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Evaluation of a Hierarchical Classification Method and Statistical Comparison with Pixel-Based and Object-Oriented Approaches

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ABSTRACT

Aims Producing a land use/land cover map is a fundamental step in different studies. This study aimed to assess the ability of hierarchical, pixel-based and object-oriented classification methods to produce land use/cover maps.

Materials & Methods This study was conducted in the Harat-Marvast basin of Yazd Province, Iran using Landsat imagery of 2016 (paths 161 and 162, row 39). The hierarchical image classification method was tested for land use/cover mapping. A statistical comparison between three algorithms, namely pixel-based, object-oriented and hierarchical image classification was performed using the McNemar test. An intensive field survey was also accomplished to obtain training and test samples.

Findings The kappa coefficients for pixel-based, hierarchical and object-oriented techniques were 0.76, 0.83 and 0.94, respectively. Results also showed that the performance of SVM and hierarchical algorithms are significantly different with aχ^2f 112.3 which shows the superior performance of the hierarchical algorithm.

Conclusion It was shown that the object-oriented approach performed significantly better than the two above-mentioned methods (χ^2= 149.6). As the computational costs of object-oriented methods are relatively high, the hierarchical algorithm can be suggested when there are limitations in time or computational infrastructures. Therefore, the hierarchical algorithm can be used instead of simple pixel-based algorithms for land use/cover mapping.

Keywords Hierarchical Classification; Land Use/Cover Mapping; Object-Oriented Approach; SVM

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Introduction

Land use is the use of land by humans. Land use change represents changing from one land use to another over time, for example, from natural forest to residential areas or range lands to bare lands [1]. Land use mapping is of paramount importance in several applications and research areas such as natural resources conservation, soil erosion, hydrology, etc. [2]. Land use has a great impact on different natural processes. Therefore, assessing the different land uses can help managers and stakeholders establish better managerial plans [1]. Remote sensing is an effective tool that can be used to produce land use/cover maps with acceptable accuracy and precision in large areas with required replications [2, 3]. Producing accurate land use/cover maps is a fundamental step in land use planning and management. Assessing existing land use/cover in addition to providing accurate methods of monitoring changes is very important for land managers, authorities and planners. The main goal of the land use planning process is to allocate land uses which is consistent with the needs of people while protecting future resources. Land use/cover maps can be used in different cases such as quantifications of impervious areas for runoff estimation, vegetation canopy calculations, assessment of irrigation water needs, environmental assessment of undeveloped and vacant lands, producing fire hazard maps, urban planning assessments, etc [4].

There are several methods for land use/cover mapping using satellite images, from visual classification to unsupervised assessments to progressively complex and powerful approaches [5]. Visual interpretation is a technically easy approach that can be only used in limited areas because this approach is very labor intensive [6]. Producing land use maps using automatic methods is more popular, particularly for large regions [7]. There are two main approaches for this: pixel-based and object-oriented; each of these can be further divided into supervised and unsupervised approaches [8-10]. Pixel-based approaches use only spectral information of pixels to categorize them into different classes. However, object-oriented approaches use spatial, geometric and topological information as well as spectral information in the classification process [11].

The support vector machine (SVM) was identified as one of the pixel-based classification approaches based on the non-probabilistic classification method. SVM is an advanced machine-learning algorithm that has been accepted recently for its potential to categorize linear and nonlinear data. SVMs are useful for various classification problems in processing large data. SVM is based on learning from the sample, and this method requires distinct training and testing data [12]. Classifying satellite imagery only by introducing some training samples and applying a classification method such as maximum likelihood or SVM may not produce acceptable results because land use mapping and severe spectral variability in remotely-sensed imagery are inherently very complex. Therefore, a hierarchical pixel-based classification approach was developed to tackle this problem. In this approach, different classes are classified into several steps using different ancillary data such as digital elevation model, slope, etc.

Several studies have been conducted on pixel-based and object-oriented classification methods in different fields. Berhane *et al.* [5] compared pixel-based and object-oriented techniques to classify wetlands. They used different classification approaches such as ISODATA, maximum likelihood and random forest. Results showed that random forest and object-oriented methods had the highest accuracy of 87.9% and 84.6%, respectively. Moosavi *et al.* [13] have produced a landslide inventory map using pixel-based and object-oriented approaches. They optimized the mentioned approaches using the Taguchi method. They demonstrate that object-oriented approaches significantly outperformed the pixel-based classification methods (Z value of 5.70) in producing a landslide inventory map. Zoleikani *et al.* [14] investigated pixel-based and object-oriented classifications for land cover mapping in urban regions. Results showed that classifying pan-sharpened images by object-oriented methods produced better outcomes (90.47 %) than classification results of pixel-based classification method (77.33 %). Ouyang *et al.* [15] compared pixel-based and object-oriented approaches to VHR imagery for mapping saltmarsh plants. The results of this study demonstrate that object-oriented approaches would be superior to pixel-based methods for classifying herbaceous plant species in terms of accuracy. Keyport *et al.* [16] compared pixel- and object-based methods for detecting landslides from very high-resolution images. Their results indicate that the object-based method can identify the majority of landslides with a few false positives when compared to pixel-based unsupervised classification. Fathizad *et al.* [17] evaluated desertification using remote sensing technique and object-oriented classification algorithm in the Iranian central desert. They showed that this approach had an acceptable ability in desertification detection. Khiali *et al.* [18] analyzed satellite image time series using a graph-based representation. They demonstrate that their method had a good performance to detect spatio-temporal entities. Yan *et al.* [19] performed object-oriented segmentation based on multi-feature combination with remote sensing images to detect building earthquake damage. They show that this method has a satisfactory performance for segmentation and identification of building earthquake damage. Rasuly *et al.* [20] used object-oriented techniques for monitoring the coastline changes of Caspian Sea. They show that this method can accurately detect the changes in coastline.

Since the object-oriented method (unlike the pixel-based method) uses several different properties, it has several fundamental benefits over pixel-based approaches. The object-oriented method analyzes sets of homogenous pixels as objects instead of using conventional pixel-based classification unit so that it improves the salt-and-pepper effect mostly faced in pixel-based classifications [21]. In the object-oriented approach, image objects can be made at numerous scales [22]. However, object-oriented methods are relatively time-consuming and need high technical abilities. Therefore, developing simple and efficient methods can be of great importance for land use/cover mapping. Usually, a comparison between different classification methods is performed by simply comparing their overall accuracy and kappa coefficients. This type of comparison may incur some deficiencies. For example, if a classification method is just one percent more accurate than the other one, it would be identified as the best approach. However, it may have more computational cost. Therefore, a statistical comparison is vital. The objective of this study is to evaluate the performance of a hierarchical classification approach and statistical comparison with common object-oriented and pixel-based methods.

Materials and Methods

Study area

The study area of Harat-Marvast basin is located between 53°50′6" and 54°32′36" E. longitude and 29°47′6" and 30°35′21" N. latitude (Figure 1). The two main cities situated in this basin are Harat and Marvast. This basin covers almost 2890 km^2. The average rainfall and temperature of the area are about 80 mm and 18.5℃, respectively (Department of Natural Resources and Watershed Management of Yazd). The main land uses/covers in the area are agriculture, rangeland, playa, mountain and residential areas. According to the De Martonne method, the climate of the area is hyper-arid (Department of Natural Resources and Watershed Management of Yazd). This area is mostly covered with Neogene sediments. Poor rangelands account for a large part of the region. The main agricultural produce of the area is pistachio.

Figure 2 shows the flowchart of the current research. Landsat imagery of 2016 (paths 161 and 162, row 39) were acquired from the NASA website (earthexplorer.usgs.gov). Essential pre-processing operations were performed on the images. Two images were mosaicked to cover the study area. Auxiliary data and maps such as DEM, slope, and so on were produced. A land-use map was produced using three classification algorithms i.e. pixel-based, hierarchical and object-oriented. An intensive field survey was also accomplished to obtain training and test samples. The aforementioned steps are explained in detail in the following sections.

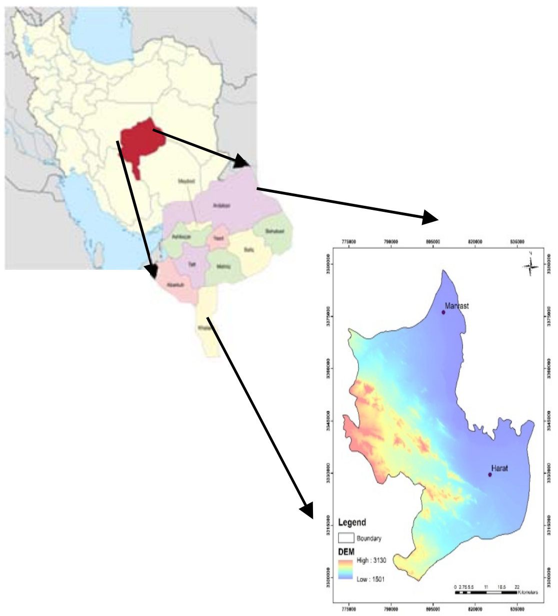

Figure 1) Map and situation of the study area

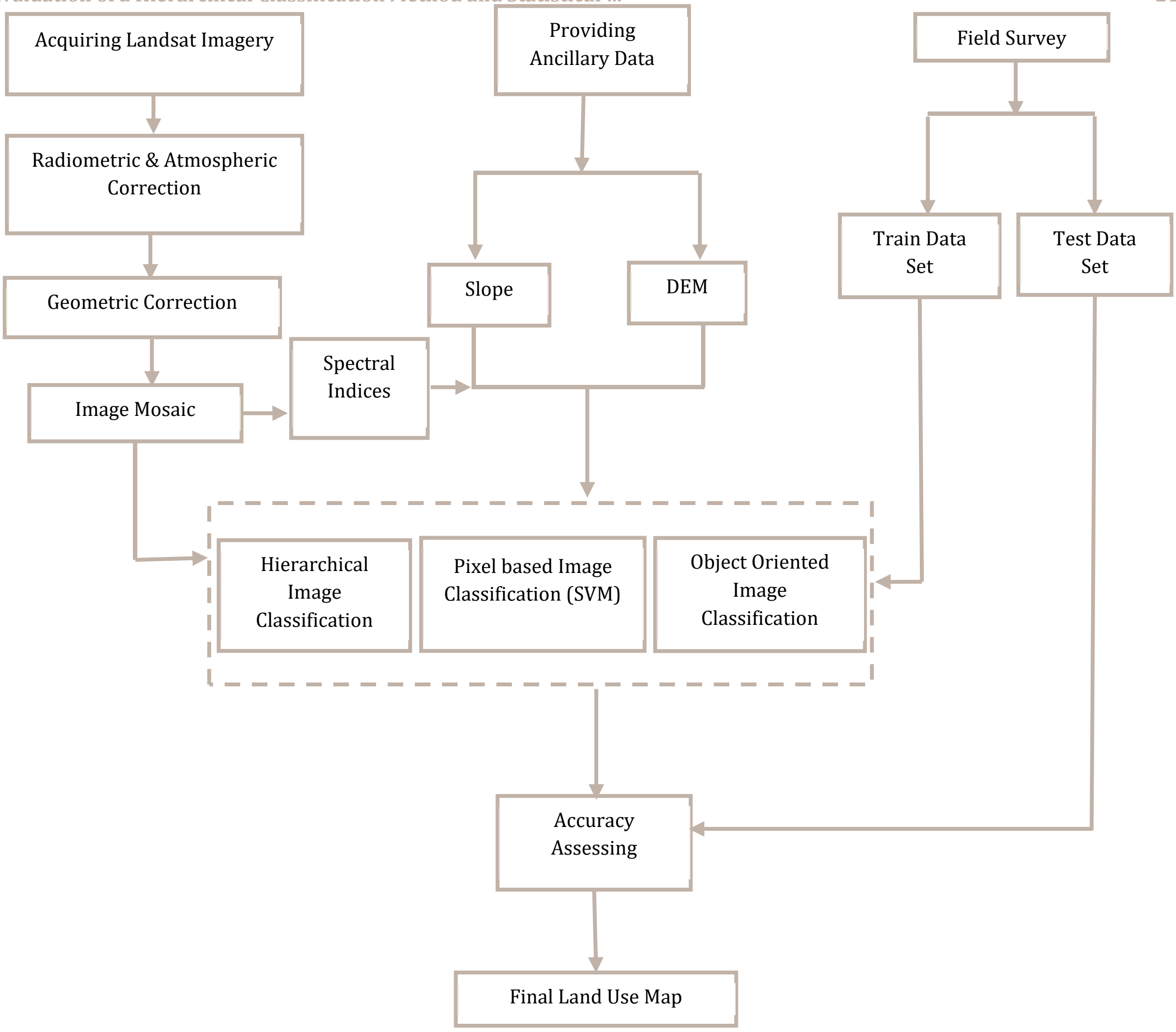

Figure 2) Flowchart of the study

Data collection and image pre-processing

Landsat images were used to produce land use/cover maps. For the purpose of this study, Landsat images of 2016 were acquired. Landsat 8-OLI from path 161 and 162, row 39 were downloaded from the United States Geological Survey (USGS) website. Preprocessing operations on the satellite images is necessary before land use classification. Image preprocessing involves one-step radiometric and atmospheric corrections in which the multi-spectral images are converted to surface reflectance values using the Fast Line-of-sight Atmospheric Analysis of Spectral Hyper cubes (FLAASH) algorithm [23]. Several ancillary data were used in this study. Digital Elevation Model (DEM) was produced from the standard topographic maps at 1:25,000 scale using ArcGIS 10.3 software. The slope map was derived from DEM. Normalized Difference Vegetation Index (NDVI) was calculated from three satellite images, i.e. February 15, May 5 and July 8. An intensive field survey was also carried out to collect training samples using a Garmin GPS with a spatial accuracy of 5m. A total of 250 points were collected for five land use/cover classes. The field data were divided into two categories, and 70% of the data was used in the training process and the remaining 30% was used for testing the result of the classification models.

Land use mapping

Hierarchical image classification

Although auxiliary data can be used as inputs in pixel-based classification techniques such as SVM, due to the complexity of land use, simple one-step classification approaches may have some deficiencies in classifying images with high accuracy. Therefore, hierarchical image classification was developed in which the classes were separated step by step. First, the agricultural land class was isolated using NDVI by selecting 0.2 as the threshold. Then, slope and

DEM maps were used to determine the mountainous areas. Afterward, residential areas were separated by using the NDBI index and thermal bands. After separation of the aforementioned land uses, deserts and rangelands were separated due to large spectral differences using training samples by the maximum likelihood classification method.
The NDVI can be calculated based on red and near infrared (NIR) bands using equation 1.

$$\mathrm{NDVI} = \frac{R_{NIR} - R_{Red}}{R_{NIR} + R_{Red}} \quad (1)$$

Where: R_{NIR} is the reflectance of NIR radiation and R_{Red} is the reflectance of visible red radiation [24]. NDVI can be effectively used to determine vegetation cover. Vegetation cover has low red and high near infrared reflectance which results in high, positive NDVI values. Some phenomena such as snow, water, clouds and soil absorb significantly higher amounts of NIR and, therefore, produce lower NDVI values [25]. Built-up regions have an extreme increase in their reflectance from SWIR and NIR bands, whereas vegetation has a somewhat larger or smaller DN value on the SWIR band than on the NIR band. This can be used to determine the build-up areas on satellite imagery. The standardized differentiation of these bands, as shown in equation 2, will result in low values (near to 0) for vegetated areas and negative values for water bodies. This index has positive values for built-up areas [26, 27].

$$\mathrm{NDBI} = \frac{R_{SWIR} - R_{NIR}}{R_{SWIR} + R_{NIR}} \quad (2)$$

Pixel-based method

There are two main classification methods i.e. unsupervised and supervised approaches. Unsupervised approaches do not need human knowledge [28]. Supervised image classification is a three-stage approach. The first stage introduces some known areas for each class. In the second stage, a statistical method is used for categorizing spectral values and assigning unknown pixels to the classes according to the greatest similarity and some pre-defined decision rules. In the final stage, the accuracy of the classification is evaluated [14, 29]. After fundamental preprocessing, the SVM method was used to classify Landsat image to different information classes. It is a commonly used and powerful machine learning approach. Several previous studies show that SVM makes better classification results compared to other classification methods such as maximum likelihood [30]. The SVM approach works based on the statistical learning theory (SLT) [31, 32] and uses hyperplanes for separating different information classes in a multi-dimensional feature space. Different kernels such as linear, polynomial, radial basis function (RBF), and sigmoid can be used to illustrate more complex shapes than linear hyperplanes [33]. In this approach, an optimal hyperplane is produced using minimum training samples; therefore, high accuracy can be obtained using small training sets [34]. This is one of the most important advantages of the SVM method, particularly for remote sensing data. Some structural parameters, which should be set in the SVM, are gamma (c) in the kernel function, penalty parameter, number of pyramid levels and classification probability threshold value [9]. SVM mainly uses four types of kernel functions i.e. linear, polynomial, radial basis function and sigmoid [35]. These kernel functions are used to separate different data classes. Although it is a binary classifier, it can be generalized and transformed to a sequence of n binary classifications to solve n-class problems [36]. In this model, hyperplanes are constructed using training samples [37]. In order to optimize the value of these parameters, a common trial and error approach was performed. Schematic illustration of a SVM model using a linear kernel function is demonstrated in Figure 3.

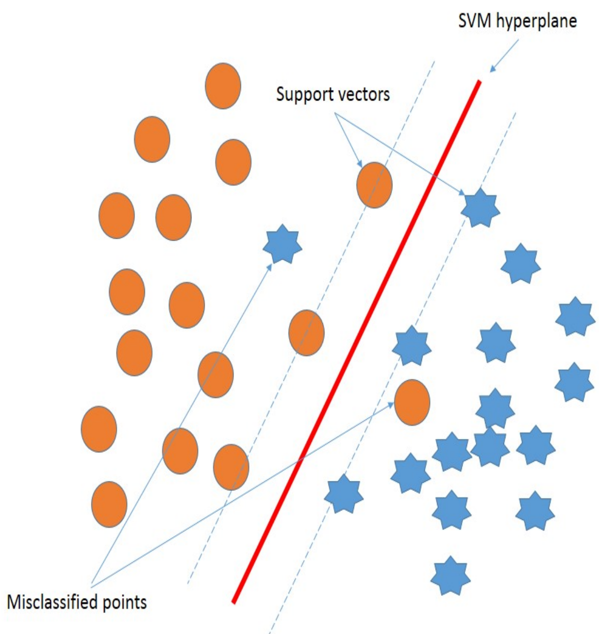

Figure 3) Schematic illustration of the SVM model

The data adjacent to the hyperplanes are defined as support vectors. This method used a penalty parameter that allows the identification of misclassification observed in the input data set [13].

Object-oriented method

In the object-oriented approach, pixels are first categorized to some homogenous areas called objects. Then, the objects are classified based on different spatial or spectral properties. The object-oriented classification was done using eCognition software. eCognition works based on a new technology for object-oriented and multi-scale image analysis. Following an object-oriented approach, the part of image information which is not represented in single pixels is made accessible [38]. Object-oriented image classification includes two main steps: image segmentation and classification. In the segmentation process, the image is split into homogeneous image segments. In segmentation step, different properties such as color, shape, compactness and scale is considered [7].

The scale parameter is a dimensionless value which is related to the object size. It depends on the heterogeneity of the image phenomena. The shape parameter shows the tradeoff between the color homogeneity of a segment and the homogeneity of shape. A lower value of the shape produces more homogenous segments from the aspect of spectral properties, and the higher values produce segments with higher color heterogeneity. The compactness parameter adjusts the smoothness of the object borders [38].

In the first step, a separation between agricultural and non-agricultural areas was done. To achieve this, a quad tree algorithm with scale parameter of 0.08 was used so that NDVI greater and equal to 0.2 is assigned to "agriculture" class and NDVI less than 0.2 is assigned to "non-agriculture" class. The NDVI threshold was determined using ground-based samples. In the next step, a multi-resolution segmentation was performed on the "non-agriculture" class with color and compactness parameters of 0.4 and 0.5, respectively for the separation of mountain, desert, rangeland and residential areas. Areas with elevations greater than 1600 masl and slopes greater than 18% were considered as mountain classes. Thermal bands and NDBI index were used for the separation of residential areas. The remaining classes, i.e. desert and rangeland, were divided using NDVI and thermal bands.

Accuracy assessment

After producing maps through different classification methods, the accuracy of the maps was assessed in order to identify the best classification approach. Confusion matrix is generally used to represent accuracy in each map and conclude the superiority of one map over another [39]. Overall accuracy and kappa coefficients can be obtained using error matrix. Overall accuracy is a common criterion that indicates the percentage of pixels that were categorized in correct classes [40]. The kappa coefficient is the criterion of the agreement between observed and predicted values by chance. Kappa coefficient ranges from 0 to 1. Higher values of Kappa coefficient indicates that the classification is more reliable [41].

In order to statistically compare the accuracy of the mentioned classification algorithms, the McNemar test was used to compare two related Kappa coefficient [42, 43].

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

where f_{ij} indicates the frequency of sites lying in the confusion matrix element i, j [44]. Since all three classification algorithms have the same samples (i.e. related kappa coefficients), x^2 was used to compare the results between them. The hypothesis that two Kappa coefficients are equal is rejected if x^2 is greater than 3.84 (95% confidence level).

Findings and Discussion

As mentioned before, three different methods were applied to produce land use/cover maps. Figure 4 shows the land use/cover map produced by SVM. Table 1 shows the confusion matrix of the SVM method.

Overall accuracy and kappa coefficient values of the method were estimated to be 88% and 0.76, respectively. According to Table 1, in the SVM approach, agriculture and residential classes has lower producer's accuracy than other classes. It is also visually clear in the map that these classes are not properly isolated. On the other hand, rangeland has the highest accuracy. Results of SVM classification are more unsatisfactory than the other methods. The best values of Gamma, penalty parameter and pyramid level were 0.1, 100 and 1, respectively. The best kernel function was also polynomial. These values were determined by a trial and error approach. Figure 5 represents the land use map resulting from hierarchical method. Table 2 shows the results of accuracy assessment of the hierarchical method.

The hierarchical method has an overall accuracy of 92% and kappa coefficient of 0.83. In this method, rangeland has the highest user's accuracy and desert has the lowest user's accuracy. Thus, in SVM and hierarchical pixel-based classification methods, the salt and pepper effect can be seen. Figure 6 illustrates the results of object-oriented classification technique. Results of accuracy assessment of the object-oriented method is shown in Table 3.

This method outperforms the other two methods with the overall accuracy and kappa coefficient of 97% and 0.94, respectively (Table 4). According to Table 3, in the object-oriented method, the producer's and user's accuracy are 85.36 and 97.9, respectively for the agriculture class. This means that 85.36% of the agriculture areas are correctly determined and 97.9% of the regions that were classified as agricultural are actually this class in reality. The producer's accuracy of agriculture is less than other land uses but it is acceptable. The producer's and user's accuracy for residential area are 97.85 and 100, respectively; this means all residential area are categorized correctly by this method. The results of the three aforementioned classification methods (Tables 1 to 3) show that the producer's and user's accuracy of SVM and hierarchical methods are approximately between 52 to 96%, while for the object-oriented method, this value is between 85 and 100%.

The object-oriented approach also outperforms the two aforementioned classification methods in terms of producer's and user's accuracy. This superior performance of the object-oriented method may be attributed to two main reasons:

1. Several different characteristics of the phenomena are involved in the object-oriented method. Segmenting the image into several different objects simulates the visual interpretation performed by humans to recognize different phenomena. On the other hand, this method takes the advantages of numerical computation of different features such as shape, texture, geometry, etc. which makes it stronger than human visual interpretation.

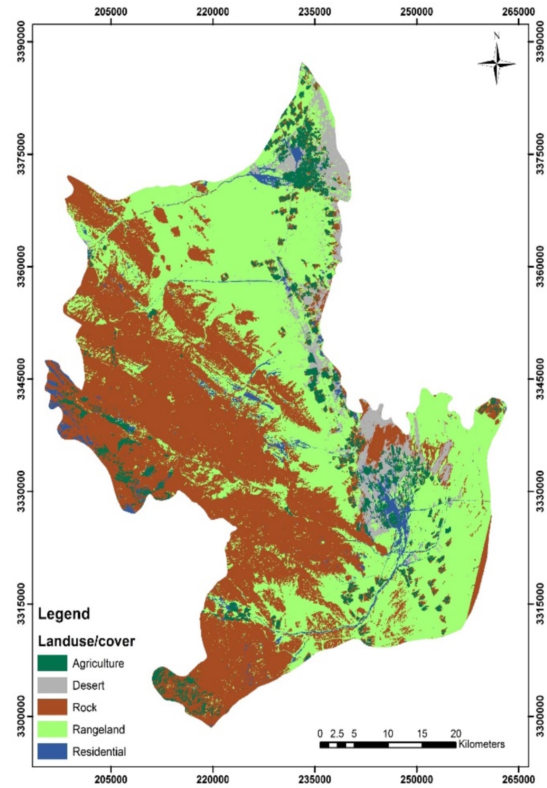

Figure 4) Land use/cover map produced by the pixel-based classification method (SVM)

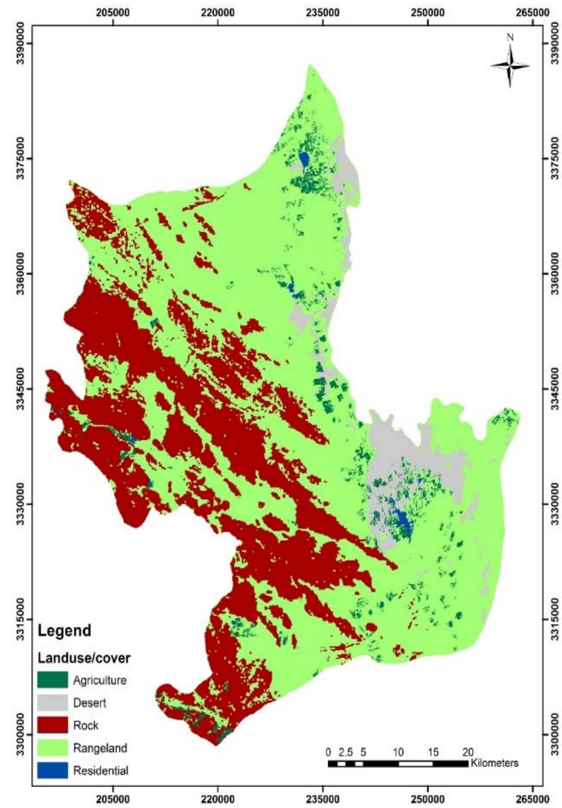

Figure 5) Land use/cover map produced by the Hierarchical method

Table 1) Confusion matrix of the SVM method

	Ground Truth (Pixels)					User accuracy
Class	**Agriculture**	**Desert**	**Mountain**	**Rangeland**	**Residential area**	
Agriculture	100	0	9	7	60	56.82
Desert	0	525	5	126	129	66.88
Mountain	60	57	1164	225	19	76.33
Rangeland	4	0	140	5392	35	96.79
Residential area	0	0	67	62	270	67.67
Total	164	582	1385	5812	513	-
Producer accuracy	60.97	90.21	84.04	92.77	52.63	-

Table 2) Confusion matrix of the Hierarchical method

	Ground Truth (Pixels)					User accuracy
Class	**Agriculture**	**Desert**	**Mountain**	**Rangeland**	**Residential area**	
Agriculture	104	0	0	0	9	92.03
Desert	0	542	0	150	0	78.32
Mountain	0	18	1190	50	50	90.98
Rangeland	60	0	195	5552	54	94.73
Residential area	0	22	0	60	400	82.99
Total	164	582	1385	5812	513	-
Producer accuracy	63.41	93.13	85.92	95.53	77.97	-

Table 3) Confusion matrix of the object-oriented technique

	Ground Truth (Pixels)					User accuracy
Class	**Agriculture**	**Desert**	**Mountain**	**Rangeland**	**Residential area**	
Agriculture	140	0	3	0	0	97.9
Desert	0	562	0	40	0	93.35
Mountain	0	0	1291	30	0	97.73
Rangeland	24	20	91	5742	11	97.52
Residential area	0	0	0	0	502	100
Total	164	582	1385	5812	513	-
Producer accuracy	85.36	96.56	93.21	98.79	97.85	-

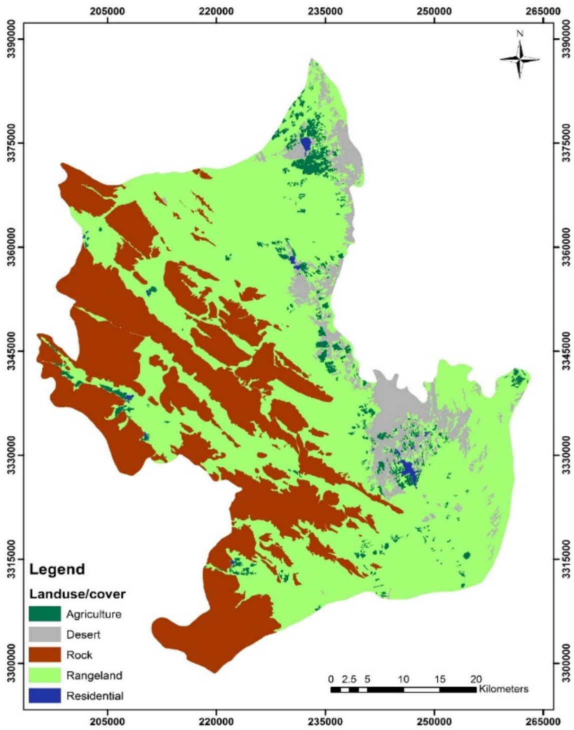

Figure 6) Land use/cover map produced by the object-oriented technique

Table 4) Accuracy assessment results

Parameter	**Overall accuracy** (%)	**kappa**
Pixel-based classification	88	0.76
Hierarchical method	92	0.83
Object-oriented technique	97	0.94

2. Segmentation (if it is performed correctly) causes the edges to be more clearly determined than pixel-based approaches.

Statistical comparison of the classification methods shows that the difference between the performance of the SVM and hierarchical algorithms is statistically significant (x^2= 112.3). It means that hierarchical algorithm performed far better than the SVM method. The performance of hierarchical and object-oriented algorithm is significantly different (x^2= 149.6). It shows that the object-oriented method significantly outperforms both SVM and hierarchical algorithms. It is necessary to map land use for monitoring natural resources and detecting the relationship between natural phenomena and human beings. Three classification methods i.e. SVM, hierarchical method and object-oriented were used to produce land use/cover map. Of these methods, the object-oriented method had better performance than the two other pixel-based methods. This method had the highest overall accuracy and kappa coefficient because it uses segment instead of pixels for classification. It also uses auxiliary data besides spectral information.

Diagram 1 shows a comparison between the areas of different land use/covers in different classification methods. This diagram shows that there is agreement between the results of object oriented and hierarchical classification methods in terms of land use/cover areas. As the classification maps and this figure demonstrate, these two methods have determined the classes very similar to each other, especially for urban, desert and agriculture areas. Detecting agriculture and urban areas is of great importance because this information can be very important for decision makers and managers of a region. Object-oriented approaches have some advantages over traditional and simple pixel-based classification methods. The change of classification units from pixels to image objects decreases within-class spectral variation and generally removes the so-called salt-and-pepper effects that are typical in pixel-based classification.

On the other hand, along with spectral information, lots of features characterizing objects' spatial, textural and contextual properties are used as ancillary information to potentially improve classification accuracy in object-oriented classification methods. The traditional pixel-based classification method can't make the best use of the relationship between pixel and pixels around it which makes the classification results become incoherent caused "salt and pepper phenomenon". However, the hierarchical method, which is basically pixel-based, can deal with the most important disadvantages of traditional pixel-based classification methods. This method uses ancillary data in addition to spectral data and can be efficiently used for producing land use/cover maps.

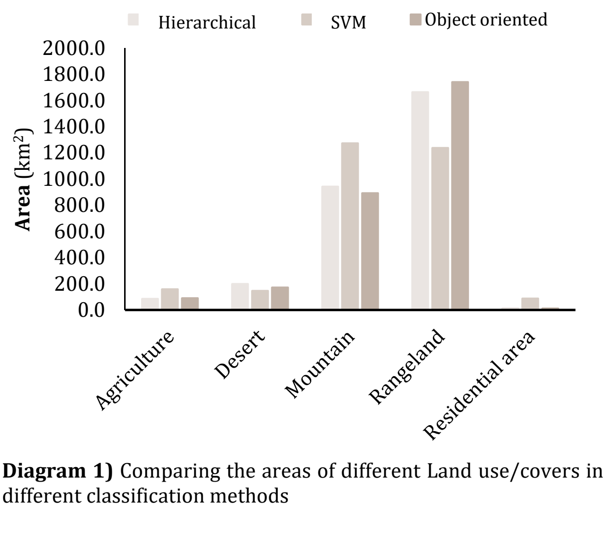

Diagram 1) Comparing the areas of different Land use/covers in different classification methods

Despite several advantages, there are some drawbacks associated with the object-oriented methods. The first point that should be taken into account is that the final quality of image classification is strongly related to the image segmentation that is performed in the first step. On the other hand, classification error can be accumulated due to the error in both image segmentation and classification process. Finally, if an object is wrongly classified, all pixels in this object will be wrongly classified. Statistical comparison of the classification methods showed a significant difference between their performances. It was shown that the hierarchical method outperformed the SVM, and object-oriented significantly outperformed the hierarchical method. Results are consistent with those of Mohammady *et al.* [6] which show the superiority of performance of what they called the synthetic method; this, to some extent, is similar to the hierarchical method in comparison with the supervised classification algorithms such as SVM. Assessing other pixel-based approaches such as random forest can be the object of future studies. The failure of PBC techniques is due to the fact that these methods are based on the assumption that individual classes exhibit uniform visual properties. As the spatial resolution increases, the interclass variation increases and this property of class uniformity is hampered leading to very poor performance. Object-oriented methods can appropriately deal with these disadvantages. However, in object-oriented methods under-segmentation results in image objects that cover more than one class and thus introduce classification errors because all pixels in each mixed image object have to be assigned to the same class. Features extracted from mis-segmented image objects with over-segmentation or under-segmentation errors do not represent the properties of real objects on the Earth's surface (e.g. shape and area), so they may not be useful and could even reduce the classification accuracy if not chosen appropriately.

Conclusion

The computational cost of the object-oriented method is higher than pixel-based methods. However, hierarchical method can cope with the pixel-based classification problem and produce precise results with relatively lower computational cost.

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