A COMPARISON OF PIXEL-BASED AND OBJECT-BASED CLASSIFICATION METHODS, A CASE STUDY: ISTANBUL, TURKEY

Z. D. Uca Avci*, M. Karaman, E. Ozelkan, I. Papila

Istanbul Technical University, Center for Satellite Communications and Remote Sensing, Maslak, Istanbul, Turkey.
(damla, muhittin, emre, papila)@cscrs.itu.edu.tr

Abstract - Since thematic classes are represented with high spectral variance, pixel-based classifications generally result with incontinuous and inhomogeneous outputs. Object-based classifications overcome this problem by the approach similar to human seeing and interpreting activity. First, image is segmented into smaller objects, and then image objects are assigned to classes according to their spectral reflectance statistics, shape & texture properties, and neighborhood relations. Segmentation and classification can be structured as a multi-level network. The final output is formed by obtaining the classification results from the most suitable level for each thematic class.

In this study, in order to investigate an appropriate method for a general landcover mapping, isodata and maximum likelihood methods of pixel-based image classifications were compared with condition based and nearest neighbor methods of object-based classifications. Tests were applied on a multispectral SPOT 5 data of Istanbul, Turkey. The results showed that the performance of condition-based method is better than the others.

Keywords: Pixel-based, object-based, classification, SPOT5, land use.

1. INTRODUCTION

Monitoring land cover of cities and the surrounding environment, and detecting the change is critical since the most intensive interactions between human beings and the environment take place in these regions in addition to its unnaturally rapid occurring. An accurate extraction of present land cover information is important to be a reference to find out the change characteristics, dimension, and the related effects. (Qian, J. et al., 2007) There are many applications of land cover mapping and extraction of land use information in the literature.

Object-based classification has been one of the recent methods applied to multispectral satellite data in many applications. Many researchers used object based image analysis for extraction of land cover objects. Kong et al. (2006) and Mo et al. (2007) employed object based methods for land cover classifications. Chen et al. (2007) demonstrated the potential of object-based image analysis to map urban land cover by the application done for Beijing city using ASTER data with a relatively high accuracy.

There are some applications that compared the classification results of traditional methods with object – based methods and showed that object-based methods perform generally better than traditional methods. Platt and Rapoza (2008) compared results of both methods for a mixed urban-suburban-agricultural landscape and they found that the combination of segmentation into image objects, use of the nearest neighbor classifier, and the integration of expert knowledge yielded substantially improved classification accuracy when compared to a per-pixel method.

After a review that includes screening several thousand abstracts, more than 820 OBIA-related articles comprising 145 journal papers, 84 book chapters and nearly 600 conference papers, T. Blaschke mentioned "The pixel paradigm is beginning to show cracks and the OBIA (object based image analysis) methods are making considerable progress towards a spatially explicit information extraction workflow, such as is required for spatial planning as well as for many monitoring programmes." in his paper. (T. Blaschke, 2010)

In this study, the unsupervised and supervised methods of pixel-based classification were applied and compared with the condition-based and nearest neighbor methods of object-based classifications, respectively. It is aimed to find out the accuracies of these two methods with and without the effect of human supervision.

2. STUDY AREA AND DATA USED

Istanbul is a metropolitan city, with its nearly 13 million population. (IBB, 2010) The city boundaries cover forests and agricultural fields, 7 big water basins in addition to urban areas. The land cover / land use change of Istanbul is very rapid and a fast, accurate and economic way to monitor the change is very important.

In this study, a region surrounding the Bosphorus was selected as a study area. (Figure 1.)
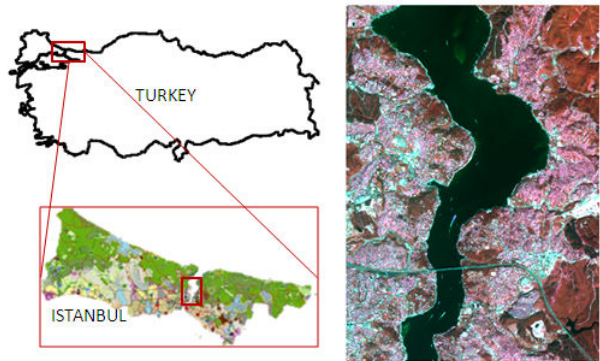

Figure 1. Study area**

Multispectral SPOT 5 image retrieved on October 2nd 2009 was used. The data that has 10 m. spatial resolution and 4 bands was obtained as processed at level 2A.

In the application, Erdas Imagine and Definiens Professional softwares were used.

3.   METHODOLOGY

A remote sensing image consists of rows and columns of 'pixel's, which is the smallest unit of an image and contains the value of measured spectral reflectance. Pixel-based approaches assign a pixel to a class fundamentally according to its spectral properties. This method has been the approach used for years. (Casals-Carrasco et. al., 2000)
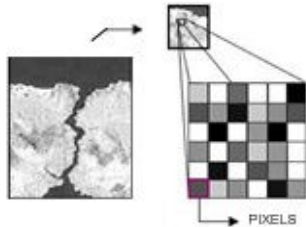

Figure 2. Pixel-based analysis.

One of the recent methods is the object-based image processing method. It is based on the process similar to human seeing and understanding action, which primarily involves being concentrated on recognizing the objects and then evaluating properties and relationships for identification.
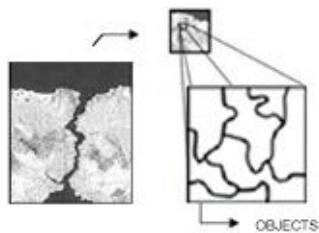

Figure 3. Object-based analysis.

In this study, data was classified by using both methods. For each method, a selected unsupervised and supervised method is applied.

3.1   Pixel-Based Classification Methods
Pixel-based methods are based on classifying remote sensing images pixel by pixel, by using a set of rules to decide whether different pixels can be grouped for having similar characteristics. (Elachi and Zyl, 2006) There are the supervised and unsupervised classification methods used traditionally, in which the classes are determined by 'a priori' or 'a posteriori' identification, respectively.

Unsupervised classification is based on clustering the pixels into a number of spectral classes. After pixels are labeled to these spectral classes, the spectral classes are labeled manually to the classes of interest. Iterative Self Organizing Data Analysis Technique (ISODATA) classification is the most commonly employed method in remote sensing.

Supervised classification is based on choosing representative pixels for each of the desired classes, then running one of the classification algorithms that label the pixels in an image as information classes. In general, the elements of training data set are used to estimate the parameters (class signatures) for particular classes. Maximum likelihood classification is the

most common method in the literature. (Benedictsson et. al., 1990)

In this study, isodata and maximum likelihood classification methods are applied for pixel-based analysis.

3.2   Object-Based Classification Methods
Object-based approaches are image classification methods that run the classification through the image objects, which are pre-established after a segmentation process.

Segmentation is the partitioning of image into image objects according to a certain criterion of homogeneity. (Yan, 2003) In this study, multiresolution segmentation which is a patented technique of Definiens Software was used for image object extraction. In this process, similar neighboring pixels are included in the same segment as long as the heterogeneity in the spectral and spatial domains is minimized. In other words, the decision of an image object extraction is performed by a homogeneity criterion. The criterion depends on pixel values in the spectral domain and shape properties in the spatial domain. In the spectral domain, it is measured by a weighted standard deviation over the spectral channels. In the spatial domain, it depends on compactness and smoothness, which can be defined as the ratio of an object's border length to the object's total number of pixels, and the ratio between the lengths of an object's border to the length of the object's bounding box, respectively. (Yoon et.al., 2004, Benz, 2001; Baatz and Schape, 1999a)

After segmentation, the classification algorithm runs to assign image objects into suitable classes. Classification is performed by consideration of spectral and additional properties of image objects. One of the important properties of object-based approach is using a soft classifier. A degree of probability is used to express an object's assignment to a class instead of deciding if a pixel belongs to a certain class or not as in traditional hard classifiers. Hence, the membership value lies between 1.0 (full membership) and 0.0 (non-membership). (Baatz et.al., 2002)

The other important property is the hierarchical structure of classification which represents the information of image data in different resolutions simultaneously. The image is analyzed on several resolutions, and the best suited level for each object of interest is used. The hierarchical network of segments and objects clearly implicit their relations; each object links with its neighbors, subobjects and super-objects. (Wang et. al., 2004; eCognition User Guide 4)

In object-based classification, if the decisions are made according to the degree of similarity to the class definitions which are described by a condition or combination of some conditions, then it is an unsupervised method. The method is supervised, when the class assignments are based on the comparison of statistical calculations between the image objects to be classified and the training set. It is named as nearest neighbor classification by Definiens A.G.

4.   APPLICATION

4.1   Pixel-Based Classifications
ISODATA classification was performed with the parameters such as, number of classes specified: 100, maximum number of iterations: 10, the convergence threshold: 0.950. The result of unsupervised classification was 100 spectral clusters. Combining the spectral clusters, 6 land cover types was

identified. There was one land cover type that had to be identified as a mixed class of urban with vegetation. The classes are forest, water, urban, vegetation+urban, road and bare soil. The unsupervised classification result is presented in figure 2a.

Maximum likelihood classification was performed for 8 information classes. The homogeneous areas manually identified to be used as training samples. The same information classes were defined with the unsupervised classification. The supervised classification result with 6 land cover types is presented in figure 2b.
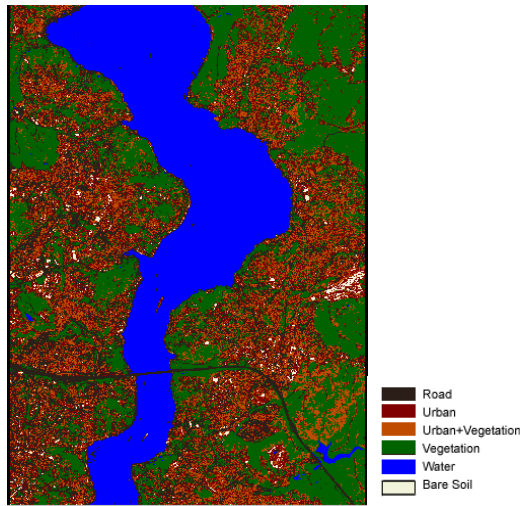

Figure 4. Isodata classification image.

Histograms of isodata and maximum likelihood classification results are given in Table A, where y-axis is in thousands.

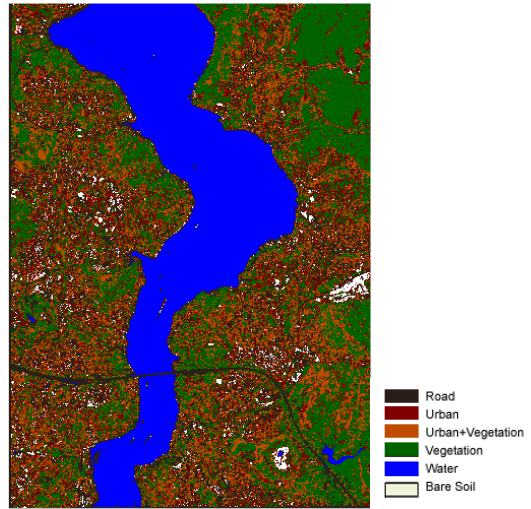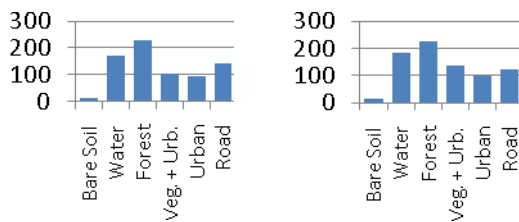**Table A.** Histograms of a) isodata b) maximum likelihood classifications.

Figure 5. Maximum likelihood classification image.

4.2 Object-Based Classifications

For condition-based classification, the image was particularly segmented in three layers; as a next step, the classification was performed on three levels. The scale parameters were set to 200, 60 and 10. The results seem satisfying to fit the information class extraction when the composition of homogeneity criterion was selected as: color 0.7, shape 0.3 (smoothness: 0.5, compactness: 0.5). After segmentation, class descriptions were determined. The features used in class definitions were selected as in Table B. The condition-based classification result is presented in figure 3a.

Table B. Features used in class definitions.

Forest	Band 2
Water	Maximum Difference (Band 1)
Urban	GLCM Homogeneity (Band 2)
Vegetation+Urban	Band 1
Road	Length/Width
Bare Soil	Brightness

For supervised classification, the same segmentation parameters were used. First, training objects were selected. Then nearest neighbor classification was performed which resulted as in figure 3b.

Histograms of condition-based and nearest neighbor classification results are given in Table C where y-axis is in thousands.

Table C. Histograms of a) condition-based and b) nearest neighbor classification.
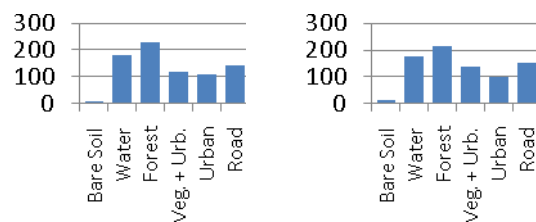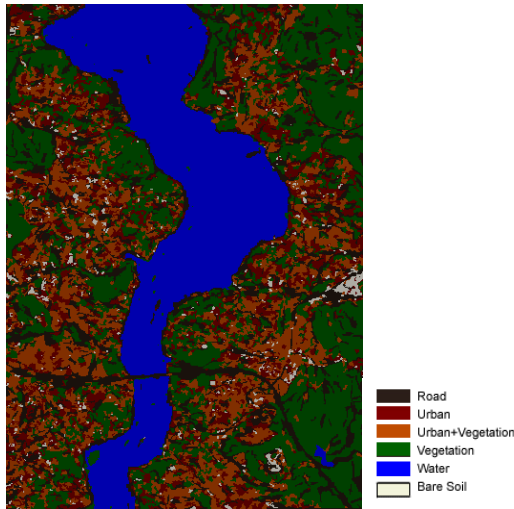
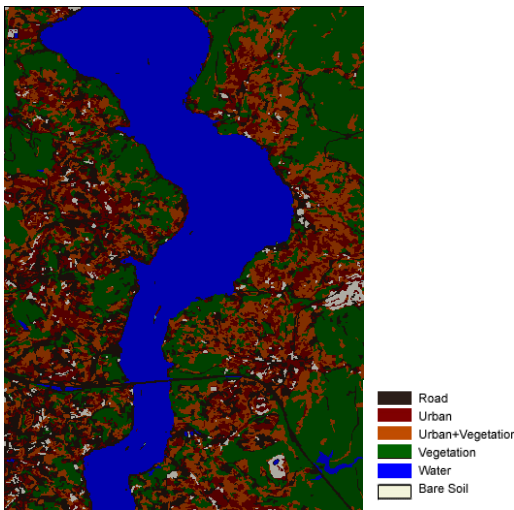**Figure 6.** Condition-based classification image.

Figure 7. Nearest neighbor classification image.

5. RESULTS

The evaluation of the results was done in three ways. First, to determine the accuracy of the classification process, the comparison of classification results with the ground truth was performed. Secondly, histograms of the classifications were compared. Finally, classification results were visually analyzed.

To express the accuracy, error matrix was prepared for each classification. The overall accuracies were found to be 75% for isodata, 82% for maximum likelihood, 88% for condition-based and 85% for nearest neighbor classifications. When focused on the class histograms, water and forest classes were found to be consisting of nearly same number of pixels independent from the method applied. Bare soil was mixed with Road and Urban in isodata classification. Road class was found to be covering nearly same number of pixels in both unsupervised methods, however, it was seen that the road detection performance was not the same. It was mixed with the urban class in pixel-based classification. By visual analysis, it was seen that roads were best extracted in condition-based classification.

6. CONCLUSION

The study was practiced for generalized land classes. The mixed class vegetation+urban was used since the urbanization of Istanbul is not so uniform and the class types were organized to be the same for each method to make them available for comparison.

It is seen that object-based classification results were better than the pixel-based classification. It is thought that, the advantage of condition-based classification which performs better than others is the use of direct definitions for object criteria in class descriptions.

REFERENCES
Baatz, M., Benz, U., Dehghani, S., Heynen, M., Holtje, A., Hofmann, P., Lingenfelder, I., Mimler, M., Sohlbach, M., Weber, M. and Willhauck, G., 2002. eCognition 3.0 User Guide Definiens Imaging

Baatz, M. and A. Schäpe,, 1999. Multiresolution Segmentation: An Optimization Approach for High Quality Multi-Scale Image Segmentation, XI. Beitrage zum AGITSymposium, Salzburg.

Benedictsson, J. A., P. H. Swain, and O. K. Ersoy. 1990., Neural Network Approaches Versus Statistical Methods in Classification of Multisource Remote Sensing Data. IEEE Transactions on Geoscience&Remote Sensing 28, (4): 540–551.

Benz, U., 2001. Definiens Imaging GmbH. Object Oriented Classification and Feature Detection, IEEE Geoscience&Remote Sensing Society Newsletter.

Casals-Carrasco, P., S. Kubo, and B. Babu Madhavan. 2000; Application of Spectral Mixture Analysis for Terrain Evaluation Studies. Int. J. of Remote Sensing 21, (16)(Nov.): 3039-3055

Chen, Y., Shi, P., Fung, T., Wang, J., Li, Y., 2007. Object-Oriented Classification for Urban Land Cover Mapping With ASTER Imagery, Int. J. of Remote Sensing, V.28, p. 4645-4651(7)

Elachi C. and Zyl J., 2006, Introduction to the Physics and Techniques of Remote Sensing, John Wiley & Sons, Inc.

Kong, C., Xu, K., Wu, C., 2006. Classification and Extraction of Urban Land-Use Information from High-Resolution Image Based on Object Multi-Features, J. of China Univ. of Geosciences 17 (2), 151_157.

Mo, D.-K., Lin, H., Li, J., Sun, H., Xiong, X.-J., 2007. Design and Implementation of a High Spatial Resolution Remote Sensing Image Intelligent Interpretation System. Data Science Journal 6 (Supplement), S445_452.

Platt, R.V., Rapoza, L., 2008. An Evaluation of an Object-Oriented Paradigm for Land Use/Land Cover Classification. The Professional Geographer 60 (1), 87_100.

Qian J., Zhoua Q., Houa Q., 2007, Comparison of Pixel-Based and Object-Oriented Classification Methods for Extracting Built-Up Areas in Aridzone, ISPRS Workshop on Updating Geo-Spatial Databases with Imagery, China, August 28-29

T. Blaschke, 2010, Object Based Analysis for Remote Sensing, ISPRS J. of Photogrammetry and Remote Sensing 65, 2_16

Wang Z., Wei W., Zhao S., Chen X., 2004 Object-oriented Classification and Application in Land Use Classification Using SPOT-5 PAN Imagery, IEEE, pp. 3158-3160.

Yan, G., 2003, Pixel Based and Object Oriented Image Analysis for Coal Fire Research, ITC International Institute for Geo-information Science and Earth Observation, Msc. Thesis

Yoon G. W., Park J. H., Choi K. H., 2004, Land-cover Supervised Classification using User-oriented Feature Database, Volume 4, 20-24 Sept. pp. 2724 – 2726, Geoscience and Remote Sensing Symposium, IGARSS '04. Proceedings.

**map source: http://www.ibb.gov.tr (Istanbul M. Municipality)