LAND USE CHANGES MONITORING OVER 30 YEARS AND PREDICTION OF FUTURE CHANGES USING MULTI-TEMPORAL LANDSAT IMAGERY AND THE LAND CHANGE MODELER TOOLS IN RAFSANJAN CITY (IRAN)

Introduction
Change detection is the process of identifying differences in the condition of an object or phenomenon through observation at different times [1]. The ability to understand and anticipate land use patterns changes is imperative for decision-makers and policymakers who are concerned about public resources [2]. Urbanization is an unavoidable process due to economic evolution and fast population growth. The unsustainable use of agricultural lands near urban settlements may include serious consequences such as land depreciation and desertification [3]. So far, many studies have been done on this subject such as urban expansion [4–6], flooding and drought [7–9]. But fewer studies have been conducted in relation to future changes prediction. In this study we decided to predict and model of future changes using trends of past changes. For this purpose we first used the satellite imagery techniques [10–12] to prepare land use map over 30 years in Rafsanjan city, Iran and then, based on the last 30 years land use changes and some effective variables on land use changes, we tried to predict the future changes using the Land change modeler tools of IDRISI software. The land change modeler works on the basis of the artificial neural networks that have become a popular tool in the analysis of remotely sensed data [13].

KEYWORDS:
Urban expansion, Change detection, Remote sensing, Geosciences, Kerman.

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The purpose of this study is predicting and modeling of future changes in the Rafsanjan area, using remote sensing and GIS. The multispectral satellite data obtained from Landsat 5 (TM), 7 (ETM+) and 8 (OLI) for the years 1986, 1992, 1998, 2004, 2010 and 2016, were used respectively. The supervised classification technique was applied to multi-temporal Landsat images. Rafsanjan city was classified into four major LU classes including urban areas, pistachio gardens, bare-land, and salt. Change detection analysis was performed to compare the quantities of land use class variation between time intervals. The results revealed both increase and decrease of the different LU classes from 1986 to 2016. Generally, the conclusions indicate that during the study period, Urban areas and pistachio gardens have increased by 6.89% (10.47 km2) and 12.76% (34.18 km2) while bare-land and salt have decreased by 13.43% (35.97 km2) and 9.96% (26.68 km2), respectively. In order to predict the future land use changes map, we used the Land change modeler tools of IDRISI software. Consequently, the predicted land use map of 2022 was prepared based on the trend of 30 years of land use changes and effective variables.

Fig. 1. Situation of Rafsanjan in Kerman province of Iran
Рис. 1. Положение Рафсанджана в иранской провинции Керман

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Materials and methods

Study area

Rafsanjan is situated in the north of Kerman province, Iran. (Fig. 1). The area under research is approximately 270 km². Its coordinates are 30°32' to 30°45' north and 56°10' to 54°17' east. The area has an annual rainfall of less than 100 mm, and the climate of the area is hot and arid. Sarcheshmeh Copper mine, that is considered as the second largest copper deposit worldwide is located 50 km south of Rafsanjan and some people in Rafsanjan are working on this copper mine [14–17]. Pistachio is the main product of Rafsanjan and it has been known as Iran's center of pistachio cultivation and one of the most important areas for pistachio agriculture in the world. The annual production of pistachio in Iran is about 200 thousand tons, while 60% of it comes from Rafsanjan. Irrigation of pistachio gardens has been carried out through the qanats in the past, but nowadays, due to the drying of the qanats, it is done through deep wells [18]. The expansion of this city mainly depends on the regions cultivation. Observation has shown that substantial changes have taken place in this area.

Image preprocessing

Two main sets of data that were used in this study are: Satellite data and digital topographic maps. Enhanced Thematic Mapper (ETM+), Landsat Thematic Mapper (TM), and Operational Land Imager (OLI) images (with path/row 160/39) acquired in 1986, 1992, 1998, 2004, 2010 and 2016, respectively, to be analyzed beside the digital topographic maps digitized from hardcopy topographic maps with a scale of 1:50,000 that were useful for geometric correction of the satellite images and for some ground truth information. Then, ground information was collected between 1992 to 2016 for the purpose of supervised classification and classification accuracy assessment. Performance of the study was carried out in four steps (Fig. 2):

1. Providing and performing some corrections on satellite data from six different time periods.
2. Preparing of Rafsanjan land use map.
3. Selecting effective variables to land use changes prediction.
4. Prediction of future land use changes through the integration of the effective variable maps and land use map

Fig. 2. General flowchart of the process for the study

Рис. 2. Общая схема исследования
of different time periods by using the land change modeler tools in IDRISI software [19].

The aim of image preprocessing is to modify the visual interpretability of an image by increasing the certain difference between the features. Contrast stretching was applied to the all images and these images were prepared to the classification process. By implementing the supervised classification, the false color composites were created and interpreted visually using on-screen digitizing to ascertain land use classes that could be interpreted easily like garden and Salt. Visual interpretation was applied to distinct some classes that were spectrally could not be separated by supervised classification.

Image classification
By using digital topographic maps and ground checkpoints, supervised classification was done in Rafsanjan area to be classified into Urban areas, pistachio gardens, bare-land, and salt. 250 points in the area are used for accuracy assessment, 200 points of field data and 50 points of the land use map dated 2004 and topographic maps dated 1998. Random classified method is used for choosing the location of these points. Also, using GIS advantages, some auxiliary data and visual interpretation was integrated to improve the accuracy of the classified image.

The land change modeler
The Land Change Modeler (LCM) for Ecological Sustainability is a software solution designed to address the prompt problem of accelerated land conversion and the very specific analytical needs of biodiversity conservation. The foundation for the LCM model is based on the artificial neural network (ANN) analysis. An ANN is a system that models the way in which the brain performs a special task. ANNs have many advantages over traditional computational methods, that’s made up of nonlinear elements [13]. Inputs required by this model include 1) prior land use changes maps belong to previous years. 2) Affective variables on land use changes. The LCM model integrated mentioned layer to prepare future change detection map.

The LCM has made it possible for the user to obtain a quick estimate of the ability and the role of each variable in predicting possible land use change. In fact, the model provides a degree of correlation between variables and land uses at the end of the period by calculating the Cramer’s coefficient (v) and in the range 0–1. This correlation is presented in two ways: 1. for each variable and land use 2. For each variable and all land uses. Of course, it’s should be noted that the rate of this coefficient in each land use is also very important in order to predict land use, since it is possible that the overall Cramer’s coefficient rate for a variable to be low, but that variable should be more depended on a number of lands uses. It should be noted that the high value of the Cramer’s coefficient shows the good ability of the variable but does not necessarily guarantee the excellent performance of the model since other factors also interfere in the modeling calculations and the complex relationships between the variables. However, when its amount is very low, it is a good indication to exclude an input variable in the prediction process. In general, values close to 0.4 and above of it are considered as the appropriate value for a variable and values less than 0.15 are considered its weak ability to predict for a variable [20].

Results and discussion

Land use maps
The output images of land use and analysis was presented in this section. The results of the visual interpretation of satellite images related to 1986, 1992, 1998, 2004, 2010, and 2016 have been shown in Fig. 3. The images used in this research were classified as the maximum likelihood classification method, and the regions of interest were prepared manually for classifying. Therefore, the images were categorized into four classes of urban areas, pistachio gardens, bare-land and salt (Fig. 3).

In order to calculate accuracy of classification, earth data should be compared to classified images in an error matrix. There are different methods to investigate accuracy of classification such as general accuracy, user accuracy, Kappa coefficient, etc. among which Kappa coefficient is more appropriate because of considering classified incorrect pixels. In this regards, educational samples from urban areas classes, pistachio gardens, bare-land and salty lands were prepared for each year and then compared with land use maps of the same year and for comparison of accuracy, the error matrix was first created and then Kappa accuracy and overall accuracy for each year have been presented in Table 1. Only Kappa accuracy numbers and overall accuracy have been given. According to Table 1, the obtained results have fairly good accuracy, with a mean Kappa accuracy of 0.83 for all land use maps and a mean overall accuracy of 89%.

Table 1 / Таблица 1

| User’s accuracy (%) | Kappa statistic | Land use |
|---------------------|-----------------|----------|
|                     | Kappa землепользования | Статистика |
| 89 | 0.85 | 1986 |
| 90 | 0.82 | 1992 |
| 92 | 0.87 | 1998 |
| 82 | 0.76 | 2004 |
| 93 | 0.88 | 2010 |
| 88 | 0.81 | 2016 |
| 89 | 0.83 | Mean |

The total area of the studied region is 26784.28 hectares. Regarding the changes in the level of each existing uses during the 1986 to 2016 period, it has been tried to describe the situation of the area of each use in different years in Table 2. The trend and magnitude of land use change were analyzed for a period of 30 years from the benchmark year, 1986. The three decadal trend of land use change revealed that there
was a major increase in the pistachio gardens that can be represented by an exponential growth model. In this study, the general trend of built-up areas has shown an increasing trend due to population expansion and its demand for infrastructure development. Significant change between 1986 and 2016 is that bare-land and salt areas are got converted to urban areas and pistachio gardens. From change analysis of land use between 1986 and 2016 it was observed that there is an increase in urban areas by 6.89% and decrease in bare-land by 13.43% and decrease in salt by 9.96%. Pistachio gardens was found to increase by 14.31%. Here the main change is that bare-land got converted to build up area.

**Selecting effective variables to predict land use changes**

It was tried to select variables that are effective on the land use changes and introduce into the model at this stage of the research. The main variables affecting the changes according to the characteristics of the region can be distance from the road, distance from the river, slope, and aspect [21; 22]. Therefore, to enter the variables mentioned land changing modeler, it is necessary them to be mapped out (Fig. 4).
Table 2 / Таблица 2

| Class name          | 1986   | 1992   | 1998   | 2004   | 2010   | 2016   |
|---------------------|--------|--------|--------|--------|--------|--------|
| Urban areas         | 2875.40| 3144.19| 3715.56| 3988.23| 4054.87| 4722.40|
| Pistachio gardens   | 13413.15| 14569.91| 15541.48| 15958.25| 16741.01| 16831.62|
| Bare-land           | 5817.25| 3758.38| 3058.87| 2910.87| 2795.1| 2219.58|
| Salt                | 5678.48| 5311.80| 4468.37| 3926.93| 3193.3| 3010.68|

*Fig. 4. The effective variables maps on prediction (A) Slope and rivers, (B) Aspect, and (C) Roads*

Рис.4. Эффективные переменные прогноза: A – уклон и реки, B – аспект и C – дороги

**Land use change monitoring**

It is possible to analyze and map land use changes over a period of times using land-change modeler tools. It is first necessary to enter the land use maps related to the first and the last periods of the course in order to achieve this goal. Therefore, the land use maps prepared of satellite images that had vector-based structure entered into the IDRISI software and their structure with a cell size of 30 meters was converted to Raster. Then, the changes occurred during the period 1986–1992, 1992–1998, 1998–2004, 2004–2010 and 2010–2016 were detected and analyzed using these maps (Fig. 5). At this stage, the potential for conversion of each class to other class was calculated based on input data including the distance from the road, the distance from the river, slope and aspect and land use maps derived from the maximum likelihood method. In other words, the probability that each pixel is changed in future was calculated. Many variables affecting change such as distance road, slope, and aspect during the time will be constant, so they have a static trait; some others, such as distance from the road and distance from residential areas, have a dynamic state and can be changed over
In the course of time, in fact, expand over the time, when new roads are built, and distance from roads also changes. In the LCM program, two methods have been predicted for modeling the Conversion potential: logistic regression and artificial neural networks. While the logistic regression method performs the potential of converting each use to another use separately, the artificial neural network method, in addition, is able to group the potential of converting sets of uses into other uses in a set of sub-models, or even can model and calculate the potential of converting all uses to other uses in a single sub-model. In this research, the input variables of slope, aspect and land use map of existing as static and variables of distance from the road and the distance from the river margin were entered as a dynamic and the potential of converting all land uses were modeled using artificial neural networks method and logistic regression. So, using the LCM tools, the land use prediction map of 2022 was prepared (Fig. 6). It can be seen, a lot of changes will occur in classes in future.

The significant change occurred in land use between...
The predicted Land use 2022

Fig. 6. The land use prediction map of future

The purpose of this study was to recognize a trend for land use changes that occurred in the last thirty years. To predict future changes, Landsat imagery and GIS techniques were used. Land use images are developed in IDRISI and the future land use image was predicted using Land Change Modeller of IDRISI software. Also, the applicability of the LCM tools was investigated in our study. It was concluded that the study area has undergone a very intense land use change as a result of development plans either agricultural or urbanization. A significant increase in urban settlements has taken place as well as a great increase in agricultural land. According to the trend of change, the largest change was related to pistachio gardens class about 12.76%, which indicated the most changes in land use classes. So, if the conditions do not change, the amount of agricultural use will increase, which this can create significant problems such as destructive environmental consequences followed by the lack of groundwater resources in the study area.

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Целью данного исследования является прогнозирование будущих изменений с использованием многократных снимков ландшафта и инструментов моделирования изменений в городе РАФСАНДЖАН (ИРИАН)

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