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Monitoring and Analysis of Land Use Changes Using Satellite Images and Remote Sensing (Case Study: Sabzevar City)

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Abstract

Remote sensing is one of the effective tools to study the process of land use change on a large scale and in a short time. In this research, the aim is to monitor and analyze land use changes using satellite images and remote sensing from 2010 to 2020 in Sabzevar city with Landsat images. For research, preprocessing included atmospheric correction and radiometric and geometric correction. A total of 200 ground control points were collected to classify and evaluate the accuracy of the classification with the maximum probability classification algorithm in the ground visit. The classification results showed that the forest area in 2010 was equal to 68980.21 hectares, which with the change of use and its conversion to residential use, barren and rainfed agriculture in 2020 reached 66044.99 hectares, ie 2935.22 hectares, its area has decreased. Residential use with its growth in 2010 to 2020 has increased from 2855.89 to 4563.98, ie 1708.09 hectares. Land use changes in semi-dense rangeland have also decreased from 167164.89 to 153287.68 hectares, i.e. 13877.21. Kappa coefficient and overall accuracy in 2020 were 98.42 and 97.84, respectively, which was the highest value compared to previous years. In this study, it can be recommended that the government increase the vegetation of the land to protect pasture and forest uses against further changes, and to compensate for these changes, to plant fast-growing forests.

***Keywords**:* Land Use, Remote Sensing, Maximum Probability, Landsat

1. Introduction

Physical development of cities is a dynamic and inevitable process during which the physical boundaries of the city expand in different directions and cause a change in the land cover of the region. By planning the use of urban lands and land management, urban growth can be directed in the most appropriate direction to meet the needs of urban residents, natural resources, lands around the city and agricultural land to be maintained. Land use and urban land use maps, in addition to different land use categories, specify the spatial pattern, type and intensity of land use and can be used for current and future urban land planning (Feizizadeh et al., 2007). Awareness of the types of land cover and human activities in different parts of it, in other words, how to use the land, as basic information for various

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planning is of particular importance. Land cover maps from satellite imagery play an important role in regional and national assessments (Knorn, 2009). Land cover, its dynamics and changes are important variables that have a serious impact on the environment and environmental processes (Foody, 2000). The use of remote sensing technologies and the use of satellite data in the preparation of land cover maps, reduce costs, save time, increase accuracy and speed. Digital processing of satellite images and their classification, i.e. sampling a limited area of the image and generalizing it to the whole image in a short time, will help save time and costs of projects (Zahedifard, 2002).

2. Research Background

Much research has been done on the efficiency of satellite imagery and remote sensing in assessing land use change. In a study, NOAA satellite AVHRR sensor images were used to classify rice crops and estimate its cultivation area in Guilan province. For this purpose, the multi-time classification method based on daily maximum NDVI extraction was used to remove the cloud. The results show 91.96% accuracy of the calculated cultivated area compared to the reference map (Ansari Amoli and Alimohammadi Sarab, 2011). The main purpose of the study conducted by (Cheruto et al., 2016) was to understand the quantitative changes of land use in the Macuni region of Kenya in the years 2016-2000. The classification was performed using the maximum probability algorithm and ERDAS software. The images used were received from Landsat 7 in 2016-2015 and 2000 and the area in question was divided into 7 sections in terms of user changes. The built-up areas were arable land, water resources, forests, shrubs, meadows, and barren lands. The results showed that between 2016 and 2000, significant land use changes of the above-mentioned classification were observed in the mentioned area. Atta et al. (2017) evaluated and predicted the changes and horizontal distribution of cities using multi-time images and the CA_MARKOV model in Gonbad Kavous. According to the research results, growth changes between 1987 and 2010 for urban use, 217.3%, irrigated lands 53.5%, rainfed lands - 40.4%, barren lands - 7.87% and parks - 198.6%, respectively. The growth of the city of Gonbad Kavous in the coming years was predicted to be irrigated arable lands around the south, southeast and east. (Joa et al, 2021) stated that the land cover classification obtained from multi-year NDVI performs better than multispectral data. An accurate classification based on the time series of plant clusters in seasonal forests allows seasonal variation of land cover classes in rainy and dry seasons as well as inter-seasonal transitions. The most important variables that helped accurately were the red, near-infrared (NIR), and short-infrared (SWIR) bands in the multispectral classification of identical dates and dry season months, most closely related to the multi-year NDVI classification. (Mohammadi et al., 1400), studied the trend of land use change in the watershed of Mahidasht plain using remote sensing images. The results of the study showed that in the first period of the study (1987) the highest land use area was related to rainfed lands with an area of 1558.63 square kilometers and the lowest area was related to residential lands or an area of 15.77 square kilometers. Also in the second period (1987-2000), the largest land use area was related to rainfed lands with an area of 1465.74 square kilometers. (2021, Guan et al), in Japan, land use change was modeled using the CA-Markov method. Although their main goal was to model urban lands, but they also predict the change of use of agricultural and forest lands by 2042. According to their forecasts, from 2006 to 2042, the level of agricultural land will decrease from 36% to 28% and forest land from 44% to 41%, and urban and man-made land will increase from 12% to 16%.

Since the main purpose of remote sensing technology is to identify and differentiate terrestrial phenomena and place them in specific groups or classifications, the classification of satellite images can be considered as the most important part of changing satellite information. Brought. Today, one of the most common and accurate classification methods used is the maximum probability method that has been used in this research.

3. Materials and Methods

3.1. Study Area

Sabzevar city is one of the westernmost big cities of Khorasan Razavi province which is between 36 degrees and 9 minutes and 7 seconds to 36 degrees and 22 minutes and 30 seconds north latitude and 57 degrees 37 minutes and 30 seconds to 57 degrees and 46 minutes and 10 seconds. Located east longitude. The center of this city is Sabzevar. The population of this city is 319,893 according to the 2011 census and 306,310 at the 2016 census. The main reason for population decline is the abstraction of Davarzan city from Sabzevar city in 2012. Meanwhile, the sixth city was also separated from Sabzevar city in 1399. In recent years, five cities of Joven, Jaghtai, Khoshab, Davarzan and Shashtmad have been separated from Sabzevar. Figure 1 shows a view of the study area (Khorasan Razavi Planning Management Organization,2021).

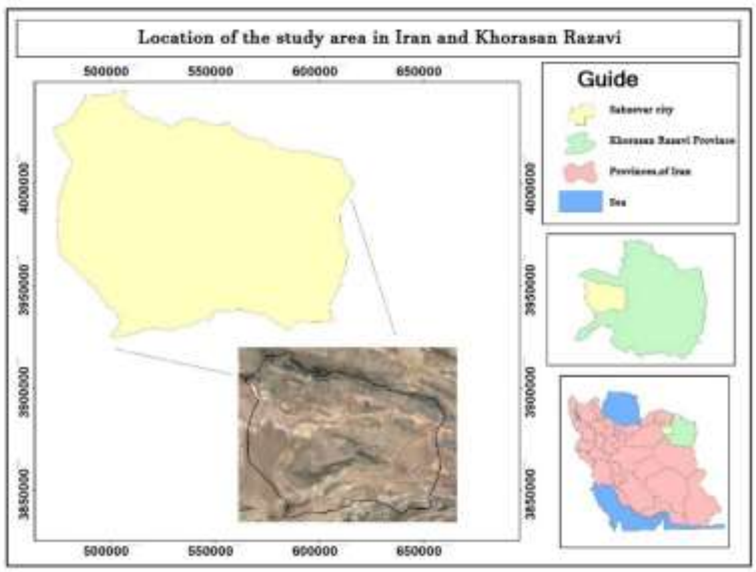

Figure 1. Map of the geographical location of the study area

3.2. Method

The method of research was spatial-field analysis, so that after conducting preliminary studies and preparing appropriate satellite images, with different amounts of educational samples and according to ground surveys, were analyzed and evaluated. The images used in the research were Landsat 5 satellite images on 08/22/2010 and Landsat 8 on 11/08/2020. In order to study land use changes, the maximum probability classification was performed on satellite images and the accuracy of the classification was evaluated.

Table 1. Specifications of the images used in the classification

Satellite	Sensors	History
Landsat 5	TM	22/08/2010
Landsat 8	OLI	11/08/2020

Band histograms were calculated and plotted separately. Usually, areas that are composed of clear water or shade, etc., have low reflection. Pixels in these regions have near-zero DNs in the near-infrared wavelength. If the histogram of the other bands is longer than the infrared band (for example, band 4 in Landsat 7) and never starts from zero. The minimum DN in band 1 and 3 histograms in dark areas (value above zero) indicates the amount of atmospheric dispersion effect, so this minimum DN can be deducted from other bands to remove atmospheric effects. In this research, FLAASH algorithm was used to eliminate atmospheric error. Equivalent rectangular algorithm was used to perform radiometric corrections. In this method, which is done automatically and using the cumulative property of values (total number of pixels between zero to each of the histogram brightness degrees), high and low contrasts are balanced and medium contrasts are uniformly They continue to the beginning and end of the histogram and the image histogram, after performing this method, approaches normal (Wolberg, 1990). Finally, using the roadmap of the 1: 25000 maps of the surveying organization and their compliance with the 2020 images, the 2020 image was first controlled compared to the 1: 25000 maps and identified as suitable in terms of geometric accuracy. Due to the fact that the images of the Landsat 8 sensor are ground reference and are provided with appropriate accuracy, the 2020 images of this sensor did not need geometric correction, but, for the geometric correction of the 2010 image related to the Landsat 5 satellite TM sensor from image-by-image method was used with reference to 2020 images.

In remote sensing data, initial calculations of some statistical indicators are useful and necessary. These calculations include mean, standard deviation, correlation matrix, variance-curarania matrix in each band. For optimal use of multispectral data, it is necessary to determine the best band composition. Choosing the best band composition through visual comparison of FCC images is difficult and time consuming. Therefore, a parameter called a favorable index factor can be used for the following two purposes:

A) Determine the most appropriate band composition for the FCC

B) Determining the most appropriate bands for digital classification (et al Chavez, 1988)

The number of multiple band combinations resulting from spectral bands must be constructed and compared. Based on the following equation, the number of r combinations obtained from the bands used can be calculated

To classify satellite images, a supervised classification was used and the maximum probability method was used. The maximum likelihood method is one of the most accurate classification methods reported in most researches (Hopkins et al., 1988; Richards and Richards, 1999). In this method, the probability that a pixel can belong to any of the available classes is calculated and then the pixel is assigned to the class that is most likely (Godarzi Mehr et al., 2012). For the study area, 7 land uses were identified, including residential lands, low-density rangeland, semi-density rangeland, rainfed agriculture, irrigated agriculture, grove, and barren areas. Land use maps for 2010 and 2020 were prepared using Google Earth software and existing maps of land use in the study area with a scale of 1: 25000, and using supervised classification by maximum probability method.

To evaluate the accuracy of the classification, educational samples were used that were not involved in the classification process. Training samples should be obtained from ground sampling data by GPS. For each class, 75% of the pixels were used as training samples in the classification and the remaining

25% of the pixels were used as validation samples. The accuracy of the classified maps was evaluated using the parameters of overall accuracy, kappa coefficient, producer accuracy, user accuracy, additional error and deletion error. Overall resolution is the average of the classification accuracy and is obtained by the ratio of the number of correctly classified pixels to the total number of pixels classified in all classes. Another accuracy parameter derived from the error matrix is the kappa coefficient, which calculates the accuracy of the classification relative to a completely random classification (Mather and Tso, 2016). The advantage of the kappa coefficient over the overall accuracy is in using the margin values of the error matrix to calculate the accuracy. Overall accuracy and kappa coefficient deal with all classes and do not provide information about each class. In addition, the overall accuracy is an optimistic estimate and always calculates the accuracy above the actual value. To calculate the accuracy of each individual class, parameters such as user accuracy and manufacturer accuracy must be used. In the error matrix table, the deletion and addition error are also expressed. Extra error is the percentage of pixels that do not belong to the class in question, but are in that class. Deletion error is the percentage of pixels that originally belonged to the class in question, but were mistakenly placed in another class (Alipour et al., 2014).

4. Findings and Discussion

The geometric correction error for the 2010 image, which was corrected by image-by-image method, was 0.38. The highest ranking of OIF Images TM index out of 20 combinations is 457 and OLI is among the 35 combinations made of 357 as described in Table 2. Figures 2 and 3 show the outputs of the selected band composition.

Table 2. Results of OIF index analysis in study years

OIF index	Band names	Image
146.51	*Band 7 Band 5 Band 4*	TM
278.41	*Band 7 Band 5 Band 3*	OLI

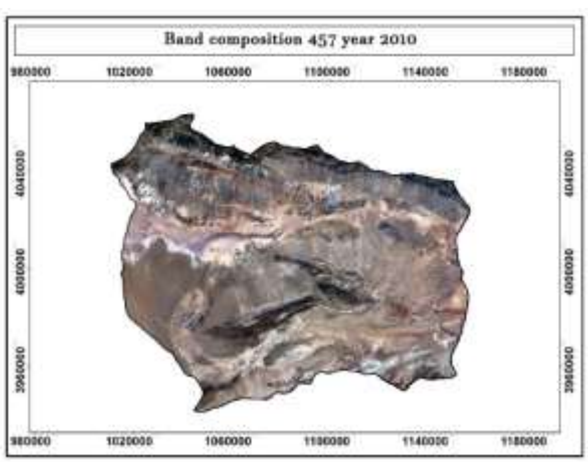

Figure 2. Band composition 457 of 2010

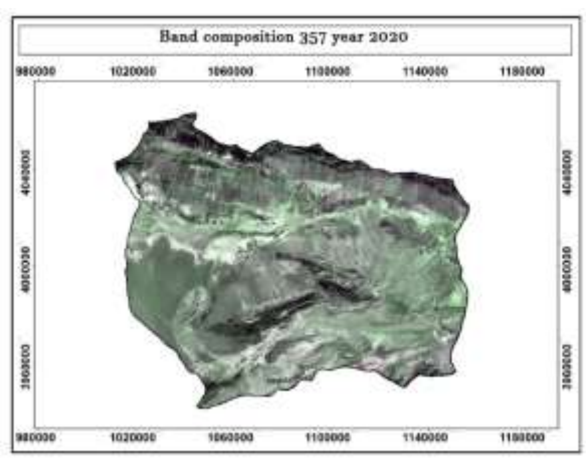

Figure 3. Band composition 357 in 2020

In this research, after making corrections, sampling points were collected in two stages; One is before classification, which is known as training points, and the other is training points, which are taken after classification and applied to the image to evaluate the accuracy of the classification. It should be noted that some of the educational examples have been obtained through field studies and others through the use of Google Earth images. Table (3) shows land use classes and educational and harvesting examples.

Table 3. Land use classes

Row	Land Use	Number of samples taken through GPS field studies	Number of samples taken via Google Earth	Number of training examples in software
1	Residential land	30	150	130
2	Low density pasture	50	120	90
3	Semi-dense pasture	20	40	40
4	Dry farming	35	50	30
5	Watery agriculture	25	35	40
6	A grove	40	45	85
7	Barren areas	50	65	115

Then, the image classification was done with the maximum probability method, and using satellite images of different Landsat land use sensors during 2010 and 2020, it has been extracted, which can be seen in Figures 4 and 5.

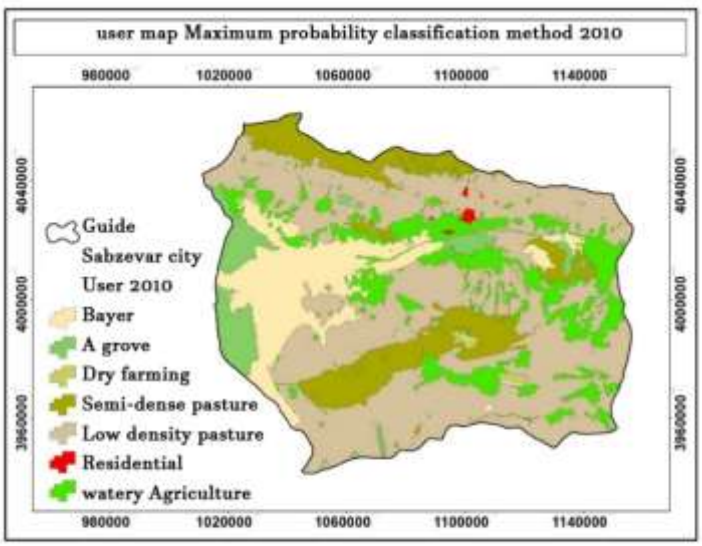

Figure 4. User classification map of 2010

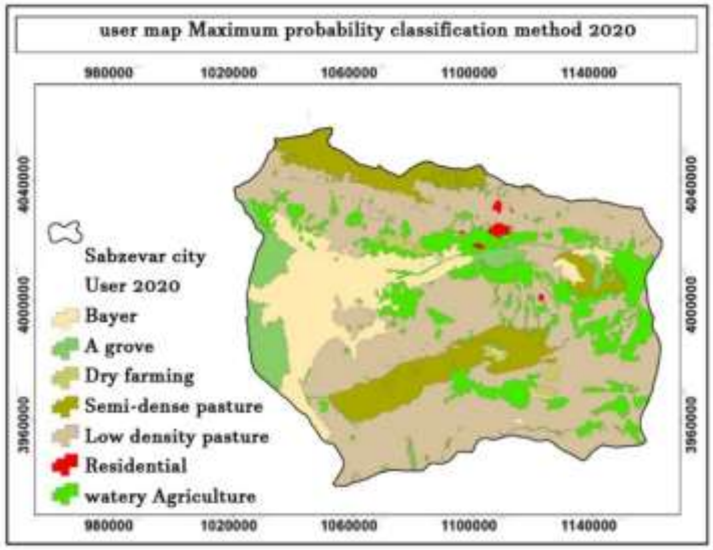

Figure 5. User classification map of 2020

The results of image classification showed that the forest area in 2010 was equal to 68980.21 hectares, which with the change of use and conversion to residential use, barren and rainfed agriculture in 2020 reached 66044.99 hectares, i.e., 2935.22 hectares, its area has decreased. Residential use with its growth in 2010 to 2020 has increased from 2855.89 to 4563.98, i.e,. 1708.09 hectares. Land use changes in semi-dense rangeland have also decreased from 167164.89 to 153287.68 hectares, ie 13877.21. The results of the classification also show that while the growth and development of urban areas and the conversion of agricultural lands, pastures and groves to residential and rainfed agriculture has always been positive, during 2010 to 2020 this trend was very increasing, so that almost 70% of urban area increased in the length of the last 10 years belongs to the years 2010-2020. After classification and evaluation of changes, kappa coefficient and overall accuracy of classification were calculated to evaluate the proposed research method, the results of which can be seen in Table (5). Usage changes in the study interval are also shown in Figure 6.

Table 4. Area of floors (ha) based on the maximum probability method in the period 2010-2020

Row	User classes	2010	2020
1	Residential lands	2855.89	4563.98
2	Low density pasture	645146.05	654219.52
3	Semi-dense pasture	167164.89	153287.68
4	Dry farming	8744.84	15820.94
5	watery Agriculture	188623.69	182703.11
6	A grove	68980.21	66044.99
7	Barren areas	171585.63	176460.99

The results show high kappa coefficient and overall accuracy in newer images, which can be attributed to the existence of ground control samples closer in time to these years and greater resolution of these images.

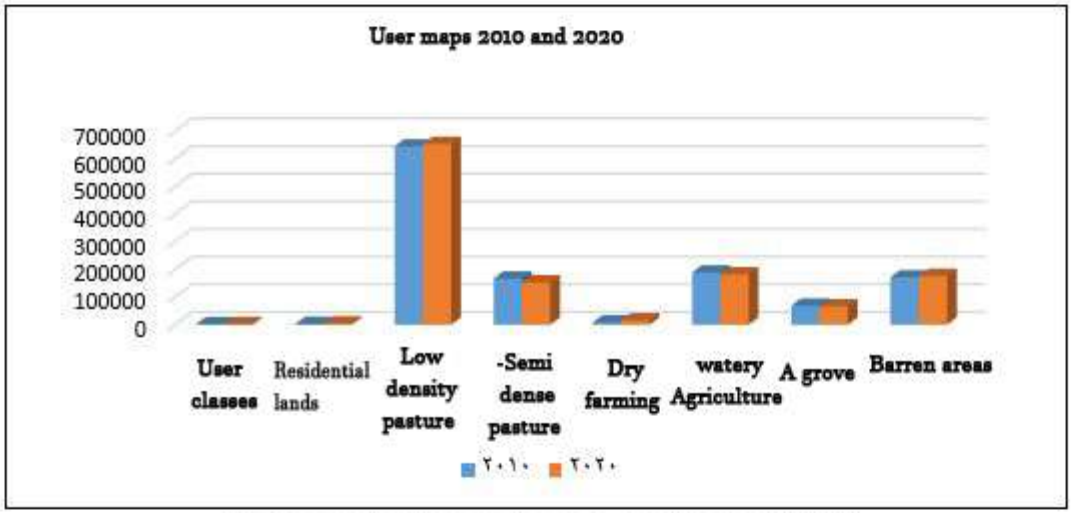

Figure 6. Landscape changes in 2010 and 2020

Table 5. Kappa coefficient and overall accuracy of classification of the study area

Statistical parameter	Year 2010	Year 2020
Kappa coefficient	95.36	97.84
Overall accuracy	97.91	98.42

With the rapid increase of urban population, the changes related to the body and urban spaces are accelerated and these changes lead to change of use, destruction, destruction of green spaces of forests, gardens and agricultural lands around the city. This study sought to evaluate the land use changes of the city with the maximum probability method, and multi-time satellite images in the remote sensing platform and spatial information system. The results showed that the growth and development of residential and barren land use in Sabzevar is not in line with other land uses and this has led to the growth of land use area in the city and barren areas. What can be deduced from this research is that remote sensing technology is very efficient in detecting changes over different time periods and if complete data and multi-time images are available, useful results can be achieved that in combination with intelligent algorithms can provide solutions. To predict, he offered to prevent the problems of unbalanced growth of the city and the development of an area. Using this technique reduces costs and saves time. The results of the research with the results of research (Hajian Boroujeni et al., 2016) that monitored and analyzed changes in land cover and land use in Chaharmahal Bakhtiari province and also research (Mohammadi et al., 1400), (et al., Guan, 1400) that all the results are correct Approved satellite image processing in evaluated changes. Based on this, suggestions are presented as follows.

- Using images with high spatial resolution such as SPOT, IRS, ASTER, etc., which will provide more accurate results of classification and user changes to the researcher.
- Using the automated cell model to predict changes in the coming years.
- Continuous monitoring of changes in pristine land uses, including forests and pastures in the study area.

References

Asghari Saraskanrood,. Mohammadnejad Arouq, V., & Emami, H. (2019). Investigation of land use changes using basic and object-oriented pixel methods and analysis of the effects of land use change on soil erosion (Case study: Maragheh city). *Quantitative geomorphological research, 8*(1), 160-178.

Hajian Borujeni, F., Fakhran Isfahani, S., Madadi, H., & Moradi, H. (2016). Monitoring and analysis of land cover and land use changes in Chaharmahal Bakhtiari province. *The first national conference on natural resources and sustainable development in Central Zagros*, Shahrekord University of Natural Resources and Earth Sciences.

Zahedifard, N., & Khajehuddin, J. (2004). Application of digital data sensor TM in preparing the land use map of Bazft river basin. *Journal of Water and Soil Sciences (Agricultural Science and Technology and Natural Resources), 8*(2), 91-105.

Atta, B., Rahnama, M. R., & Arkhi, S. (2017). Evaluation and Prediction of Changes and Horizontal Distribution of Cities Using Multi-Time Images and CA_MARKOV Model (Case Study: Gonbad Kavous). *Journal of Spatial Planning, Scientific Quarterly - Research of Golestan University, 7*(23), 25-40.

Feizizadeh, B., Azizi, H., & Valizadeh, Kh. (2007). Land use extraction of Malekan city using satellite images + ETM Landsat 7. *Journal of Environmental Management, 2*(1), 74-93.

Mohammadi, S. Si., Tavakoli, M., Zarafshani, K., & Mehdizadeh, H. (2021). Investigation of land use change in the watershed of Dasht-e Mahi Dasht using remote sensing images. *Sustainability, Development and Environment, 2*(2), 53-70.

Najarpour Siahkal, R., Kavousi Kalashmi, H., Zarang, N., Dadashi, M. Detection of vegetation changes using SAVI index and RS and GIS techniques (Case study of Babaoli Siahkal watershed). *Twenty-second National Geomatics Conference and Exhibition*.

Alipour, F., Aghkhani, M., Abasspour-Fard, M., & Sepehr, A. (2014). Demarcation and estimation of agricultural lands using ETM+ imagery data (case study: Astan ghods razavi great farm). *Journal of Agricultural Machinery, 4*, 244-254(In Persian).

Ansari Amoli, A., & Alimohammadi Sarab, A. (2011). Rice area estimation by using multi-temporal classification method and AVHRR data. *Spatial Planning (Modares Human Sciences), 15*, 1-16(In Persian).

Chavez, P. S. (1988). An Improved Dark-Object Subtraction Technique for Atmospheric Scattering Correction of Multispectral Data, remote Sensing of Multispectral Data. *Remote Sensing of Environment, 24*(3), 459-479.

Guan, D., Li, H., Inohae, T., Su, W., Nagaie, T., & Hokao, K. (2011). Modeling urban land use change by the integration of cellular automaton and Markov Model. *Ecological Modeling, 222*(20-22), 3761- 3772.

Foody, G. M. (2000). Mapping Land Cover from Remote Sensed Data with a Softened Feed forward Neural Network Classification. *Journal of Intelligent and Robotic Systems, 29*(4), 433-449.

Mather, P., & Tso, B. (2016). *Classification methods for remotely sensed data*. CRC press.

Mather, P. M. (2005). *Computer processing of remotely-sensed images*. Third Edition, John Wiley and Sons, Ltd, 319p.