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COMPARISON OF PIXEL-BASED AND OBJECT-BASED CLASSIFICATION METHODS FOR SEPARATION OF CROP PATTERNS

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Abstract

Determination and classification of plant patterns with satellite images is most suitable method for preparation of source inventory. The use of high resolution satellite imagery is quite widespread for separation of land use types. Pixel based classification methods are widely used to classify images. The choice of classification methods in satellite images directly affects the success of the research. In recent years, the use of object-based classification method to determine the plant pattern as parcels is being investigated. In this study, we present an example to determine the crop pattern as parcels using pixel and object based classification methods.
The study was conducted in Isparta-Turkey. Quickbird-2 satellite image, ERDAS and e-Cognition Developer Trial 8.8 software were used. Maximum likelihood and Isodata algorithms of Pixel-based classification methods and, multiresolution segmentation operator of object-based classification methods were used to classify satellite imagery.
Object-based classification method was determined to be more successful than pixel-based classification method, based our analyses.

***Key words**: Quickbird, land use types, image classification, object based classification.*

INTRODUCTION

The range of resolutions available for satellite imagery lends itself to the mapping of land cover at a number of scales. High-resolution images obviously contain more information than low-resolution images. Therefore, it is reasonable to suggest that coarser resolution data can be used to create small-scale land cover maps, whereas higher resolution data can map land cover in greater detail (Colombo et al., 2004; Whiteside, XXX). High spatial resolution images have been increasingly used for the classification of urban land use/plant patterns. Classification methods used to determine the land cover/plant patterns are pixel and object based. The high spectral variations within the same land cover, spectral confusion among different land covers and the shadow problem often lead to poor classification performance by the traditional per-pixel spectral-based classification methods (Moran, 2010). However, the interest in object-based classification has increased because it has been shown that there exists a relationship between the pixel and object sizes, which was not a factor in pixel-based classification methods (Blaschke, 2010).

The object-based classification method is a combination of separation into segments and contextual classification. The first step that is based on the object-based image analysis was image segmentation (Castilla and Hay, 2008). The segmentation process separates the image into segments that are arranged according to the classification of spectral, geometric, textural and other characteristics of the objects (Veljanovski et al., 2011). The selection of appropriate parameters is an important step in the image segmentation process. Multi-resolution segmentation is based on the selection of optimal parameters to study the result of a series of segmentation that is based on trial and error. The choice of optimum parameters depends on the user's experience and observation capabilities. This trial and error segmentation processes take a long time (Tong et al., 2012).

The sizes and shapes of the objects can be further distinguished with object-based classification methods that allow many new applications in the data received by the very high spatial resolution satellite.

Multi-resolution segmentation of object-based image analysis, on the other hand, results in objects with different sizes and shapes, which are meaningful and better represent the real size and shape of land cover types (Salehi et al., 2011). The land use types (LUTs) and plant patterns can be determined and classified by this software and classification algorithms. In this study, we compared the pixel- and object-based classification methods for determining land use types and plant patterns.

MATERIALS AND METHODS

The study was carried out within the boundaries of Güneykent municipality on Gönen district in Isparta (Figure 1). The climate conditions of the study area are mixed types of the Central Anatolia Region and Mediterranean, and the altitude is 1250 m.

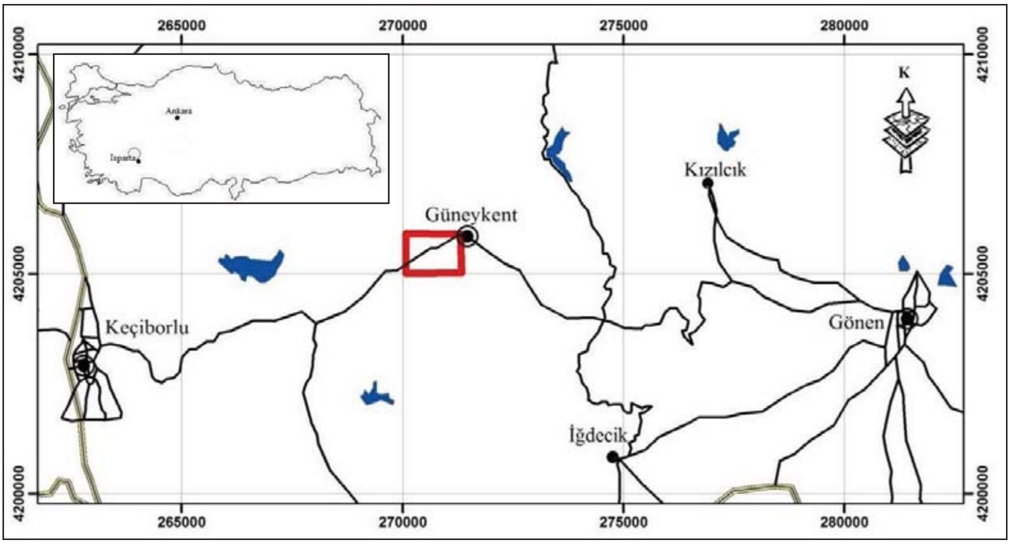

Figure 1. The location of the study area

Quickbird-2 satellite data dated 06.08.2006 is used with a 0.61-m panchromatic and 2.44-m multispectral bands. ERDAS IMAGINE 9.1, ArcGIS 9.1 and eCognition Developer Trial 8.8 softwares were used. Geometric correction, image sharpening and image enhancement were performed for photo interpretation using 4, 3, 2 band combinations. The first step of photo interpretation was determining the characteristics of land use types and plant patterns in the image. Second, the image object and land use types/plants were compared. The image was interpreted based on the information obtained from these parameters. Land surveys were performed in parcels at the test area. In the land survey, data about the morphological properties of land use and plant patterns were collected. The digital land use parcel map was produced using ArcGIS software and a database of this map was set up. ERDAS software was used in pixel-based classification of satellite images (Erdas, 2002). eCognition software was used to classify the satellite image according to the object-based method. In this method, the multi-resolution segmentation algorithm was selected. The image segmentation algorithm was grouped into pixels as homogeneous parts in close proximity according to the spectral and spatial extent. For selection of optimal parameters, segmentation operations were performed by testing different shapes, compactness and scale parameters using 4, 3, 2 band combinations on the Quickbird-2 satellite image of the study area.
The shape factor and compactness factor were chosen as 0.1 and 0.5, respectively in the multi-resolution segmentation process. The satellite image of the study area was separated into

segments by testing different scale parameters. Training classes were created using the standard nearest neighbour method. After classification of the Quickbird image using this algorithm, control points were selected randomly in the image. The plant patterns obtained from the LUT map were assigned as class value of the control points. After entering, all the points were checked for accuracy by the software. The accuracy of the data generated from the object-based method was determined according to the interpretation of the object-based classification and parcel maps.

RESULTS AND DISCUSSIONS

LUTs in the study area

The study area consisted of stubble, quince, almond, settlements, walnut, bare soil, apple, nursery, nut, broad-leaved *Rosa damascena* Mil., mixed garden, poplar, cherry, forest, reeds, vegetable, fodder crops, poor vegetation cover LUTs and plant patterns. The distribution according to LUTS and plant patterns of the study area are given in Table 1. The view of the field work is shown in Figure 2. In the study area, quince cover is the least 2.03 (0.22%) and bare soil cover is the most, 258.71 (27.43%).

Figure 2. A view of the field work

Visual image properties of LUTs/Plant pattern parcels

Fruit trees have regular inter-row and intra-row spacing. Therefore, it is seen in a regular manner on satellite images. Crown-width and planting pattern, as well as inter-row and intra-row spacing are important criteria in the separation of fruit types. Rose damascena areas can be separated because of the planting pattern, while they show similarity to perennial plants in hue. Planting pattern is seen in longitudinal, parallel rows in the north-south direction in the flat terrain and as the perpendicular direction to the slope in the sloping terrain. Pixel reflection shows heterogeneous-appearing parcels where the higher plants consist of mixtures of soil, vegetation and perennial crops.

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Table 1. LUTs distribution and plant patterns of the study area

LUTs/Plant Patterns	Total area (da)	%
Stubble	13.98	1.48
Quince	2.03	0.22
Almonds	16.30	1.73
Settlements	72.3	7.67
Walnut	12.62	1.34
Bare soil	258.71	27.43
Apple	33.01	3.50
Nursery	45.50	4.83
Nut	3.45	0.37
Broad-leaved	65.76	6.97
Rose damascena	103.90	11.02
Mixed Garden	29.08	3.08
Poplar	45.88	4.86
Cherry	47.10	4.99
Forest	29.33	3.11
Reeds	18.31	1.94
Vegetable	62.46	6.62
Fodder Crops	21.86	2.32
Poor Vegetation cover	61.55	6.53
Total	943.13	100.00

Annual plants such as crop and fodder crops cover the soil surface. LUTs such as bare soil, dry grass or fallow show a homogeneous appearance. These can be clearly distinguished from the other factors. Poplar has a thin, longitudinal crown-width perpendicular to the pattern. It is typically planted in a single row on the road and parcel edge. Shadow on the parcels is masked by spectral reflectance in the satellite image. Thus, the accuracy of visual interpretation was reduced. These events show the classification method, which is based on spectral, geometric, textural and other features of the objects. Morphological appearance and interpretation of LUTs and plant patterns that are located in the study area are given in Figure 3.

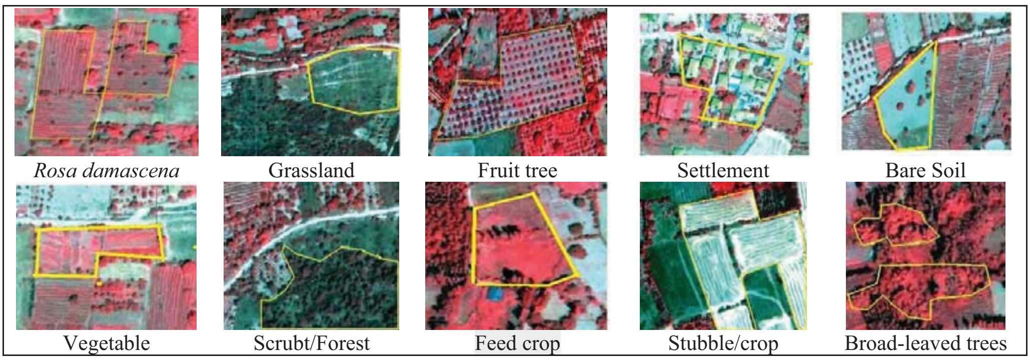
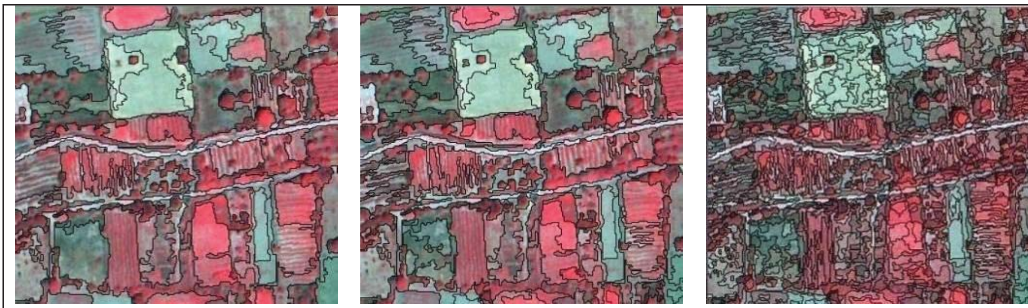


Figure 3. Morphological appearance and interpretation of LUTs and plant patterns that are located in the study area

Pixels and object-based classification
Scale parameters were taken as 100, 75 and 25. The most appropriate scale parameters for separating segments were determined to be 100. A comparison of the scale parameter is given in Figure 4. The Maximum Likelihood Decision Rule (19 classes) of the supervised classification and the ISODATA method (20 classes) of the unsupervised classification revealed the most appropriate methods. Eight land use types/crop pattern classes were grouped by combining the classes.

Land use types/crop patterns that were separated with the highest accuracy using object-based classification were determined to be rose damascena parcels (67.16%), stubble/crop parcels (58.93%), settlements (78.40%), scrub areas (56.13%) and fruit plants (37.02%). Land use types/crop pattern that was separated with the highest accuracy using supervised classification were vegetable parcels (100%), feed crop parcels (85.71%) and bare soil areas (76.51%). Land use types/crop pattern that were determined using unsupervised classification showed lower accuracy than other classification methods (Figure 5).

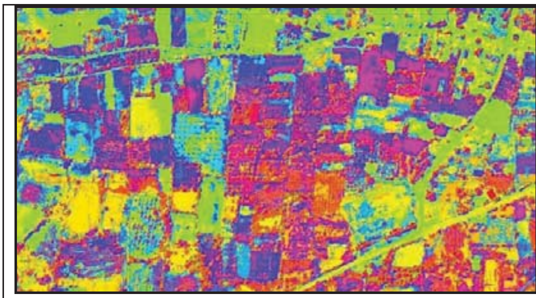


Scale: 100, shape: 0.1, compactness:0.5

Scale: 75, shape: 0.1, compactness: 0.5

Scale: 25, shape: 0.1, compactness: 0.5

Figure 4. Comparing of segmentation parameters in the object-based classification



Unsupervised Classification

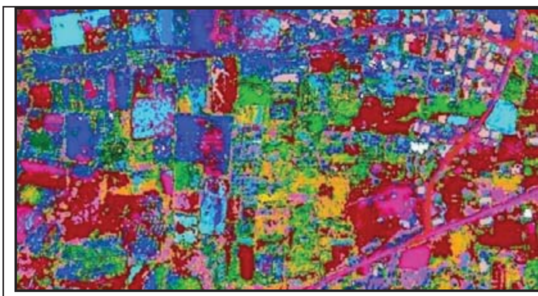
Legent

	Rosa d.		Scrub
	Stubble/crop		Fruit tree
	Bare Soil		Feed crop
	Vegetable		Settlement

Object-based Classification

Legent

	Rosa d. 1		Fruit tree
	Rosa d. 2		Vegetable
	Rosa d. 3		Feed crop
	Road		Barel Soil
	Stubble/crop		Barel Soil
	Stubble/crop2		Scrubt



Supervised Classification

Legent

	Rosa d.		Scrubt
	Stubble/crop		Fruit tree
	Barel soil		Feed crop
	Vegetable		Settlement

Figure 5. Pixel-and object-based classification of LUTS and plant patterns that are located in the study area

CONCLUSIONS

In the study, the multi-resolution segmentation process using scale factor 100, shape factor 0.1 and compactness factor 0.5 in object-based classification was determined to be the most successful method for separating of land use types/plant patterns. The unsupervised classification method showed the least accuracy.

The success of the classification decreases if classifications were only made based on the spectral information of the image when the high-resolution data were used to determine land use types/plant patterns (Salehi et al., 2011).

Selecting the most appropriate scale parameters according to size of the objects is very important for the success of the classification in the multi-resolution segmentation algorithm (Smith, 2010). In general, small-scale parameter values are suitable in classifications that were made on images with the aim of uncovering small objects. Uses of large-scale parameter values are suitable to separate large objects (Duro et al., 2012). In this method, precisely correct segmentation options do not exist. Thus, numerous attempts were made until optimal segments appropriate for the purpose of this study were determined. It is important to establish appropriate structures from pixels to objects by providing the appropriate homogeneity.

In conclusion, the object-based classification method gives the highest accuracy in higher plants and perennial crops that consist of a mixture of soil and vegetation. For homogenous patterns such as bare soil, vegetables and feed crops, the supervised classification method was found to be more successful than the object-based method. Therefore, elimination of the soil reflections is an essential factor in studies that are proposed for the classification of vegetation patterns. The accuracy of separation is believed to increase by combining with the vegetation index of the object-based classification method.

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