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Improving the Accuracy of Land Use/Cover Maps using an Optimization Technique

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ABSTRACT

Mapping of Land use/cover is important for many activities of planning and management, especially in arid areas. Nowadays, satellite imagery and remote sensing techniques, which provide timely and high capability data, are widely used in producing this kind of mapping. The main objective of this study is to produce an actual land use map using advanced pixel-based (MLP, SVM, and SOM) approaches. The most important challenge, in this case, is to determine the optimum structure of classification methods. The Taguchi method is used to optimize the structure of MLP, SVM, and SOM methods. Results show that the Taguchi method can be effectively used to cope with this problem. It significantly reduces the number of classification tests. We also showed that there are significant differences between the results of the SVM method with those of the MLP and SOM methods ($\chi 2$ more than 100) and that SVM model is more efficient than other methods. The accurate map produced by the optimized SVM approach (Overall accuracy of 0.93) showed that this method has a better performance.

Keywords Land Use/Cover Map; Taguchi Method; Optimization; Pixel-Based Classification

CITATION LINKS

[1] Function-analysis and valuation as a tool to assess land ... [2] Spatial variability of soil features affected by landuse ... [3] Intelligent approaches to analysing the importance of land use ... [4] Socio-economic factors influencing land use changes in ... [5] Land use change prediction using a hybrid ... [6] Two centuries of land use changes influenced by intensive ... [7] Land use change effect on physical, chemical, and ... [8] The use of structural information for improving land-cover ... [9] An assessment of some factors influencing multispectral ... [10] Frequency-based contextual classification and gray-level ... [11] Estimations for percentage of impervious area ... [12] Exploring a V-I-S (vegetation-impervious surface-soil) ... [13] Comparison of gray-level reduction and different texture ... [14] Producing a landslide inventory map using pixel-based ... [15] Random ... [16] An assessment of support vector machines for land cover ... [17] Random forest classifier for remote sensing ... [18] Assessing the extent of agriculture/pasture and secondary ... [19] Random forests for land cover ... [20] Benchmarking classifiers to optimally integrate terrain analysis ... [21] Land cover change assessment using decision trees, support ... [22] Comparison of pixel-based and object-oriented classification ... [23] Comparison of advanced pixel based ... [24] Statistical learning ... [25] Improving forecasting performance by employing the ... [26] The optimum conditions for comminution of magnetic ... [27] Simulation of Future Land use map of the catchment area, with ... [28] Introduction to the physics and techniques of remote ... [29] Classification methods for remotely ... [30] Mapping continuous distributions of land cover: A comparison ... [31] Neural networks and physical systems with emergent ... [32] Remote Sensing Digital Image ... [33] Self-organized formation of topologically ... [34] Comparison of supervised and unsupervised learning algorithms ... [35] Image classification using SOM and SVM feature ... [36] A practical guide to support vector classification ... [37] Applicational aspects of support vector ... [38] Landslide susceptibility assessment using SVM machine ... [39] Object-oriented image analysis for mapping shrub encroachment from ... [40] High spatial resolution satellite imagery, DEM derivatives ... [41] Automated classification of landform elements using object-based image ... [42] Reviving legacy population maps with object-oriented ... [43] Parameter selection for region-growing image ... [44] Thematic map comparison: Evaluating the statistical ... [45] Biostatistical ... [46] Distribution-free statistical ... [47] Land use planning using a quantitative model and geographic information ... [48] Support vector machines (SVMs) versus ... [49] Land-cover classification using ASTER multi-band ...

Introduction

As one of the most significant natural resources, land is the basis for life activities. Land use shows the way in which the human uses land in addition to the natural cover of lands. Land use/cover information is essential for planners, stakeholders, those who mage land resources [1]. Assessment of land use/cover changes is also very important to study their effect on different aspects of human life e.g. land degradation, erosion, dust storms, etc. Proper land management needs an understanding of the existing status of the land. Having knowledge about current land use/cover in conjunction with a correct means of monitoring change over time, is critical for land management.

Remote sensing can be a good tool for producing land use/cover maps. Several studies have been conducted using land use/cover maps in different fields [2-7]. However, there are several difficulties associated with using remote sensing for land use/cover mapping e.g. spectral mixture, the spectral similarity between different land use/covers, low spatial resolution of remotely sensed imagery, etc. Spectral, contextual, texture, and structural information are extracted to assist the characterization of different and complex land surfaces and to improve the accuracy of identification [8-13].

In order to have more reliable inventory maps, satellite image processing techniques can be suitable. Image processing techniques fall into two groups: Pixel-based and object-oriented approaches. The traditional digital image analysis approaches, which exclusively gain statistical methods, have proved to be constrained for detecting targets of greater complexity [14]. Each pixel is classified by pixel-based techniques regardless of neighboring pixels. Some studies have been done using pixel-based approaches [15-21].

A number of pixel-based approaches are available for image classification, such as maximum likelihood, minimum distance, parallelepiped, ISODATA, K-mean, etc. [22]. This approach has some deficiencies in classification, especially in dealing with the rich information content of high resolution data, for example, Geoeye multispectral (VNIR) and very high resolution (VHR) satellite imageries. In fact, these conventional pixel-based approaches use only gray values; but the advanced pixel-based techniques such as multilayer perceptron (MLP) support vector machine (SVM) and self-organizing map (SOM) regarding the texture, tone, and some other characteristics [23]. A neural network, as a supervised classification, is a method that is first trained from known data and then uses this data to categorize unknown pixels. Support vector machines (SVMs) demonstrate a set of theoretically superior machine-learning algorithms. Development of SVM was first caused by the exploration and formalization of learning machine capacity control and over-fitting issues [24].

A significant challenge in these cases is the determination of the optimum combination of affecting parameters on the performance of classification approaches. Trial and error approaches are generally time-consuming and costly. A fractional factorial design of experiments such as the Taguchi method can be an effective way to overcome this problem. Taguchi developed a family of FFE matrices that could be utilized in various situations. This method has been often utilized to optimize the design parameters (based on a signal-to-noise parameter) and significantly minimize the overall testing time and the experimental costs [25, 26] following a systematic approach to restrict the number of experiments and tests. The main objective of this study is to produce a Land use/Cover Map using Taguchi-based optimized advanced pixel-based approaches and also to compare these methods by statistical indices.

Methods

Study Area

The study region is located in the western part of Mehriz, Yazd province, Iran with an area of 206km^2 between 54°02′ to 54°15′ E. longitude and 31°31′ to 31°41′ N. latitude. The minimum and maximum elevations in this region are 1800 and 4075m a.s.l, respectively. The area is located in the dry mountainous belt with relatively mild summers and cold winters. The mean annual precipitation and temperature are 205mm and 17°C, respectively. A thermal regime of this region is Mediterranean having cold winters and hot summers with July and January as the warmest and coldest months respectively [27]. The Landsat 8 multispectral imagery (11 bands with spatial resolution of 15 and 30m) for September 21, 2014 was used in this study (Figure 1).

The main goal of this study was to produce land use/cover maps combining different pixel-based approaches and Taguchi optimization method.

Figure 2 shows the flowchart of the study. In this study three pixel-based classification methods i.e. MLP, SOM, and SVM approaches were used. These methods have several parameters in their structure that should be tuned. Taguchi optimization method was used to determine the optimum values for these parameters. For example in the SVM method, kernel type, gamma, and penalty parameters and pyramid levels should be optimized. Optimization of these parameters using a trial and error approach is somewhat tedious and time-consuming. As is shown in figure 2, in the first step, the Landsat image of the region was downloaded from the NASA database. Required image preprocessing such as geometric and radiometric corrections were implemented on the image. After preprocessing step, structural parameters of MLP, SOM, and SVR were determined and the appropriate Taguchi orthogonal arrays were selected, accordingly. The Taguchi based required classification tests were then implemented and the results were imported to the optimization process. After determining the best structure of classification methods, best land use/cover maps for each classification method were produced. Finally, the accuracy assessment criteria were used to determine the most accurate land use/cover map.

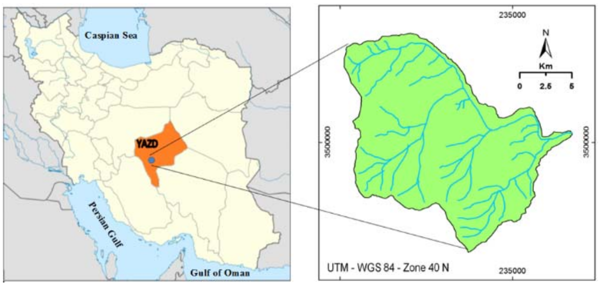

Figure 1) The location of the study area

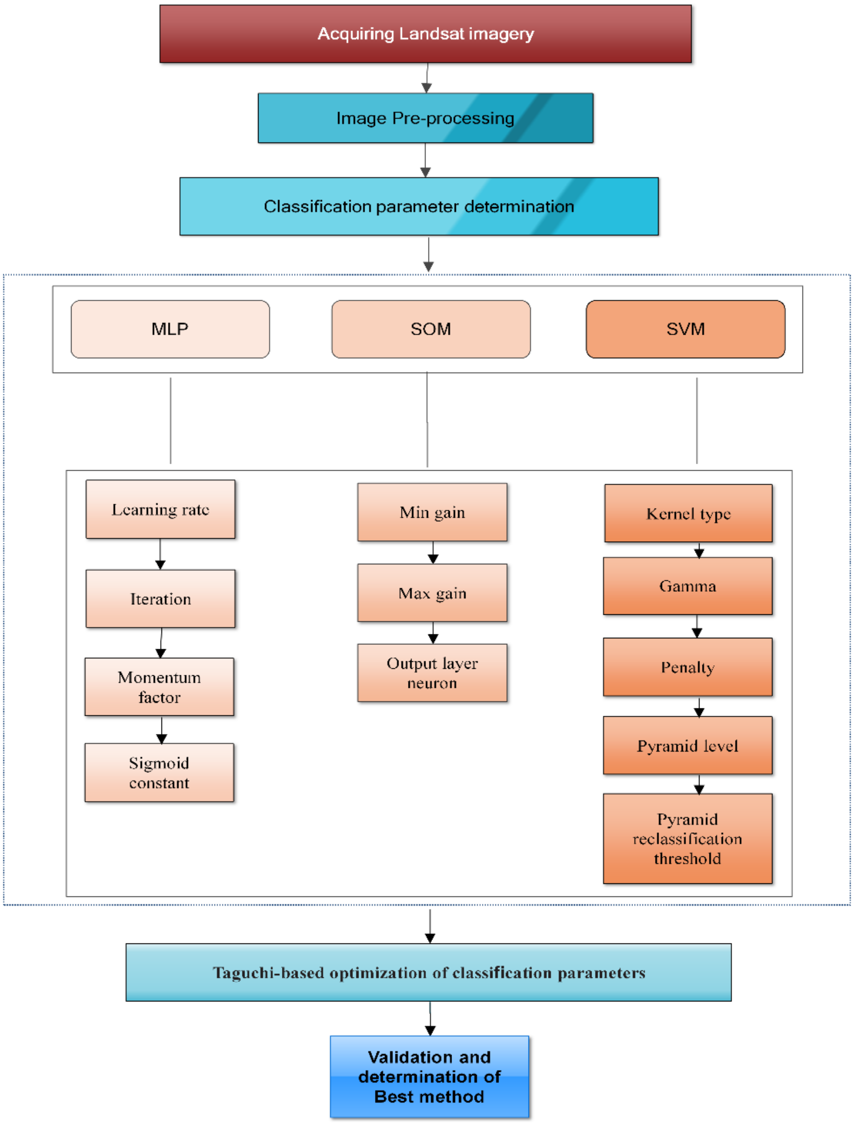

Figure 2) Flowchart of the study

Image Classification

Pixels are the smallest units in an image. Spectral information of each pixel is used in image classification. There are two important types of image classification i.e. Supervised and unsupervised classification approaches. In image classification similar pixels are labeled as specific classes. These rules segregate the total data space into subsets divided by decision boundaries. Then, all pixels that fall within a number of pixels are labeled as belonging to a distinct class [28]. As the landsat images are medium resolution, pixel-based classification approaches are used in order to produce a land use map of the study area. This classification approach is briefly discussed below.

Three essential steps were conducted, that is, selecting training samples representative of different information classes; executing classification algorithms; and finally, assessing the accuracy of the classified images through analysis of a confusion matrix [29]. Training samples were selected according to the ground truth data. These homogenous areas were identified in the image to form the training samples for all of the information classes. Three advanced supervised pixel-based classifications, i.e., MLP, SVM, and SOM were conducted in this part. The advantage of neural networks is due to the high computation rate accomplished by their inherent parallelism that is the result of a potent arrangement of interconnections (weights) and simple processors (neurons) that makes processing of very large data sets possible. This approach is generally called nonparametric [30]. The revenue of a neural network depends on how appropriate it has been trained. During the training phase, the neural network learns about regularities presented in the training data and, based on these regularities, constructs rules that can be extended to the unknown data. This is one of the particular abilities of neural networks [29]. Multi-Layer perceptron (MLP) is a feed forward neural network with one or more layers between input and output layers. In Feed forward neural networks, there is an input-output data flow. In this network a backpropagation learning algorithm is used to tune the input and layer weights. MLPs are greatly used for pattern classification, recognition, prediction, and approximation. To solve problems that are not linearly separable, Multi-layer perceptron can be used. In the neural network classification, the most common algorithm for updating the neuronal activities and the interconnection in a multilayer perceptron (i.e., back-propagation algorithm) was used in the supervised classification of images by the ENVI software package. Back-propagation consists of two main steps, forward and backward propagation, in order to obtain its adjustment of the neural state. In this approach, learning occurs by regulating the weights in the node to minimize the difference between the output node activation and the desired output. The error is back propagated through the network, and weight modification is made using a recursive method [31, 32]. NDVI, EVI, NDBI indices and a DEM model (digital elevation model) have been used in addition to the original image in the three approaches of MLP, SVM, and SOM (Figure 3).

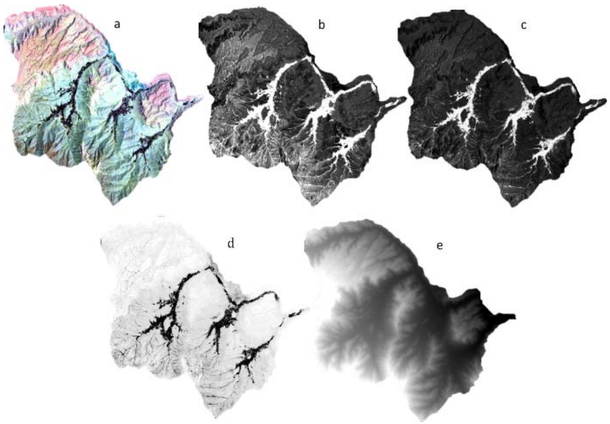

Figure 3) (a) The original image; (b) NDVI Index; (c) EVI Index; (d) NDBI Index; (e) DEM

Artificial neural network as a learning based artificial intelligence approach, can be used for classification of data. Self-Organizing Map (SOM) is one of the powerful methods for clustering and classification of different types of data. In these networks, all neurons in the hidden layer compete for being activated. These activated neurons are then called winning neurons. Such competition can be implemented using negative feedback paths between the neurons. Depending on the result, these neurons will reorganize themselves to get better results. For these reasons, such network is called a Self-Organizing Map (SOM) that was first developed by Kohonen [33]. Self-Organizing Maps have a different functionality in comparison with other ANNs. They can use a neighborhood function to conserve the topological properties of the data. SOM works in two modes i.e. training and mapping. In the training mode, it builds the map with the help of input examples, while "mapping" automatically classifies a new input vector. SOM can also be useful in clustering data without knowing the class membership of the input data [34].

The main objective of the SOM model is to convert a received pattern of specific dimension into a one or two-dimensional discrete maps and to complete this conversion adaptively in a topologically ordered way. This network depicts a feed forward structure with a single computational layer consisting of neurons arranged in 1D or 2D grid. Higher dimensions are possible but are not very common. Grid topology can be square, hexagonal, and so on. An input pattern to the SOM network represents a localized region of "activity" against a quiet background [35].

The SVM is also a classification system resulting from statistical learning theory which provides good classification results from complex data. There are four main kernel types in SVM, all tested in this study, including, linear, polynomial, radial basis function, and sigmoid. All of which are different ways of mathematically representing a kernel function [36]. This approach is a binary classifier in which n-class problems can be transformed into the sequence of n binary classification tasks [37]. The SVM varies from other separating hyperplane approaches in the way the hyperplane is built from the training points [38]. Figure 4 shows a linear SVM as an example that uses a linear kernel defining the SVM hyperplanes. The data close to the hyperplane defines the support vectors of such hyperplane. This method utilizes a penalty parameter which identifies misclassification that is observed in the input data set (Figure 4).

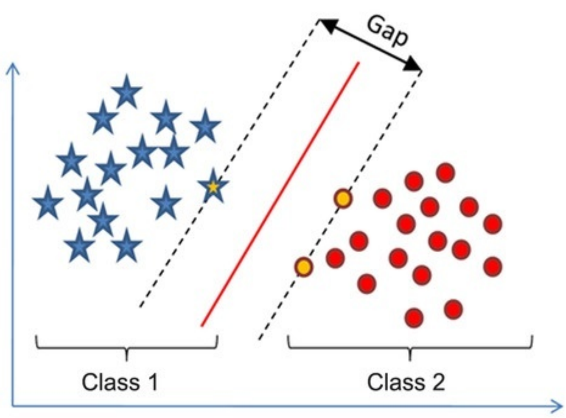

Figure 4) Linear support vector machine example

All of the above-mentioned classification approaches have several parameters that need to be tuned and optimized. For instance, Learning rate, Momentum F, Sigmoid constant, and the number of iterations in the MLP-based; and Min gain, max gain, and output layer neuron in the SOM-based; and gamma, penalty parameter, pyramid reclassification, and pyramid level in the SVM-based method should be optimized.

Taguchi-Based Optimization of Classification Parameters

Using a trial and error approach to optimize the above-mentioned parameters is often time-consuming; thus, an optimization method is recommended. Several other approaches are also used by researchers to optimize pixel-based and object-oriented classification parameters [39-42]. Most of which, however, just optimize the scale not the combination of these parameters. To determine the optimum combination of classification parameters, Taguchi method is used in this study as a robust statistical approach [14]. Taguchi's orthogonal array experimental design, as an alternative to standard factorial designs are utilized to examine the effect of many different parameters on the performance attribute in a reduced set of experiments. This array is a type of design where the columns for the independent variables are 'orthogonal' to one another. The use of these tables makes the design of experiments very simple and consistent. Taguchi orthogonal array designs are typically used in design experiments with multiple level factors. They can be thought of as a general fractional factorial design. In this step, the kappa coefficients in the pixel-based approaches [43] are maximized. The kappa coefficient is a well-known index and POF is a combination of a spatial autocorrelation index (e.g., Moran's I index; Table 1).

In the SVM classification method, an initial test showed that radial and sigmoid kernel functions did not render acceptable results due to the type of kernel function that could not accurately classify and cluster the pixel values (DNs). Thus, the confusion matrixes obtained from these classifications showed unfavorable results and these kernel functions were eliminated from more analysis.

Table 1 shows the parameters that affect the performance of MLP, SOM, and also SVM approaches. According to the number of factors and their levels, the appropriate Taguchi orthogonal arrays were determined. Therefore, L16, L26, and L27 orthogonal array were used to optimize MLP, SOM and SVM parameters. Numbers 1 to 5 show the levels of each parameter. In fact, Taguchi minimizes the number of tests using standard orthogonal arrays.

For example, L27 (5^3) corresponds to an orthogonal array of five parameters, each of which has three levels for SVM approaches, and offers just 27 tests instead of 69 tests that are mandatory in a full factorial design of the experiment. In the next step, classification tests were performed according to the selected orthogonal arrays. In the MLP, SOM and SVM classification tests, the kappa coefficient, were calculated for each test specified in the orthogonal arrays. A scaling factor is a factor in which the mean and standard deviation are proportional. We can identify scaling factors by examining the response tables for each control factor. A scaling factor has a significant effect on the mean with a relatively small effect on the signal-to-noise ratio. This indicates that the mean and standard deviation scale together. Thus, we can use the scaling factor to adjust the mean on target but not affect the S/N ratio.

Then, an analysis of the signal-to-noise (S/N) ratio was used to evaluate the classification results. As this study aimed to maximize the kappa coefficient, the S/N ratio with 'higher is better' (HB) characteristics were selected for the study rather than the two other types of S/N ratio analyses including 'lower is better' (LB) and 'nominal is best' (NB). The S/N ratio for the HB type was then calculated based on the following equation:

$$SNR = -10log_{10}\left(\frac{1}{n}\sum\frac{1}{y_i^2}\right) \qquad (1)$$

Where n is the number of repetitions under the same experimental conditions (i.e., 1 in this study), and y represents the result of measurement. Here, y is the kappa coefficient for MLP, SOM, and SVM. The Means response table and figure were then obtained, and the optimal conditions were recognized. As a final point, the confirmation tests under these optimal conditions were carried out.

Accuracy Assessment

In order to assess the accuracy, confusion matrixes were used for pixel-based approaches. A confusion matrix is a square array of dimension r × r, where r is the number of classes. The matrix shows the relationship between two samples of measurements taken from the area that has been classified. The evaluation of the statistical significance of the difference in accuracy between two classified images has often been based on the comparison of the kappa coefficient calculated for each map. The kappa coefficient was then calculated using Equation:

$$\hat{K} = \frac{\theta_1 - \theta_2}{1 - \theta_2} \qquad (2)$$

The McNemar test that is based on the standardized normal test statistic can be used to compare two related kappa coefficients [44, 45] (Diagram 1):

$$\chi^2 = \frac{(f_{12} - f_{21})^2}{f_{12} + f_{21}} \qquad (3)$$

Where f_{ij} indicates the frequency of sites lying in confusion matrix elements i and j [46]. As two pixel-based approaches have the same samples (i.e., related kappa coefficients), this statistical index was used to compare results between them.

Table 1) Factors and their levels used for optimization in pixel-based approaches

Factor	Description	Level 1	Level 2	Level 3	Level 4	Level 5
		MLP approach				
A	Learning rate	0.01	0.1	0.15	0.16	–
B	Iteration	1000	5000	10000	15000	–
C	Momentum factor	0.5	0.6	–	–	–
D	Sigmoid constant	1	2	–	–	–
		SOM approach				
A	Min gain	0.0001	0.001	0.01	0.1	0.5
B	Max gain	0.0005	0.005	0.05	0.5	1
C	Output layer neuron	5	10	15	20	50
		SVM approach				
A	Kernel type	Polynomial	Radial basis	Sigmoid	–	–
B	Gamma	0.001	0.1	1	–	–
C	Penalty	100	1000	10000	–	–
D	Pyramid level	1	2	3	–	–
E	Pyramid reclassification threshold	0.1	0.5	1	–	–

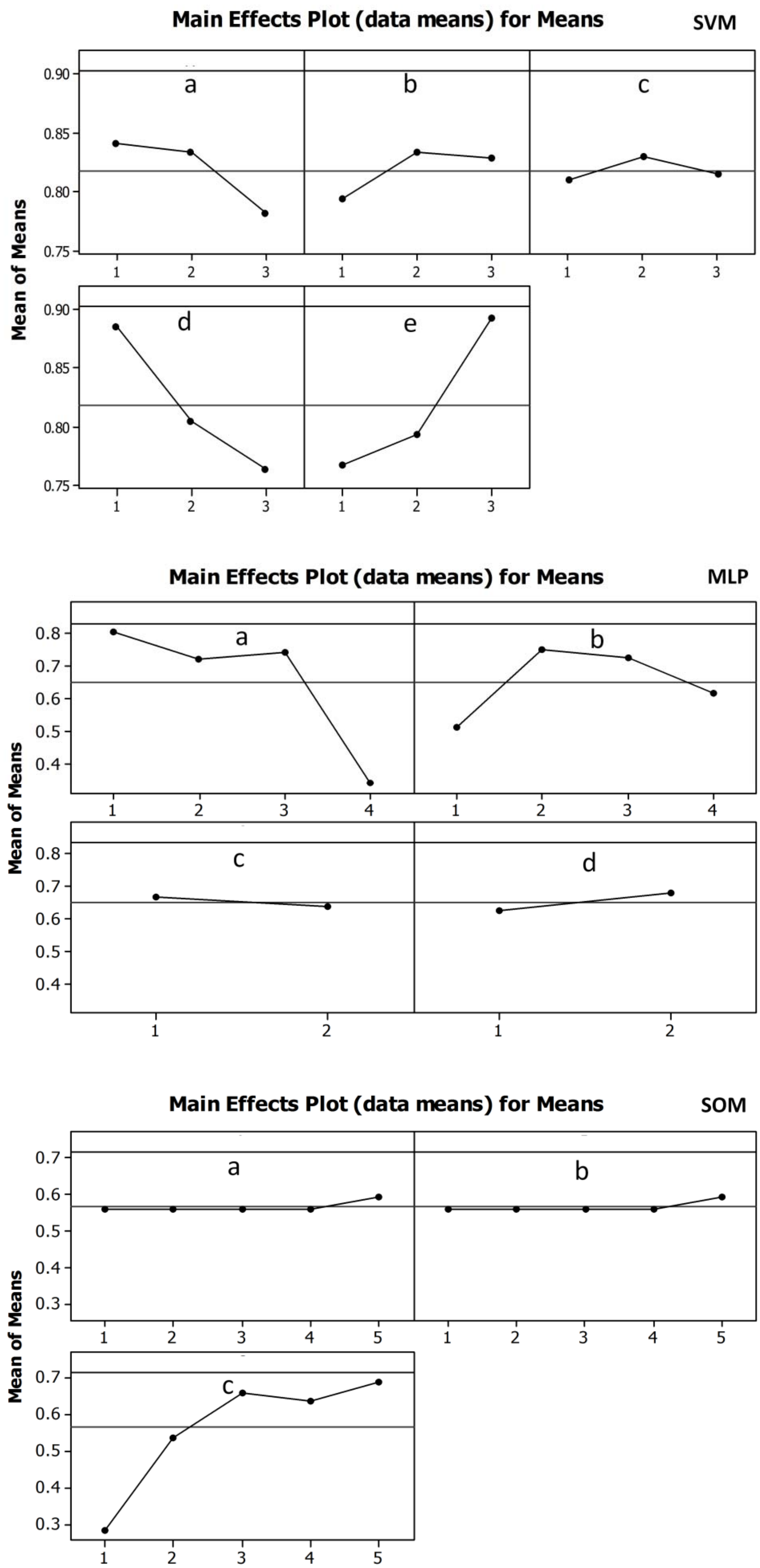

Diagram 1) Main effects plot (data means) for Means for study variables of (a) SVM, (b) MLP and (c) SOM

Results and Discussion

Optimization results

As already explained, 27, 16, and 26 classification prototypes were tested for SVM, MLP and SOM approaches according to the Taguchi orthogonal array, respectively. The L27 (5^3) orthogonal array and the values of the kappa coefficient obtained through classification tests for SVM approaches have been presented in Table 2. Table 3 and Figure 4 show the values of main effects plot (data means) for means for the SVM, MLP, and SOM approaches. The boldface figure refers to the maximum values for data means of a certain factor among three, four, and five levels, and thus it shows the optimal conditions for each classification. As Table 3 and Diagram 1 show, the optimum conditions for the SVM approach are as follows: (i) kernel function: polynomial; (ii) gamma: 0.1; (iii) penalty parameter: 1000; (iv) pyramid levels: 1; and (v) pyramid reclassification threshold: 1. The optimum conditions for the MLP approach are also as follows: (i) learning rate: 0.01; (ii) iterations: 5000; (iii) momentum factor: 0.5; (iv): sigmoid constant: 2. The optimum conditions for the SOM approach are also as follows: (i) min gain term: 0.5; (ii) max gain term: 1; (iii) output layer neuron: 50 (Table 2).

Table 2) L27 orthogonal array and kappa coefficients for SVM classification approach

	L27 (Combination of different levels)					Kappa (SVM)
	A	B	C	D	E	
Test1	1	1	1	1	1	0.868
Test2	1	1	1	1	2	0.866
Test3	1	1	1	1	3	0.886
Test4	1	2	2	2	1	0.811
Test5	1	2	2	2	2	0.838
Test6	1	2	2	2	3	0.912
Test7	1	3	3	3	1	0.707
Test8	1	3	3	3	2	0.751
Test9	1	3	3	3	3	0.919
Test10	2	1	2	3	1	0.657
Test11	2	1	2	3	2	0.729
Test12	2	1	2	3	3	0.910
Test13	2	2	3	1	1	0.902
Test14	2	2	3	1	2	0.913
Test15	2	2	3	1	3	0.923
Test16	2	3	1	2	1	0.776
Test17	2	3	1	2	2	0.799
Test18	2	3	1	2	3	0.888
Test19	3	1	3	2	1	0.682
Test20	3	1	3	2	2	0.682
Test21	3	1	3	2	3	0.856
Test22	3	2	1	3	1	0.634
Test23	3	2	1	3	2	0.701
Test24	3	2	1	3	3	0.867
Test25	3	3	2	1	1	0.866
Test26	3	3	2	1	2	0.866
Test27	3	3	2	1	3	0.875

Classification and Accuracy Assessment results

As the pixel-based classified images often suffer from a lack of spatial coherency (speckle or holes in classified areas), [47] clumping and generalization were performed to smooth them and to eliminate the few isolated pixels that did not have geomorphological significance. The clump function was then used to remove the pepper and salt effect in different classes by combining meaningless pixels with the larger class. Diagram 1 show the best pixel-based classification results and final inventory maps.

Table 4 shows the summary of confusion matrices for SVM, MLP, and SOM approaches MLP and SOM approaches have an approximately poor performance and several misclassifications happened in them. This poor performance may be related to SOM and MLPs classifiers, the tested data sets which need more hidden units and the complexity which is controlled by keeping the number of these units small, whereas the SVMs complexity does not depend on the dimension of the data sets (Table 3). SVMs based on the minimization of the structural risk, whereas MLP classifiers implement empirical risk minimization. So, SVMs are efficient and generate near the best classification as they obtain the optimum separating surface which has good performance on previously unseen data points. However, the main difference is in the complexity of the networks. The MLP network implementing the global approximation strategy usually employs very small number of hidden neurons [48]. The main benefit of SVM method is that it can formulate the learning problem, using a quadratic optimization task. It significantly decreases the number of operations in the learning mode. It is very important for large data sets, where SVM algorithm is usually much quicker (Table 4).

The McNemar test on the other hand, shows that there is a statistically significant difference between MLP and SVM methods with a χ^2 value of 154 and between SOM and SVM methods with a $\chi2$ value of 233 (insignificant at the 95% confidence level). This result is consistent with Moosavi et al [14] who showed that SVM outperformed the ANN method in classifying VNIR imagery data. The hypothesis that two kappa coefficients are equal is rejected if χ^2>3.84 (95% confidence level). The mentioned certain values are obtained from χ^2 statistical table (Figure 5).

Clumping and generalization can improve the appearance of pixel-based classification removing isolated misclassified pixels, but the spectral heterogeneity in each of the information classes and spectral similarities between different phenomena are still challenging. For example, within the SOM approach classification, many of the pixels classified as agriculture are actually diffused rock. So the number and area of agricultural lands are overestimated in this approach. This result is in accordance with the results of Bagan and wang [49].

Table 3) The Mean for factors in each level for SVM, MLP and SOM approaches (Larger is better)

Level	Factors				
	A	B	C	D	E
SVM					
1	0.840	0.793	0.809	0.885	0.767
2	0.833	0.833	0.829	0.805	0.794
3	0.781	0.828	0.815	0.764	0.893
Delta	0.059	0.040	0.020	0.121	0.126
Rank	3	4	5	2	1
MLP					
1	0.804	0.513	0.665	0.623	–
2	0.721	0.750	0.639	0.680	–
3	0.742	0.727	–	–	–
4	0.339	0.617	–	–	–
Delta	0.465	0.236	0.026	0.057	–
Rank	1	2	4	3	–
SOM					
1	0.557	0.557	0.281	–	–
2	0.557	0.557	0.534	–	–
3	0.557	0.557	0.659	–	–
4	0.557	0.557	0.639	–	–
5	0.592	0.592	0.689	–	–
Delta	0.035	0.035	0.408	–	–
Rank	2.5	2.5	1	–	–

Table 4) Confusion matrices of Taguchi analysis for the three classification approaches

	SVM			MLP			SOM		
	PA (%)	UA (%)	CK	PA (%)	UA (%)	CK	PA (%)	UA (%)	CK
Agri	83.75	63.21	0.83	79.41	30.68	0.79	63.16	13.64	0.62
Garden	98.22	99.77	0.98	76.92	72.41	0.74	100	0.34	1
Range	95.12	91.12	0.94	89.83	81.54	0.88	85.52	80.26	0.83
Rock	95.85	98.10	0.93	92.93	96.68	0.88	89.12	95.81	0.80
Urban	94.05	94.89	0.92	79.84	86.48	0.74	61.15	87.22	0.48
Kappa		0.93			0.83			0.77	
OA		0.95			0.87			0.79	
V(K)		0.0000299			0.0000850			0.00012	

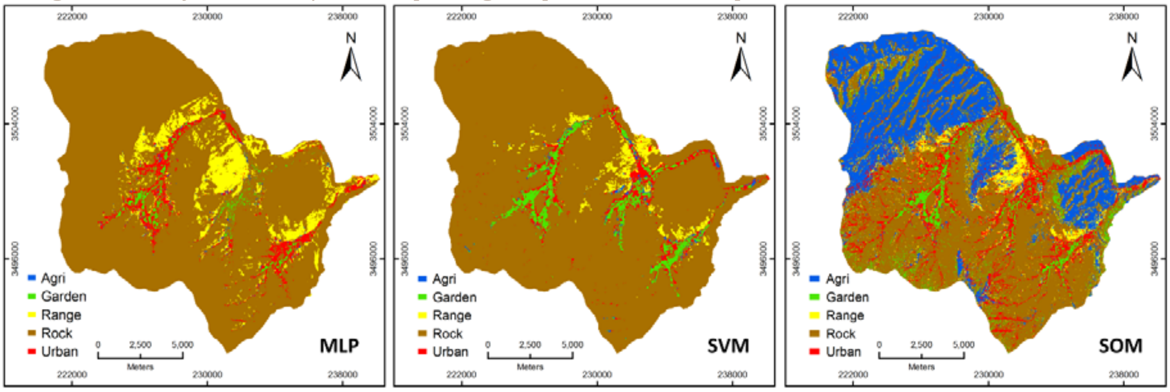

Figure 5) Results of MLP, SVM and SOM classifications

The main limitation of this study is that only pixel-based methods were examined. Although these methods are robust, they have their own limitations. Therefore, it can be suggested for future works to couple Taguchi method with object-oriented methods in order to produce more reliable land use/cover maps.

Conclusion

The proposed technique implemented here is an efficient classification of images using the Taguchi-based optimized SOM, MLP, and SVM based feature extraction methods. After determining the optimal parameters for all three ways attempted to comparison with each other. The results of this study show a statistically significant difference in the accuracy between the pixel-based SVM approaches for Land use/Cover characterization and the MLP and SOM classifiers. We also demonstrated that the Taguchi method can be effectively used to optimize the structure of the classification methods. Using Taguchi orthogonal arrays makes it very easy and consistent to find the best combination of classification parameters performing a limited number of tests.

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