COMPARISON OF PIXEL-BASED AND OBJECT-ORIENTED CLASSIFICATION APPROACHES USING LANDSAT-7 ETM SPECTRAL BANDS

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PS ThS 11

KEY WORDS: Remote Sensing, Land Cover, Classification, Landsat, Multispectral

ABSTRACT:

In this study, land cover types in Zonguldak test area were analysed on the basis of the classification results acquired using the pixel-based and object-oriented image analysis approaches. Landsat-7 ETM with 6 spectral bands was used to carry out the image classification and ground truth data were collected from the available maps, aerial photographs, personal knowledge and communication with the local people. In pixel-based image analysis, firstly unsupervised classification based ISODATA algorithm was realised to provide priori knowledge on the possible candidate spectral classes exist in the experimental area. Then supervised classification was performed using the three different approaches of minimum-distance, paralellepiped and maximum-likelihood. On the other hand, object-oriented image analysis was evaluated through the eCognition software. During the implementation, several different sets of parameters were tested for image segmentation and nearest neigbour was used as the classifier. Outcome from the classification works show that the object-oriented approach gave more accurate results (including higher producer's and user's accuracy for most of the land cover classes) than those achieved by pixel-based classification algorithms.

1. INTRODUCTION

Classification based on pixel-based approaches to image analysis is limited at present. Typically, they have considerable difficulties dealing with the rich information content of high-resolution data e.g. Ikonos images, they produce inconsistent classification results and they are far beyond the expectations in extracting the object of interest. This situation brings meaningful operator intervention to the implementation. Due to mentioned nature of classical methods, new and object-oriented image analysis of eCognition software can be used. Such algorithm requires one or more image segmentations which should aliso be supported by the additional information like contextual or textual to make the segments more appropriate for improve classifications.

Object-oriented approach takes the form, textures and spectral information into account. Its classification phase starts with the crucial initial step of grouping neighboring pixels into meaningful areas, which can be handled in the later step of classification. Such segmentation and topology generation must be set according to the resolution and the scale of the expected objects. By this method, not single pixels are classified but homogenous image objects are extracted during a previous segmentation step. This segmentation can be done in multiple resolutions, thus allowing to differentiate several levels of object categories.

In this study, Landsat-7 ETM image Zonguldak testfield of Turkey has been realized by PCI Geomatica V9.1.2 and eCognition 3.0 software packages. Classical and the object-based classification techniques have been implemented. Several tests have been carried out to match with the successful segmentation, then the classification by entering different parameters to the used software. Authors, finally compare the pixel-based and object-based approaches with the detailed explanation of the obtained results.

2. CLASSICAL VERSUS OBJECT-ORIENTED CLASSIFICATION TECHNIQUES

The overall objective of classical image classification procedures is to automatically categorize all pixels in an image into land cover classes or themes. 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 manifest different combinations of DNs based on their inherent spectral reflectance and emittance properties. In this light, a spectral "pattern" is not at all geometric in character. Rather, the term pattern refers to the set of radiance measurements obtained in the various wavelength bands for each pixel. Spectral pattern recognition refers to the family of classification procedures that utilizes this pixel-by-pixel spectral information as the basis for automated land cover classification. In this study, three different classical plus one objecvt-oriented classification techniques have been employed in sequence. For the classical methods e.g. minimum-distance, parallelepiped and maximum likelihood, detailed information can be found at Lillesand and Kiefer, 1994. In the following paragraphs, main background of eCognition 3.0 software based on object-oriented image analysis is given.

Segmentation is the first and important phase in the eCognition software and its aim is to create meaningful objects. This means that the shape of each object in question should ideally be represented by an according image object. This shape combined with further derivative colour and texture properties can be used to initially classify the image by classifying the generated image objects. Thereby the classes are organised within a class hierarchy. Each class can have a sub- or super-class and thus inherit its properties from one or more super-classes or to its

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subclass (es). With respect to the multi-scale behaviour of the objects to detect, a number of small objects can be aggregated to form larger objects constructing a semantic hierarchy. Likewise, a large object can be split into a number of smaller objects which basically leads to two main approaches of image analysis: A top-down and a bottom-up approach (see eCognition User Guide, 2003 and Benz, U., et al., 2003). In eCognition both approaches can be realised performing the following steps:

- Creating a hierarchical network of image objects using the multi-resolution segmentation. The upper-level image segments represent small-scale objects while the lower-level segments represent large-scale objects.
- Classifying the derived objects by their physical properties. This also means that the class names and the class hierarchy are representative with respect to two aspects: the mapped real-world and the image objects' physically measurable attributes. Using inheritance mechanisms accelerates the classification task while making it more transparent at the same time.
- Describing the (semantic) relationships of the network's objects in terms of neighbourhood relationships or being a sub- or super-object. This usually leads to an improvement of the physical classification res. the class hierarchy.
- Aggregating the classified objects to semantic groups which can be used further for a so called 'classification-based' segmentation. The derived contiguous segments then can be exported and used in GIS. The semantic groups can also be used for further neighbourhood analyses.

These steps describe the usual proceeding when working with eCognition. While the first two steps are a mandatory, the latter two steps may be advisable according to the user's objectives and content of the image.

In the segmentation phase, following parameters should be assigned as accurate as possible, of course, suiting with the reality.

Scale parameter: this parameter indirectly influences the average object size. In fact this parameter determines the maximal allowed heterogeneity of the objects. The larger the scale parameter the larger the objects become.
Color/Shape: with these parameters the influence of color vs. shape homogeneity on the object generation can be adjusted. The higher the shape criterion the less spectral homogeneity influences the object generation.
Smoothness/Compactness: when the shape criterion is larger than 0 the user can determine whether the objects shall become more compact (fringed) or more smooth.

Segmentation phase is folloed by the classification of images. eCoginition software offers two basic classifiers: a nearest neighbour classifier and fuzzy membership functions. Both act as class descriptors. While the nearest neighbour classifier describes the classes to detect by sample objects for each class which the user has to determine, fuzzy membership functions describe intervals of feature characteristics wherein the objects do belong to a certain class or not by a certain degree. Thereby each feature offered by eCognition can be used either to

describe fuzzy membership functions or to determine the feature space for the nearest neighbour classifier. A class then is described by combining one or more class descriptors by means of fuzzy-logic operators or by means of inheritance or a combination of both (see Figure 1). As the class hierarchy should reflect the image content with respect to scale the creation of level classes is very useful. These classes represent the generated levels derived from the image segmentation and are simply described by formulating their belonging to a certain *level*. Classes which only occur within these levels inherit this property from the level classes. This technique usually helps to clearly structure the class hierarchy.
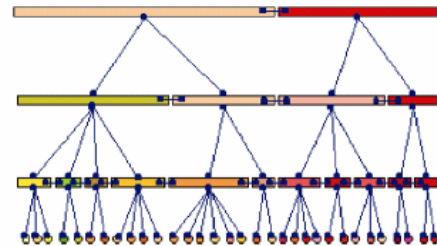

Figure 1. Hierarchical network of image

3. STUDY AREA AND IMAGE DATA

The test site is Zonguldak and its close vicinity, located in Western Black Sea region of Turkey. It is famous with being one of the main coal mining area in the world. Although losing economical interest, there are several coal mines still active in the region. Testfield has a rolling topography, in some parts, with steep and rugged terrain. While urbanized part is located alongside the sea coast, there are agricultural and forested areas inner regions. The elevation ranges roughly up to 1800m.
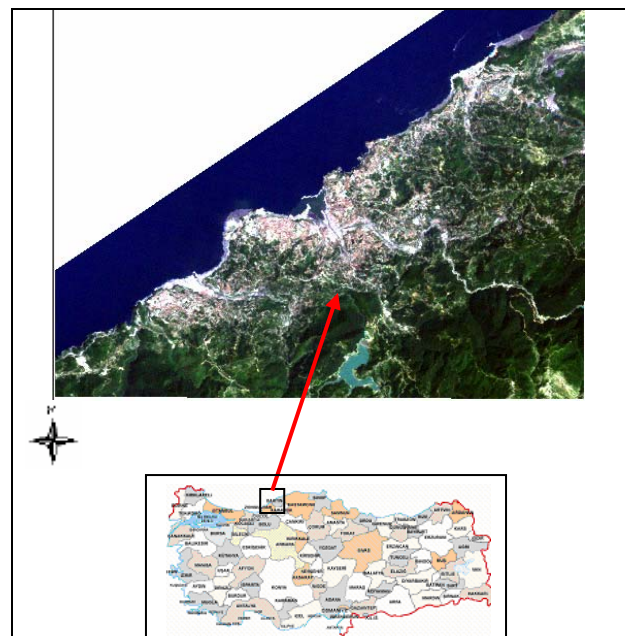

Figure 2. Landsat ETM+ image (band 3,2,1) of the study area

For the analysis, Landsat-7 ETM image (see Figure 2) covering the test site and taken on 04.07.2000 has been utilised. At the processing phase, all spectral channels expect thermal one were used and their properties are given in Table 1. Reference datasets employed during the classification procedures of

Landsat-7 ETM images includes the topographic maps, aerial photographs, orthophotos and personal knowledge about the area. However, before the image classification processes, geometric correction of Landsat images was completed. For this purpose, 21 uniformly distributed GCPs digitized from the 1:25,000 scales topographic maps of the interest area were used. Planimetric accuracy of these GCPs can be expected in the range of 7.5m. On Landsat images, linear features appeared sharp enough, so GCPs are mainly selected from road crossings and bridges. Digital image coordinates for GCPs were measured manually using the GCPWorks module of PCI system with the sub-pixel point determination. Then, affine transformation was applied between the GCPs's image and ground coordinates. Root means square errors for X and Y directions were found to be 0.69 pixels (20.7m) and 0.67 pixels (20.1m) respectively. After producing transformation function, for image registration, bilinear resembling method was used to determine the pixel values to fill into the output matrix from the original image matrix.

Table 1. Phenomena revealed by different bands of Landsat 7 ETM+ data

Band	Phenomena revealed
0.45-0.52 μm (visible blue)	Shorelines and water depths (these wavelengths penetrate water)
0.52-0.60 μm (visible green)	Plant types and vigor (peak vegetation reflects these wavelengths strongly)
0.63-0.69 μm (visible red)	Photosynthetic activity (plants absorb these wavelengths during photosynthesis)
0.76-0.90 μm (near IR)	Plant vigor (healthy plant tissue reflects these wavelengths strongly)
1.55-1.75 μm (mid IR)	Plant water stress, soil moisture, rock types, cloud cover vs. Snow
10.40-12.50 μm (thermal IR)	Relative amounts of heat, soil moisture
2.08-2.35 μm (mid IR)	Plant water stress, mineral and rock types

4. CLASSIFICATION AND RESULTS

4.1 Pixel-based classification

Pixel-based classification of Landsat ETM image of interest area was realized in two steps. In the first phase, ISODATA (Iterative Self Organizing Data Analysis Technique) has been applied and thus, spectral clusters have been determined, which gives pre-knowledge about the site. Amongst the obtained clusters, some have been eliminated or combined based on the ground truth materials. Finally, 7 main classes have been used as training areas for the classification procedure (see Figure 3).
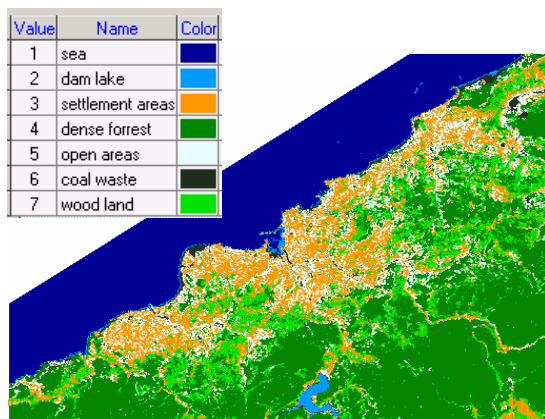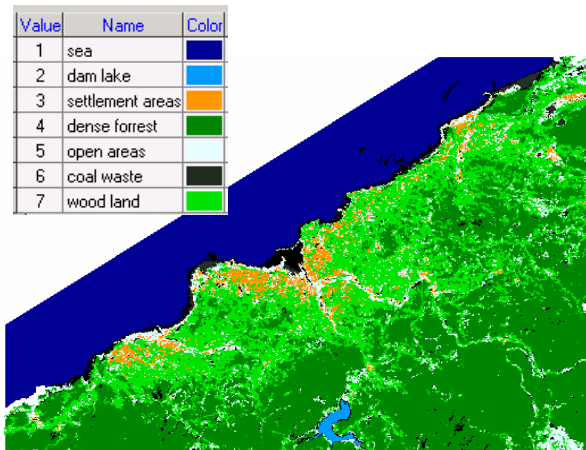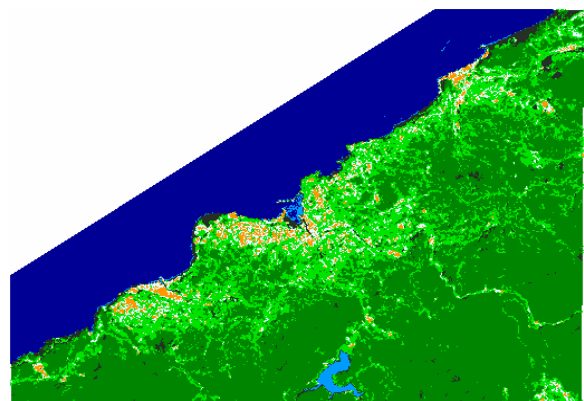

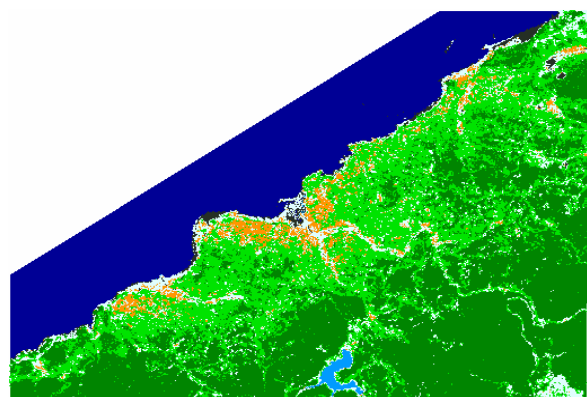Figure 3. Result of ISODATA unsupervised classification.

In the second stage, supervised classification algorithms (parallelepiped, minimum-distance and maximum-likelihood) have been applied respectively to the Landsat image based on the determined training patterns and reference materials. For comparative analysis of each method, same training sites have been utilized with the same colour information. Classifications have been undertaken by the related module of PCI Geomatica V9.1.2 software package and respective results are given in Figure 4.

a. Result of Paralellpiped classification.

b. Result of Minimum distance classification.
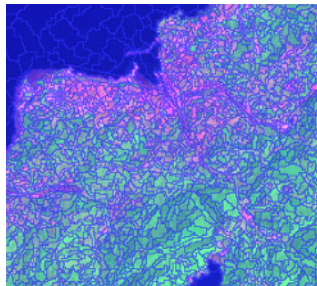

c. Result of Maximum-Likelihood classification.

Figure 4. Results of classical supervised classification techniques (a. Paralelpiped, b. Minimum Distance and c. Maximum Likelihood).

4.2 Object-based Classification

Object-based segmentations were tried using different scale parameters given in Table 2. As can be realized that the smaller scale increases the dimensionality and dividing the object into the sub-groups, while the larger scale combines the multi-segments into one (see Figure 5).

Table 2. Segmentation parameters used for Landsat ETM+

Level	Scale Parameter	Color	Shape	Smoothness	Compactnes s
Level 1	5	0.7	0.3	0.9	0.1
Level 2	10	0.5	0.5	0.5	0.5
Level 3	25	1.0	0	0.5	0.5

(a)

(b)

(c)

Figure 5. Image segmentation using three different scale parameters (a= 5, b=10, and c=25).

From the acquired levels, most suitable one, level-3 has been selected for the classification of Landsat 7 image. Based on the properties of each spectral band, segments have been analysed with different paprameters in the related classes. As a result, the prominent segments are grouped and located in the correponding classes. Then, classification procedure is completed by assigning the relevant class colour to segments and classified image is represented in Figure 7.
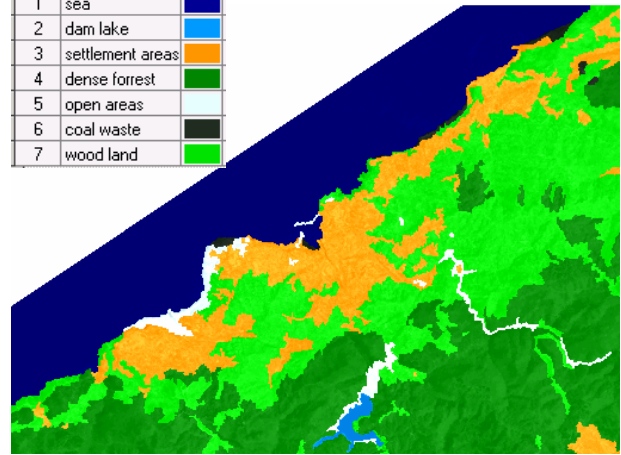

Figure 6. Results of Object-based classification

After classification phase, eCoginiton software gives the users accuracy statistics of the acquired classes. Figure 6 shows such statistics of the classified image by error matrix based on the samples.

Figure 7. Error matrix and statistical values for Level 3.

4.3 Accuracy of the Classification Results

Classification accuracy in remote sensing is to determine the agreement between the selected reference materials and the classified data. For this purpose, 350 pixel in the study have been selected randomly and their agreement with ground truth has been analysed. Then, error matrix has been generated and given in Table 3. This table includes not only the producer's and the user's accuracy values are given but also the kappa statistics are mentioned.

Looking at the Table 3, settlement, open and green areas acquired by pixel-based methods have normal user's accuracy, but they smaller producer's accuracy. In general, amongst the pixel-based approaches, maximum-likelihood classification gives the most accurate results. The reason behind is that in this method, the average vector and the covariance matrices are estimated with the higher accuracy. Of course, such a condition depends upon the avaialbility of enough traning patterns for each class and this requirement has already been realized.

Table 3. Accuracy results for classified image from pixel-based classifications and object-oriented image analysis.

Class Name	Paralellpiped Classification			Minimum Distance Classification			Maximum-Likelihood Classification			Object-Oriented Classification		
	Producer's Accuracy %	User's Accuracy %	Kappa Statistic	Producer's Accuracy %	User's Accuracy %	Kappa Statistic	Producer's Accuracy %	User's Accuracy %	Kappa Statistic	Producer's Accuracy %	User's Accuracy %	Kappa Statistic
Sea	92.632	100.000	1.0000	94.737	100.00	1.000	94.737	100.00	1.0000	100.00	100.00	1.0000
dam lake	0.000	0.000	0.0000	0.000	0.000	0.000	0.000	0.000	0.0000	100.00	100.00	1.0000
settlement areas	11.111	66.667	0.6486	16.667	100.00	1.000	11.111	66.667	0.6486	50.00	75.00	0.6670
dense forrest	94.792	65.942	0.5307	98.958	56.548	0.401	93.750	67.164	0.5475	100.00	100.00	1.0000
open areas	15.094	61.538	0.5467	9.434	62.500	0.558	16.981	47.368	0.3798	80.00	66.70	0.6280
coal waste	12.500	100.000	1.0000	12.500	11.111	0.090	12.500	33.333	0.3177	80.00	50.00	0.4420
wood land	45.000	38.710	0.2055	31.250	35.211	0.160	52.500	41.584	0.2428	91.70	91.70	0.8890

Table 4. Kappa and overall accuracy values for pixel-based classifications and object-oriented technique.

Accuracy Statistics	Paralellpiped Classification (%)	Minimum Distance Classification (%)	Maximum-Likelihood Classification (%)	Object-Oriented Classification (%)
Overall Accuracy	64.571	62.571	66.857	81.30
Overall Kappa Statistic	0.532	0.499	0.558	0.766

However, object-oriented classification produced more accurate results. The reason for this is that the compactness of the segments. Thus, kappa and the overall accuracy are much better. In table 4, while overall accuracy was 81.30 for object-based segmentation, it was only 66.86 for the best classical classification technique of maximum likelihood. For kappa values, some trends occurred and it is 0.77 for object-based image analysis.

5. CONCLUSION

In this paper, new object-oriented image analysis technique has been compared with the classical and the well-known image classification methods using Landsat-7 ETM image of Zonguldak testfield. In the implementation of the tests, paralelepiped , minimum-distance and the maximum-likelihood approaches are taken as pixel-based methods. Their capacity with used Lansdat image has been analysed based on the ground truth materials over the interest area. Howver, on the other hand, eCognition software for object-based classfication works in hierarchy, first with segmentation, then the fuzzy classication. Detailed accuracy results were obtained as error matrices and they show that the object-based image anaysis is far beyond the classical methods in terms of accurate classification of the objects.

6. ACKNOWLEDGEMENTS

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