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Comparison of different algorithms for land use mapping in dry climate using satellite images: a case study of the Central regions of Iran

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Abstract

The objective of this research was to determine the best model and compare performances in terms of producing land use maps from six supervised classification algorithms. As a result, 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) were considered in three areas of Iran's dry climate. The selected study areas for dry climates were Shahreza, Taft and Zarand in Isfahan, Yazd, and Kerman Provinces, respectively. Three Landsat ETM$^+$ images and topographical maps of 1:25,000-scale were used in the present study. In addition, training samples for each land use were constructed using GPS and extensive field surveys. The training sites were divided into two categories; one category was used for image classification and the other for classification accuracy assessment. Results show that for the dry climate areas, *Maximum Likelihood* and *Support Vector Machine* algorithms with averages of 0.9409 and 0.9315 Kappa coefficients are the best algorithms for land use mapping. The *ANOVA* test was performed on Kappa coefficients, and the result shows that there are significant differences at the 1% level, between the different algorithms for the dry climate zones. These results can be used for land use planning, as well as environmental and natural resources purposes in study areas.

Keywords: Arid Regions; Land Cover; Remote Sensing; SVM

1. Introduction

An accurate land cover map is essential for many planning and management activities and for modeling and understanding the Earth as a system (Salberg and Jenssen, 2012). The use of data from satellites for land use mapping, is a quick method that was widely utilized by researchers in the last decade (Pal and Mathur, 2005; Schneider, 2012; Zhou *et al*., 2013; Jacqueminet *et al*., 2013). Analysis of these data creates images of human interaction with the natural environment thereby providing an impression of land use. Also, analysis of these multi spectral images can help to better identify land cover (Szuster *et al*., 2011; Tigges *et al*., 2013; Shim, 2014). Image classification methods can be subdivided into two general approaches, 1) supervised and 2) unsupervised. In the supervised approach, images are classified according to samples each of which is representative of one class, known as a training set. In unsupervised methods, the images are classified based on spectral information, available by default (Halder *et al*., 2011).

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Several different classification algorithms are used to produce land use maps from remote sensing and satellite images namely Maximum Likelihood, Neural network and Support Vector Machines (Tso and Mather, 2001; Franklin and Wulder, 2002; Frery *et al*., 2007; Lu and Weng, 2007; Rogan *et al*., 2008; Blaschke, 2010). It is not clearwhich algorithm in image classification is more suitable to produce land use/cover maps in dry areas. Therefore, a comparison of different image classification algorithms, for determining the most accurate algorithm is necessary, in the unique and fragile environments of the world. In summary, this body of research, despite covering many regions of the world, has considered only a few classification algorithms. In dry areas with significantly large populations of residents, natural resources are under stress and accurate information on land use is necessary for planning. However, a specific algorithm was not introduced for image classification, during land use mapping in these areas. The overall aim of this research was to evaluate the potential of different classifiers in the dry region for land use mapping.

2. Material and methods

2.1. Study sites and data

Since Iran is located in an arid zone, about 85% of the country has arid, semi-arid and hyper arid ecosystems. As a result of the location of Iran, the amount of precipitation is less than a third of the average in the world. Most of Iran is located in the Irano-Turanian Zone, characterized by high spatio-temporal variation of precipitation almost between 100 and 300 mm. The average temperature in this area is generally above 24°C. In this study, three areas were selected based on dry climate conditions, distribution and data requirements namely Shahreza (32° 01' 0" N and 51° 52' 0" E) in Esfahan Province, Taft (31° 44' 0" N and 54° 12' 0" E) an area of the Yazd Province and Zarand (30° 48' 0" N and 56° 36 0" E) an area of the Kerman Province, all located in the central part of Iran. Most of Iran is located in arid and semi arid climates (Fig. 1). According to the nearest weather stations to each area and average annual precipitation, based on the Dumbarton climate classification, all three case studies in the central part of Iran had dry climates (Table 1).

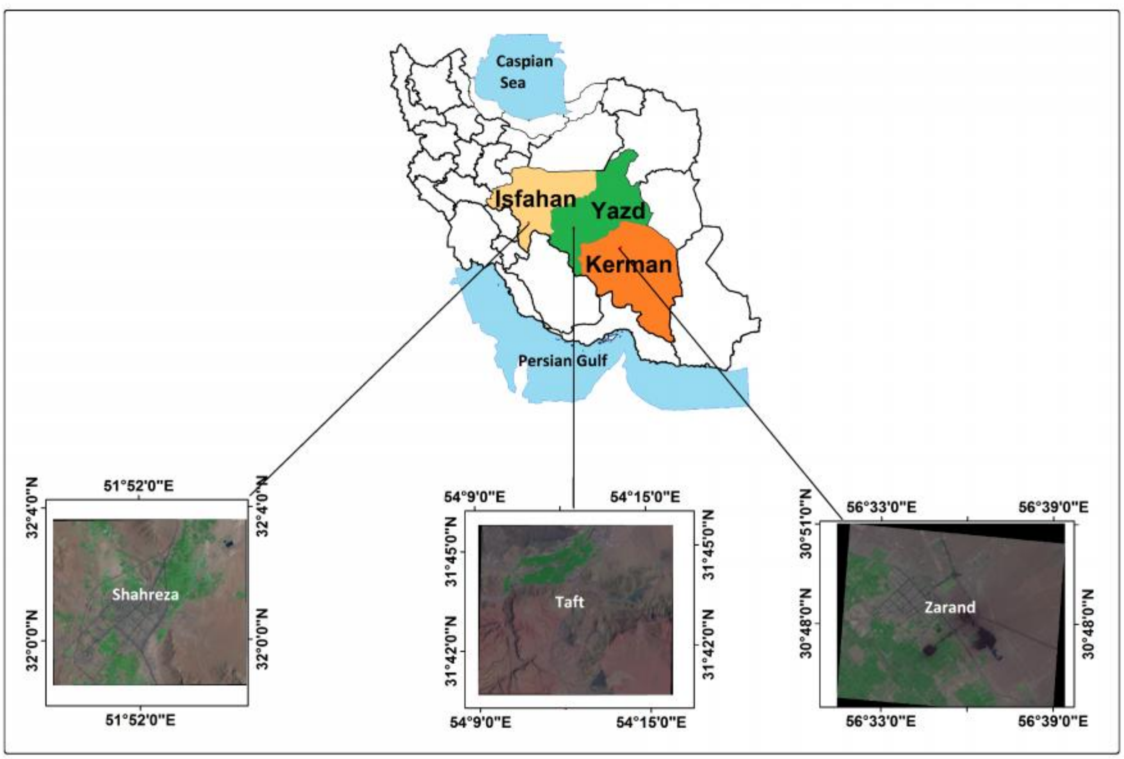

Fig. 1. Geographic location of case studies in the central zone of Iran

Table 1. A summary of the metadata in dry climate areas

Climate	Case study	Area (Hectare)	Average precipitation (mm)	Available Landsat data
Dry	Shahreza	9560	140	2006.06.10
	Taft	9198	164	2006.08.06
	Zarand	10761	111	2005.08.05

In this study, ETM+ images of Landsat were used to produce land use and also topographic maps with scale of 1:25000, were used for each of the study areas.

2.2. Classifiers

Maximum Likelihood is one of the most effective algorithms for image classification (Jensen, 2005; Bargiel, 2013). In most studies, this method has been distinguished as the most accurate (Hopkins *et al*., 1988; Richards and Jia, 2005; Halder *et al*., 2011). The algorithm is used to calculate the weighted distance (WD) or likelihood Z of the unknown measure vector Y, belonging to one of the unknown classes and Mc are based on the original Bayesian Equation (1) (Otukei and Blaschke, 2010).

Z=ln(at)–[0.5ln (|covt|)]–[0.5(Y–At)T(covt–1)(Y–At)] (1)

In this equation, Z = weighted distance (likelihood), t = a unique class, Y = the measuring vector for targed pixel, At = the mean vector in sample of target class t, a t = percent probability which any target pixel is a member in t class, Covt = the covariance matrix of the pixels in sample of class t, |Covt| = determinant of Covt, Covt-1= inversed Covt (matrix algebra), ln = natural logarithm function, T = translocation function (matrix algebra) (Srivastava et al., 2012).

Artificial Neural Network is one of the nonparametric algorithms used for image classification that does not need to assume a normal distribution of data (Kavzoglu and Mather, 2003; Qiu and Jensen, 2004; Foody, 2004; Lu and Weng, 2007; Dixon and Candade, 2008). The ANN weights were initialized using the uniform distribution. Learning rate was set to 100 and 0.01, for the hidden layer and the output layer, respectively; therefore the stopping criteria on 0.001 was fixed. The typical activation logistic function is expressed in Eq. (2) (Schalkoff, 1997; Friedman and Kandel, 1999):

$$O_j = 1/(1+e^{-knet_j}) \quad (2)$$

where O_j is the output of external input j, k is a gain factor. The term net_j can be computed using Eq. (3) (Schalkoff, 1997):

$$net_j = \sum_i w_{ji} o_i \quad (3)$$

where, w_{ji} is the weight of interconnection channel to unit $_j$ from unit $_i$ and o_i is the output of the external unit i.

Researches are currently ongoing, regarding the methods of satellite image classification and the Support Vector Machine (SVM) is a recently introduced algorithm for satellite image classification to map land use (Huang *et al*., 2002; Salberg and Jenssen, 2012; Hannv *et al*., 2013). SVM is a non-parametric approach to classification that contains a set of related learning algorithms used for classification and regression (Bray and Han, 2004; Han *et al*., 2007; Remesan *et al*., 2009; Zare Abyaneh *et al*., 2011; Hannv *et al*., 2013). SVM is a theory originally proposed by Vapnik and Chervonenkis (1971) and later discussed in detail by Vapnik (2000). SVM is a classification system derived from the theory of statistical learning, which decreased uncertainty in the model structure and fitness of data is one of the aims of SVM (Oommen *et al*., 2008).

Recent studies show that the SVM is more accurately classified than the other methods (Gualtieri and Cromp, 1998; Oommen *et al*., 2008; Halder *et al*., 2011; Mountrakis *et al*., 2011; Srivastava *et al*., 2012a; Hannv *et al*., 2013). The support vectors are data points and lie at the edge of each class hyperplane in feature- space and close to the optimal separating hyperplane OSH (Sanchez-Hernandez *et al*., 2007; Szuster *et al*., 2011).

This study used the kernel functions namely linear, polynomial, sigmoid kernels, and the radial basis function (RBF). Also in this study, the multiclass ENVI image processing environment was used for the SVM pair-wise classification strategy. This method is based on producing a binary classifier for each pair of classes, choosing the class with the highest possibility of identification across the pair-wise comparisons series. A suite choice of kernel, permits the data to be separated into the feature space, contrary data are non-separable in the original input space. The four Support Vector Machine kernels were used in this study (polynomial, linear, Sigmoid and radial basis) (Petropoulos *et al*., 2010; Petropoulos *et al*., 2011).

The Minimum Distance to Mean classification algorithm, after determining the spectral mean for each band, determines the average value of pixel allocation for each training set and each class is compared to the distance from the pixel value that is not classified to the average pixel value for each class and then the pixel is allocated to a class with the lowest average distance (Richards, 1999; Ghimire and Wang, 2012).

The Mahalanobis Distance classification algorithm is the other image classification method. It is very similar to the Minimum Distance to mean algorithm, except that in this algorithm covariance matrix can also be used. The Mahalanobis distance is a value between two data points in the space that was defined by relevant features (Zhang *et al*., 2011; Xing *et al*., 2003). This method assumes that the histogram bands are normal (Richards, 1999).

Spectral Angle Mapper is another image classification method that is based on spectral classification. In this algorithm, a dimensionless angle is used to assign pixels to a spectrum band. This algorithm determines the desired spectrum by using similarities between two spectral bands to calculate the angle between two spectra (Mazar et al., 1988; Luc *et al*., 2005). When this algorithm is used the data is calibrated to reflect the effects of light and albedo (Kruse *et al*., 1993; Sohn and Rebello, 2002; Luc *et al*., 2005).

Several researches have been conducted to compare different satellite image classification algorithms (Demorate, 1998; Elizabeth *et al*., 2006; Al-Ahmadi and Hames, 2009; Rajesh and Yuji, 2009; Perumal and Bhaskaran, 2010; Brian *et al*., 2011).

In the studies mentioned, only a few classification algorithms were applied. The main objective of this study was to introduce a specific algorithm for image classification for land use mapping in dry areas which are yet to be mapped. This is important because in dry areas with significantly large populations of residents, there is pressure on natural resources and accurate information of land use is required, also more than 85% of Iran is located in this zone.

2.3. Geometric image corrections

For geometric corrections, the image to map method was used. This means that for every area, 25 control points from vector layers of topographic maps such as roads and channels were extracted. The points were then determined by matching them to the corresponding points on images. After removing any unsuitable point by the non-parametric polynomial method, geometric image corrections were done with 20 to 23 control points, and pixel RMSE between 0.18 and 0.22.

3. Results and discussion

To produce land use maps for each case study, different algorithms such as Support Vector Machine, Maximum Likelihood, Neural network, Minimum Distance, Mahalanobis Distance and Spectral Angle Mapper were used. Data for existing land use was determined by GPS and field visits, thus training set samples for each land use were constructed. The training sets were divided into two categories randomly; one category was used for image classification (70%) and the other category was used for classification accuracy assessment (30%) (Table 2).

Table 2. Characteristics of the training sites

Climate	Case study	Land use	Training (m^2)	Accuracy Assessment (m^2)
Dry	Shahreza	Residential	64100	26000
		Agriculture	226900	87600
		Desert	1278000	412000
	Taft	Residential	37430	11700
		Agriculture	197800	57000
		Desert	1212900	386500
	Zarand	Residential	110770	41300
		Agriculture	891765	366934
		Desert	1094358	350740

In each area, fixed training sets were used for different classification algorithms and did not change. The same situation was observed for assessment training sets. Finally, land use maps were produced by 6 classification algorithms for, Shahreza (Fig. 2), Taft (Fig. 3) and Zarand (Fig. 4).

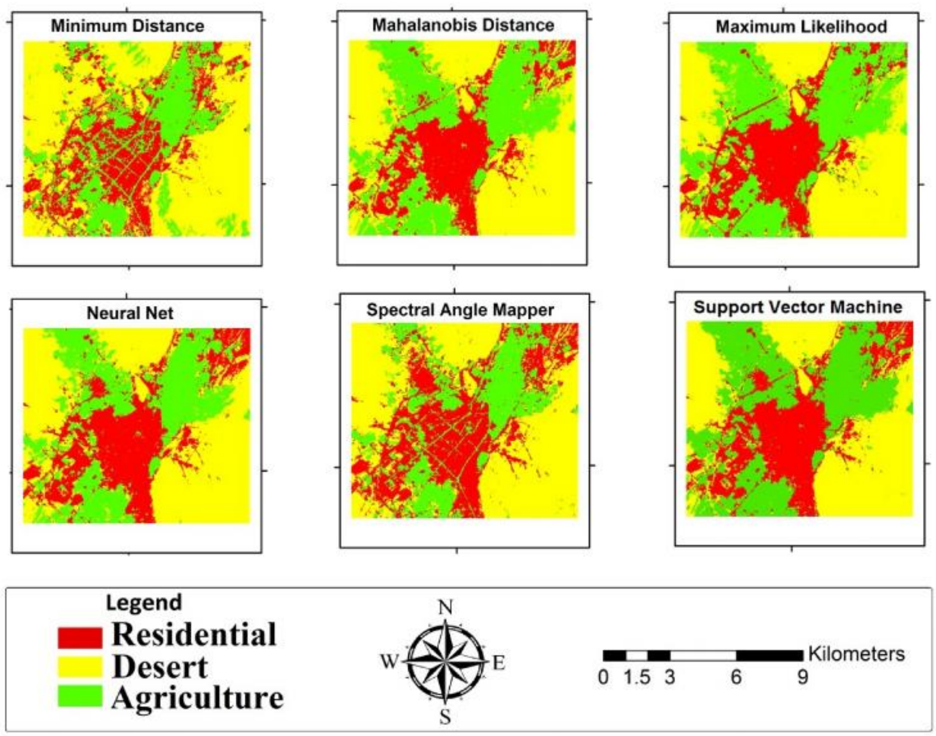

Fig. 2. Land use maps with 6 classification algorithms for Shahreza

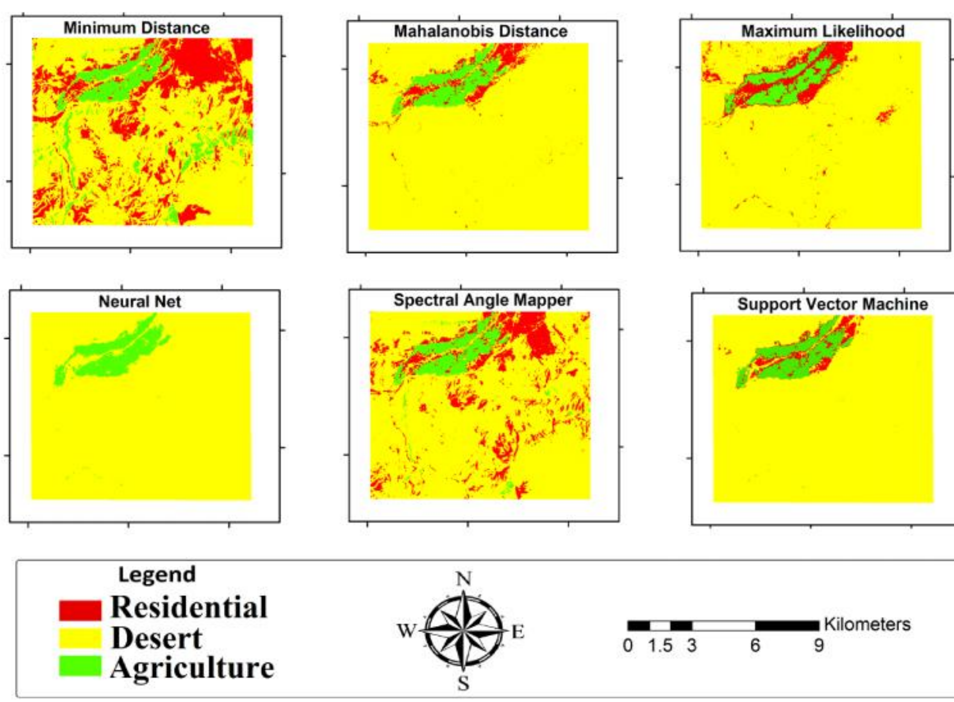

Fig. 3. Land use maps with six (6) classification algorithms for Taft

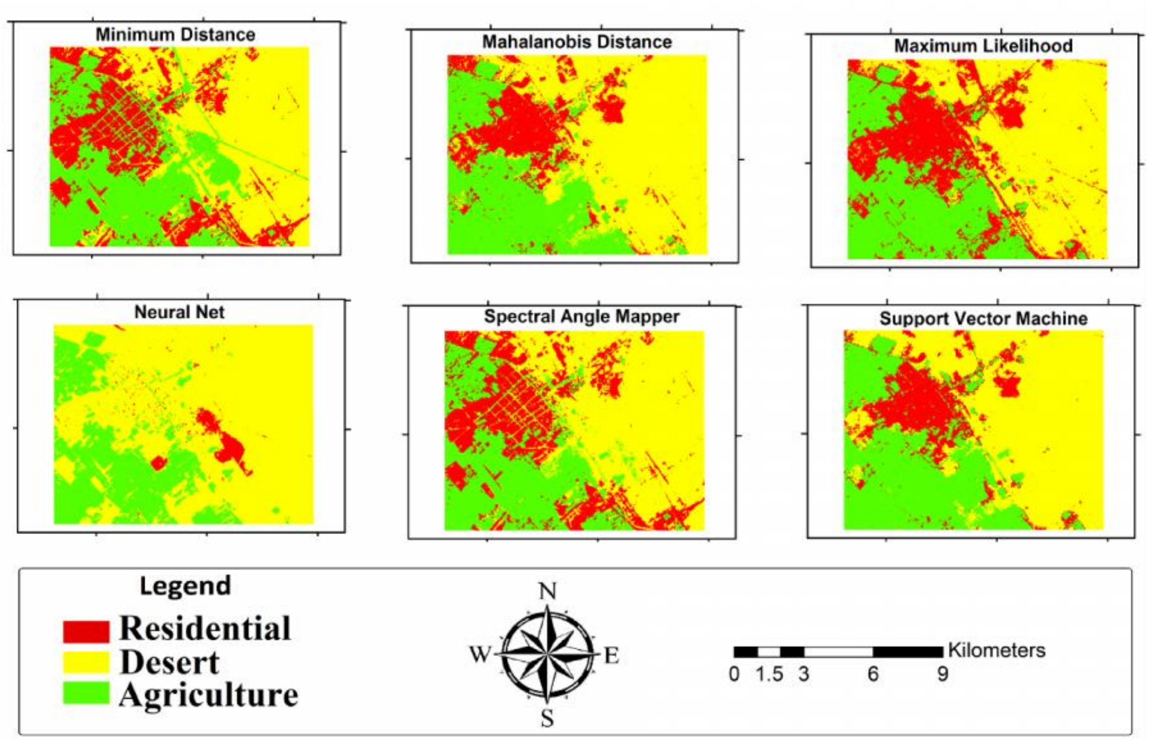

Fig. 4. Land use maps with six classification algorithms for Zarand

3.1. Classification assessment

After image classification of the training sets, classification assessments were done on some training sets not used for image classification. In this study, Kappa coefficient (k) and overall accuracy coefficients (Ov.) were used for classification assessments (Aguilar *et al*., 2012; Srivastava *et al*., 2012). Kappa coefficient is the most common assessment coefficient (De Backer *et al*., 2009; Aguilar *et al*., 2012). This is because this coefficient uses pixels that are in wrong classes (Galton, 1892; Smeeton, 1985).

The equation for Kappa is:

$$\text{Kappa} = \frac{P(o) - P(c)}{1 - P(c)} \qquad (4)$$

where P(o) is the correctly observed pixels, and P(c) is the hypothetical probability of chance agreement (Table 3).

Table 3. Accuracy coefficients of six (6) image classification algorithms for case studies

Classify algorithm	Dry Climate					
	Shahreza		Taft		Zarand	
	K	Ov.	K	Ov.	K	Ov.
Mahalanobis Distance	0.6356	82.95	0.9797	99.88	0.6785	80.16
Maximum Likelihood	0.9624	99.78	0.9624	99.78	0.8979	94.1
Minimum Distance to Mean	0.5998	76.82	0.1044	65.09	0.1044	65.09
Neural network	0.5468	79.16	0.9325	99.64	0.6104	79.23
Spectral Angle Mapper	0.3078	88.39	0.3078	88.39	0.7517	84.78
Support Vector Machine	0.8529	92.8	0.9938	99.96	0.9477	97.1

3.2. Statically Analyses

One way ANOVA (Analysis Of Variance) was used for statistical assessment of Kappa coefficients for each case study (De Backer *et al*., 2009; Aguilar *et al*., 2012). Results show that Kappa coefficients in three case studies had significant differences at the 1% level for dry climate areas (Table 4). Also, Duncan's test was used to compare means and prioritizations of the six (6) classification algorithms for dry climate (Fig. 5) (Duncan, 1995).

Table 4. Kappa coefficients ANOVA analyses for six (6) algorithms in dry and humid climates

Climate		Sum of Squares	df	Mean Square	F	significance
	Between group	1.072	5	0.214	5.547	0.007*
Dry	Within group	0.464	12	0.039		
	Total	1.536	17			

* The mean difference is significant at the 0.05 level or P- value <0.05.

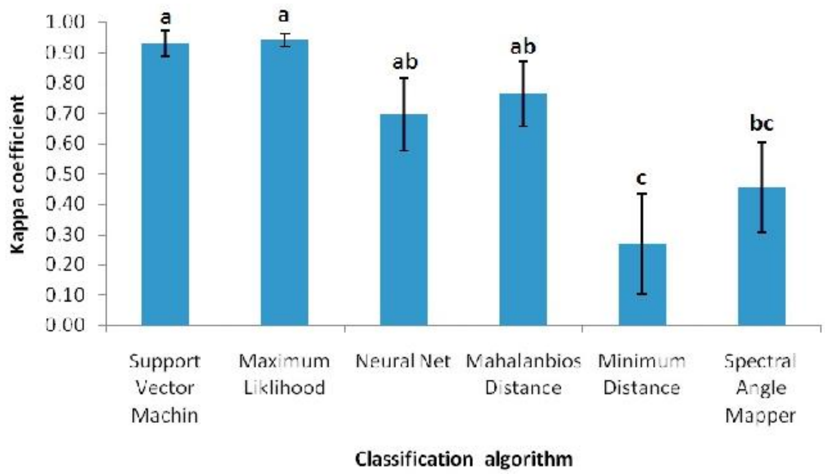

Fig. 5. Duncan's classification method for six image classification algorithms in dry climates.

Duncan's classification show that the six methods used in dry climates are in 4 categories (a, ab, bc and c). Results show that support vector machine and maximum likelihood algorithms are in one category (a), and these algorithms produce the most accurate land use maps for dry zones. However, neural net and Mahalanbios Distance algorithms could produce good and accurate land use maps, according to the high value of Kappa (more than 0.65). The variation of accuracy coefficients in three case studies by maximum likelihood is less than the other five algorithms. Minimum distance and spectral angle mapper have the highest standard error value and the stability of these algorithms to produce land use maps is too low.

4. Conclusion

In this study, six image classification algorithms were applied to evaluate dry climate areas in the Irano-Torani zone of Iran. Also, for classification assessment, the ground true points approach was used to determine Kappa coefficient and overall accuracy. The results obtained from three areas were used to produce land use map by studies algorithms. Results of the one way ANOVA for Kappa coefficient for the dry climates show that Maximum Likelihood and Support Vector Machine with averages of 0.9404 and 0.9315 Kappa coefficients are the best classification algorithms, to produce land use maps in these dry climate areas. Also, the results of this study show that for the support vector machine, the maximum likelihood algorithms and the standard error of the algorithms was smoother than the other algorithms. It means that variation of accuracy assessment for these algorithms which used to produce land use in different area in dry climate region is less than others. The reason for this difference may be due to change in the digital number (DN); in the dry climate areas the color domain (DN) was low, so the SVM and MLC methods could severance the land cover types more than the other classifiers. In dry climate regions there is not any significant difference between SVM and MLC, wherever, the MLC showed the more accurate results. Neural network and Mahalanobis Distance are in same level to produce land use map in dry regions.

In dry climates, it is very important to validate the produced maps, because the difference between the worst and the best algorithms in Kappa coefficient is 0.6714. This means that choosing the appropriate algorithm to produce land use is more important in the Irano- Torani zone. This study confirms the results of Gualtieri and Cromp (1998), Huang *et al*. (2002), Oommen *et al*. (2008), Szuster *et al*. (2011) and Chu et al. (2012); however, these researchers almost studied regions that could be regarded as humid or coastal in nature. When it comes to land use mapping, one of the advantages of the SVM algorithm is that it produces highly accurate classified images from small training sets (Mantero *et al*., 2005; Halder *et al*., 2011; Mountrakis *et al*., 2011; Salberg and Jenssen, 2012). SVM has been found to achieve a higher level of accuracy than contemporary conventional methods of classification (Melgani and Bruzzone, 2004; Foody and Mathur, 2004; Pal and Mather, 2005). This advantage helps environmental and natural resources managers to quickly provide images with accurate information, thus saving time and cost (Mountrakis *et al*., 2011). Further studies are required to focus on algorithms with high accuracy, in order to achieve the optimum parameters of these algorithms and for a more accurate classification of satellite images.

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