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Comparisons of Object-Oriented and Pixel-Based Classification of Land Use/Land Cover Types Based on Lansadsat7, Etm$^+$ Spectral Bands (Case Study: Arid Region of Iran)

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Abstract: In this study, land cover types of Kashan test area were analyzed on the basis of the classification results acquired using the pixel-based and object-based image analysis approaches. Landsat7 (ETM$^+$) with six spectral bands was used to carry out the image classification and ground truth data were collected from available maps (Soil and Saline soil maps, Topographic map and Geological map), field observation and personal knowledge.In pixel-based image analysis supervised classification was performed using the Minimum distance through Geomatica V.9.1. On the other hand, object-oriented image analysis was evaluated through eCognition software. During the implementation, several different sets of parameters were tested for image segmentation and standard nearest neighbor was used as the classifier. The results of classified images have shown that the object-oriented approach gave more accurate results, (Including higher producer's and user's accuracy for most of the land cover classes) in the studied arid region than those achieved by pixel-based classification algorithms.

Key words: Land cover , multispectral segmentation , classification , landsat7 , remote sensing

INTRODUCTION

Earth observation from space so called remote sensing, offers powerful capabilities for understanding, forecasting, managing and decision making about our planet's resources. Remotely sensed image data from earth observation sensor systems is widely used in a range of terrestrial and atmospheric application, such as land cover mapping, environmental modeling and monitoring and the updating of geographical databases. For these applications, remote sensing methods and techniques have been proved to be a very useful tool and usually a thematic map is required [2, 9]. A thematic map displays the spatial variation of a specified phenomenon, such as land cover type, soil type or vegetation type. The trustworthiness and reliability of these thematic maps depend on how we analyze remotely sensed images.

Remotely sensed image analysis is a challenging task. One popular and commonly used approach to image analysis is digital image classification. The purpose of image classification is to label the pixels in the image with meaningful information of the real world [8]. Through classification of digital remote sensing image, thematic maps bearing the information such as the land cover type; vegetation type etc. can be obtained [13].

In this study there are two-classification approaches selected. One is traditional pixel based image analysis approach and the other one is the object-oriented image analysis approach.

Typical method of classification of remote sensing imagery has been pixel based. Normally, multispectral data are used to perform the classification and, indeed the spectral pattern present within the data for each pixel is used as the numerical basis for categorization. That is different feature types with different combination [10, 12]. Pixel based approach is based on conventional statistical techniques, such as supervised and unsupervised classification. In supervised classification the image analyzed "supervised" the pixel categorization process by specifying, to the computer algorithm, numerical description of the various land cover types present in a scene. In order to this representative sample sites of known cover type, called training area are used to compile a numerical "interpretation key "that describes the spectral attributes for each feature type of interest. Each pixel in the data set is then compared numerically to each category in

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the interpretation key and labeled with the name of the category it looks more like.

Recently, considerable advancements have been made in the development of object-based, object oriented image analysis approach is the approach to image analysis combine spectral information and spatial information, so with object oriented image analysis approach not only the spectral information in the image will be used as classification information, the texture and context information in the image will be combined into classification as well [4]. The image will be segmented into objects that form the classification units and will be treated as a whole in the classification peocess. Object oriented image classification approach is based on fuzzy theory, in which an0 object will be classified into more than one class with different membership values [11]

The most evident difference between pixel-based and object-based image analyses is that first, in object oriented image analysis; the basic processing units are image objects or segments, not single pixels. Second, the classification in object oriented image analysis are soft classifies that is based on fuzzy logic. Soft classifies use membership to express an object's assignment to a class. The membership value usually lies between 1.0 and 0.0 where 1.0 expresses a complete assignment to a class and 0.0 expresses absolutely improbability. The degree of membership depend on the degree to which the objects fulfill the class-describing condition. One advantage of these soft classifications lays their possibility to express uncertainties about the classes' descriptions. And finally unlike pixel-based classification, the object oriented approaches as output a thematic map composed of geographical entities labeled with land cover classes and, as much, can be directly sorted into GIS databases, creating or updating usable geo information [5, 6].

The spectral and also spatial resolution of 30 m of Landsat Enhanced Thematic Mapper (ETM^+) data are important characteristics for land use/land cover mapping. Ideally the spectral response should be homogenous within the land cover unit boundary and different from adjacent units, research shows that Landsat bands have a good potential for responding to the differences in land cover properties and hence the separation of land cover types. Also ETM^+ data is the cheapest and available remote sensing data for Kashan area that we can use for test on classification of arid region land cover/land use types.

The main objective of this study is to compare pixel-based and object-based techniques for the classification of LANDSAT 7(ETM^+) imagery of kashan Area of Iran, according to land cover and land use.

MATERIALS AND METHODS

The research was carried out in the Kashan area located in the central Kavir of Iran (Fig. 1).

Geographical coordinates of the area between 33°45′ to 34°45′ N and 51° to 51° 30′ E. The study site covers an area of approximately 90000 ha. The area has an arid climate, with cold winter and hot dry summer, the amount of annual rainfall is 139 mm, most of the precipitation falls in spring and winter. The mean annual, the summer maximum and the winter minimum temperatures are 19.46°C, 42.51°C and -1.97°C respectively. The soil temperature regime is thermic and the soil moisture regime is aridic and approximately level to undulating topography area.

Cloud-free ETM^+ data, collected Aug. 9, 2002 were used in this study, summer data provide a large proportion of bare soil and a minimum of vegetation in poor range and sparse farms area where cereal is a major crop. According to the Landsat World Reference

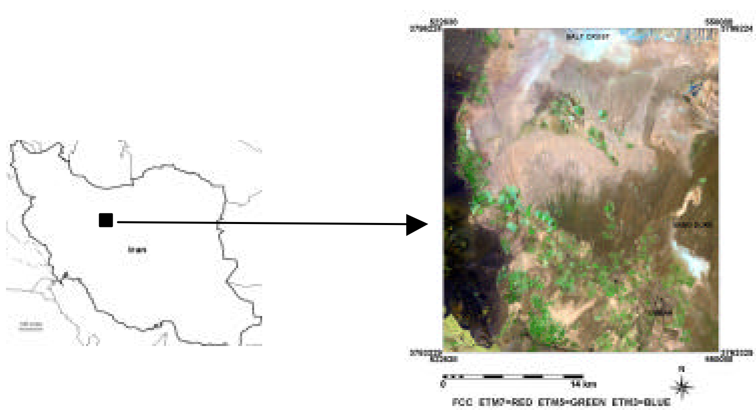


Fig. 1: The study area-Kashan-Iran

Table 1: Landsat7 and ETM$^+$ characteristics

Band number	Spectral range (micron)	Ground resolution (m)
1	0.45 to 0.515	30
2	0.525 to 0.605	30
3	0.63 to 0.690	30
4	0.75 to 0.90	30
5	1.55 to 1.75	30
6	10.40 to 12.5	60
7	2.09 to 2.35	30
8	0.52 to 0.9	15
Swath width	185 Kilometers	
Repeat coverage interval	16 days (233 orbits)	
Altitude	705 Kilometers	
Quantization	Best 8 of 9 Bits	
Inclination	Sun-synchronous, 98.2 degrees	

System (WRS), the satellite image for the study area is located at Path 164, Row 36; its ID is 080021001002100034 and was obtained from the sensors on board of Landsat7.

The ground truth data were collected from field observation, personal knowledge and; Soil and saline soil maps of Abshirin and Aran area 1:50000 scale.

Geological map of Aran area 1:100000 scale and Topographic maps of Abshirin and Aran area 1:50000 scale.

Image processing: The images were georefrenced using UTM map projection for zone 39 and datum of WGS84. The images were resampled to 28.5 m for 1, 2, 3,4,5,7 bands, 14.25 m for panchromatice and 57 m for thermal bands per pixel, using the nearest neighbor technique. The subarea of 967*1157 pixels were extracted for a more detailed comparative analysis. In order to produce test area, false color composite from ETM$^+$ bands of 7,5 and 3 were used, while all of the six bands (ETM$^+$ 1,2,3,4,5 and7 bands) were used for classification by two methods object-based and pixel-based.

Accuracy assessment: Another area that is continuing to receive increased attention by remote sensing specialists is that of classification accuracy [10]. Ecognition supplies a method to assess the accuracy by error matrix based on test areas (ground truth). By defining the ground truth mask, eCognition generates an error matrix automatically. In order to compare the accuracy of the classification result created by the two approaches, pixel-based and object-based, the same set of ground truth was used; here the classification image created in eCognition was exported into Geomatica V.9.1 software.In Geomatica the classified images were crossed with the ground truth map (test area) to perform the error matrix (Table 3 and 5).

Pixel-base classification: Supervised classification was performed using ETM$^+$ bands. In supervised classification, the basic steps followed are (1) select training samples which are representative and typical for that information class; (2) perform classification after specifying the training samples set and classification algorithms;(3) assess the accuracy of the classified image through analysis of a confusion matrix which is generated either through random sampling or using test areas as reference data [7]. ILWIS academic version 3.2 was used for minimum distance classification, test area production and accuracy assessment.

Training samples are selected according to the ground truth. These homogenous areas are identified in the image to form the training samples for all of the information classes. The selected algorithm for performing the supervised classification is the minimum distance classification. In this algorithm first the mean spectral value in each band for each class is determined. These values comprise the mean vector for each class. A pixel of unknown identity may be classified by computing the distance between the value of the unknown pixel and each of the class means, if the pixel were further than an analyst defined distance (distance threshold) from any class mean, it would be classified as “unknown” [10]. This distance threshold could vary for each class depending on the expected degree of compactness of that class. Compactness might be estimated from the standard deviation for each feature of the pixels making up the training sample for a given class.

Object-base classification: eCognition professional version 4.0 was used for object-oriented analysis and classification.

Segmentation is the main process in the eCognition software and its aim is to create meaningful objects. This means that an image object should ideally represent the shape of each object in question. This shape combined with further derivative color and texture properties can be used to initially classify the image by classifying the generated image objects. Thereby the classes are organized within a class hierarchy. With respect to the multi-scale behavior of the objects to detect a number of small objects can be aggregated to form larger objects constructing a semantic hierarchy. In performing the segmentation of ETM$^+$, six spectral bands (ETM$^+$1, 2, 3, 4, 5&7) took in the segmentation process with a full weight (1.0) [1, 3].

Table 2: Segmentation parameters used for image

Segmentation level in object hierarchy	Scale parameter	Homogeneity criterion Color	Homogeneity criterion Shape	Shape criterion Smoothness	Shape criterion Compactness	Segmentation mode
1	10	0.2	0.8	0.1	0.9	Normal
2	17	0.6	0.4	0.6	0.4	Normal
3	20	0.5	0.5	0.5	0.5	Normal

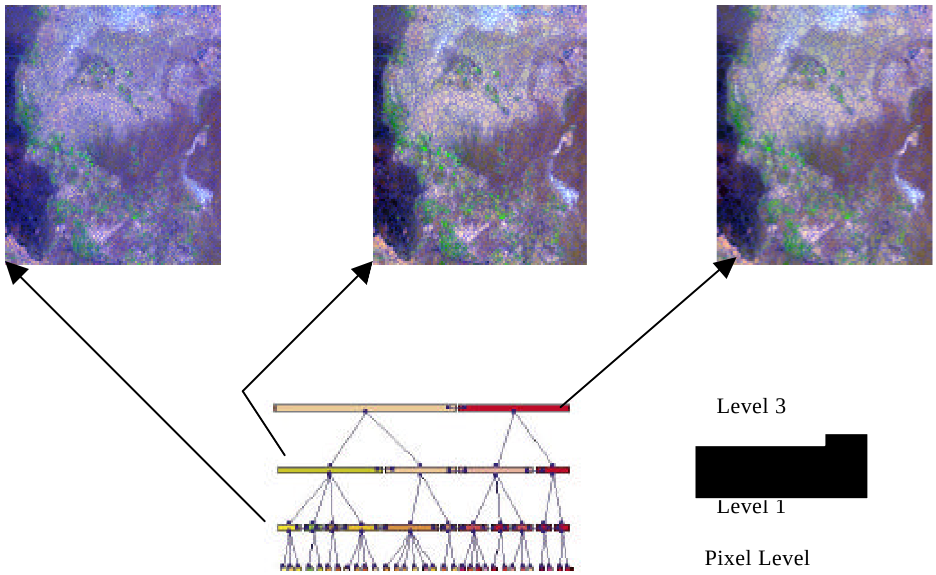


Fig. 2: Hierarchical net of image objects derived from image segmentation, level 1(scale parameter 10), Level 2 (scale parameter 17), level 3(scale parameter 20)

Object-base segmentation was tried using different scale parameters (Table 2). As can be realized that the smaller scale parameter increases the dimensionality and dividing the object into the sub-groups while the larger scale combines the multi segment into one. By testing different segmentation parameters, finally according visual comparison and ground truth and personal knowledge a set of segmentation parameters were selected. Based on these parameters, segmentation process is performed (Fig. 2)

After deciding how many classes need to be distinguished, considering the image classification objective, class name and class color need to be identified through classification are, Agriculture (Agr.), Alluvial fan (Al.), Desert crust (DC.), Non saline soil (NS-S), Orchard (Or.), Outcrop-igneous (OC-I), Outcrop-limestone (OC-L), piedmont (Pi), Rural (Ru.), Saline soil (SS.), Salt crust (SC.), Sand dune-longitudinal (SD-L), Small sand dune (SS-D.) and Urban (Ur.) After assigning classes, the nearest neighbor algorithm defined as classifier. Using nearest neighbor, as the classifier which is similar to supervised classification and therefore training areas have been selected. In eCognition the training areas are training objects; one sample object covers many typical pixel samples and their variation. Starting with a few samples and adding only necessary samples in subsequent steps is a very efficient way to come up with a successful classification [3].

RESULTS

Pixel-based and objects oriented image analysis approaches have been performed by classifying the remote sensing image of Landsat ETM$^+$. The accuracy of the classification result using these two approaches has also been assessed by creating the error matrix using the same test area as reference data. Comparisons of the results of the accuracy assessment showed that object oriented image analysis attains higher overall accuracy and higher land cover class accuracy (producer's accuracy and user's accuracy) for most of the classified land cover class.

Pixel based classification results: Pixel based image analysis means that the classic image classification

Table 3: Confusion matrix for pixel-based image classification

Classes	Agr.	Al.	DC.	NS-S.	Or.	OC-I.	OC-L.	Pi.	Ru.	SS.	Sc.	SD-L.	S-SD.	Ur.	Producer accuracy
	Classification result														
Test set															
Agr.	352	0	0	7	0	0	7	0	0	12	0	0	0	0	0.93
Al.	0	297	0	0	0	47	0	0	0	0	0	0	0	0	0.86
Dc.	0	0	262	46	0	0	0	0	0	0	0	0	0	0	0.58
NS-S.	0	0	0	117	0	0	0	0	0	0	0	0	0	0	1.0
Or.	0	0	0	0	138	0	0	0	0	0	0	0	0	0	1.0
OC-I.	0	42	0	0	0	680	0	0	0	0	0	0	0	0	0.94
OC-L.	0	0	23	5	0	0	206	0	0	0	0	0	0	0	0.88
Pi.	0	97	0	0	0	1	0	234	0	0	0	0	0	0	0.70
Ru.	0	0	0	0	0	0	0	1	143	19	0	1	26	170	0.40
SS.	0	0	0	0	0	0	0	0	0	275	0	0	0	1	0.99
SC.	0	0	0	0	0	0	0	0	0	0	391	0	0	0	1.0
SD-L.	0	0	0	0	0	0	0	124	0	0	0	422	44	0	0.72
S-SD.	0	0	0	0	0	0	0	0	4	0	0	21	395	0	0.94
Ur.	0	4	0	0	0	0	1	41	92	27	0	5	69	139	0.37
User accuracy	1	0.68	0.92	0.67	1.0	0.93	0.96	0.58	0.6	0.82	1.0	0.94	0.74	0.45	
Overall accuracy = 0.81															

method that classifies remote sensing images according to the spectral information in the image and the classification manner is pixel by pixel and one pixel only belongs to one class.

In supervised classification, the image analyze supervises the pixel categorization process by specifying, to the computer algorithm, numerical descriptors of the various land-cover types present in an image. Training samples that describe the typical spectral pattern of the land cover classes are defined. Pixels in the image are compared numerically to the training samples and are labeled to the land cover class that has similar characteristics. There are three basic steps involved in the supervised classification method: training stage, classification stage and accuracy assessment stage, these three stages are applied in the classification process of ETM$^+$ spectral bands.

Landsat7 ETM$^+$ with 6 bands (bands1-5 and bands7) was used for supervised classification. Combining the fieldwork survey of the study area and also the image classification objective, the fourteen-information classes needed to be identified by automatic image classification. These information classes are introduced before. Training samples are selected according to the ground truth from fieldwork; these homogenous land cover areas are identified in the image to form the training samples for all of the information classes. The selected algorithm for performing the supervised classification is the

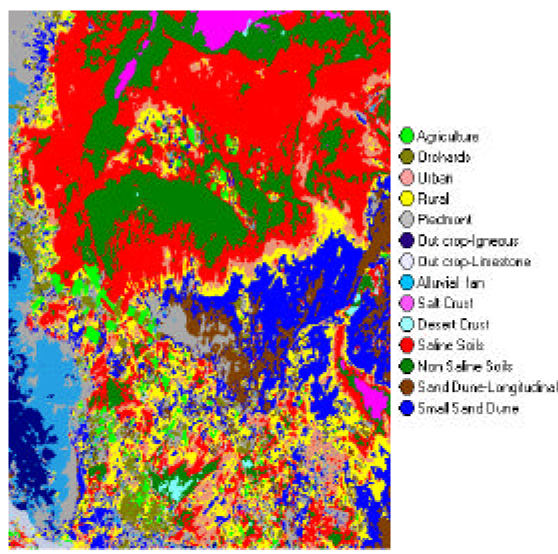


Fig. 3: Pixel-based classification result

minimum distance classifier. Classified image shows distribution of land covers /use types according this algorithm (Fig. 3).

A classification is not complete until its accuracy is assessed [10]. This explains the importance of accuracy assessment of the classification result. Accuracy assessment is a general term for comparing the classification result to the ground truth, in order to determine the accuracy of the classification process.

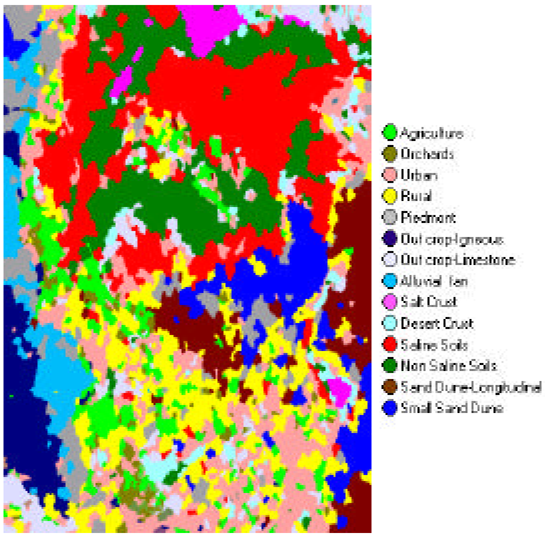


Fig. 4: Object-based classification result

One of the most common methods of expressing the classification accuracy is the preparation of a classification error matrix or confusion matrix.

Accuracy assessment result is given in Table 3 and Table 5. As we see in Table 3 the overall accuracy for pixel base image classification is 81%. Information classes of "salt crust" and "orchard" have both high producer's and user's accuracy, but the information classes of "urban' has a low producer's and user's accuracy. The reason of this low accuracy is that there is a similarity between the roof of settlement building materials and other land cover such as "rural", "saline soil", "piedmont" and "small sand dune", in their spectral reflectance. By image classified pixels of "urban", "rural", "saline soil", "piedmont" and "small san dune" could be grouped into one object; this could be due to the miss-classification between these five class.

Object base classification results: In eCognition, classified image objects are not only assigned to one class or not, but also get a detailed list with the membership values of each of the class contained in the class hierarchy. An image object is assigned to the class with highest membership value, as long as this highest membership value equals at least the minimum membership value that can be edited. It is significant for the quality of a classification result the highest membership value of an image object is absolutely high, indicating that the image object attributes are well suited to at least one of the class description [3]. Due to eCognition fuzzy classification concept, an image object has memberships in more than one class. The classification with the highest assignment values is taken as the best classification result.

Table 4: Best classification result

Class	Objects	Mean	StdDev	Min	Max
Agriculture	245	0.57	0.20	0.10	1
Orchard	98	0.53	0.21	0.10	1
Urban	458	0.69	0.18	0.10	1
Rural	351	0.83	0.10	0.46	1
Piedmont	94	0.89	0.06	0.73	1
Out crop-igneous	101	0.80	0.20	0.21	1
Out crop-limestone	140	0.62	0.15	0.17	1
Alluvial fan	81	0.91	0.08	0.51	1
Salt crust	45	0.77	0.18	0.24	1
Desert crust	78	0.68	0.19	0.12	1
Saline soils	374	0.89	0.08	0.59	1
Non-saline soils	250	0.87	0.10	0.49	1
Sand dune-longitudinal	109	0.90	0.08	0.68	1
Small sand dune	114	0.93	0.06	0.76	1

Table 4 shows the accuracy assessment for classification results of ETM^+ data for best classification result and Fig. 4 shows the image classification result. As we can see from this table the best classification value for all land cover classes except for "agriculture" and "orchard" classes are high. The classes mean value and standard deviation show that most of the objects were classified with high membership values.

Accuracy assessment result is given in Table 5. It is the error matrix by test area. From Table 5 it can be seen that the overall accuracy is 91%, considering the producer's and user's accuracy of individual class, for the "Agriculture" the producer's accuracy is 87% and the user's accuracy is 78%. This means 87 percentage of the agriculture is correctly identified and also 78% of the area that is classified as "agriculture" is truly this category. For the "salt crust" the producer's and user's accuracy is 100 and 83% respectively. By the result we can say all of the "salt crust" is correctly identified and 83% of the area that is classified as "salt crust" is truly this category.

Also we can see there are four classes with the lowest producer's and user's accuracy. They are information classes "agriculture", "orchard", "piedmont" and "Rural", for the "rural" the producer's and user's accuracy are 73% and 83% respectively, for the "piedmont" the user's accuracy is 80%,for the "agriculture" the user's accuracy is 78% and for "orchard" the user's accuracy is 72%.There is significant confusion between "rural" and "urban" and "orchard" and "agriculture" and between "piedmont" and "agriculture" and "sand dune-longitudinal" and between "agriculture" and "orchard". From field survey it was found that information class "piedmont " mainly

Table 5: Confusion matrix for object-based image classification

Classes	Classification result Agr.	Al.	DC.	NS-S.	Or.	OC-I.	OC-L.	Pi.	Ru.	SS.	Sc.	SD-L.	S-SD.	Ur.	Producer accuracy
Test set															
Agr.	348	0	0	0	20	0	10	10	10	0	0	0	0	0	0.87
Al.	0	307	0	0	0	0	0	0	0	0	0	0	19	0	0.94
Dc.	0	0	274	0	0	0	34	0	0	0	0	0	0	0	0.89
NS-S.	0	0	0	112	0	0	0	0	0	5	0	0	0	0	0.95
Or.	4	0	0	0	134	0	0	0	0	0	0	0	0	0	0.97
OC-I.	0	0	0	0	0	674	0	0	0	0	48	0	0	0	0.93
OC-L.	26	0	0	0	0	0	208	0	0	0	0	0	0	0	0.89
Pi.	0	0	0	0	0	0	0	302	0	0	30	0	0	0	0.91
Ru.	32	0	0	0	32	0	0	0	263	0	0	0	0	33	0.73
SS.	0	0	0	16	0	0	0	0	0	260	0	0	0	0	0.94
SC.	0	0	0	0	0	0	0	0	0	0	391	0	0	0	1.0
SD-L.	0	0	0	0	0	0	0	65	0	0	0	525	0	0	0.89
S-SD.	38	0	0	0	0	0	0	0	0	0	0	0	382	0	0.91
Ur.	0	0	0	0	0	0	0	0	42	0	0	0	0	336	0.89
User accuracy	0.78	1.0	1.0	0.88	0.72	1.0	0.83	0.80	0.83	0.98	0.83	1.0	0.95	0.91	
Overall accuracy = 0.91															

along the agriculture area, by image segmentation pixels, which are located along the boundary of "piedmont" and "agriculture" could be grouped in to the same objects with pixels of "agriculture". By object-oriented classification pixels that are "agriculture" could be classified as "piedmont" by being in the same object. Also from field survey information class "rural" is characterized by having the mixture "orchard" and "agriculture" and some similarity "urban" information. The reason of confusion between "rural" and "urban" is because approximately the material of these two classes is similar and this causes the spectral information of these two classes to be similar. By image segmentation pixels of "urban" and "rural" could be grouped into one object; this could be due to the miss-classification between these two classes and the reason of the confusion between "rural" and "orchard", because there are mixed pixels of rural and orchard. So by image segmentation pixels of "rural" and "orchard" could be grouped into one object; this could be case the miss-classification.

Except these four information classes having low producer's and user's accuracy; the other information classes have high or relatively high producer's and user's accuracy.

DISCUSSION

Pixel-based and object-oriented image analysis approaches have been performed by classifying the remote sensing image of Landsat7 (ETM^+). Accuracy of the Classification result using these two approaches has also been assessed by creating the error matrix.

Comparison of the result of the accuracy assessment shows that object oriented image analysis attain higher overall accuracy and higher individual producer's and user's accuracy for each classified land cover class. Table 6 and 7 show the accuracy assessment results of the classification with pixel based and object oriented image analysis.

Comparing these two classification results class by class, except the land cover types "agriculture", "orchard", "outcrop-limestone", "saline soils" and "Salt crust" the producer's and user's accuracy of the classification result using object oriented approach are higher than those using a pixe l based approach (Fig. 5). This can be explained from two aspects of the two classification approaches.

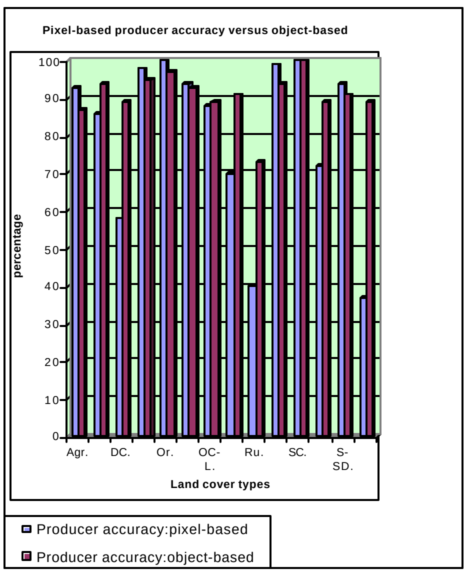
From the characteristics of the two classification methods, in object oriented image analysis, object is not a single pixel takes part in the classification. Properly performed segmentation creates good image objects that facilities the extraction from the image. From the classifiers that are used in two approaches, in object oriented, the classifier is Nearest Neighbor (NN). The NN classifier has the following advantages; NN evaluates the correlation between object features favorably; NN overlaps in the feature space increase with its dimension and can be handled much easier with NN; NN allows very fast

Table 6: Accuracy of pixel-based image classification

	Land cover types													
Accuracy	Agr.	Al.	DC.	NS-S.	Or.	OC-I.	OC-L.	Pi.	Ru.	SS.	SC.	SD-L.	S-SD.	Ur
User's accuracy (%)	100	68	92	67	100	93	96	58	60	82	100	94	74	45
Producer's accuracy (%)	93	86	58	100	100	94	88	70	40	99	100	72	94	37
Overall accuracy (%)	81													

Table 7: Accuracy of object-oriented image classification

	Land cover types													
Accuracy	Agr.	Al.	DC.	NS-S.	Or.	OC-I.	OC-L.	Pi.	Ru.	SS.	SC.	SD-L.	S-SD.	Ur
User's accuracy (%)	78	100	100	88	72	100	83	80	83	98	83	100	95	91
Producer's accuracy (%)	87	94	89	95	97	93	89	91	73	94	100	89	91	89
Overall accuracy (%)	91													



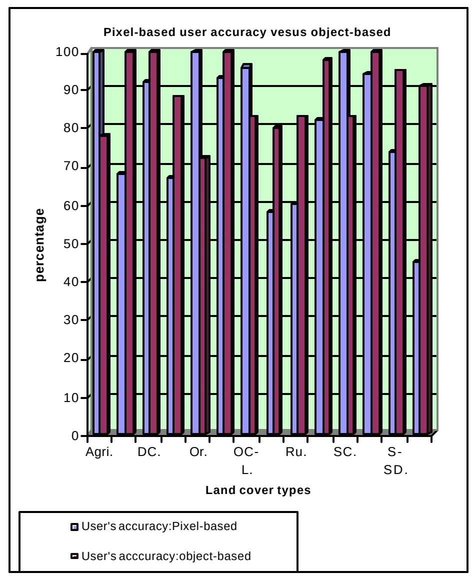


Fig. 5: Comparison between pixel-based and object-based accuracy

and easy handling of the class hierarchy for the classification.

In the pixel-based approach, the classifier is the minimum distance classifier. In this method for the spectral value of a pixel to be classified the distance towards the class means are calculated, if the shortest (Euclidian) distance to class mean is smaller than the user-defined threshold, then this class name is assigned to the output pixel, else the undefined value is assigned.

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