 2008 and 2018

Land use type	1998		2008		2018		% Change 1998-2018
	Area/Km^2	Area (%)	Area/Km^2	Area (%)	Area/Km^2	Area (%)	
Built-up areas	0.0657	0.0187	3.834	1.092	21.319	6.073	0.817
Bare land	201.914	57.526	203.962	58.11	186.616	53.168	-1.174
Vegetated areas	7.447	2.121	5.002	1.425	8.244	2.348	-0.51
Water bodies	141.564	40.332	138.192	39.371	134.811	38.408	-1.075
Total	350.9907	100.0	350.9907	100.0	350.9907	100.0	-

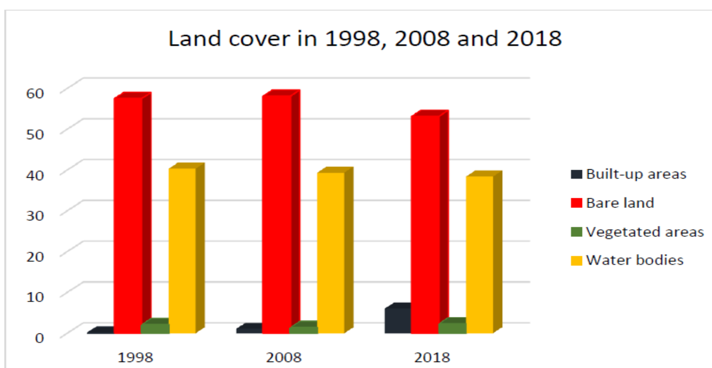

Fig. 4 - LULC in 1998, 2008 and 2018

3.2. Change detection analysis using LCM method

The built-up areas have increased substantially and have somehow reduced the area of bare land. Analysis and Highlighting of LULC changes between 1998 and 2008 showed that during this period approximately 200.81 km^2 of the bare land area was reduced and added to other classes, especially Water bodies.

In the following, the results of the analysis of changes for 2008 - 2018 were significantly different from the previous period. During this period, the class of the bare land has been reduced to about 23.08 km^2 and added to other classes, especially the Built-up areas. Built-up areas have seen significant growth during this period, the total area of this class has risen from 0.05 km^2 to 21.25 km^2 in the period 1998-2008. Figs. 5 and 6 show the distribution of LULC levels.

According to the figures, most Net changes in the period 1998-2008 belong to the Water bodies with 62.40 km^2 and in the 2008 - 2018 time period, the Built-up areas with 16.32 km^2 have the highest net change.

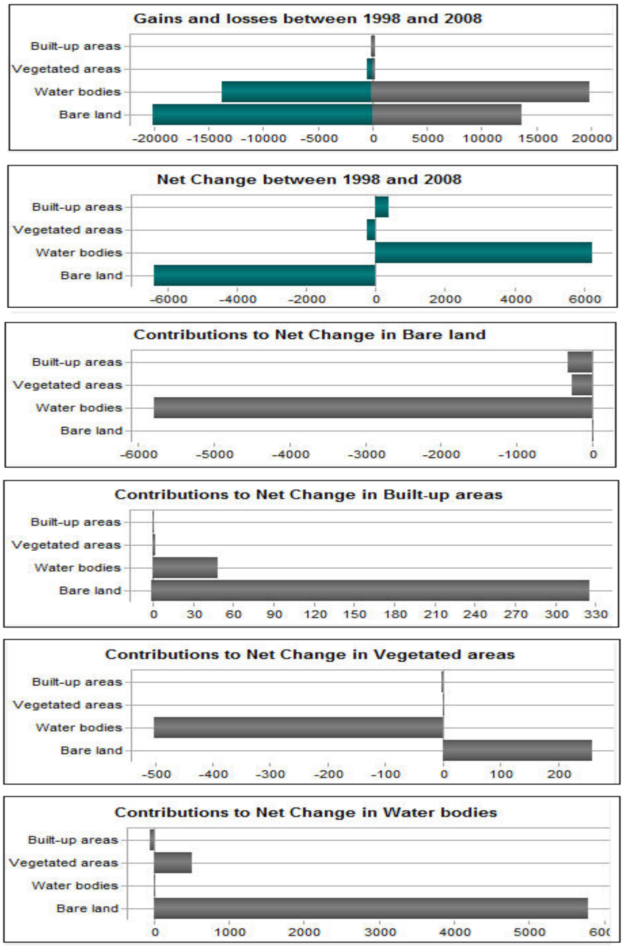

Fig. 5 - Trend analysis 1998–2008

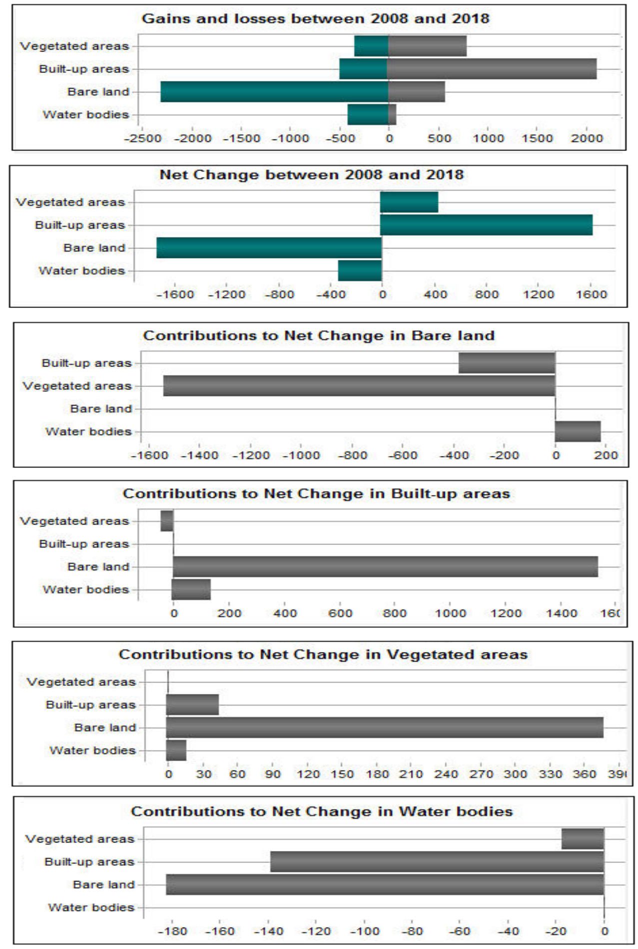

Fig. 6 - Trend analysis 2008–2018

Figs. 7 and 8 show the spatial map of total LULC changes that occurred between 1998 - 2008 and 2008 - 2018 in the study area. In other words, the resulting maps show where each LULC has become another.

During the period 1998-2008 most changes were related to the conversion of bare land into Water bodies with 194.92 Km^2. The conversion of Water bodies to bare land with 137.05 km^2 is another major change in the region. The map of total LULC changes in the South Pars Special Economic Zone, which occurred between the period 2008–2018 indicates where each LULC has changed to another LULC within 8 years.

According to the calculations made during this period, most changes are related to the conversion of bare land to Vegetated areas with 17.41 km^2. In addition, the Bare land has been converted into Built-up areas of 5.01 km^2. Table 3 also shows the area of Converted LULC changes to each other during the desired periods. The observations and results were similar to observation by Ashournejad et al. (2019).

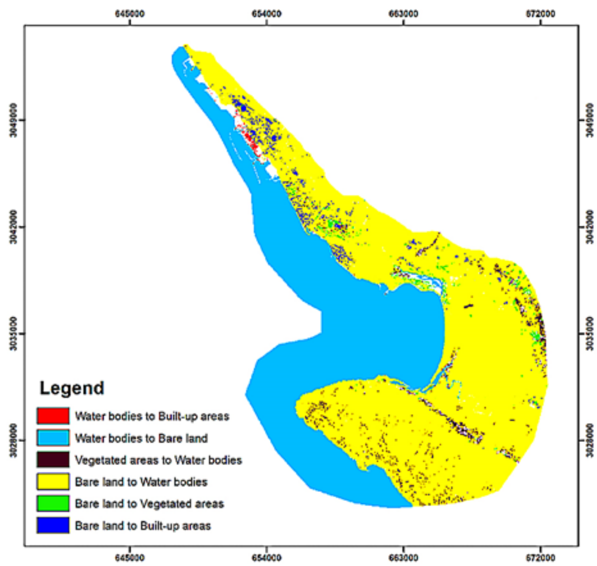

Fig. 7 - Map change 1998–2008

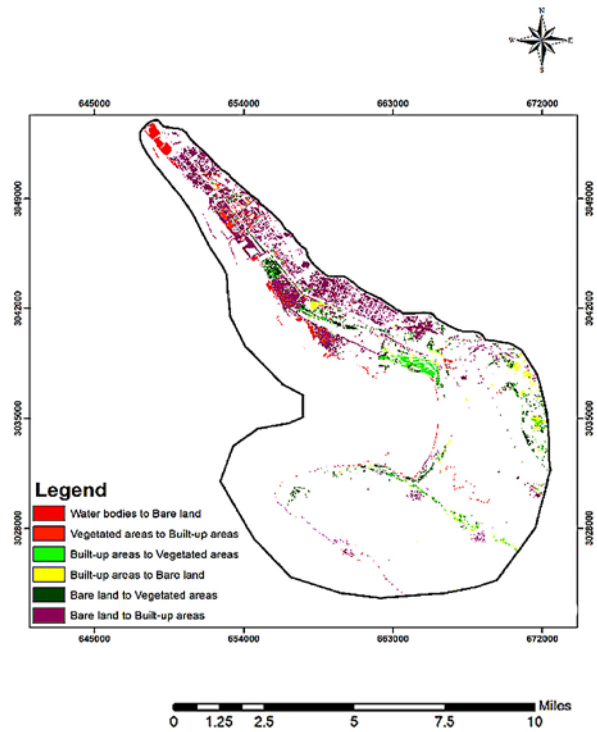

Fig. 8 - Map change 2008 – 2018

Table 3 - LULC in 1998, 2008 and 2018

Land use type	1998 - 2008 Area / Km^2	Land use type	2008 - 2018 Area / Km^2
Water bodies to Bare land	137.059	Water bodies to Bare land	2.470
Bare land to Water bodies	194.929	Vegetated areas to Bare land	2.026
Vegetated areas to Water bodies	5.089	Bare land to Vegetated areas	17.411
Bare land to Vegetated areas	2.615	Built-up areas to Vegetated areas	2.284
Bare land to Built-up areas	3.264	Bare land to Built-up areas	5.018
Water bodies to Built-up areas	0.533	Vegetated areas to Built-up areas	2.740

3.3. Trend and direction of LULC changes between 1998 and 2008

The results of the trend and direction maps for LULC changes show that the larger the number found on the map, the more the area was susceptible to further changes. It can also be said that the area under study has the most change in the period in that area (Aburas et al., 2015). Fig. 9 shows areas with red and orange colours indicating that the use of Built-up areas has changed more than other areas, and more pixels of other LULCs have been converted to Built-up areas over 10 years.

In other words, changes in the area from Bare land and Water bodies to Built-up areas have decreased from the south to surrounding areas. But these changes have occurred from Vegetated areas to Built-up areas in the northern areas.

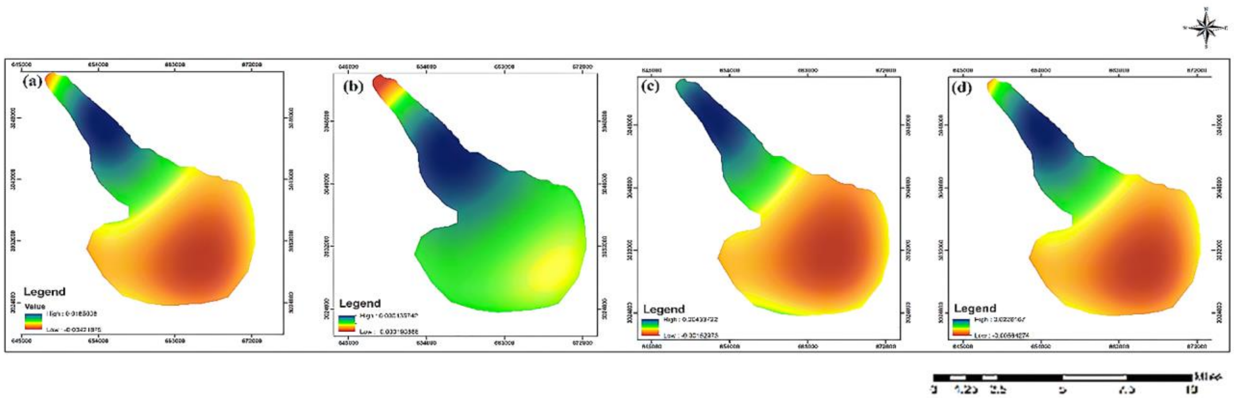

Fig. 9 - Trend changes map (a) Bare land to Built-up areas; (b) Vegetated areas to Built-up areas; (c) Water bodies to Built-up areas; (d) All classes to Built-up areas.

3.4. Trend and direction of LULC changes between 2008 and 2018

Fig. 10 shows the trend and direction of LULCs change over the 8 years. The largest number on the map indicates the area most susceptible to change and it can be said that the area in question has the most change in the time period under study. In other words, more pixels than other LUs have been converted to built-up areas within 10 years. According to the results, most of the changes in the Built-up areas occurred in the southern part of the study area and gradually decreased in the surrounding areas.

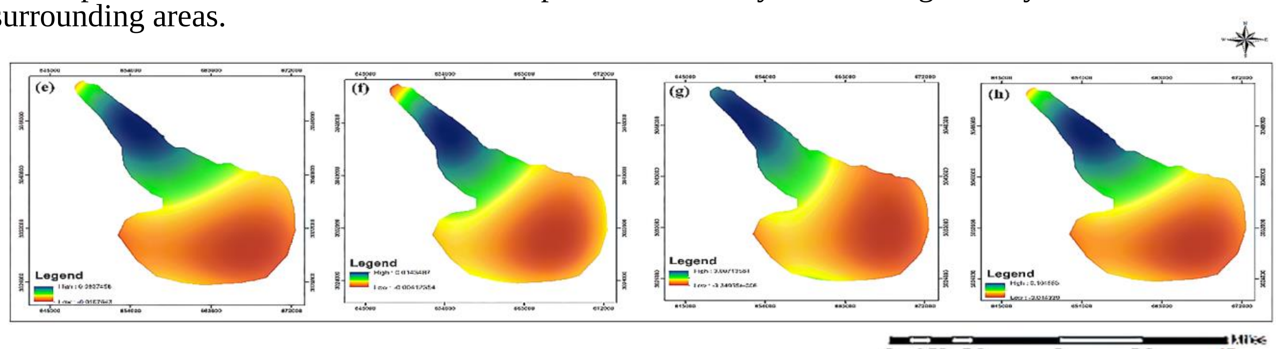

Fig. 10 - Trend changes map (e) Bare land to Built-up areas; (f) Vegetated areas to Built-up areas; (g) Water bodies to Built-up areas; (h) All classes to Built-up areas.

Validation of modeling

3.4.1. Validation of CA Markov prediction – kappa indices of agreement and disagreement

The international scientific community has called for research into land cover change, specifically models that predict spatial patterns of future change (Lambin et al., 2003; Turner et al., 1995). Modelers are satisfying this need with a variety of approaches (Baker, 1989; Pontius et al., 2004; Hall et al., 1995; Veldkamp & Fresco, 1996; Geoghegan et al., 1997; Mertens & Lambin, 1997;

Liverman et al., 2000; Wu & Webster, 1998). In most cases, the models are connected to a raster-based GIS.

Scientists are required to necessarily develop statistical methods to validate such models, because it is essential to know their prediction accuracy (Pontius & Schneider, 2001). Pontius (2002) has suggested the use of Kappa statistics for testing accuracy in terms of location (Kappa for location) and quantity of correct cells (Kappa for quantity).

Therefore, land use and land cover change data derived from satellite images for describing and projecting land use and cover changes establishes the validity of the predicted results of the CA Markov process in this study.

For validation, a map of simulated future change is compared to a map of recent real land cover change. For appropriate validation, the map of reality used for validation should not be used in calibration (Pontius & Schneider, 2001). Here, the LULC of 2018 is predicted using LULC maps of 1998 and 2008, derived from Landsat satellite images (TM sensor).

This provides a method to measure agreement between two categorical images, a "comparison" map (here the predicted LULC of 2018 in Fig. 11 and a "reference" map (LULC map derived from Landsat image of 2018 in Fig. 3c. The comparison map is the result of CA Markov model simulation results, whose validity is to be assessed against a reference map that depicts reality.

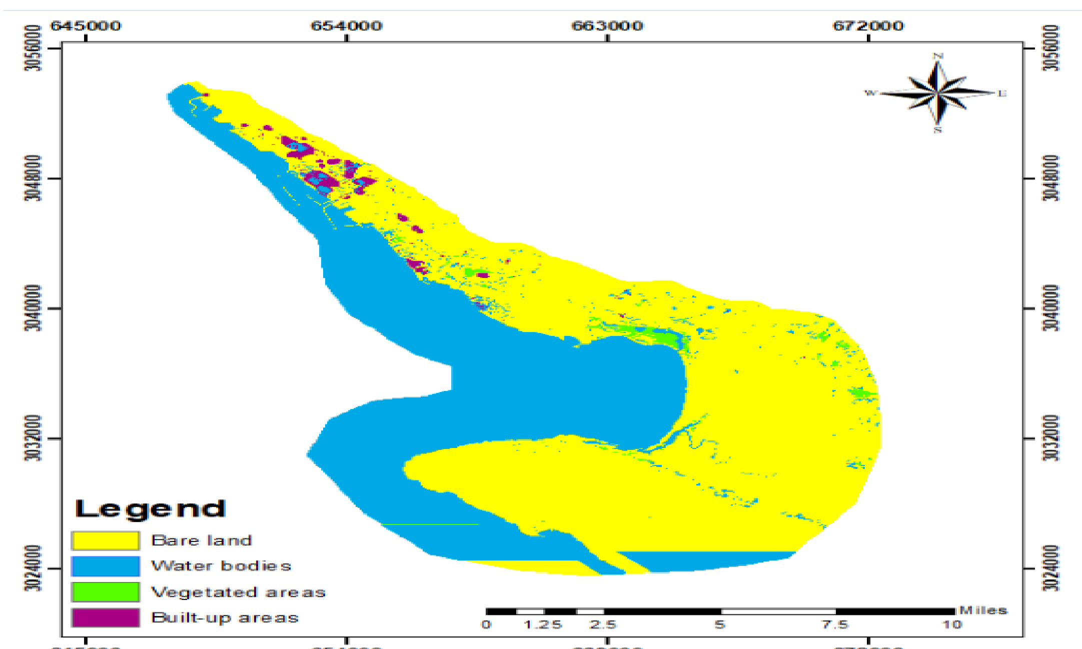

Fig. 11 - Predicted LULC of 2018 Using 1998 and 2008 LULC

The statistical methods separate error and agreement by components due to specification of quantity and location. The simulated map of 2018 is compared to the reference map of 2018, a Kappa for quantity and location statistics is derived (see Table 4). The statistics for location showing Kno is 0.8816, Klocation is 0.9330, Klocation Strata is 0.9330 and Kstandard is 0.8499 Table 5.

The results indicate that CA Markov model's ability to specify grid cell level location of future change is nearly perfect (here Klocation value is 0.9330, where Klocation value of 1 is perfect).

And Kquanteity shows the quantity of the model's ability to predict the number of pixels calculated by Equation 1 (Mondal et al., 2016).

$$Kquanteity = \frac{M\ (m) - NQML}{PQML - NQML} = \frac{0.9053 - 0.5750}{0.9044 - 0.5750} = \frac{0.3303}{03294} \cong 1 \qquad (1)$$

Table 4 - Agreement/disagreement according to ability to specify accurately quantity and location to predict 2018 LULC.

S1. No.	Information of location	Information of quality		
		No [n]	**Medium [m]**	**Perfect [p]**
1	Perfect [P(x)]	P (n) = 0.6181	P(m) = 0.9438	P(p) = 1.0000
2	Perfect Stratum [K(x)]	K(n) = 0.6168	K(m) = 0.9438	K(p) = 1.0000
3	Medium Grid [M(x)]	M(n) = 0.5750	M(m) = 0.9053	M(p) = 0.9044
4	Medium Stratum [H(x)]	H(n) = 0.2000	H(m) = 0.3690	H(p) = 0.3797
5	No [N(x)]	N(n) = 0.2000	N(m) = 0.3690	N(p) = 0.3797
	Agreement chance		0.2000	
	Agreement quantity		0.1690	
	Agreement strata		0.0000	
	Agreement grid cell		0.5363	
	Disagree grid cell		0.0385	
	Disagree strata		0.0000	
	Disagree quantity		0.0562	

Table 5 - Kappa index of agreement to ability to specify accurately quantity and location to predict 2018 LULC

Statistics	Index
Kno	0.8816
Klocation	0.9330
Klocation Strata	0.9330
Kstandard	0.8499

3.5. Predicting LULC Change Based on the Markov Model

In this study, modeling and predicting LULC changes for the South Pars Special Economic Zone for 2028 based on LULC maps derived from the classification in 2008 and 2018. In the first step, in the Markov model, the 2008 LU classification map as an old map and the 2018 LULC classification map as a new map were introduced, and the transfer probability matrix and the transfer area matrix for the next ten years were calculated with an error of 0.15.

This model predicts the likelihood of what cell will become a cell in the future, based on changes in the cells of the images over a period of time. The ability of the Markov chain is that it can calculate the probability that one class will convert to another. Fig. 12 shows the predictions of LULC changes for 2028 for the South Pars Special Economic Zone. According to this prediction, as a result of the development of petrochemical industries and the increase in construction the coastline has advanced to the sea, and the Water bodies class has been reduced by about 19 percent and added more to the Built-up areas. Mishra and Rai (2016) obtained the predicted results with the observed LULC map for future evaluation based on the statistical results of the classes.

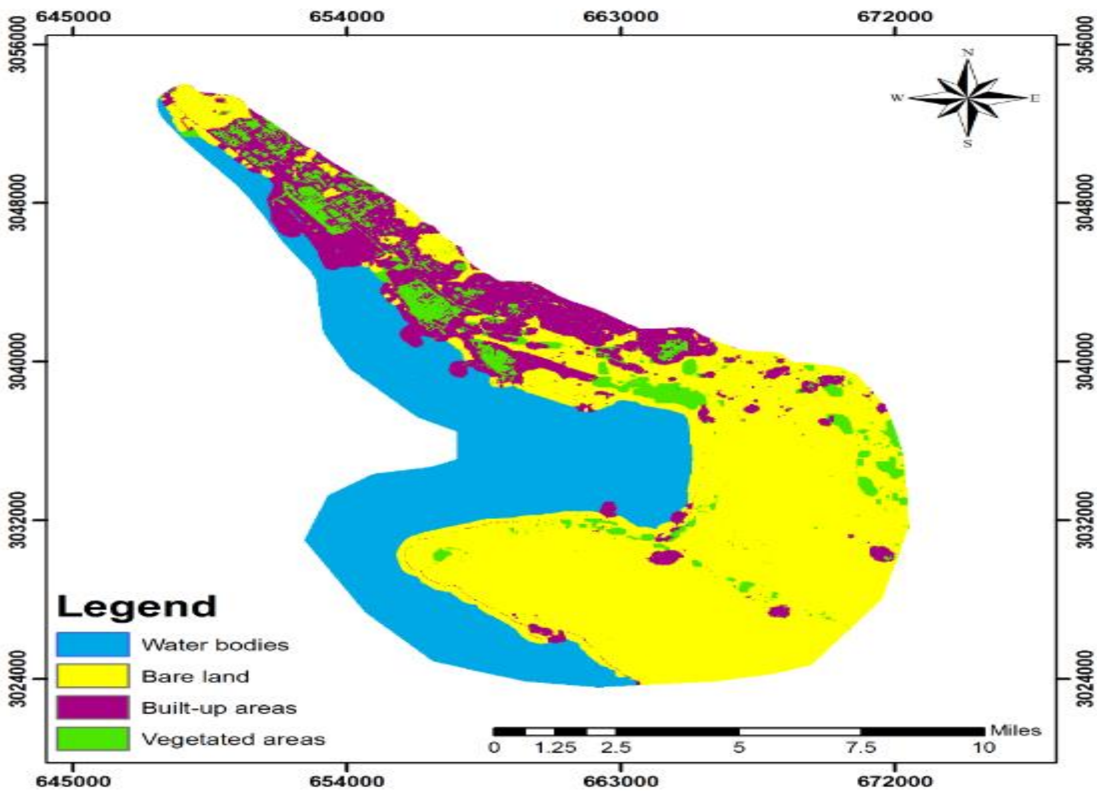

Fig. 12 - Predicted LULC for 2028

Also, the expansion of industry and the increase in construction can be attributed to the 12% reduction in bare land in the study area. Vegetation areas will increase by 65 percent in 2028. Finally, LULC changes accounted for 56 percent growth in 2028 based on the CA-Markov model. Table 6 shows the status of the predicted LULC for 2028.

Table 6 - Predicted LULC for 2028

Land Use	2028	
	Area/Km^2	Area (%)
Built-up areas	48.656	56
Bare land	165.961	-12
Vegetated areas	23.243	65
Water bodies	113.130	-19
Total	350.99	100

Fig. 13 shows the trend of LULC from 1998 to 2028. As the line graph shows, if the construction and migration process continues to work especially for this area, we will face further advances towards the coast, which will have a very bad future for the beaches, the sea, the aquatic and it affects the whole environment of the region. This research and its statistical results are consistent with other studies such as (Zhang et al., 2021; Hamad et al., 2018; Mondal et al., 2016; Aburas et al., 2015 and Sisodia et al., 2014).

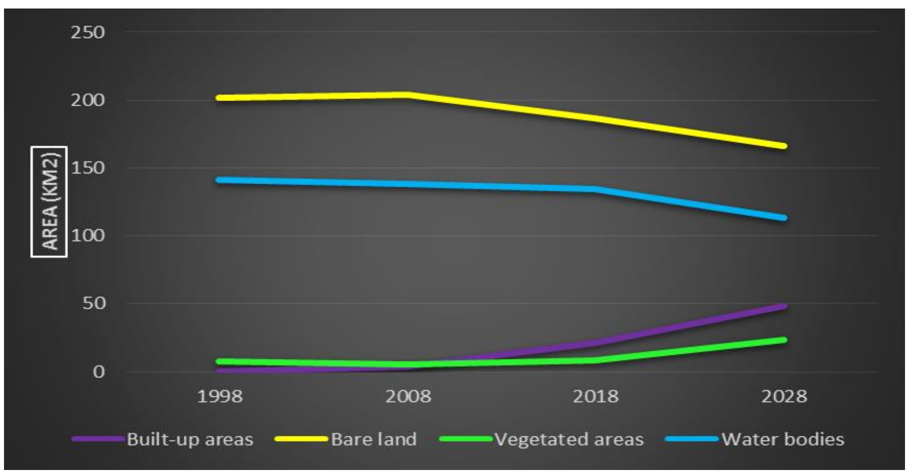

Fig. 13 - LULC trend 1990–2028

4. Conclusion

The results of monitoring LULC maps for twenty years (1998 to 2018) showed that the area has experienced many LULCs changes. In our study, most of the changes related to built-up areas increased by 0.81% and Bare land decreased by -1.174%.

Similarly in this regard, there are researchers such as Stephenne and Lambin (2001), and Feng et al. (2018) who have used modern methods such as LCM, MLP, and CA-Markov, and their results showed an increase that occurs in urban and residential areas.

The results of the present study show the conversion of LULCs over the 20 years that bare land and water bodies have undergone many changes. Currently, land-change modelers are not being held accountable for their prediction of future landscapes. Most land-change modelers fail to validate models and fail to state the uncertainty in future predictions.

Consequently, policymakers and the general public develop opinions based on misleading research that fails to give them the appropriate interpretations required to make informed decisions. Validation efforts to a known point in time are necessary to estimate the uncertainty for the extrapolation to an unknown point in time.

CA Markov LULCC Model prediction results were tested and validated in this study using traditional kappa for location statistics (Mondal et al., 2016). The results of the prediction of the LULCs changes showed that the Vegetation will increase by 65 percent, built-up areas by 56 percent, bare lands and water bodies will decrease by 12 percent and 19 percent by 2028, respectively. In this regard, Dewan and Yamaguchi (2009), revealed that substantial growth of built-up areas resulted in a significant decrease in the area of water bodies, cultivated land, vegetation, and wetlands. By accepting the hypothesis that the development of the petrochemical industry from 1998 to 2018 has led to drastic changes in LULC and environmental degradation, it is fitted with the probability of expected transfer prepared using the LCM and Markov methods.

Consequently, urban land expansion has been largely driven by elevation, population growth, and economic development. Predictions indicate that LULCs changes are significant and that the process of industrial development, especially petrochemicals, will lead to increased labor migrations, thereby continuously increasing built-up areas and advancing the coastal area to the sea, additionally, this has led to shoreline changes and the restoration of the ecological environment of the study area faces serious challenges.

It is possible to establish a model to predict the trends in land uses in a certain period of time through the study of past land use changes, which could provide some basis for scientific and effective land use planning, management and ecological restoration in a study area and guidance for regional socio-economic. The current research based on the results shows that there have been many changes in LULCs, so managing these conditions to conserve natural and human resources requires more attention from executive organizations and responsible experts. Therefore, paying attention to these changes and predicting the future will result in better decisions and management, so considering all of these factors will lead to sustainable development and do not lead to environmental degradation and pollution.

Declarations

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