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Optimization of support vector machine parameters for image classification and land use mapping in humid and dry climates based on Sentinel-2 images

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Abstract

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~~In this study, we aimed to~~ This study aimed to optimize Support Vector Machine (SVM) algorithm parameters forto producinge land use maps from~~by~~ satellite images in selected humid and dry climate~~s~~ areas of Iran. ~~Three sites including Shahreza, Taft, and Zarand were selected as suitable sites to study dry~~

~~climate area (located in central part of Iran) and other 3 sites including Kordkoi, Noor, and Talesh (located in northern part of Iran) were selected as being representative of the humid climate area. For image classification and land use mapping in the study area, s~~Seven values for both Gama in the Kernel function and penalty parameters (0.001, 0.01, 0.1, 1, 10, 100, and 1000) were tested using the radial basis ~~function (RBF) of SVM classification algorithm. Additionally, 400 control samples and 200 control points were employed to classify and validate each study site, respectively. Results indicate that for each of the three humid climate areas, support vector machine algorithm with a mean of 77.6 and 66.82 overall accuracy (OA) coefficients is an acceptable classification algorithm for selected humid and dry climate areas, the penalty parameters in both types of climates showed direct relationship with OA. However in dry climate area, OA shows higher steps in reduction, while the penalty parameters was less than one. We found that the penalty parameters < 0.01 gives the lowest values of overall accuracy in produced land use maps. On the other hand, the penalty parameters > 100 results in a higher accurate land use maps. Moreover, there is a variable behaviour in terms of user and produce accuracy for two studied climate types changing in penalty parameters. Also, changes in gamma values in kernel function were not effective in accuracy assessment for all six studied sites in humid and dry climate area. In conclusion, the generated maps in the studied sites can be useful guide for future land use planners, environmental, and natural resources purposes in Iran and beyond.~~

Keywords: ~~Support vector m~~Machine learning, Penalty parameter, Land use mapping, Remote sensing.

1. Introduction

Knowledge of land cover is important for many planning and management activities and for modelling and understanding the Earth as a system (Jacqueminet et al., 2013; Salberg and Jenssen, 2012; Thanh Noi and Kappas, 2018). Using data provided by satellites for~~in~~ land use mapping is a comprehensive and rapid~~quick~~ method which is now~~and~~ widely employed by many researchers (Pal and Mather, 2005; Schneider, 2012; Yousefi et al., 2017, 2015b; Zhou et al., 2007). Analysis of satellite~~these~~ data creates images of human interactions with the natural environment.~~ that provides an impression of land use. Therefore, e~~Examination of~~ning these~~ multi spectral images can be used help to~~ better~~ identify land cover (Matinfar et al., 2007; Szuster et al., 2011; Tigges et al., 2013; Shim, 2014). Here, ~~I~~image classification methods can be subdivided into two general approaches; supervised and unsupervised. In the supervised approach, images are classified according to each sample that is representative of one class, known as a training set. In unsupervised methods, the images are classified based on spectral information, available by default (Oommen et al., 2008; Halder et al., 2011).

Several different classification algorithms that produce land use maps from remote sensing and satellite images can be cited, such as maximum likelihood (ML), neural network (NN), and SVM (Hames, 2009; Srivastava et al., 2012; Jacqueminet et al., 2013; Li et al., 2014; Yousefi et al., 2015a; Lindquist et al., 2012; Gola et al., 2019; Mohammadi et al., 2019). Support vector machine is one of the most popular algorithms used in image classification (Filipovych and Davatzikos, 2011; Kesikoglu et al., 2019; Li and Cheng, 2005; Mohammadi et al., 2019; Srivastava et al., 2012; S. Yousefi et al., 2016). SVM is a new supervised classification method derived from statistical learning theory that often delivers more robust ~~have better~~ classification results from complex and noisy data compared to more traditional classification methods (Srivastava et al., 2012; S. Yousefi et al., 2016). Most ~~of~~ image classification algorithms have variables and parameters requiring ~~which have different roles on image classification algorithm and need to be~~ optimisation. ~~ed for any region to access more accurate data.~~

Wentz et al. (2006), comparing some existing land use mapping methods with Land sat TM images in Arizona State in the US, reported~~found~~ high accuracy of satellite images for land use mapping. Another study (Al-Ahmadi and Hames, 2009) ~~in (Al-Ahmadi and Hames, 2009),~~ in arid areas of Saudi Arabia compared four image classification algorithms for ETM+ images and reported~~. They found~~ that the Maximum Likelihood algorithm was more accurate than other algorithms currently used for land use mapping. Similarly, Thapa and Murayama (2009a) working in Japan, reported~~, in a study in Japan compared some algorithms to land use mapping for town areas with ALOS satellite images. Results showed that~~ the use of the fuzzy approach for~~on final~~ generating~~ed~~ maps compare. ~~to supervised and unsupervised methods. Another study~~ Working in India, ~~(~~Perumal and Bhaskaran, 2010~~)~~, compared ~~some~~ different image classification algorithms for~~to~~ land use mapping from~~by~~ IRS images and found Mahalanobis Distance with 0.97 kappa coefficients more accurate than parallel piped, maximum likelihood, minimum distance to mean (MDM), neural network, and spectral angle mapper (SAM). ~~Szuster et al. (2011), in a study based on the coastal tropical areas of Thailand found that SVM with an overall accuracy of 94.15 was the most accurate algorithm. In a study in northern and central parts of Iran (Yousefi et al., 2015a) found that SVM and NN the most accurate classification methods using Land sat images~~. Most ~~R~~recently, ~~(~~Núñez et al., 2019~~)~~ used classification techniques in conjunction with~~of~~ high-resolution satellite imagery to map 50 selected cities ~~of study~~ of the National Urban System in Mexico.~~, during 2015–2016.~~ This study reported that the~~ey found~~ artificial neural network classifier delivered the best performance (overall accuracy of 92.2%). ~~a better single classification method. In addition, the same study found similar results for support vector machine (overall accuracy of 89.8%) and maximum likelihood (overall accuracy of 89.2%).~~ Helber et al. (2019) ~~–~~reported patch-based land use and land cover classification ~~approach~~ using Sentinel-2 satellite images and reported~~; they found~~ an overall classification accuracy of 98.57% with the proposed novel dataset. Kesikoglu et al. (2019) investigated the performance of ANN, SVM and MLH techniques for land use/cover change detection at the Sultan Marshes Wetland, Turkey and reported~~. They found~~ that the highest overall accuracy in image classifications was delivered by the~~using~~ SVM method.

The main difference between the present study and the approaches described in the aforementioned literature is that special optimization parameters w~~as~~ere developed and applied for image classification and land use mapping in humid and dry climate~~s~~ areas based on Sentinel-2 images using ~~the~~ SVM. A novel optimization method was developed for ~~methods. This is mostly because in~~ humid and dry regions since these are characterised by ~~where significantly~~ large ~~number of~~ populations live and accordingly,~~,~~ there is pressure on natural resources meaning that land use monitoring and plannjng are required. ~~and thus requires accurate information of land use.~~

The optimum range of SVM parameters, including the penalty parameter and Gamma in the kernel function, are not well understood with respect to using SVM to produce land use maps in dry and humid regions. Therefore, comparison of different ranges of these parameters in SVM-driven classification is required to to determine the most accurate land use maps ~~is necessary spatially~~ in these unique and fragile environments.~~ Previous studies which cover many regions around the globe, have considered only determining optimum range of penalty parameter and Gamma in kernel function of SVM classification in humid and dry areas where significantly large populations live, the natural resources are under stress, and accurate information on land use is necessary for planning. However, a specific range of penalty parameter and gamma in kernel function of SVM for image classification in order to land use mapping in these areas are understudied.~~ The main aim of this study, therefore, was~~is~~ to evaluate the potential of different ranges of these two important parameters in the SVM algorithm to improve the accuracy of land use mapping~~and sensitivity analysis of mentioned parameters~~ in humid and dry regions using satellite imagery. ~~for land use mapping~~

2. Material and methods

2.1 Study sites and data sources

Three study areas were selected for each climate (dry and humid), according to their distribution and data requirements. Shahreza, an area of Esfahan Province, Taft an area of Yazd Province and Zarand, an area of Kerman Province were selected as areas with dry climate. These are~~, and~~ all located in the central part of Iran (Fig. 1). Also, Kordkoi, an area in Golestan Province, Noor, an area in Mazandaran Province and Talesh, an area in Gilan Province were selected as areas with humid climate, and these are all located in the northern part of Iran (Fig. 1~~2~~). According to the annual reports of the nearest weather stations, and evaluation of the average annual precipitation of each study area, ~~and~~ based on the Dumbarton climate classification, all three case studies in the north and the three case studies in the central part of Iran were categorised as humid and dry climate areas, respectively (Table 1).

Commented [AC2]: The paper needs a location map of the study areas as Fig. 1

Fig 1~~2~~. Geographic location of the case studies in Iran.

The first step to produce a land use map is collecting accurate data. For this purpose, the Sentinel-2 satellite images provided by earth observation program Copernicus (https://earthexplorer.usgs.gov/) were used for generation of land use maps of the selected study areas. Topographic maps with the scale of 1:25,000 were used for image classification of each selected areas.

Table 2. Metadata ~~S~~summary for the ~~of the metadata~~ ~~in~~ humid and dry climate study areas.

Climate	Case study	Area (Hectare)	Average precipitation (mm)	Available Sentinel-2 images

Humid	Kordkoi	11358	970	2019.08.13
	Noor	8919	1,030	2019.06.12
	Talesh	10761	1,130	2019.07.25
Dry	Shahreza	9560	140	2019.08.08
	Taft	9198	164	2019.08.10
	Zarand	10761	111	2019.08.07

2.2 Support vector machine (SVM)

Research regarding the most suitable methods for~~of~~ satellite image classification is ongoing and, in this context, SVM is a recently introduced algorithm~~ for satellite image classification to map land use~~ (Huang et al., 2002; Li and Cheng, 2005; Salberg and Jenssen, 2012; Zhang et al., 2013). More specifically, SVM is a non-parametric approach to classification that contains a set of related learning algorithms used for~~to~~ classification and regression (Bray and Han, 2004; Han et al., 2007; Remesan et al., 2009; Abyaneh et al., 2010; Srivastava et al., 2012; Zhang et al., 2013). The theory underpinning SVM was~~is a theory that~~ originally proposed by ~~(~~Vapnik et al.~~,~~ (1995)~~)~~ with further discussion by~~and later discussed in detail by~~ ~~(~~Weston et al.~~,~~ (2001), Engineering and Africa (2002), Oommen et al. (2008) and Filipovych and Davatzikos (2011)~~.~~ ~~SVM is a classification system derived from theory of statistical learning, which decrease uncertainty in the model structure and the fitness of data are aims of SVM (Engineering and Africa, 2002; Filipovych and Davatzikos, 2011; Oommen et al., 2008)~~. Using the~~By~~ decision surface that maximizes the margin between ~~the~~ classes, SVM is able to distinguish~~it separates~~ the classes. In most studies, ~~Most times~~ the surface is referred to as ~~called~~ the optimal hyper-plane, whilst~~and~~ support vectors are the data points closest to the hyper-plane. Here, ~~T~~the support vectors are the crucial elements of the training set. The ~~P~~penalty parameter in SVM allows a certain degree of misclassification, which is ~~exclusively~~ very important for those training sets where class separation is challenging. ~~that are not separable.~~ In essence, the penalty parameter provides a means of c~~C~~ontrolling the trade-off between “allowing training errors” and “forcing rigid margins”. ~~is the role of penalty parameter. It creates a soft marginal that allowed some of misclassifications, as it allows some training sets on the wrong side of the hyper-plane.~~ Increasing the value of the penalty parameter in the SVM algorithm increases the rate of misclassifying pixels and forces the creation of a more accurate model. ~~that may not generalize well. Penalty parameter in SVM is a floating-point value greater than 0.01.~~ In most remote~~ly~~ sensing software, the default value of the penalty parameter is 100.0. ~~The penalty parameter defines a certain degree of misclassification in classification process, which is particularly important for non-separable training sets.~~ According to the different types of land use and corresponding land surface reflection in dry and humid regions, it is very important to identify the optimum range of the penalty parameter in the SVM algorithm, since the latter is being increasingly used~~ which use frequently~~ to produce~~s~~ land use maps from~~by~~ sentinel satellite images. Consequently, the work reported herein seeks to build upon ~~R~~recent studies which have demonstrated that the SVM ~~has~~ classifier~~d~~ is more accurate~~ly~~ than ~~the~~ other methods (Mantero et al., 2005; Xu and Gong, 2007; Thapa and Murayama, 2009b; Srivastava et al., 2012; Tigges et al., 2013). ~~One advantage of the SVM algorithm is that it can solve the problem of imbalances between the training sites (Huang et al., 2002).~~

The kernel function permits the training data to be projected in a major space where it may be increasingly possible to detect a superior sequestration buffer for the OSH (Engineering and Africa, 2002; Szuster et al., 2011). In this study, the Radial Basis Function (RBF) was implemented as a kernel function. Moreover, the ENVI 5.3 image multiclass processing environment ~~multiclass~~ was used for the SVM pair-wise classification strategy. This method is based on producing~~e~~ a binary classifier for each pair of classes and~~,~~ selecting~~choosing~~ the class that is~~are~~ closest to the higher possibility of identification across the pair-wise comparisons.

~~series. A suite choice of kernel permits the data to be mostly separable in the feature space, contrary to are non-separable in the original input space.~~ In this~~present~~ study, the radial basis function (RBF) of SVM kernels was used, viz.: ~~and show in Eq. (1).~~

Radial basis function: $K(x_i, x_j) = \exp(-y\|(x_i,x_j)\|^2), \gamma > 0$ (1)

Where y is the kernel function width, ~~polynomial degree term is~~ d is the polynomial degree term and o is the bias term in the kernel function. ~~showed with o.~~ For all the selected kernels, ~~the~~ common parameters were set for ~~t, which were~~ the pyramid levels, the classification probability threshold value and the penalty parameter. Here, a ~~M~~maximum value (i.e., 1,000) was set in all cases for the penalty parameter, forcing all pixels in the training data to converge to a class. For all kernels, the pyramid parameter was set to a value of zero. Zero was also used for the~~a~~ classification probability threshold, to ensure~~restrict~~ all image pixels were assigned~~to get~~ just one class label, and that no pixels ~~to~~ remained unclassified (Petropoulos et al., 2010, 2011).

2.3 Geometric image corrections

~~For the study areas,~~ The image to map method was used to correct geometric images for the study areas. This means that, for every area, 25 control points from vector layers of topographic maps such as roads, channels, and residential places were extracted, the points were then determined by matching them to the corresponding points on the satellite images. After removing any unsuitable point by the non-parametric polynomial method, the geometric image corrections were finalised~~done~~ with 20 to 23 control points, yielding a corresponding ~~and~~ pixel toot mean square error (RMSE) of between 0.12 and 0.17. Figure 2 presents~~show~~ the methodological flowchart for the work reported in this paper. ~~of methodology in present study~~.

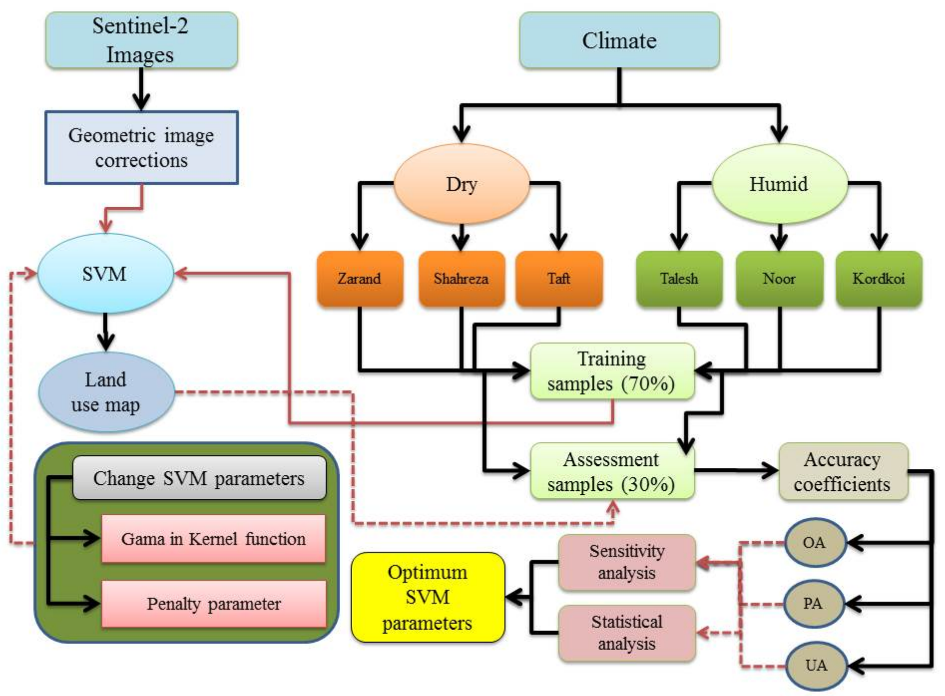


Fig. 2 Flowchart of the SVM optimisation methodology.

3. Results and discussion

~~The algorithm of SVM was used to produce land use maps for each study areas. Data~~ Training ~~D~~data represented by~~for~~ existing land use in the study areas was determined by GPS ~~data~~ and field ~~survey~~surveys.~~, thus training set samples for each land use were constructed.~~ The training sets were randomly divided into two categories~~ randomly~~; one category (70%) was used for image classification ~~(70%)~~ and the other (30%) ~~category was used~~ for assessing classification accuracy ~~assessment (30%)~~ (Table 2).

Table 2. Training data summary for the study areas. ~~Characteristics of the training sites~~

Climate	Case study	Land use	Classification category~~Training~~ (m^2)	Accuracy assessment category (m^2)
Humid	Kordkoi	Forest	712,700	209,300
		Residential	58,800	23,000
		Agriculture	452,000	145,000
	Noor	Forest	675,200	248,000
		Residential	92,600	35,000
		Agriculture	466,000	123,000
	Talesh	Forest	626,000	266,000
		Residential	61,500	27,000
		Agriculture	304,700	98,400
		Water body	23,200	8,000
Dry	Shahreza	Residential	64,100	26,000
		Agriculture	226,900	87,600
		Desert	1,278,000	412,000
	Taft	Residential	37,430	11,700
		Agriculture	197,800	57,000
		Desert	1,212,900	386,500
	Zarand	Residential	110,770	41,300
		Agriculture	891,765	366,934
		Desert	1,094,358	350,740

In each area, the same training sets were used for different parameters of SVM classification. ~~The same situation was observed for assessment training sets and assessment matrix. Finally,~~ ~~l~~Land use maps were finalised using the ~~produced by~~ SVM classification algorithm on the basis of pinpointing the~~in~~ best values of the penalty parameter and gamma in the kernel function for both climatic types (Figs. 3-8). ~~humid climate including; Talesh (Fig. 3), Noor (Fig.4) and Kordkoi (Fig.5). In addition land use maps for dry climate were produced based on the best values of penalty parameter and gamma in kernel function for Zarand (Fig. 6), Shahreza (Fig.7) and Taft (Fig.8).~~

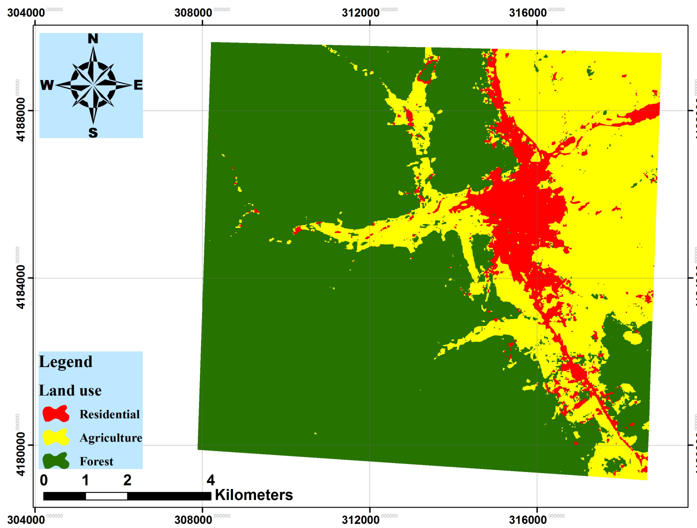


Fig. 3 Final SVM-based~~Produced~~ ~~L~~land use map for~~in~~ the Talesh study area. ~~based on SVM~~

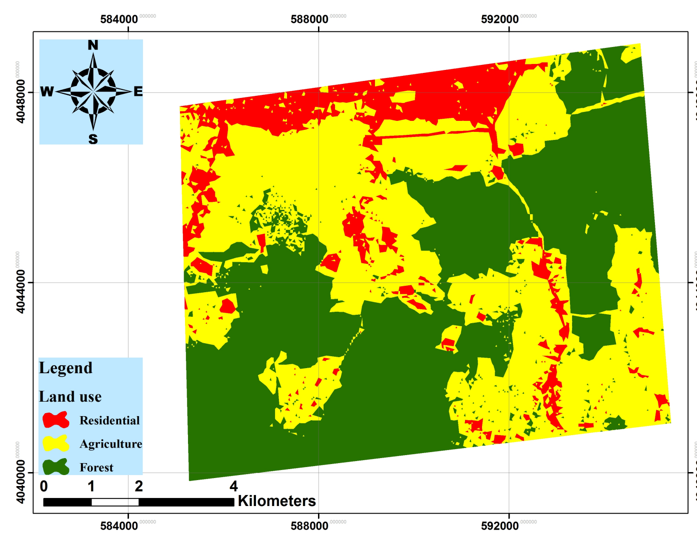


Fig. 4 Final SVM-based ~~Produced~~ ~~L~~land use map for the~~in~~ Noor study area. ~~based on SVM~~

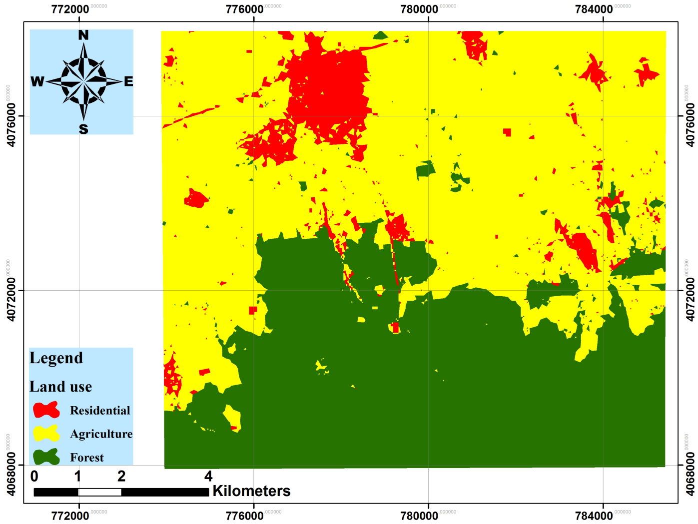


Fig. 5 ~~Produced~~ Final SVM-based ~~L~~land use map for the~~in~~ Kordkoi study area. ~~based on SVM~~

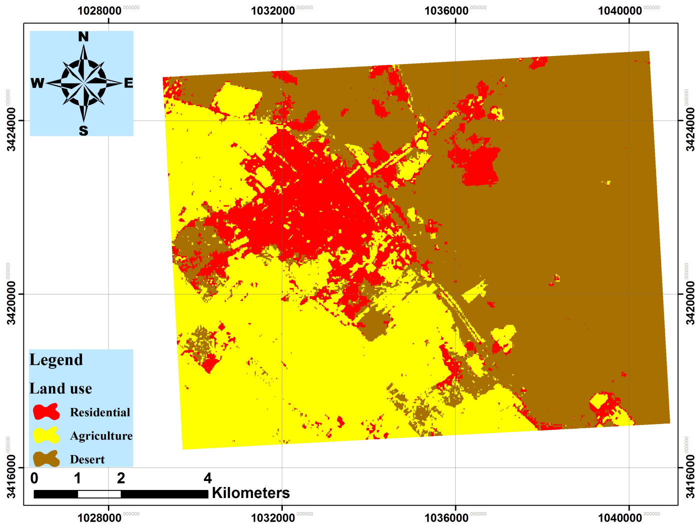


Fig. 6 Final SVM-based~~Produced L~~land use map for the~~in~~ Zarand study area. ~~based on SVM~~

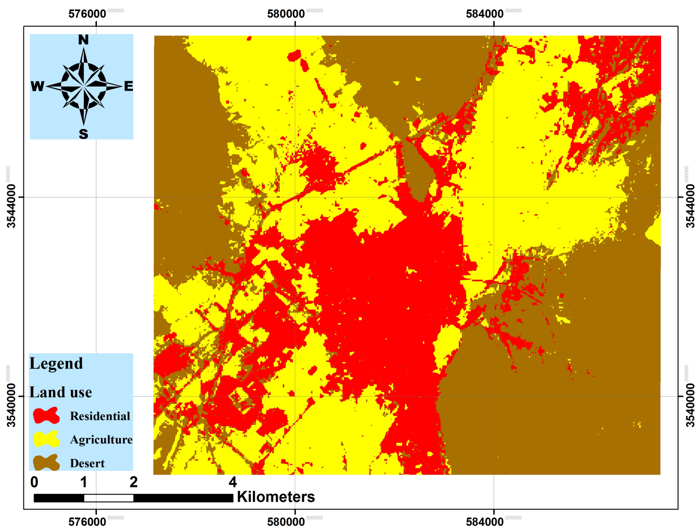


Fig. 7 Final SVM-based~~Produced L~~ land use map for the~~in~~ Shahreza study area. ~~based on SVM~~

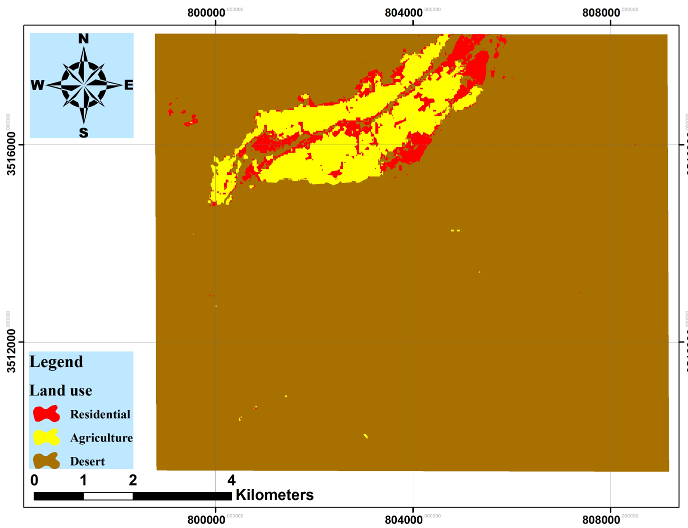


Fig. 8 Final SVM-based~~Produced L~~land use map for the~~in~~ Taft study area. ~~based on SVM~~

3.1 Classification assessment and sensitivity analysis

After image classification of the training sets, classification accuracy assessments were performed~~done~~ randomly on the remaining portion (30%) of the training sets. ~~that were not used for image classification process. In this study~~Here, we used overall accuracy ~~coefficients~~ (OA), user accuracy (UA,) and produce accuracy (PA) ~~were employed for classification assessments~~ (De Backer et al., 2009; Srivastava et al., 2012; Aguilar et al., 2013; Yousefi et al., 2018). The ~~R~~results for~~of present study in~~ all study sites ~~on dry climate (Shahreza, Taft, and Zarand) and humid climate (Noor, Talesh, and Kordkoi) regions~~ demonstrated that by decreasing the penalty parameters, the overall accuracy decreased (Fig. 9). Additionally, accuracy reduced more sharply~~decreasing trend had a greater slope~~ after the penalty parameters~~ which~~ were less than 0.1 (Fig.9). ~~Totally, the~~Across the study sites, overall accuracy~~ for six study sites have a~~ ranged between~~of~~ 30~~-~~% to 96% (Fig. 9).~~, and for all study sites it will be stable at penalty parameters less than 0.01 (Fig. 9). In addition, the results indicated that~~ Alterations to the Gamma values ~~alterations~~ in the Kernel Function did not affect~~show any effect on~~ the accuracy coefficients in either of the climatic areas. ~~both dry and humid climate areas.~~

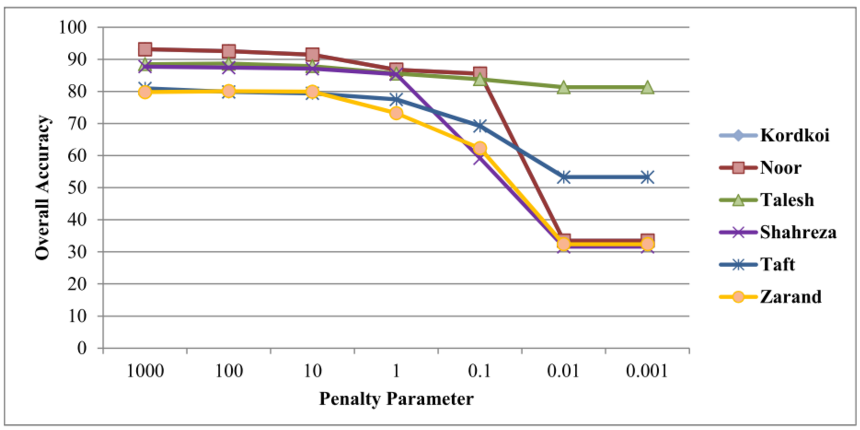


Fig. 9 Sensitivity analysis of OA for the six study areas.

The producer's accuracy refers to the probability that a certain land cover or use is classified correctly. ~~LC/LU of a region on the real is classified as what really it is. According to produce accuracy results, in this study the optimise penalty parameter values in agriculture lands is 1,000. However, in~~For the Shareza and Zarand study areas, ~~by~~ decreasing the penalty parameters reduced the ~~the~~ producer accuracy~~ will be changed~~ to 0 when~~ile~~ the penalty parameter was~~is~~ less than 0.1 (Fig. 10). In the ~~addition, in~~ case of the producer accuracy for the agriculture class, ~~the~~ penalty parameters exceeding~~more than~~ 1 returned~~give an~~ acceptable accuracy values ~~in accuracy~~ for both the dry and humid climate study sites (Fig. 10). The variability of the producer accuracy for the~~in~~ residential land category in conjunction with varying the~~by~~ penalty parameter was ~~change is~~ high.~~, but in general they have a decreasing trend by decreasing the values of penalty parameters.~~ In the humid climate study cases, forest is one of the important classes. Therefore, it can be concluded that the selection of the methods for classification of forest lands using satellite images has an important bearing~~role~~ on the accuracy of the final results. Here, the Producer accuracy results for the~~in~~ forest class were not sensitive to variations in the~~show that by changing the~~ penalty parameter (Fig. 10). ~~the values of produce accuracy did not change too much and it's almost stable for three case studies in humid climate areas (Fig. 10).~~ In contrast, the Producer accuracy for the~~of~~ desert class in the dry climate areas was very sensitive to variations in the~~by~~ penalty parameter. ~~are too variable. For two case studies i.e., Zarand and Shahreza the increasing trend in produce accuracy values lead to decreasing of the penalty parameters values, especially by penalty parameters less than 0.1 the produce accuracy increase dramatically even to 100% level (Fig. 10).~~

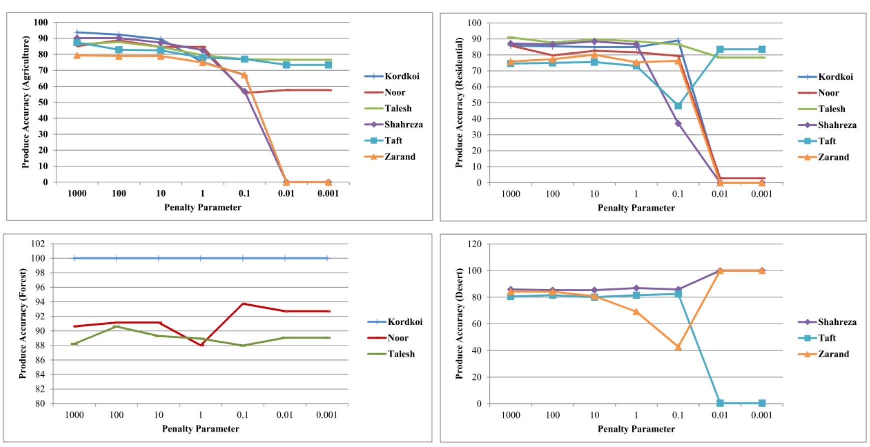


Fig. 10 Sensitivity analysis of PA for the six study areas.

~~**Fig. 4** Sensitivity analysis of penalty parameter for study sites.~~

User's accuracy (Fig. 11) plays an important role in the classification of each study class. We found that the user accuracy for agricultural~~e~~ lands in the humid areas was ~~on three case studies is~~ more stable than in the case of the dry climates, when altering ~~by change in~~ the penalty parameter. ~~Penalty parameters less than 0.1 have very high decreasing in agriculture produce accuracy of dry climate case studies.~~ The highest values of the user accuracy for the residential class in both the humid and dry climates pertained to ~~belonging to~~ penalty parameters exceeding~~more than~~ 100.~~, in addition decreasing trend in user accuracy of residential class for dry climate is higher than the humid climate case studies. These results also show, that the user accuracy of forest class in humid area, almost have a stable reaction by increasing penalty parameters (Fig. 11).~~

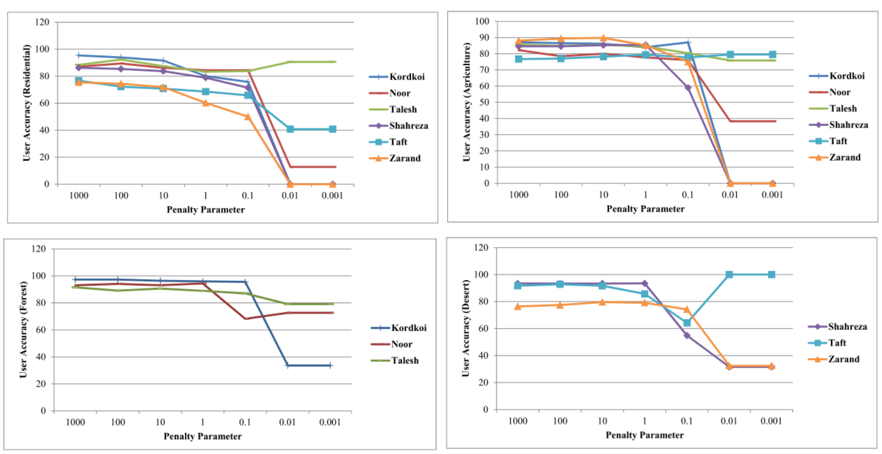


Fig. 11 Sensitivity analysis of UA for the six study areas.

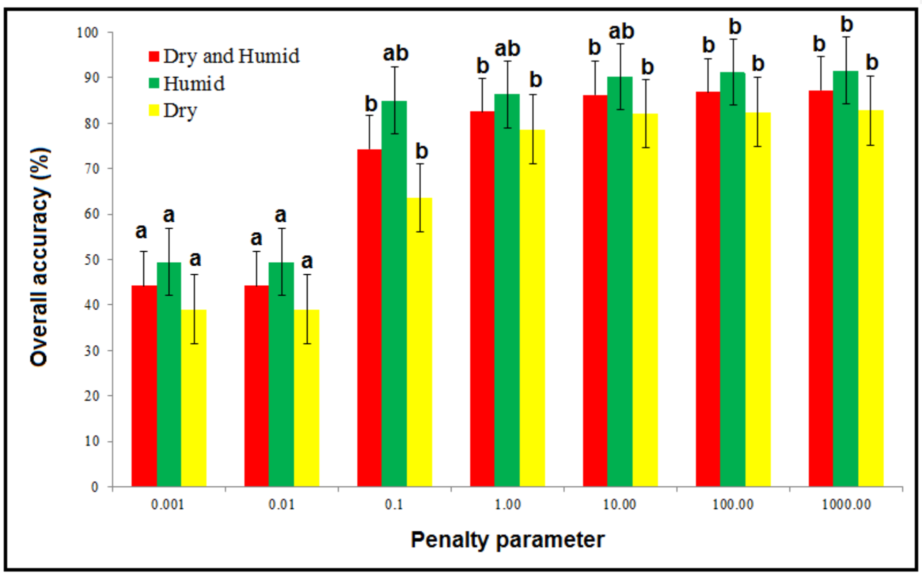
~~The s~~Statistical comparisons ~~e~~ of means ~~analysis (Tukey's test) for humid and dry climate study sites show~~confirmed that the overall accuracy of the ~~produced~~ maps generated using ~~by~~

different values of the penalty parameter were~~have~~ significantly different~~ee~~ at the 99 % level of confidence (Table 3). In addition, for both the dry and humid climate areas, the overall accuracy using~~with~~ different penalty parameter values was characterised by~~showed~~ significant differences at the 99% level. ~~as well.~~

Table 3. One-way ANOVA comparison of~~es~~ mean results for overall accuracy.

Climate sites	Df	Mean Square	F	Sig.
Humid and Dry together	6	2,307	15.08	0.000
Humid	6	1,129	5.13	0.006
Dry	6	1,211	20.08	0.000

~~Results of Tukey's homogeneous grouping show that the overall accuracy classified in three groups based on different values of penalty parameter in humid climate areas. In addition, for dry and both climates (dry and humid) categorised in two groups (Fig. 12).~~



~~Fig. 12~~ ~~Tukey's homogeneous grouping for dry, humid and both (dry and humid together climate~~

~~Figure 12~~Overall, our findings suggested that ~~show that~~ penalty parameter less than 0.01 generated~~give us~~ the lowest values of overall accuracy for the~~in produced~~ maps, whereas~~in other sides the~~ penalty parameters exceeding ~~higher than~~ 100 produced the most~~high~~ accurate land use maps. Generally speaking, the ~~produced~~ maps for the~~in~~ humid climate study sites had~~ve~~ higher accuracy than those for the dry climate study sites across the full ~~in all~~ range of penalty parameters. SVM has been found to achieve a higher level of accuracy than contemporary conventional methods of classification (Foody and Mathur, 2004; Melgani and Bruzzone, 2004; Pal and Mather, 2005; Saleh Yousefi et al., 2016). The ~~R~~results of our~~this~~ study agree with those reported by~~confirm~~ the results of (Gualtieri and Cromp, 1999), (Huang et al., 2002), (Oommen et al., 2008), (Szuster et al., 2011) and (Mohammadi et al., 2019). Our work here extends previous work by exploring the sensitivity of accuracy to SVM parameter values. ~~,~~ ~~that mentioned to the higher accuracy of SVM in compare with other image classification methods such as ML, ANN, and MD. However, those researchers did not mentioned to the SVM parameters values. One of the advantages of the SVM algorithm for land use mapping is producing highly accurate classified images from small training sets (Halder et al., 2011; Mantero et al., 2005; Mountrakis et al., 2011; Salberg and Jenssen, 2012). Results of present study and the advantages of defined optimum SVM parameters help environmental and natural resources managers to provide land use maps in dry and humid climates with more accuracy quickly, thus saving them time and cost.~~

4. Conclusions

Land cover mapping is an essential prerequisite ~~basic step~~ for managing many natural resources. ~~and environmental~~. ~~integrated management. It produces a high accuracy land use map~~

~~is essential to better environmental modelling.~~ In this context~~Recently~~, the SVM algorithm has~~ve~~ been introduced as an ~~high~~ accurate~~cy~~ method for satellite image classification for~~to~~ producing~~e~~ land use maps, but the optimization of SVM parameters requires further research. Accordingly, our ~~The main aim of current~~ research ~~was to~~ optimized~~ation of~~ SVM algorithm parameters to produce more accurate land use maps using Sentinel-2 images of~~in~~ humid and dry climate areas in~~s of~~ Iran. ~~In present study seven values for Gama in Kernel function (0.001, 0.01, 0.1, 1, 10, 100, and 1000) and seven values in penalty parameters (0.001, 0.01, 0.1, 1, 10, 100 and 1000) was tested in RBF of SVM classification algorithm. Results showed that for two studied humid climate areas, overall accuracy coefficients in the SVM algorithm has a range of 30% to 95% in different range of penalty parameter values. Higher values of penalty parameter give us more accurate land use maps in dry and humid climates. Also, we found that the penalty parameter in both climates have a direct relationship with OA, produce accuracy and user accuracy. However, in dry climate when this parameter is less than 1, we have a higher decrease on OA. Results demonstrated that change in gamma in kernel function value is not effective to changes on accuracy assessment for all six studied sites in humid and dry climates.~~ The findings of our work provide a basis~~present study are a key to~~ for yielding more accurate land use maps from~~by~~ Sentinel-2 images in dry and humid climate regions more generally. More investigations are however, required to confirm the more generic applicability of our findings. ~~on variability of classifiers in different source of satellite images await for future studies.~~

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