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Remote Sensing and Land Use Extraction for Kernel Functions Analysis by Support Vector Machines with ASTER Multispectral Imagery

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Abstract

Land use is being considered as an element in determining land change studies, environmental planning and natural resource applications. The earth's surface study by remote sensing has many benefits such as, continuous acquisition of data, broad regional coverage, cost effective data, map accurate data, and large archives of historical data. To study land use / cover, remote sensing as an efficient technology is always desired by experts. In this case, classification could be considered as one of the most important methods of extracting information from digital satellite images. Selecting the best classification method and applying the proper values for parameters extremely influences the trust level of extracted land use maps. This research is an applied study which attempts to introduce Support Vector Machines (SVM) classification method, a recent development from the machine learning community. Moreover, we prove its potential for structure–activity relationship analysis on Aster multispectral data of the central county in the Kabodar-Ahang region of Hamedan, Iran. Accuracy of SVMs method is varied by the type of kernel function and its parameters. The purpose of this research is to find the accuracy of land use extraction by SVM method using a Polynomial and radial basis functions kernel with their estimated optimum parameters in addition to comparing the results with Maximum Likelihood Method. Most of the scientists imply that Maximum Likelihood Method is suitable for classification. Therefore, we try to compare SVM with ML method and to deliberate the efficiency of this new method in classification progress on Aster multispectral data. The accuracy of SVM method by Polynomial and radial basis functions kernel with optimum parameters and ML classification methods achieved 93.18%, 91.77% and 88.35 % respectively. By comparing the accuracy of these methods, SVM method by Polynomial kernel was evaluated as suitable. Therefore, we can suggest using SVM method especially with the use of a Polynomial kernel to determine land use. In general, the results of this research are very practical in natural resources conservation planning and studies. Also, this study verifies the effectiveness and robustness of SVMs in the classification of remotely sensed images.

Keywords: *Support Vector Machines, Radial basis function, Polynomial kernel, Maximum likelihood, ASTER, Kabodar-Ahang.*

1. Introduction

Land use/cover (LULC) maps based on satellite data are one of the most crucial elements in scientific earth research and application in the world [1, 2]. For many years, land use/cover has been used for fundamental variables such as natural resources, agriculture, environment, forestry, geology and hydrology by managers, researchers and planners [3, 4, 5, 6, 7, 8, 9 and 10]. Sort extraction of land use/cover increases in remote sensing because of its ability to measure different levels of ground spatial and temporal scale, and various image processing techniques such as classification [11, 12, 13, and 14]. Also, we have seen the advantages of remote sensing data such as obtaining multiple consecutive data, extensive regional coverage, cost data, accurate data and a large archive of information.

One of the major approaches to extracting land use/cover classification is in the presence of different algorithms in remote sensing [11]. Since getting the first Landsat satellite images in the early 1970's we have developed greatly [15, 16].

Dealing with the importance of this issue, researchers have used different statistical and non-statistical methods in order to achieve land use classification, and hence, extensive research has been done on the performance and theoretical principles of classification methods. Among all of the satellite image classification methods, support vector machine classification method is one of the most important methods of supervised classification which is based on training samples [17] and allows image classification with the desired accuracy. Recently, the support vector machine (SVM) has become very popular and is reported as one of the most powerful classifiers [18]. A recent classification algorithm from the machine learning community was introduced and applied to a well-known problem in the field of land use discovery. As a control, the algorithm is compared to

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several intelligent classification techniques that are currently being used to tackle the problem. The important advantage of this method is that it requires no previous knowledge about the statistical distribution of data. Furthermore, the SVM method can reduce classification errors while increasing resolution [19]. Common kernel methods to convert binary SVM as a multi-class classifier are linear, sigmoid, polynomial and radial basis function. Also the kernel parameters are effective in their accuracy of classifying progress [20, 21 and 22].

SVM method in the processing of satellite images has been very useful for land use and covering map extraction and classification [11, 20, 23, 24, 25, 26, 27 and 28]. In this case, some researchers have used the ASTER and ETM+ data to extract the Land use/cover map based on the maximum likelihood and SVM methods especially those containing two kernels, Radial Basis Function, and polynomial [28, 29, 30]. SVM methods with Radial Basis Function valuated better than other public classification methods such as Maximum Likelihood Method [20, 31]. In other studies done to evaluate the results of forest fires in Greece, land use maps using SVM method with different Kernels were produced. Considering an evalution based on the accuracy of classification results with Kappa values in the range of 0.92 to 0.95, this method has been introduced as one of the best methods in satellite image classification. In this research, land use extraction was performed by using remote sensing imagery [32].

The present study investigated the use of the SVM classification method with multispectral data from the Advanced Spectral Emission and Reflection Radiometer (ASTER) imagery in the central county of the Kabodar-Ahang region located in Hamadan Province in the northwestern part of Iran *(Fig.1c)*. For image processing classification methods, maximum likelihood and support vector machine by Polynomial and radial basis functions kernel with their estimated optimum parameters was applied. Finally, by comparing the classification accuracy assessment parameters with the results of classification algorithms a more reliable and accurate method was introduced.

2. Study area

The Kabodar-Ahang region experiences cold weather condition. It is located north-west of the Hamedan county of Iran and is limited from the north to Khodabande, from the east to Razan, from the south to Hamedan and north-east to Bijar and Ghorve. This area is located between longitudes 48°20′ E to 48° 50′E and latitudes 35° 0′N to 35° 20′N (Fig. 1*c*). This region is divided into 3 parts; central, Gol Tape and Shirin Soo. In this research, we studied the Central country of the region for accuracy evaluating the SVM with two kernels (radial basis kernel and polynomial) and ML methods. At 75 kilometers North West of Hamedan near the central county, there is an unbelievable natural formation called Ali Sadr Cave. In this research, we decide to assess the land use of the central county in order to understand how this cave is affected.

3. Methodology

In this research Aster imagery from August 20th, 2001(level 1B) was used due to evaluating accuracy of land use. In addition, 1:50,000 scale topographic maps (supported by National Cartography Center in IRAN) were used to perform the geometric correction as well as the training data in steps (in order to perform supervised classification), and classification (as control points in the evaluation of classification accuracy). Also, GPS data taken during field work to collect training data, was used for classification.
Data processing in this research includes three steps: pre - processing, processing, and post-processing.

3-1. Geometric and Atmospheric corrections

Geometric deviations of digital images are usually high, therefore these images can not be used directly as planimetric maps. In order to compensate for this, geometric corrections were used to adapt the digital layer with the earth's surface [33]. For geo referencing in this research, topographic maps with a 1:50000 scale and GPS control points were used. In order to performing this process, Sufficiency control points (20 points) with the appropriate distribution of the study area were collected. The function of Geo coding in PCI-Geomatica software was implemented in each image. Nearest Neighbor Method was used for the resampling of images and 0.42 pixels calculated as RMSE.

To assess the atmospheric error in satellite images, numerical values of pixels in the image of the water bodies were calculated. Due to the atmospheric error and necessity of its removal, the method of Log residuals was used for reducing the number of dark pixels.

When a detailed correction due to lack of detailed information for atmospheric correction is not possible, normalization will amend the data and topography in a way that makes it independent from the effects of the sun's spectrum and topography [34]. This normalization can be run by using the remains of the log, based on the relationship between brightness (raw data) and reflection. This technique is based on the assumption that the geometric mean calculated values of pixels in each band and the geometric mean values of each pixel are assigned to the same band. By using this method, the atmospheric effects on the image become normal [35].

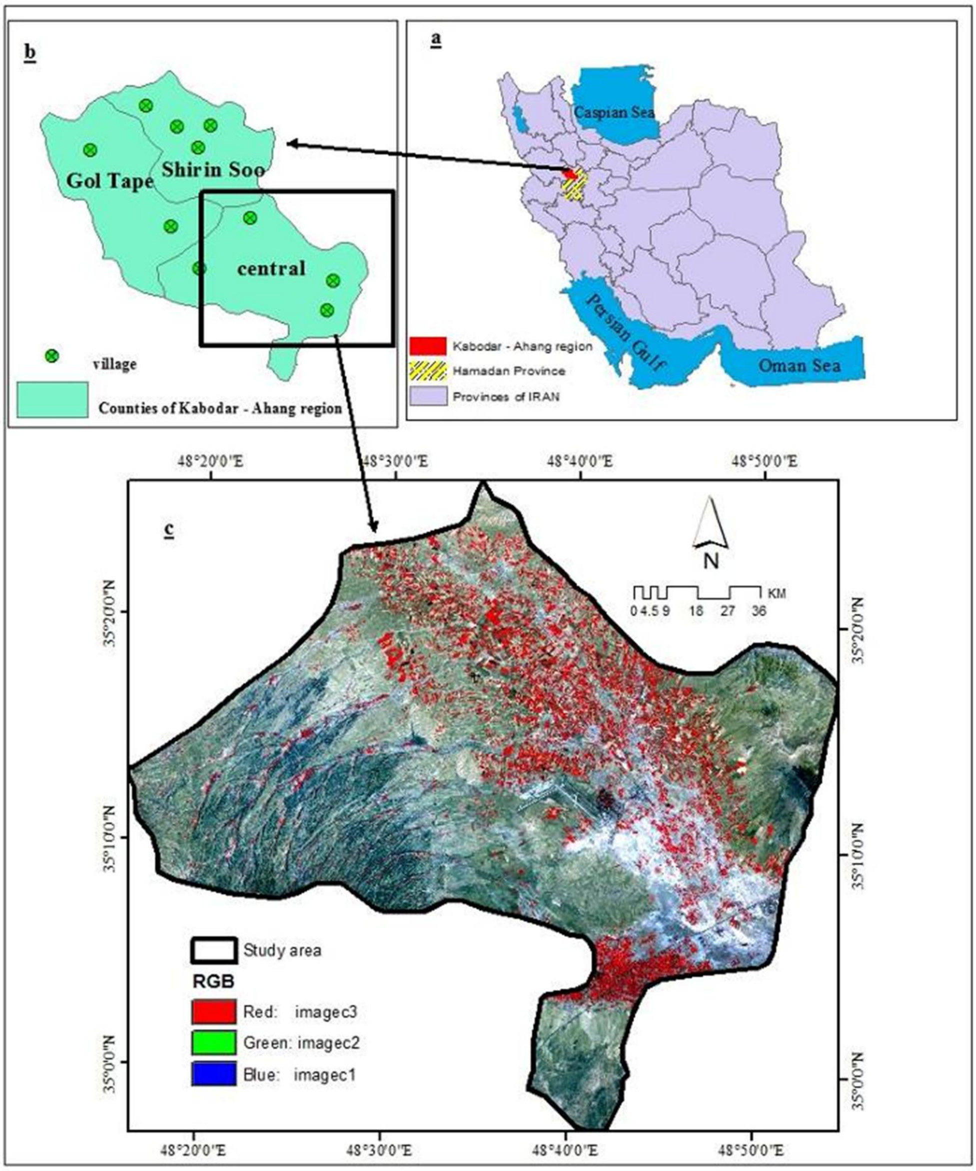

Fig. 1. Study area in the central county of Kabodar-Ahang of Hamadan by Aster multispectral data (a, b and c); part a: map of provinces of IRAN by clarifying Hamadan province and Kabodar – Ahang region, part b: map of counties of Kabodar – Ahang region by clarifying central county as study area, part c: representing ASTER imagery in the study area by 1, 2, 3 visible bands as RGB color respectively.

3-2. Classification

The classification and comparison of the results is determined in classes. For this purpose, land use classes should be extracted based on image scale and spatial resolution of the satellite images. In this study,a combination of levels 2 and 3 for land use classification system of Michigan [36] has been considered. Garden, agriculture, dry land farming, pasture-class 1, pasture-class 2, pasture-class 3, and arid lands were selected for the classes.

One important way to extract information from satellite imagery is classification. One classification method is done using spectral information (as a digital number) provided in one or more spectral bands [14, 20] and attempts to classify each individual pixel are done on the basis of this spectral information. These categories are called spectral pattern recognition. In this process the numerical values of pixels (DN) can be identified and assessed their corresponding phenomena. Remote sensing provids a way to identify ground phenomena by analyzing and classifying the digital numerical values of an image. These classification methods are based on the digital number of pixels in which the phenomena have the same numerical value, and are in the same Pixel-based classification group [12, 37].

Pixel-based classification of remote sensing images can be done using different methods. Various classification algorithms have been developed since the appearance of the firstLandsat images in 1972 [20] neural networks, decision trees and SVM are among them. Various elements are effective in the improvement of accuracy in classification. These elements contain training data characteristics, appropriate pixel selection for training data and the classification method. Appropriate pixelsselection for training data depends on the familiarity and full knowledge of the region. Training, test and validation data sets for the image were formed using random pixel selection strategy, which guarantees the maximum variation and representativeness available for each class [20].

In this research for pixel – based classification progress based on satellite images of our study area, maximum likelihood and support vector machine algorithms with different kernels were used. For pixel-based classification, after determining the classes of land use / cover, the training data for each class was collected as the required number.

After the implementation of training data and the extraction of the required statistical parameters, the best band combination was selected for classification. Classification was them performed by using the mentioned algorithms. The accuracy of the maps was evaluate by the classification accuracy algorithm and the ground control points for each class. An Overall methodology of the research is shown in Fig. 2.

3-2-1. Classification by maximum likelihood algorithm

Maximum likelihood classification (MLC) method, the most popular classification method [11, 35, 38, 39, 40] is the classical parametric classification that will run second-order statistics of Gaussian probability density models for each class [20]. By using a multi-dimensional normal distribution formula, decision making levels of the Quadratic shape are made which will be parabolic, elliptical and circular. These forms of decision making levels are more flexible in dividing multi-spectral space to make the distinction of the classes precise. In addition, for the average vector, variance - covariance matrix of the data is used in this classification which uses more characteristic of the data and increases the classification accuracy [41]. The MLC algorithm assesses the variance and covariance of the classes by assuming normal distribution of all training data classes. The training data classes should be representative of the class by using more training data in order to expose more change in the spectrum properties of the continuous range [33].

3-2-2. Classification by SVM algorithm

MLC method; a parametric normally distributed method for classes that consists of several sub-classes or classes with different spectral properties, is invalid [20]. Recently to overcome this problem, some non-parametric classification methods such as artificial neural networks, decision trees and SVM have been introduced. SVM is a supervised machine learning method that performs classification based on statistical learning theory; [42] in other word, a binary method performed by determining an optimum hyperplane (k-1) in a set of training data (k), with a maximum separation of the different classes (Fig. 3 a). There are several hyperplanes used for separating two classes but just one hyperplane, called optimal hyperplane, provides maximum separation between the two classes (Fig.3 b). Moreover, the maximum distance between hyper plane and the nearest positive and negative training samples, is called margin and the points that constrain the width of margin are called support vectors [20, 22].

In SVM method, implementation in comparison with others is required to adjust fewer statistical parameters so it is more user-friendly [17] and requires less training data while stillproviding good results [32]. In this research, SVM classification was done in ENVI software by pair wise classification strategy for a multi-class classification. Generally, SVM classification is binary and linear [43] with its development and use of kernel functions used as non-linear and multiclass classifier [44].

The kernel function enables the data points to be divided in a linear hyper plane way. Overall, the SVMs have produced results of higher accuracy in comparison to the traditional approaches. However,the outcome depends on the kernel used, choice of kernel parameters and the method used to generate SVM [2].

Selecting the appropriate kernel and optimized parameters of SVM classification is the most important issue in its implementation and performance [11, 20 and 43]. More common kernels in remote sensing are Radial Basis Function and polynomial kernels [11, 19, 20, 31, 35, 43, 45 and 46]. These kernels were chosen due to the fact that they have been widely used in classification with various satellite imagery and have shown better results than other kernel types. Moreover, these kernels require only one parameter for defining which makes them more robust in implementation in contrast to other kernels. Radial Basis Function and polynomial kernels are defined in equation 1 and 2 respectively based on the following functions:

$$K(x_i, xj) = \exp(-\gamma\|(x_i, xj)\|^2),\ \gamma > 0 \quad (1)$$

$$K(x_i, xj) = (x_i xj + 1)^d \quad (2)$$

In equation 1, x_i and x_j are the set of training data and γ is a user defined parameter kernel width. γ is the reverse of the sensors spectrum bands number [35]. In equation 2, in addition to the mentioned parameters, d is the polynomial degree term in the kernel function. γ and d are the parameters controlled by users, as their correct definition significantly increases the accuracy of the SVM solution [11]. It is not clear which pairs of parameter produce the best classification result for a given data set. Therefore, optimum parameter search must be performed [47].

3-3. An assessment of classification accuracy

None of the classifications are completed until their accuracy is assessed [48]. In this research the validity of each classification was assessed using GPS to collect the ground truth points randomly. Thenthe statistical parameters for accuracy assessment such as user and producer accuracy, overall accuracy and Kappa coefficient were obtained (Table 1).

A kappa coefficient is an evaluated classification with an accuracy relative to a random classification between zero and one. Zero and one indicate that there is a completely random and correct classification respectively [48].

The overall classification accuracy which indicates the validity of the classificationfor land use maps derived from satellite imagery should be more than 85% [36].

$$Overall\ Accuracy = \sum_{i=1}^{c} E_{ii} / N \quad (3)$$

Where, c, E_{ii} and N are the number of classes, diagonal elements of confusion matrix and total number of known pixels, respectively [41].

User accuracy and producer accuracy are parameters used to evaluate the classification accuracy for different individual classes and are defined by using the confusion matrix. Producer accuracy reflects the classification accuracy of pixels corresponding to a particular class which is on the ground truth map. In other words, this number represents the probability of attributing a pixel to a particular class by a classifier if its real class is determined. But what is usually important for the user is the user's accuracy. User accuracy indicates the probability of classifying a certain class according to the same class in the ground truth map [41].

$$Producer's\ Accuracy_j = X_{jj} / \sum_{i=1}^{r} X_{ij} \quad (4)$$

$$User's\ Accuracy_j = X_{ii} / \sum_{j=1}^{r} X_{ij} \quad (5)$$

In producer accuracy, the diagonal element of each class is divided by the sum of values of each column. But for user accuracy, correctly classified pixels are divided by the sum of pixels in each row.

4. Results

In this research, the SVM method using RBF and polynomial kernels with respect to different values for the parameters d and ɣ was implemented. Also, the accuracy of these methods was compared with the maximum likelihood classification method. Amounts intended for the RBF kernel parameters, 0.01, 0.1, 0.2, 1, 5, 10, 15, 20 and polynomial kernel, are1 to 9. In all of these parameters, classification was done and the overall accuracy of classification, kappa coefficient and user and producer accuracy in each class was achieved.

Fig. 4 shows the overall accuracy of SVM method in the polynomial and RBF kernels with respect to different values of d orders and ɣ parameters, respectively.

The overall accuracy of the three methods of classification for visual comparison of SVM method with RBF and polynomial kernel functions of different parameters and MLC methods is plotted in Fig. 5. As can be seen in this figure, the SVM method with polynomial kernel function, presented the highest overall accuracy.

Also, the the use of SVM method separately in each kerneland along with some parameter values produced a higher accuracy. Thus, in Table 1, the values of user and producer accuracy in each class, overall accuracy and Kappa coefficient of the SVM method with RBF and polynomial kernel functions in the parameters with higher accuracy and also the ML method are presented.

As shown in Table 1, the overall accuracy of MLC is 88.35% with a user accuracy per each class of between 58.82 % and 100 %. This table also shows in SVM method with polynomial kernel by the d values as 3 or 5 to 9, the overall accuracy is calculated to be 93.18% in comparison to 91.77% for RBF kernel. SVM method with polynomial kernel provides higher accuracy compared with the SVM method with RBF kernel and maximum likelihood classification with increasing amounts of 1.41% and 4.83% respectively.

After testing the performance of SVM method with different kernel functions and confirming their effectiveness, land use maps were produced in the entire study area. Fig.6 is the Land use map of the central county of Kaboder-Ahang of Hamadan in 2001. Its higher accuracy is due to the use of SVM method by Polynomial kernel.

5. Discussion and Conclusion

Support vector machines (SVMs) have been usedfrequently in recent research to solve many problems of classification by producing more accurate results than conventional classification methods. In this research, polynomial and Radial Basis functions Kernels were used in order to produce land use in the Kabooder-Ahang region of Hamadan-Iran province by Aster imagery for assessing classification accuracy of SVMs in comparison to the conventional maximum likelihood method.

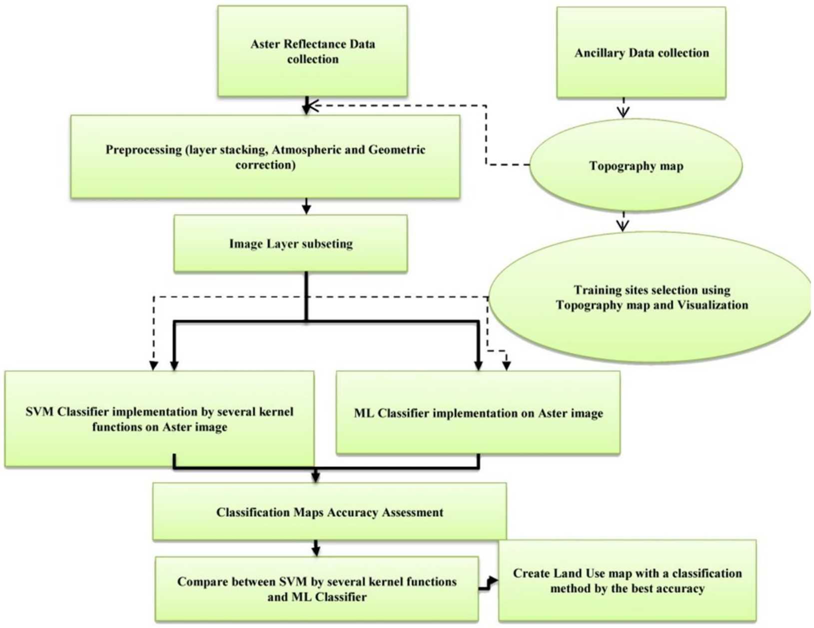

Fig. 2. Overall methodology followed for implementation of the SVM and ML methods to the ASTER imagery for deriving Land use for the study area.

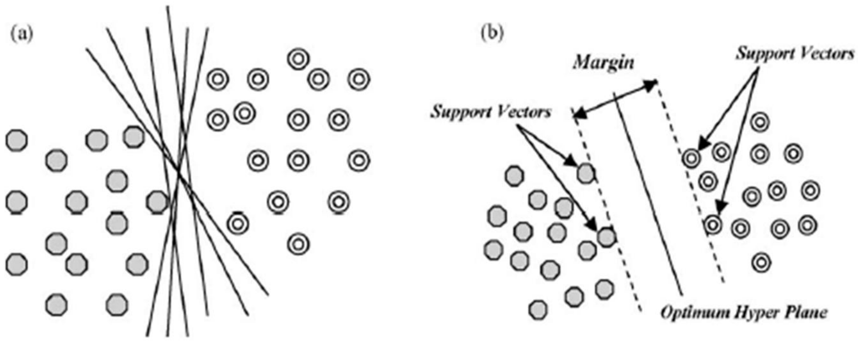

Fig. 3. Hyper planes for linearly separable data (a). Optimum hyper plane and support vectors (b) [20].

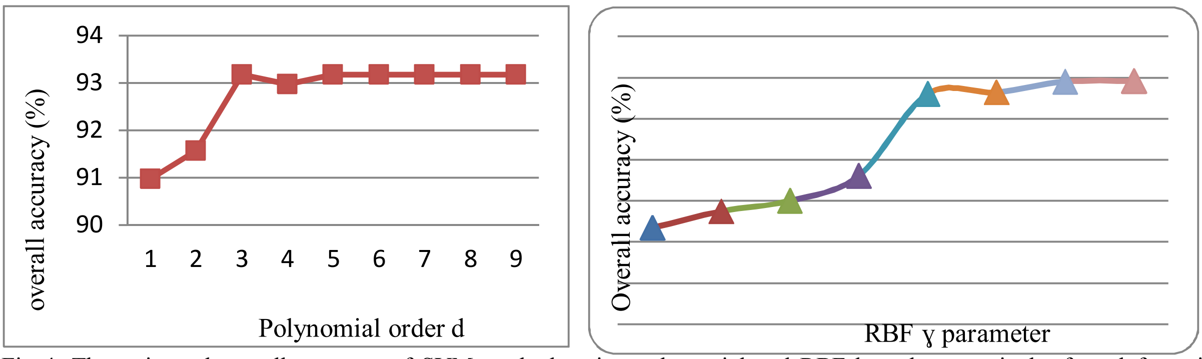

Fig 4. The estimated overall accuracy of SVM methods using polynomial and RBF kernel, respectively, from left to right with respect to various parameters

Important conclusions can be drawn by analyzing the classification results in Table 1. Accuracy of wastelands classification is calculated at 100 % which can be related to its distinctive spectral characteristics or spectral separability compared to other land use types. The rangeland classification accuracy of SVM is lower than ML method as well as the other classes. One reason may be related to the complex and close class boundaries from the high spectral resemblance to other classes along with mixed pixels in the training and test samples. By considering the accuracy of each individual class, about 1 to 14 % and an overall accuracy of 1.5%, SVMs with polynomial kernel have shown improvement in performance comparedto SVMs with RBF kernel. In assessing the influence of polynomial degree on accuracy, it was observed that an increase in the polynomial degree will increase the computation time as well.

Table 1. Classification accuracies estimated for maximum likelihood (ML) and support Vector machine (SVM) classifiers with radial basis and polynomial functions by the best parameters.

Classification methods	***SVM (Polynomial kernel)***		***SVM (RBF kernel)***		***ML***	
Land use classes	producer's accuracy	User's accuracy	producer's accuracy	User's accuracy	producer's accuracy	User's accuracy
Agriculture	96.04	95.74	96.65	92.69	84.15	99.28
Garden	93.10	89.01	87.36	93.83	97.70	68.00
Range- class1	61.90	61.90	52.38	57.89	95.24	58.82
Range- class2	45.45	83.33	36.36	66.67	81.82	90.00
Range- class3	85.71	85.71	71.43	83.33	85.71	85.71
wasteland	100.00	100.00	100.00	100.00	100.00	100.00
Overall accuracy (%)	93.18		91.77		88.35	
Kappa coefficient	0.87		0.84		0.79	

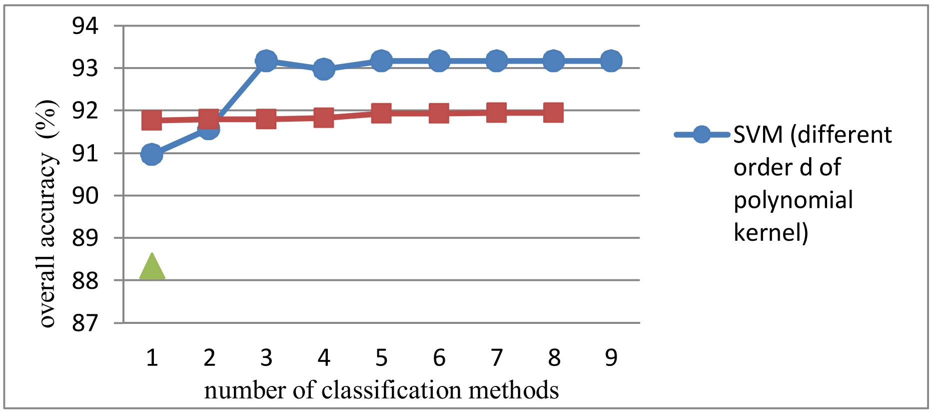

Fig. 5. Comparison of the estimated overall accuracy of SVM methods using polynomial and RBF kernel with respect to various parameters and ML method. The result of MLC is shown by one point because the parameter was not changed in this method.

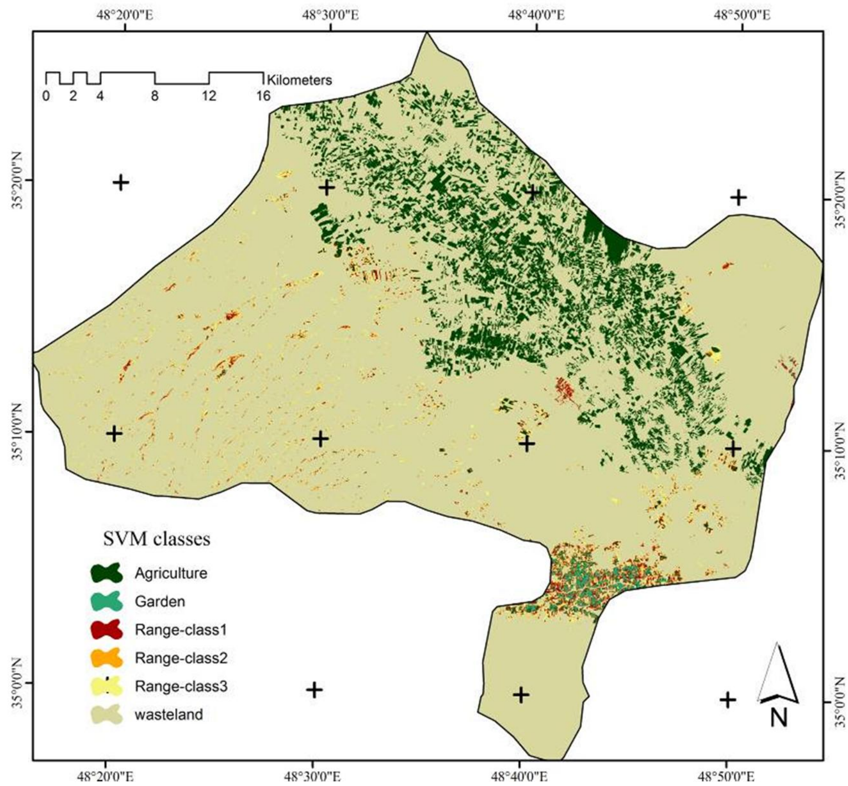

Fig. 6. Land use map using SVM method by Polynomial kernel.

According to the results, the highest classification accuracy for the polynomial degree of 5 to 9 and 3 were produced with little difference. For the radial basis function, the effect of width of the kernel function (ɣ) was selected and tested and it was found that 5 to 20 values will produce reasonable results. Compared with the considerable influence of polynomial degree the effect of change on the width of the radial basis function was less important. Therefore, the results of polynomial kernel can be varied greatly ; accurate determining of the appropriate polynomial degree is vital.

The results significantly show that the SVMs, in almost all cases, show better performance than the ML classifier in both the overall and each class accuracy. Also, the SVM with Polynomial kernel in comparison with ML method presented a 5 % improvement in the overall accuracy and required less training samples. Despite the similarity of the training samples in both classification algorithms, in this study we produced better accuracy resultswith the SVM classification. Finally, after examining and testing various parameters of Kernels in SVM method and comparing the overall accuracy with conventional method the land use map was produced using the polynomial kernel in the SVM method for Kabooder-Ahang in the Hamadan region.

This study shows comprehensively that a higher accuracy was obtained for land use usingthe SVM than the ML classification method. It seems that this method is a good alternative to conventional classification methods.

In recent years, support vector machines (SVMs) have been used in solving many problems of classification and regression. Research results show, this new method produces more accurate results than conventional classification methods. The most important issues are to determine the kernel function and their parameterswhich greatly affects the performance of support vector machines functions.

In this research, polynomial and Radial Basis Functions Kernels are used in order to produce land use in the Kaboder-Ahang region of Hamadan-Iran province using Aster imagery. The performance of SVMs for classifiction using polynomial kernel and radial basis functions was studied and the results were compared with the conventional methodandmaximum likelihood classifier.

Several important conclusions can be drawn by analyzing the classification results in Table 1. The Accuracy of wastelands classification is calculated at 100 %. This high classification accuracy can be related to its distinctive spectral characteristics or spectral separability compared to other land use types. Also noteworthy is the fact that rangeland classification accuracy of SVM classification method was lower than ML method and as well as the other classes.One reason may be related to the complex and close class boundaries from the high spectral resemblance to other classes as well as the mixed pixels in the training and test samples. Considering the accuracy of each individual class, SVMs with polynomial kernel in all cases, compared with SVMs with RBF kernel showed an improved performance of about 1 to 14 % .This proves that the ability of the polynomial kernels is more than the RBF kernel.

Kernel functions used in classification were analyzed and polynomial kernel was found to give more accurate results than the radial basis function with an overall accuracy by 1.5 %. In assessing the influence of polynomial degree on accuracy it was observed that an increase in the polynomial degree will increase computation time as well. According to the results obtained in this study, the highest classification accuracy for the polynomial degree of 5 to 9 and 3 were produced with little difference. For the radial basis function, the effect of width of the kernel function (ɣ) was selected and tested and it was found that 5 to 20 values for this function will produce reasonable results. Compared with the considerable influence of polynomial degree, changes in the the width of the radial basis function were shown to be less important. Therefore, the results of polynomial kernel can vary greatly and accurate determination of the appropriate polynomial degree is very important.

The results significantly show that the SVMs, in almsot all cases, have a better performance than the maximum likelihood classifier in both the overall accuracy and accuracy of each class. Also, the SVM classification method with Polynomial kernel in comparison to Maximum Likelihood Method presented a 5 % improvement in the overall accuracy. This method compared to the maximum likelihood method requires less training samples and as is evidenced in this study, despite the similarity of training samples in both classification algorithmswe were able to produced higher accuracy in the results by using SVM classification. Finally, after examining and testing various parameters of Kernels in SVM method and comparing the overall accuracy with conventional methodand Maximum Likelihood the land use map for the Kaboder-Ahang of Hamadan region was produced using the polynomial kernel in the SVM method.

Comprehensively this study shows that land use was produced higher accuracy with the support vector machines than the maximum likelihood classification method. It seems that this method is a good alternative to conventional classification methods.

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