
Evaluation and Comparison of Different Supervised Classification Algorithms in Lands User Map Preparation Using Satellite Images (Case Study: Miandoab City)

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Received 11 March 2020; revised 4 June 2020; accepted 28 September 2020

Abstract

Preparation of land use maps using traditional methods, in addition to spending a lot of time and money, is mainly about efficiency and it does not have the necessary accuracy. Today, satellite imagery and remote sensing techniques have a wide range of applications in all sectors, including agriculture, natural resources, and land use mapping, due to the provision of timely data and high analysis capabilities, variety of shapes, digitality, and the possibility of processing. Satellite imagery Landsat 8 for August 2020 was used, which after making the necessary corrections in the pre-processing stage, action experimentation or fusion of the desired image using the panchromatic band and spatial resolution of the image was increased from 30 meters to 15 meters. In the next step, four different classification methods, including backup vector machine, maximum probability, Mahalanoob distance, and minimum mean distance were compared. The results showed that the classification method of backup vector machine with average overall coefficients and kappa of 100 and 1, respectively, has higher accuracy than other methods. Priority accuracy of classification methods is in the form of backup vector machine, maximum probability, Mahalanoob distance, and minimum distance from the mean, respectively. Finally, by assessing the accuracy using user accuracy, producer accuracy, overall accuracy, kappa coefficient and error matrix, land use map was prepared in three separate classes.

Keywords: Land Use, Supervised Classification, Kappa Coefficient, Satellite Imagery, Miandoab

1. Introduction

The importance of land use as a major component in the management of natural resources, environmental changes, and a dynamic factor affecting living conditions requires that accurate quantitative and qualitative information be provided and related changes are determined in the short term (Akbari, 2019). Land cover maps are the first source of various scientific knowledgesuch as food security, location, agricultural management and global warming programs (Gardi, 2014). One of the most important factors for urban planning, and management, especially in order to achieve sustainable

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development in urban areas and optimal use of land, is the availability of accurate and timely information on land use status and land coverage in urban areas (Amanpour, 2017). Land use includes various types to meet various human needs. One of the main preconditions for optimal land use is known the land use patterns and knowing the changes of each land use over time (Khazayi, 2019). At present, scientists and users of remote sensing in different countries, use digital information, prepare accurate maps of land resources, including land use maps.

In Iran, researchers have done this by various methods and have done many projects in universities and research centers. According to these plans, the use of remote sensing technology is much more significant and logical compared to traditional methods and interpretation of aerial photographs in terms of accuracy and time, and expense. Therefore, in this research, it was tried to use this technology to study the methods of classification and preparation of land use maps with each other (Mazaheri, ND). Among the studies conducted on land use classification and land use mapping methods, the following studies can be mentioned. Fazeli et al. (2015) studied the performance of land use classification algorithms using image integration techniques in the area under Beheshtabad watershed and according to the classification done on the images, the results showed that the maximum probability method has higher accuracy.

Javaheri et al. (2019) studied the capabilities of land use mapping methods using satellite images of Kamyaran city. In this study, the maximum probability methods, support vector machine, and Mahalanoobi distance for supervised classification Kappa coefficient were used. The results of the research showed that the backup vector machine method with an overall accuracy of 91.4 2% and kappa coefficient of 0.88 % had good accuracy in comparison to other methods. Niazi et al. (2006) compared two methods of maximum probability classification and artificial neural network in extracting the land use map of the case study of Ilam dam basin, which showed that the neural network with the coefficient of 0.86% is more accurate than the maximum probability algorithm with a coefficient of 0.69%. Mobini et al. (2012) compared the maximum probability and fuzzy method in preparing the land use map of southern Khuzestan land using Landsat images. The results related to the general accuracy of the classification showed that the fuzzy classification method with a kappa coefficient of 0.99 2% has higher accuracy compared to the maximum probability algorithm with a kappa coefficient of 0.98%.

Khezri et al. (2016) used satellite images to prepare the land use map of Ghezel Ozan watershed using fusion technique and object-oriented processing in the software environment of Ecognition, and the final results were presented. Also, the accuracy evaluation coefficients are extracted (Overall accuracy of 81% and a kappa coefficient of 0.87 %) indicates the high accuracy of this classification method. Yousofi et al. (2011) compared different algorithms for classifying satellite images in preparing the land use map of Noor city, which showed that the classification method of the support vector machine with the average overall coefficients and kappa of 90.94% and 0.9503%, respectively, has higher accuracy than the other methods.

2. Data and Methods

2.1. Study Area

The city of Miandoab in the province of West Azerbaijan is located between two permanent rivers and the surrounding lands are surrounded by quality agricultural lands and in 2002 had a population of about 113933 people with an area of 1820 hectares in the south of West Azerbaijan province and south of Lake Urmia and at a height between 1291 to 1302 meters above the sea level. The average slope of the city is very low and totally between 0 to 2%. In terms of earthquake risk, the city of Myanadoab is in a zone without damage (10). Figure 1 shows the location map of Miandoab city.

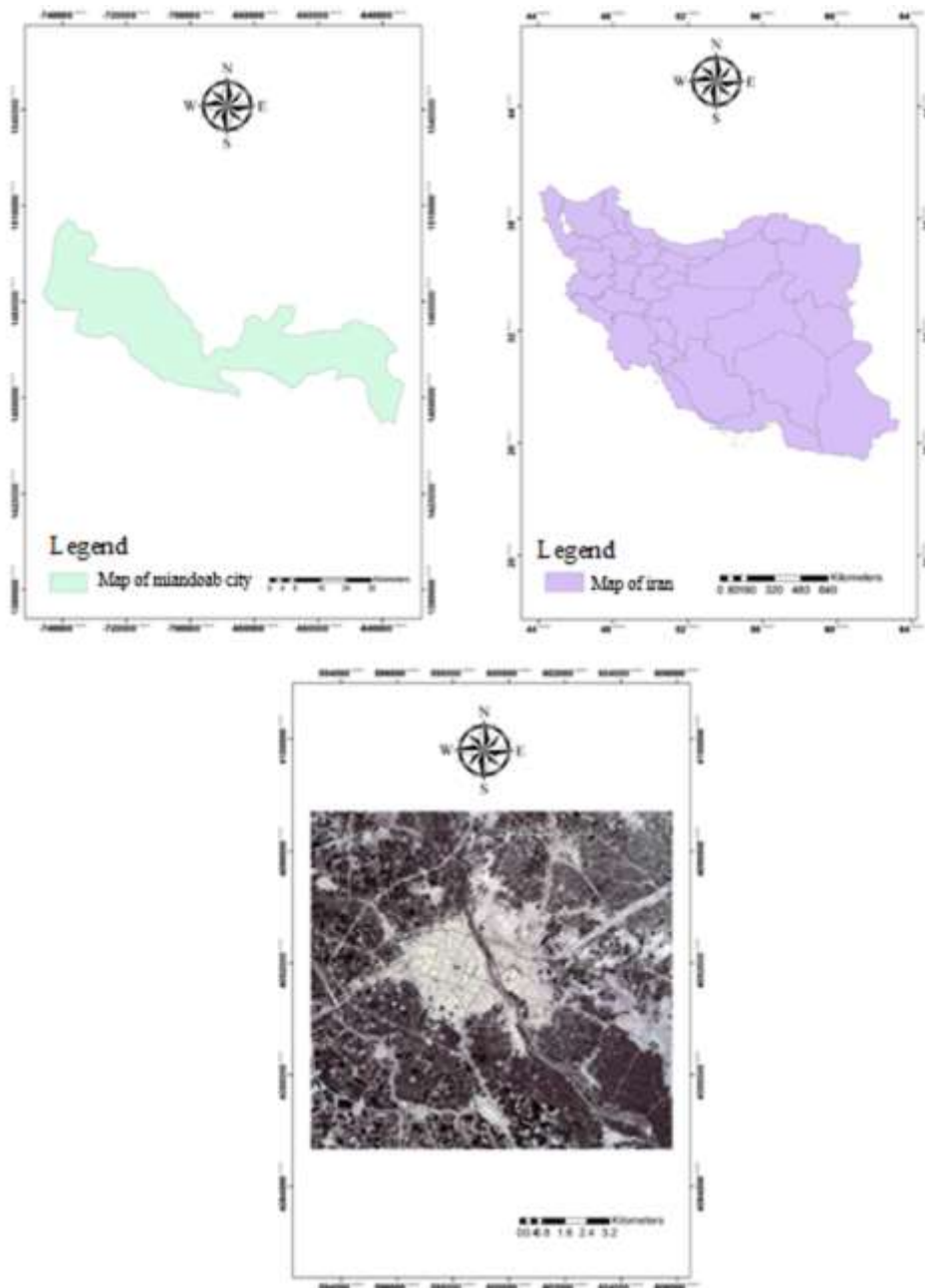


Figure 1. The geographical location of the study area.

2.2. Used Data

Multispectral and panchromatic images of Landsat 8 satellite 2020 have been used as the basis for this study. Training samples, analysis, image integration techniques, as well as land use classification algorithms were performed using the software.

2.3. Select Educational Examples

Educational examples are a set of pixels that are selected as a representative or very similar to each class. One way to find out the quality of instructional examples in classes is to separate, overlap, or spatially overlap. In this design, a combination of panchromatic and multispectral bands was used to spatially display educational samples in different classes. According to this diagram, each class is placed according to the numerical value of the pixels belonging to that educational example and in a certain range of space between the axes of the bands or the more separated from each other, shows good accuracy and correctness of determining educational examples. Figure 2 shows the spatial display of educational samples on Landsat 8 data bands.

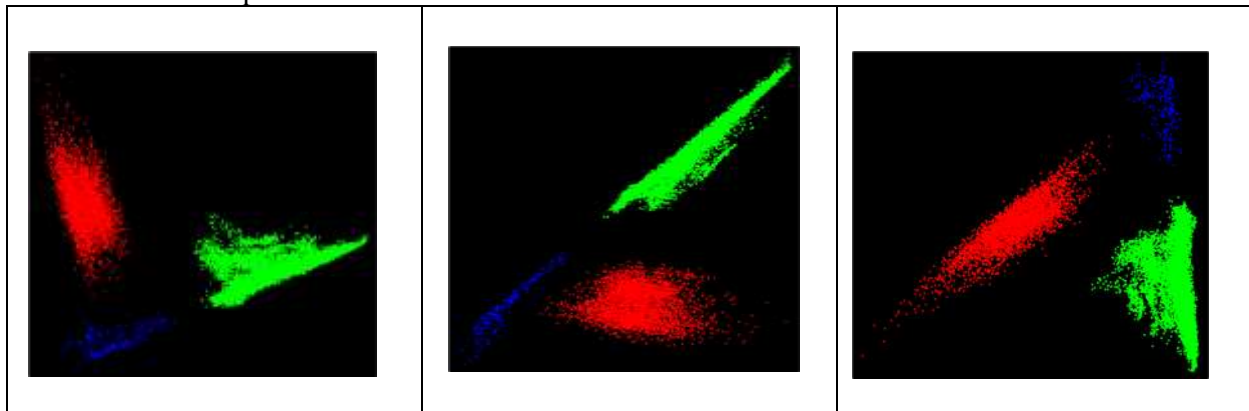


Figure 2. Spatial display of educational examples.

2.4. Image Fusion Technique

The details of earth objects are evident with the continuous improvement of the spatial resolution of remote sensing images (Liu et al., 2013). The act of highlighting or fusion spectral images using panchromatic images, to perform high spatial resolution of images can be effective in improving the accuracy of image classification (Zoleikani et al., 2017). Merge images using conversion (Gramschmidt) GS, image conversion techniques that have been investigated in this study are conversion methods of GS. The overall goal of this technique is to increase the resolution of multispectral images that have been used successfully. This method is able to preserve the properties of low spectral resolution multispectral image in the image resulting from its integration with high-resolution panchromatic data. In this study, to increase the spatial resolution of Landsat images, a panchromatic band with a spatial resolution of 15 meters was used to increase the spatial resolution of other bands from 30 meters to 15 meters.

2.5. Classification of Satellite Images

Classification of satellite images is used to attribute the digital values in the image to groups with homogeneous characteristics, to distinguish different objects or phenomena from each other (Ghose et al., 2010). The separation of similar spectral assemblies and their class division that has the same

spectral behavior is called satellite information classification (Javaheri, 2019). Classification of satellite images is done in a supervised and unsupervised way.

2.6. Supervised Classification

The reflective values of their digits are chosen to be uniform. These areas are called educational areas. The number of training areas will usually be equal to the types of species in each satellite image. Each of these species is called a class. In practice, the numerical values of each class are extracted and recorded in the name of that class. After the existence of each of these classes, it is recorded; the commentators use special computer programs to classify the remaining pixels of the image based on their correspondence with the pixel numbers of the monitored classes. In the present study, support vector machine classification, maximum probability, Mahalanoob distance, and minimum distance were used to prepare the land use map.

2.7. Backup Machine Vector Method

A backup vector machine is one of the new methods for classifying satellite images for the extraction of Land use map. A backup vector machine is one of the recently introduced methods. One of the advantages of this method is one-on-one, in other words, the categories are separated by a line or mega panels, and these lines indicate that the pixel in question is part of this category or is separated from the other category by these mega panels. The closest instructional data to superchargers is called the backup vector machine (Javaheri, 2019). Figure 3 shows the land use map prepared by the backup vector machine method.

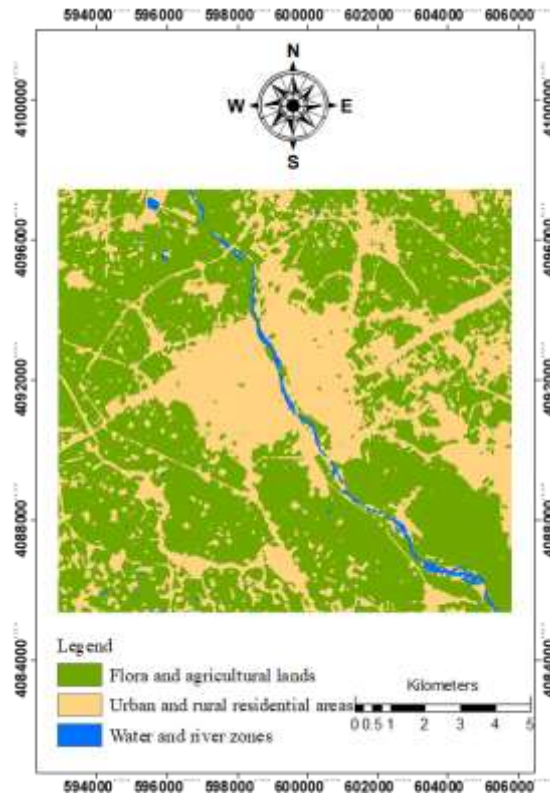


Figure 3. Land use map prepared by backup vector machine method

2.8. Maximum Probability Method

In this method, classification is based on variance and covariance. In this method, it is assumed that all educational areas have a normal distribution. In fact, instances of training classes should be representative of that class, so as many examples as possible should be used to accommodate many variations of spectral properties in this continuous range, attributing the maximum possible pixel probability to a class. It turns out that pixels are most likely to belong to that class. Therefore, the condition of normal distribution in the maximum probability method is of special importance. Figure 4 shows the land use map prepared by the maximum probability method.

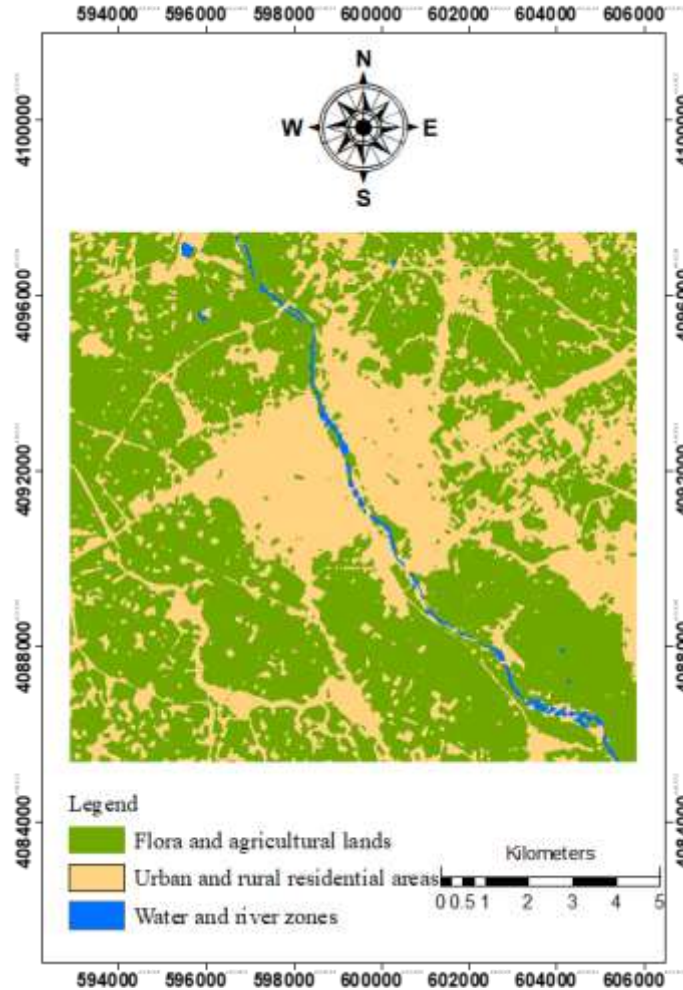


Figure 4. Land use map prepared by the maximum probability method.

2.9. Mahalanob Distance

Mahalanobi distance classification method is another classification method. This method is very similar to the method of minimum distance from the mean, except that in this method, the covariance matrix is used and in this method it is assumed that the histogram of the bands is normal (Kiani, 2014). Figure 5 shows the land use map prepared by the Mahalanob distance method.

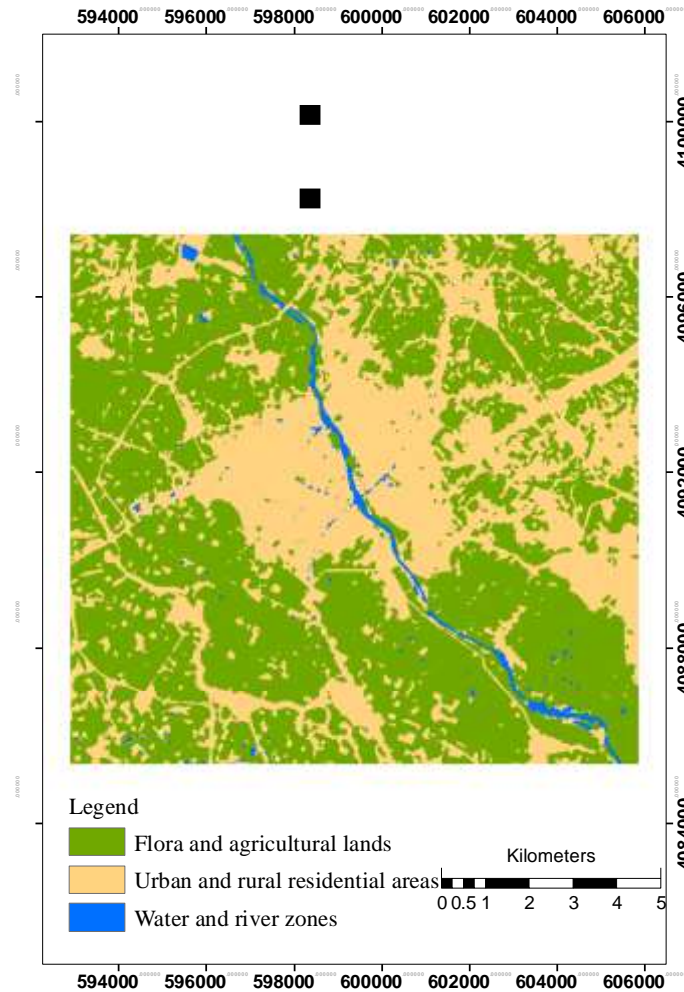


Figure 5. Land use map prepared by Mahalanob distance method.

2.10. Method of Minimum Distance from the Mean

In this classification method, after determining the pixel that has the average spectral value of the selected samples without each class, the distance of each unclassified pixel is compared with the average pixels and the desired pixel is assigned to a class that has the closest distance to its average. In the same way, all the pixels of each image belong to the relevant classes and the different classes of the image are separated (Ahmadpour, 2014). Figure 6 shows the land use map prepared by the method shows the minimum distance from the average.

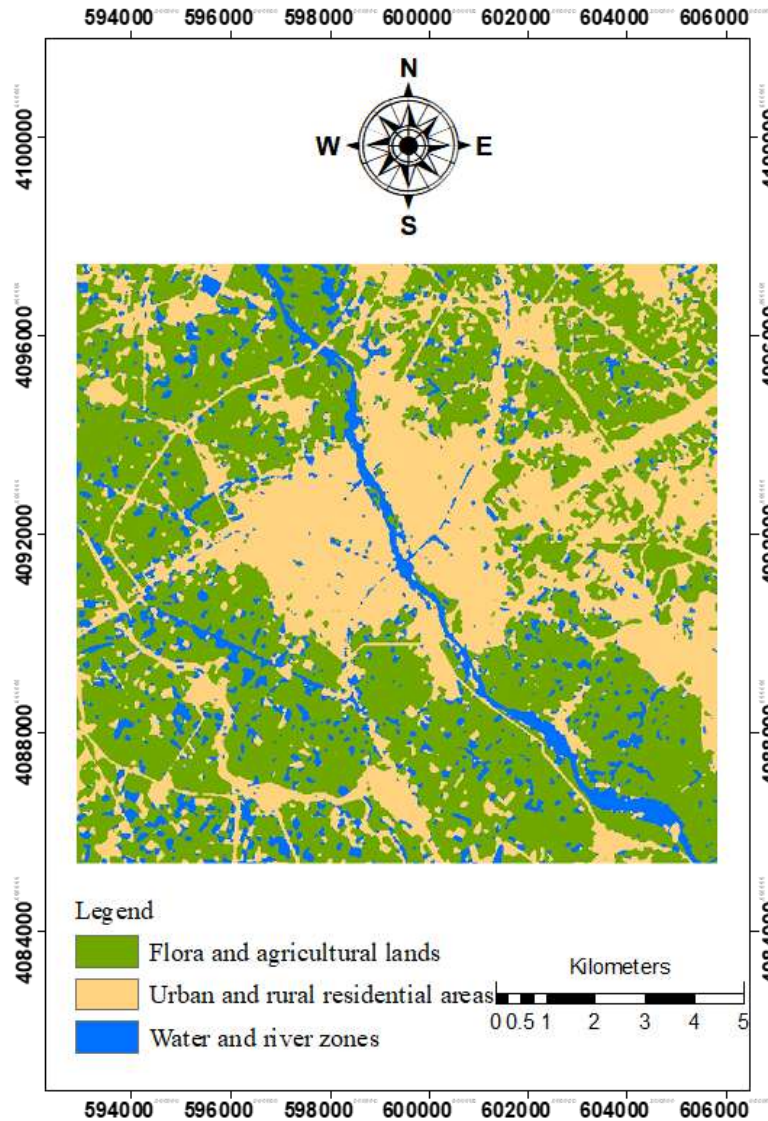


Figure 6. Land use map prepared by the method of minimum distance from the average.

2.11. Assess Classification Accuracy

The use of any kind of thematic information requires knowledge of its correctness and accuracy. After classifying the satellite images, the accuracy of the classified images are evaluated using educational examples that are not involved in the classification process. In the present study, overall accuracy coefficients, kappa coefficient, producer accuracy, user accuracy, omission errors, and commission errors were used to check the accuracy of the classification. The overall accuracy is obtained by summing the elements of the original diameter of the error matrix divided by the total number of pixels according to the following equation:

$OA = \frac{1}{N} \sum p_{ii}$ In this equation, OA is the overall accuracy; N is the number of experimental pixels, the

sum of the elements, and the original diameter of the error matrix. Due to the drawbacks of overall accuracy, the kappa index is often used in executive tasks that focus on classification accuracy, because the kappa index considers incorrectly classified pixels. The kappa index is calculated from Equation 5:

$$1) \text{ kappa} = \frac{P0-PC}{1-PC} * 100$$

This is correctly observed in the above relation $P0$, PC expected agreement. Producer accuracy is the probability that a pixel in the classification image will be placed on the ground in the same class, and user accuracy is the probability that a specific class on the ground in the same class will be placed on the classified image, which is calculated from the following equations:

$$2) PA = \frac{ta}{ga} * 100$$

$$3) UA = \frac{ta}{n1} * 100$$

In these relationships, PA is the percentage of class a accuracy for the manufacturer's accuracy, ta is the number of correct pixels classified as class a , ga is the number of pixels of class a in terrestrial reality, UA is the percentage of class a accuracy for user accuracy, $n1$ is the number of pixels Class a is defined as a result of classification based on the two accuracies mentioned, two commission error and omitted error as follows:

$$4) Ce = 1-UA$$

$$5) Oe = 1-PA$$

The Ce error assigned based on user accuracy is equivalent to the percentage of pixels that did not actually belong to the class, but the classifier considered them to be part of that particular class. Oe deleted error is the percentage of pixels that actually belong to the class in question but are classified as other classes (Yousofi et al., 2011). Tables 1 to 4 show the results of the total accuracy coefficients, kappa coefficient, producer accuracy; user accuracy, Omission error, and commission error of the four classification methods are provided.

Table 1. Backup Machine Classification Accuracy Coefficients.

Overall accuracy	Kappa coefficient	Commission	Omission	User accuracy	Producer accuracy	User accuracy factor	Classification method
100	1	0	0	100	100	Flora and agricultural lands	Backup vector machine
		0	0	100	100	Urban and rural residential areas	
		0	0	100	100	Water and river zones	

Table 2. Maximum Probability Classification Accuracy Coefficients.

Overall accuracy	Kappa coefficient	Commission	Omission	User accuracy	Producer accuracy	User accuracy factor	Classification method
99.9938	0.9998	0.01	0	99.99	100	Flora and agricultural lands	Maximum probability
		0	0	100	100	Urban and rural residential areas	
		0	0.49	100	99.51	Water and river zones	

Table 3. Mahalanob Distance Classification Accuracy Coefficients.

Overall accuracy	Kappa coefficient	Commission	Omission	User accuracy	Producer accuracy	User accuracy factor	Classification method
99.9013	0.9974	0	0	100	100	Flora and agricultural lands	Mahalanob distance
		0	0.41	100	99.59	Urban and rural residential areas	
		7.27	0	92.73	100	Water and river zones	

Table 4. Classification Accuracy Coefficients Minimum Distance from the Mean.

Overall accuracy	Kappa coefficient	Commission	Omission	User accuracy	Producer accuracy	User accuracy factor	Classification method
99.8026	0.9949	0	0	100	100	Flora and agricultural lands	Minimum distance
		0	0.81	100	99.19	Urban and rural residential areas	
		13.56	0	86.44	100	Water and river zones	

3. Discussion

Having new land use maps is very important in many areas, including natural resource management and land planning. Remote sensing data have great potential for up-to-date land use and land cover maps. Using the iterative nature of telemetry data, it is possible to identify and investigate dynamic phenomena in the environment that provide up-to-date information for management purposes. Land use and land cover are dynamic and change over time. Therefore, choosing the right satellite image is very important in conducting telemetry studies. The purpose of this study was to evaluate and compare different monitored classification algorithms in preparing a land-use map of Miandoab city using satellite images.

In this research, Landsat 8 satellite data related to the date 2020 was used to prepare a land-use map of Miandoab city. In this study, after the necessary corrections and initial preprocessing of the images, the data were classified into four methods: backup machine, maximum probability, Mahalanob distance, and minimum distance from the mean. As shown in Figure 2 to 5 and Tables 1 to 4, the classification results show the different methods using satellite image data having the best result and the highest accuracy between the four different classification methods for preparing the land-use map, related to the backup vector machine method with an overall accuracy of 100 and kappa coefficient of 1 %. After the backup vector machine method, the methods of maximum probability with general accuracy are arranged 99.9938 and kappa coefficient of 0.9998%, Mahalanobi distance with general accuracy of 99.9013, and kappa coefficient of 0.9974%, minimum distance from the average with general accuracy of 99.8026 and kappa coefficient of 0.9949 % have the highest accuracy.

Meanwhile, the results of some researchers are consistent with the results of our research. Including Yousefi et al. (2011) using different image classification algorithms, a land-use map of Noor city is prepared and it is concluded that the backup vector machine classification method is more accurate than other methods such as the neural networks. Javaheri et al. (2019) focused on the ability of methods to prepare a land-use map of Kamyaran city with maximum probability, minimum distance, support vector machine, and Mahalanooobi distance classification methods. The research showed the backup vector machine method with an overall accuracy of 91.4 % and a kappa coefficient of 0.88% has the highest accuracy.

Mirzayizadeh et al. (2015) evaluated three algorithms of support vector machine, decision tree, and fuzzy artificial neural network in preparing the ground cover map. Comparing the general accuracy and kappa coefficient obtained for the three classifiers with the appropriate band set compared to the ground reality map showed that the backup vector machine classifier with better accuracy of 91.26% and a kappa coefficient of 0.8731% has better results than other algorithms. Recent research has shown that backup vector machines are more accurate than other classification methods. One of the advantages of the backup vector machine method is that it can solve the problems in the unbalanced difference between the training samples (Yousofi et al., 2011). In general, the research results show the appropriate efficiency of Landsat 8 satellite data for land use mapping to facilitate rangeland management planning, including its suitability classification.

References

- Ahmadpour, A., Soleimani, K., Shokri, M., & Ghorbani, J. (2014). Comparison of the efficiency of three common methods of supervised classification of satellite data in the study of vegetation. *Journal of Remote Sensing and GIS in Natural Resources*, 5(3).
- Akbari, D., Moradzadeh, M., & Akbari, M. (2019). Land use change and simulation of Rasht urban growth and development using neural model and Markov chain automated cells. *Journal of Urban Planning*, 10(3).
- Amanpour, S., & Kamelifar, J. (2017). An analysis of land use changes in metropolises using satellite image analysis in ENVI environment: A case study of Ahvaz metropolis. *Geographical Information Scientific and Research Quarterly*, 26(102).

- Fazeli, A., Ghazavi, R., & Farzaneh, R. (2015). Investigating the performance of land use classification algorithms using image integration techniques in the area under Beheshtabad. *Journal of Remote Sensing and GIS*, 6(1).
- Gardi, C., Panagos, P., Van Liedekerke, M., Bosco, C., & De Brogniez, D. (2014). Land take and food security: Assessment of land-take on the agricultural production in Europe. *Journal of Environmental Planning Management*, 58, 898–912.
- Ghose, M. K., Pradha, R., & Ghose Sucheta, S. (2010). Decision tree classification of remotely. *International Journal of Advanced Computer Science and Applications*.
- Javaheri, S., Tarahi, A., & Tavakoli, A. (2019). Ability of land use mapping methods using satellite images: A case study of Kamyaran city. *Journal of the Application of GIS and Remote Sensing in Planning*, 10(4).
- Khazayi, M., Zare, M., Mokhtari, M., Rashtian, A., & Arabi, F. (2019). Comparing the accuracy of different classification methods in preparing land use map: A case study of Yazd. *Geographical Explorations of Desert Areas*, 7(1).
- Khezri, M., & Soleimani, K. (2017). Application of satellite images to prepare land use map of Ghezel Ozan watershed using fusion technique and object-oriented processing. *Journal of Geographic Information System Application and Remote Sensing in Planning*, 8(3).
- Kiani, V., Alizadeh, A., & Samani, A. (2013). Assessing the accuracy of satellite image classification using google earth database to prepare land use map: A case study of Taleghan watershed. *Geographical Information Quarterly*.
- Liu, E. C., Zhou Wan, C., Zhou Jie, M., Shao Huai, Y., & Yang, X. (2013). Combining spectral with texture features into object oriented classification in mountainous terrain using advanced land observing satellite image. *J. Mt. Sci.* 10(5), 768–776.
- Mazaheri, H., Norouzi, A., & Fatahi, M. (ND). *Evaluating the accuracy of vegetation indices method in preparing land use map*.
- Mirzayizadeh, V., Niknejad, M., & Oladi, J. (2015). Evaluation of non-parametric supervised classification algorithms in land cover mapping using Landsat 8 images. *Journal of Remote Sensing and GIS in Natural Resources*, 6(3).
- Mombeini, M., Asiyabi, M., & Kermshahi, A. (2013). Comparison of maximum probability and fuzzy methods in preparing land use map of southern Khuzestan land use. *Journal of Remote Sensing Application and GIS in Natural Sciences and Resources*, 4(2).
- Mousavi, M., & Yazdani, R. (2016). Evaluation and simulation of land use changes around cities using CA-Markov model: A case study of Miandoab city. *Scientific and Research Journal of Geography and Planning*, 20(58).
- Niyazi, Y., Ekhtesasi, M., Malekinejad, H., & Hosseini, Z. (2000). Comparison of two class methods maximum probability classification and artificial neural network in land use map extraction: a case study of Ilam dam basin. *Journal of Geography and Development*, 20.
- Yousofi, S., Tazeh, M., Mirzayi, S., Moradi, H., & Tavangar, S. (2001). Comparison of different algorithms for classifying satellite images in land use mapping: A case study of Noor city. *Journal of the Application of Remote Sensing and GIS in Natural Resources Sciences*, 2(2).
- Zoleikani, R., Valadan, Z., & Mokhtarzadeh, M. (2017). Comparison of pixel and object oriented based classification of hyper-spectral pan-sharpened images. *Indian Soc Remote Sens*, 45(1), 25–33.