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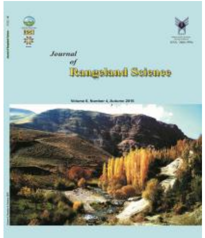

Research and Full Length Article:

Determination of Best Supervised Classification Algorithm for Land Use Maps using Satellite Images (Case Study: Baft, Kerman Province, Iran)

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Abstract. According to the fundamental goal of remote sensing technology, the image classification of desired sensors can be introduced as the most important part of satellite image interpretation. There exist various algorithms in relation to the supervised land use classification that the most pertinent one should be determined. Therefore, this study has been conducted to determine the best and most suitable method of supervised classification for preparing the land use maps involving no grazing, heavy and moderate grazing rangelands, ploughed rangelands for harvesting licorice roots and dry land and fallow lands in Baft, Kerman province, Iran. After being assured of accuracy and lack of geometric and radiometric errors, the images of Landsat and ETM+ sensors achieved on 3 July 2014 have been used. A variety of algorithms involving Mahalanobis distance, Minimum distance, Parallelepiped, Neural network, Binary encoding and Maximum likelihood was investigated based on field data which were obtained simultaneously. These algorithms were compared with respect to error matrix indices, Kappa coefficient, total accuracy, user accuracy and producer accuracy of maps using ENVI 4,5. The results indicated that the Maximum likelihood algorithm with Kappa coefficient and total accuracy of map estimated as 0.969 and 97.77% were regarded as the best supervised classification algorithm in order to prepare the land use maps. Mahalanobis distance algorithm had a low ability for recognizing two types of dry land and fallow land uses concerning the extracted maps. According to the findings, various land use maps as rangelands under three grazing intensities and ploughed rangelands to harvest the licorice roots provided by the means of algorithms related to neural networks were not of sufficient accuracy. The highest Kappa coefficient of Neural network algorithms was estimated as 0.5 and attributed to the algorithm of multilayer perceptron neural network with the logistic activation function and one hidden layer.

Key words: Rangeland ecosystem, Land use, Remote sensing, Accuracy, Neural network

Introduction

Awareness of land use type and percent regarded as a management element can contribute the planners in a variety of execution sections of management and development. Determining the position of each land use and vegetation helps the managers in the decision making. Nowadays, remote sensing data are more likely to present the required information in order to study the vegetation and land uses. Satellite images are of considerable importance due to data timeliness, variety of forms, digitalization and processing with respect to the land use maps.

As the most land use changes have been allocated to Kerman province (Saffari, 2004; Esmali and Abdollahi, 2010), it is necessary to use the satellite images as a new and cheap method. Interference of soil and vegetation reflections particularly in semi-arid and arid regions led to some difficulties in interpreting the satellite data digitally (Alavipanah, 2003). Nowadays, investigating the qualitative contents of satellite data concerning different geology studies has attracted the attention (Shirazi *et al.*, 2010). Shresth and Zinck (2001) separated the dry land uses with the accuracy given as 76% in order to draw the land use maps of Likokola River using the experimental pixels in Nepal. Vahedi (2001) has mapped the land use with the maximum likelihood algorithm using TM digital data and the supervised classification method in Jahan Nama region. Luciana *et al.* (2007) have studied the changes of forest communities in Turkey with an area of 1778 km^2 by the means of supervised classification method with the closest adjacent algorithm based on the production maps and Kappa coefficient of 0.94. They concluded that the forests had increased by 6.7%. Ahmadisani *et al.* (2008) investigated the capability of sensing images in order to prepare the density maps of Zagros forests using the supervised classification method with regard to the minimum distance, maximum likelihood and fuzzy with total accuracy and Kappa coefficient computed as 68.5 and 51.5%, respectively in Marivan.

Shirazi *et al.* (2010) introduced such indices as TSAVI (transformed soil adjustment vegetation index), DVI (difference vegetation index), IPVI (Infrared Percentage Vegetation Index) and NIR (Normalized Infrared Ratio) as suitable ones for the revival of vegetation and INT1 (Intensity within the VIS_NIR spectral range), SI3 (Salinity Index three), SI2 (Salinity Index two), TVI (Triangular Vegetation Index), PVI (Perpendicular Vegetation Index) and SI1 (Salinity Index one) for soil salinity in arid regions. Sanjari and Boromand (2013) in a study using Landsat satellite images reported that the area of industrial, residential and garden lands has been increased three decades ago. Ariapour *et al.* (2013) in a research with the maximum likelihood algorithm of supervised classification method reviewed the land use changes during 1987-2007, and concluded that due to incorrect exploitation of water resources and vegetation, the land use changes have resulted in dry lands and deserts while decreasing the vegetation percent of good rangelands. Nasri *et al.* (2013) claimed that the most land use changes from rangelands to residential areas were observed in Ardestan region, Iran 30 years ago. Faramarzi *et al.* (2013) in a study applied three algorithms of three classification involving Ginny, Entropy and interest rate in order to prepare land use maps and introduced Ginny method as the best one. Yousefi *et al.* (2015) compared different algorithms such as the Minimum Distance of Mean (MDM), Mahalanobis Distance (MD), Maximum Likelihood (ML), Artificial Neural Network (ANN), Spectral Angle Mapper (SAM), and Support Vector Machine (SVM) for land use mapping in dry climate using satellite images in central regions of Iran. Their results showed that maximum likelihood and support vector machine algorithms with the averages of 0.9409 and 0.9315 Kappa coefficients are the best algorithms for land use mapping.

Quick and continuous recognition of land use changes by the means of ordinary methods like field operations may be time-consuming, difficult and expensive. Therefore, satellite data can be considered as one of the important information sources in this regard and allow the extent study of vegetation and land use changes. Based on the basic purpose of remote sensing technology, classifying the images of desired sensors may be regarded as the most important part of studying and interpreting the satellite data (Srivastava and Gupta, 2003). Thus, this study has been conducted to determine the best supervised classification method in order to draw the land use maps in Baft, Kerman province.

Materials and Methods

Regarding the research goal, a same ecological region with various land uses involving no grazing, heavy and moderate grazing sites, ploughed lands for harvesting licorice roots, dry land and fallow lands was selected for field operations in Baft township, Kerman, Iran in 2014. This selected region had 23500 ha areas and was located at 455122 to 455125 eastern longitude and 3234357 to 3235288 northern latitude at the scale of UTM (Fig. 1). Landsat satellite image was first provided by the coordinates given in Table 1.

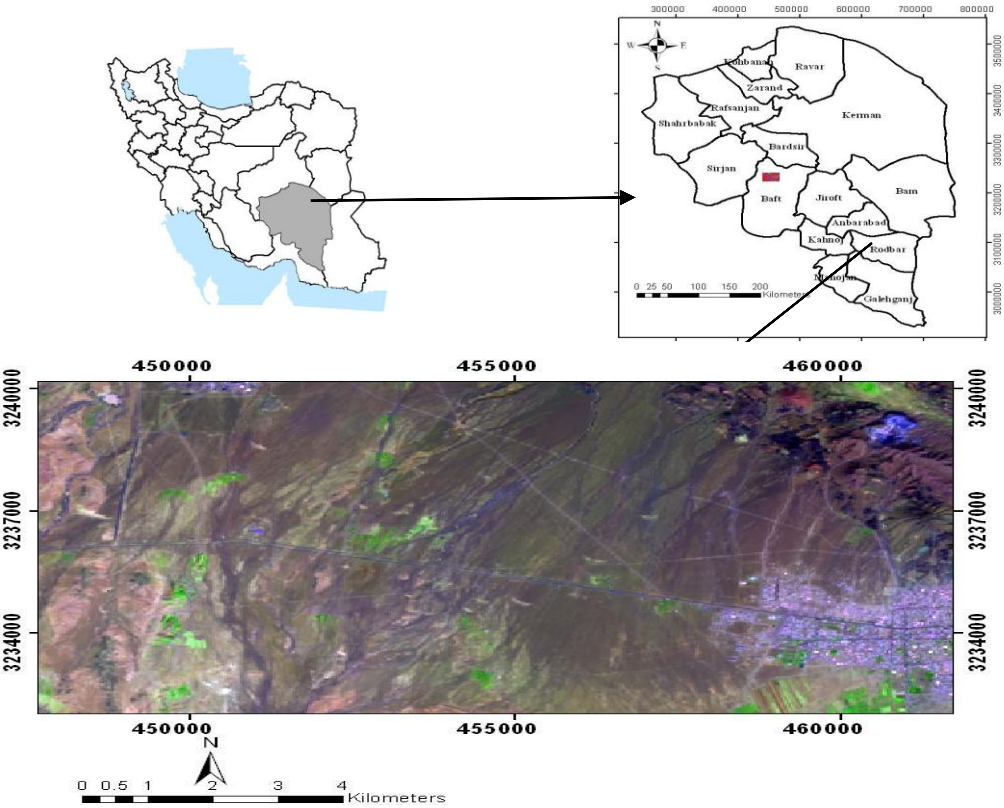


Fig. 1. Location of studied regions in Kerman province (RGB: 7,4,1 bands)

Table 1. Characteristics of Landsat satellite image

Satellite	Sensor	Spatial accuracy	Band number	Imaging time
Landsat	ETM^+	28.5 m	8	3 July 2014

Although satellite data have been corrected in terms of geometry and radiometry at different levels, it is possible to remain some primary errors or make new errors resulting from primary correction process; thus, it is essential to review the images before performing any analyses. No radiometric errors including striped disruption and repeated pixels were found in the given images. Georefrencing process was conducted by 4 sharp points for all bands and Root of Mean Square Error (RMSE) obtained less than 0.5. After being assured of no mentioned errors, Internal Average Relative Reflectance (IARR) correction and contrast improvement operation of images were done with regard to the atmospheric errors using ENVI 4.5 software (Research Systems Institute, 2008).

Algorithms including Parallelepiped, Minimum distance, Mahalanobis distance, Maximum likelihood, Binary encoding, Neural network with logistic and hyperbolic activation functions using 1 and 2 hidden layers were investigated to determine the best supervised classification algorithm.

Since the supervised classification is based on the exact recognition of desired classes, these pre-recognitions are called educational models in data classification. After selecting and specifying the classes, educational models are to be determined for each class because the method is based upon spectral features of educational models. For classifying them, educational models have been first specified in accordance with the date of studied image on the basis of field operations and field visits after preparing Region of Interest ROI Tool in order to analyze various supervised algorithms. Finally, evaluating the accuracy of maps is very important concerning the land use maps. Since the most common method for the accuracy evaluation of satellite image maps is to analyze the error matrix, such criteria as total accuracy, Kappa coefficient, producer accuracy and user accuracy in different classification scenarios have been compared. In this respect, total accuracy (Dellepiane and Smith, 1999) and Kappa coefficient (Foody, 1992) were estimated by the following equations (Equations 1 & 2):

$OA=1/N\ (\Sigma Pii)$ (1)

$K= (OA-1/q)\ (1-1/q)$ (2)

Where:

OA= the overall accuracy,

N= the total number of training pixels,

ΣPii = the sum of correctly classified pixels,

K= Kappa coefficient,

q= incorrectly classified pixels.

After selecting the best algorithm based on the mentioned criteria, the land use map has been drawn using ArcGIS 9.1 software.

Results

Results achieved by the error matrix of studied algorithms for each land use have been presented in Tables 2-10. According to these Tables, majority of land uses were recognized very well in Maximum likelihood algorithm (Table 2). Identification of heavy grazing rangeland and dry land sites were weak in Minimum distance algorithm (Table 3) and Mahalanobis distance algorithm (Table 4). There was no difference between the plowed rangeland and dry land sites in Binary encoding algorithm (Table 5). Reorganization between fallow and dry land sites was week in Parallelepiped algorithm (Table 6). Almost all land use sites had some identification interactions in Neural network algorithms with different activation functions and different hidden layers (Tables 7-10). So, in Neural network algorithm with hyperbolic activation function and 2 hidden layers (Table 8) and Neural network algorithm with hyperbolic activation function and 1 hidden layer (Table 9), all land uses had been recognized as no grazing rangeland and fallow, respectively. According to these tables, activation function of Neural network algorithms as an important factor can affect the recognition processes of land use types. These tables showed that logistic activation function is better than the hyperbolic one. In spite of Neural network with hyperbolic activation function (1 hidden layer), Maximum likelihood algorithm has the highest ability in recognizing all the different land uses.

Table 2. Error matrix of Maximum likelihood algorithm

Classes	Ground truth (%)							
	No grazing	Moderate grazing	Plowed rangeland	Heavy grazing	Fallow	Dry land	Residential areas	Total
No grazing rangeland	97.45	4.55	0	0	0	0	0	25.12
Moderate grazing rangeland	1.91	92.73	0	0	0	0	0	16.69
Plowed rangeland	0	0.91	100	0	0	0	0	5.41
Heavy grazing rangeland	0	0	0.0096	5.26	0	0.3	0	4.29
Fallow	0	0	0	0	100	0	0	3.82
Dry land	0	1.82	0.003	0.7	0	94.74	0	3.34
Residential areas	0.64	0	0	0	0	0	100	41.34

Table 3. Error matrix of Minimum distance algorithm

Classes	Ground truth (%)							
	No grazing	Moderate grazing	Plowed rangeland	Heavy grazing	Fallow	Dry land	Residential areas	Total
No grazing rangeland	84.71	1.82	0	0	0	0	0	21.5
Moderate grazing rangeland	3.82	92.73	0	0	33.33	0	0	18.4
Plowed rangeland	0	0.91	69.70	0	12.5	21.05	0	4.9
Heavy grazing rangeland	0	0	0	0.19	4.17	15.79	0	4.3
Fallow	11.46	4.55	12.12	0	37.5	0	0.39	5.9
Dry land	0	0	18.18	0.81	12.5	63.16	6.18	6.5
Residential areas	0	0	0	0	0	0	93.44	38.5

Table 4. Error matrix of Mahalanobis distance algorithm

Classes	Ground truth (%)							
	No grazing	Moderate grazing	Plowed rangeland	Heavy grazing	Fallow	Dry land	Residential areas	Total
No grazing rangeland	90.45	5.45	0	0	0	0	0.39	23.7
Moderate grazing rangeland	8.92	90.91	3.03	0	12.5	0	3.47	20.2
Plowed rangeland	0	1.82	78.79	0	12.5	0	0.77	5.3
Heavy grazing rangeland	0	0	0	0.59	0	15.79	0.39	4.6
Fallow	0.64	1.82	15.15	0	62.5	0	1.16	4.1
Dry land	0	0	3.03	0.41	12.5	84.21	1.93	4.3
Residential areas	0	0	0	0	0	0	91.89	37.8

Table 5. Error matrix of Binary encoding algorithm

Classes	Ground truth (%)							
	No grazing	Moderate grazing	Plowed rangeland	Heavy grazing	Fallow	Dry land	Residential areas	Total
No grazing rangeland	56.69	0.91	0	0	0	0	3.09	15.6
Moderate grazing rangeland	40.76	95.45	6.1	0	50	0	25.1	39.4
Plowed rangeland	0	0	42.4	7.41	29.17	47.37	8.11	8.4
Heavy grazing rangeland	0	0	0	92.59	0	10.53	0.39	4.5
Fallow	0	3.64	36.4	0	20.83	5.26	16.22	10.2
Dry land	2.55	0	0	0	0	36.84	3.09	3.0
Residential areas	0	0	15.2	0	0	0	44.02	18.9

Table 6. Error matrix of Parallelepiped algorithm

Classes	Ground truth (%)							
	No grazing	Moderate grazing	Plowed rangeland	Heavy grazing	Fallow	Dry land	Residential areas	Total
No grazing rangeland	98.09	70	0	0	54.17	0	0	38.79
Moderate grazing rangeland	0.64	26.36	0	0	8.33	0	0	5.09
Plowed rangeland	0.64	3.64	97.0	77.78	33.33	68.42	0	12.56
Heavy grazing rangeland	0	0	0	18.52	0	15.79	0	1.27
Fallow	0.64	0	0	3.7	4.17	10.53	0	0.79
Dry land	0	0	3.0	0	0	5.26	0	0.32
Residential areas	0	0	0	0	0	0	95.75	39.43

Table 7. Error matrix of Neural network (logistic activation function / 2hidden layers) algorithm

Classes	Ground truth (%)							
	No grazing	Moderate grazing	Plowed rangeland	Heavy grazing	Fallow	Dry land	Residential areas	Total
No grazing rangeland	0	0	0	0	0	0	0	0.0
Moderate grazing rangeland	77.07	11.82	0	0	0	0	0	21.3
Plowed rangeland	0	0	0	0	0	0	0	0.0
Heavy grazing rangeland	13.38	39.09	51.52	0.81	58.33	10.53	0.39	16.2
Fallow	9.55	49.09	0	0	20.83	0	0	11.8
Dry land	0	0	0	0	0	0	0	0.0
Residential areas	0	0	48.48	0.19	20.83	89.47	99.61	50.7

Table 8. Error matrix of Neural network (hyperbolic activation function / 2hidden layers) algorithm

Classes	Ground truth (%)							
	No grazing	Moderate grazing	Plowed rangeland	Heavy grazing	Fallow	Dry land	Residential areas	Total
No grazing rangeland	100	100	100.0	100	100	100	100	100.0
Moderate grazing rangeland	0	0	0	0	0	0	0	0
Plowed rangeland	0	0	0	0	0	0	0	0
Heavy grazing rangeland	0	0	0	0	0	0	0	0
Fallow	0	0	0	0	0	0	0	0
Dry land	0	0	0	0	0	0	0	0
Residential areas	0	0	0	0	0	0	0	0

Table 9. Error matrix of Neural network (hyperbolic activation function / 1hidden layer) algorithm

Classes	Ground truth (%)							
	No grazing	Moderate grazing	Plowed rangeland	Heavy grazing	Fallow	Dry land	Residential areas	Total
No grazing rangeland	0	0	0	0	0	0	0.77	0.3
Moderate grazing rangeland	0	0	0	0	0	0	0	0
Plowed rangeland	0	0	0	0	0	0	0	0
Heavy grazing rangeland	0	0	0	0	0	0	0	0
Fallow	100	100	100.0	100	100	100	99.23	99.7
Dry land	0	0	0	0	0	0	0	0
Residential areas	0	0	0	0	0	0	0	0

Table 10. Error matrix of Neural network (logistic activation function / 1hidden layer) algorithm

Classes	Ground truth (%)							
	No grazing	Moderate grazing	Plowed rangeland	Heavy grazing	Fallow	Dry land	Residential areas	Total
No grazing rangeland	63.06	0	0	0	0	0	0	15.7
Moderate grazing rangeland	0	0	0	0	0	0	0	0.0
Plowed rangeland	0.64	5.45	0	0	0	0	0	1.1
Heavy grazing rangeland	0	0	0	0	0	0	0	0.0
Fallow	24.2	87.27	0	0	37.5	0	0	22.7
Dry land	12.1	7.27	96.97	0.3	58.33	73.68	0	18.0
Residential areas	0	0	3.03	0.7	4.17	26.32	100	42.5

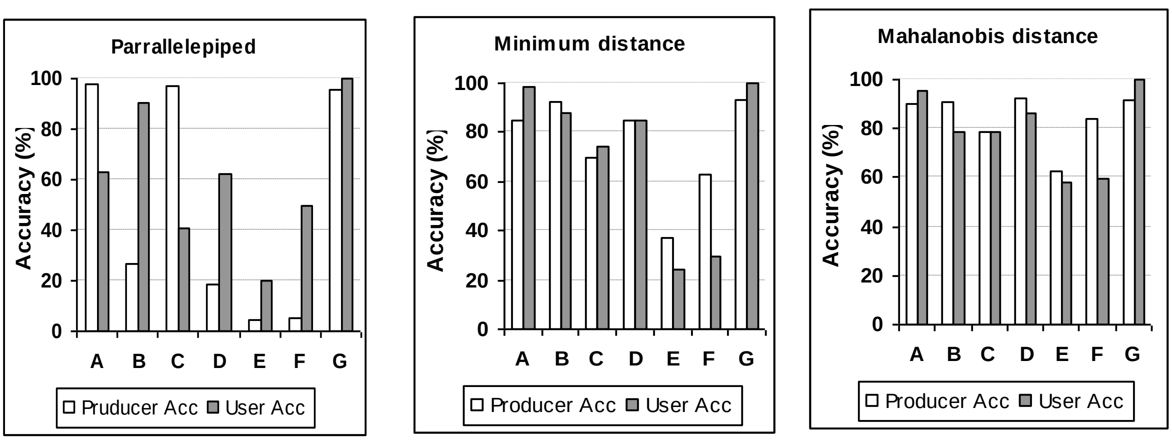
Findings of Kappa coefficient and total accuracy of desired maps concerning different algorithms have been shown in Table 11. The results illustrated that Kappa coefficient and overall accuracy of Maximum likelihood algorithm were

0.969 and 97.77, respectively and Neural network with hyperbolic activation function and 1hidden layer had minimum Kappa coefficient and overall accuracy.

Table 11. Kappa coefficient and overall accuracy for different algorithms

Algorithms	Overall Accuracy (%)	Kappa Coefficient
Parallelepiped	74.7	0.65
Minimum distance	86.5	0.82
Mahalanobis distance	89.3	0.85
Maximum likelihood	<u>97.77</u>	<u>0.9695</u>
Binary encoding	57	0.46
Neural network/logistic activation function / 1hidden layer	60.5	0.5
Neural network/logistic activation function / 2hidden layers	44.5	0.25
Neural network/hyperbolic activation function / 1hidden layer	3.8	0
Neural network/hyperbolic activation function / 2hidden layers	22.19	0

User and producer accuracies of every scenario regarding various applications have been demonstrated in Fig. 2. User and producer accuracies of Parallelepiped algorithm were minimum in fallow site. Minimum distance algorithm can separate all sites with 70% accuracy except fallow and dry land sites. Both of user and producer accuracies of all sites were above 70% in Mahalanobis distance algorithm and above 85% in Maximum likelihood algorithm. User and producer accuracies obtained by Binary encoding algorithm were acceptable only in Heavy grazing rangeland. Neural network algorithms showed that recognizing the sites by logistic activation functions was better in comparison to hyperbolic activation functions. According to these figures, user and producer accuracies of some algorithms involving Mahalanobis distance, Minimum distance, Parallelepiped, Binary encoding were the least in fallow land use despite the fact that the capability of Maximum likelihood algorithm was the highest in fallow one. Neural network algorithm with hyperbolic activation function with 1 hidden layer could only distinguish fallow land use with a user accuracy that was lower than producer accuracy. Neural network algorithm with hyperbolic activation function with 2 hidden layers could only distinguish no grazing rangeland land use with a user accuracy that was lower than the producer one. Neural network algorithm with logistic activation function with 1 hidden layer did not recognize such land uses as plowed rangeland and rangelands under moderate and heavy grazing. Some land uses including dry land, plowed rangeland and no grazing rangeland were not recognized by Neural network algorithm with logistic activation function with 2 hidden layers.



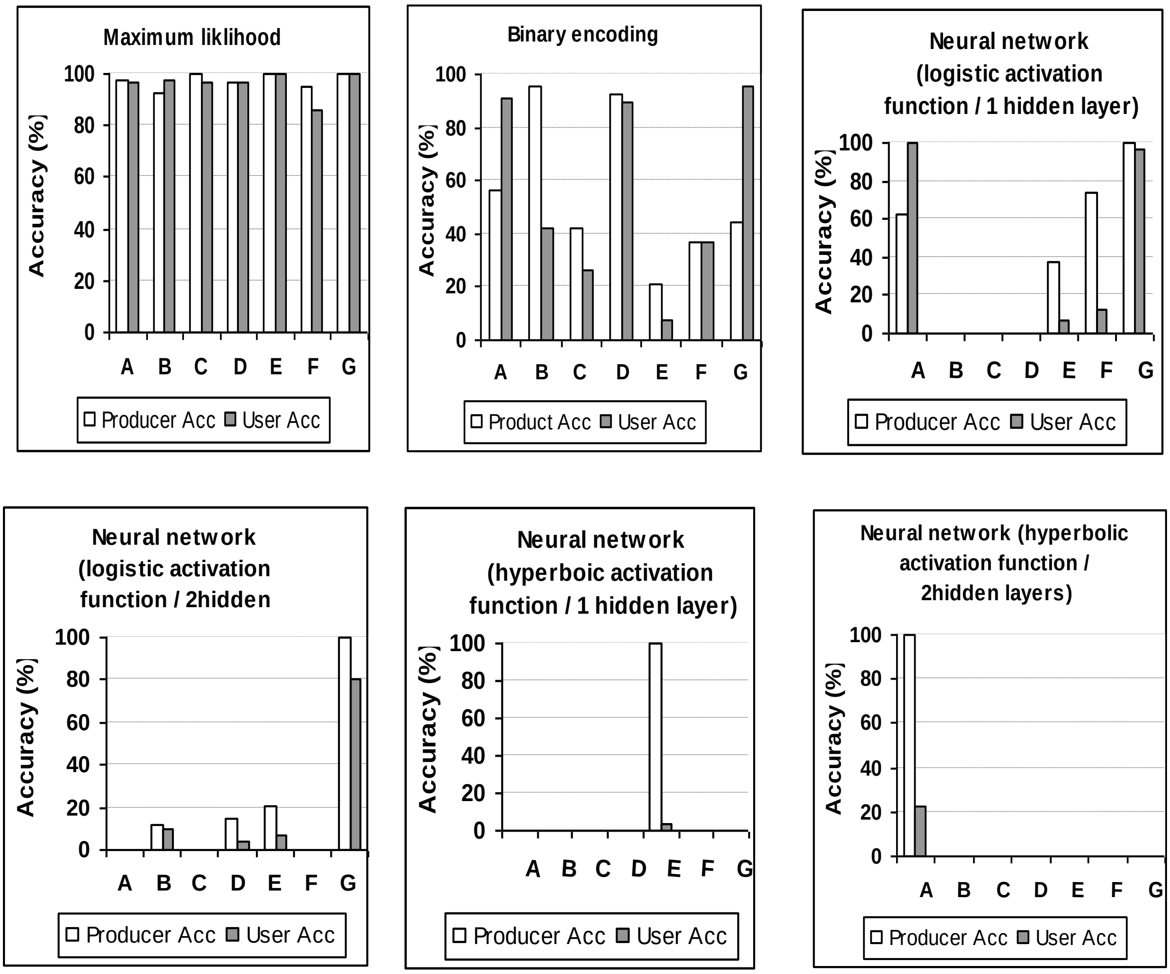


Fig. 2. User accuracy and producer accuracy of different algorithms on different land uses (land uses on x axis's included as A: No grazing rangeland, B: Moderate grazing rangeland, C: Plowed rangeland, D: Heavy grazing rangeland, E: Fallow, F: Dry land and G: Residential areas).

Finally, land use map with the best resultant algorithm was displayed in Fig. 3 by ArcGIS 9.1 software. The separation ability of supervised classification of Landsat images (ETM+ sensors) by Maximum likelihood algorithm in all the studied sites was acceptable. Therefore, the map obtained by this algorithm can be utilized in the operations related to land uses in execution sections of management and development of ecosystems of Baft township.

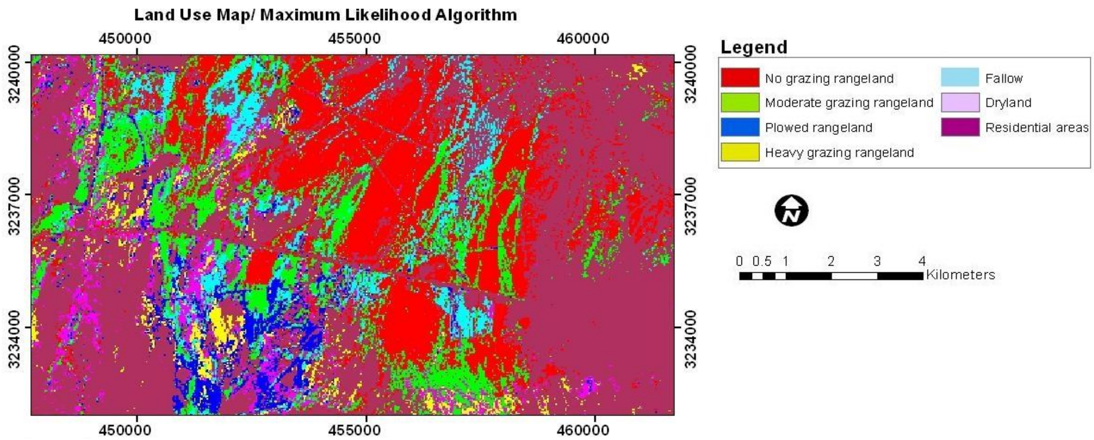


Fig. 3. The best land use map of study area by maximum likelihood algorithm

Discussion

According to the results, the maximum likelihood algorithm with Kapa coefficient and total accuracy have been estimated as 0.969 and 97.77%, respectively. This supervised classification algorithm is able to provide land use maps with low omission and commission errors so that user and producer accuracies of maps were given as 95% with regard to all land uses except the dry land one which was of the user accuracy of 85%. Low error of maximum likelihood algorithm based upon Kappa coefficient, total accuracy and user and producer accuracies is in accordance with that reported by Alavipanah *et al.* (2001), Arzani *et al.* (2009), Sanjari and Boroumand (2013) and Lillesand and Kiefer (2012) who had introduced the maximum likelihood method as the best classification method of land uses.

The results showed that although Mahalanobis algorithm was the second one to have the highest Kappa coefficient and total accuracy after the maximum likelihood algorithm, it should be mentioned that this method had higher commission and omission errors in terms of fallow land use; on the other hand, commission error is high for the Dry land use. It is difficult to recognize these two land uses in a map extracted by the means of Mahalanobis algorithm as compared to the other land uses because according to the error matrix Table, it is unlikely to separate the dry land from those with heavy grazing by the help of mentioned algorithm in comparison with maximum likelihood algorithm. This result is confirmed by the findings presented by Jafari *et al.* (2013).

Research results of error matrix Tables indicated that with respect to the other methods such as minimum distance algorithm, it is rare to distinguish the sites with heavy grazing from dry land ones. Also, separating Binary and Parallelepiped is very difficult in order to identify the fallow lands so that using binary algorithm, the abandoned lands cannot be distinguished from the ploughed licorice lands; on the other hand, using Parallelepiped algorithm is more unlikely to separate the abandoned lands (fallows) from the dry land ones.

Preparing a variety of land use maps using the related algorithms and neural network was not of sufficient accuracy and precision. The highest Kappa coefficient as 0.5 was attributed to multilayer perceptron neural network algorithm with logistic activation function and hidden layer and the omission (producer) and commission (user) error given as 100% were found for identifying three land uses as the ploughed site in order to harvest the licorice roots and heavy and moderate grazing. This result indicating low precision of neural network in order to separate various land uses corresponds to that reported by Mazaheri *et al.* (2013). Since number of educational models and their distribution type in the supervised method play significant roles in determining the precision of produced maps. In this regard, as the distribution of educational models is closer to the normal distribution, results of maximum likelihood algorithm are of higher accuracy indices (Alavipanah *et al.*, 2009) and as their distribution is irregular with no specific pattern, results of neural network methods are more exact; in addition, the increased number of samples in neural network methods can enhance their effectiveness (Alborzi, 2007).

It seems that considering the pattern of educational data presented in the current research, maximum likelihood algorithm is of more effectiveness than neural network algorithms. When maximum likelihood algorithm has a low efficiency in specifying the land uses, it is proposed that in order to increase the efficiency of neural network algorithms as a new method, number of data is to be

increased. It should be pointed out that in this paper, number of hidden layers 1 and 2 with two activation functions was tested and the hidden layer 1 with logistic activation function is more accurate than two other layers due to number of outputs or number of land uses that is low.
In general, it can be concluded that maximum likelihood algorithm regarded as the best algorithm of supervised classification method may be introduced to determine various land uses in current research. According to the results of superiority of maximum likelihood algorithm and existence of more commission error in the dry land, it is suggested that in order to remove this deficiency, such educational models with unmixed pixels and wider location area are provided.

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تعیین بهترین الگوریتم طبقه‌بندی نظارت شده جهت تهیه نقشه کاربری اراضی با استفاده از تصاویر ماهواره‌ای (مطالعه موردی: شهرستان بافت)

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چکیده. با توجه به هدف اصلی تکنولوژی سنجش از دور، طبقه‌بندی تصاویر سنجنده‌های مورد نظر را می‌توان به عنوان مهمترین بخش مطالعه تفسیر تصاویر ماهواره‌ای به شمار آورد. الگوریتم‌های مختلفی متناسب با کاربری اراضی در طبقه‌بندی نظارت شده وجود دارد که باید دقیق‌ترین آنها را مشخص نمود. بنابراین پژوهش حاضر به منظور تعیین بهترین روش طبقه‌بندی نظارت شده جهت تهیه نقشه کاربری اراضی شامل مراتع تحت سه شدت چرای سنگین، متوسط و بدون چرا، مراتع شخم خورده جهت برداشت شیرین بیان، دیمزار و دیمزار رها شده (آیش) در شهرستان بافت استان کرمان انجام شد. از تصویر تاریخ ۱۳۹۳/۰۴/۱۲ ماهواره Landsat و سنجنده ETM^+، پس از اطمینان از عدم وجود خطای رادیومتریک و هندسی، استفاده شد. بر مبنای داده‌های صحرایی برداشت شده همزمان، الگوریتم‌های مختلف (Parallelepiped, Minimum distance, Mahalanobis distance, Maximum likelihood, Binary encoding, Neural network) بر اساس شاخص‌های ماتریس خطا، ضریب کاپا، صحت کلی، صحت کاربر و صحت تولیدکننده نقشه در محیط نرم افزاری ENVI 4,5 مورد مقایسه قرار گرفتند. طبق نتایج این تحقیق الگوریتم حداکثر تشابه با ضریب کاپا معادل ۰/۹۶۹ و صحت کلی نقشه معادل ۹۷/۷۷ درصد بعنوان بهترین الگوریم طبقه‌بندی نظارت شده جهت تولید نقشه‌های کاربری اراضی در منطقه معرفی می‌شود. توانایی تشخیص دو نوع کاربری آیش و دیمزار در نقشه استخراج شده با الگوریتم ماهالانوبیس کمتر بود. طبق یافته‌ها نقشه‌های مختلف کاربری اراضی توسط الگوریتم‌های مرتبط با روش‌های شبکه عصبی از دقت کافی در تفکیک کاربری اراضی مرتعی تحت سه شدت چرایی و مرتع شخم خورده جهت برداشت ریشه شیرین بیان برخوردار نبودند. بالاترین ضریب کاپا در الگوریتم‌های شبکه عصبی پرسپترون چندلایه که معادل ۰/۵ بود به رویه تابع فعال‌سازی لوجستیک با یک لایه میانی تعلق داشت.

کلمات کلیدی: اکوسیستم مرتع، کاربری اراضی، سنجش از دور، صحت، شبکه عصبی