MAPPING THE PERI-URBAN FOREST OF THESSALONIKI AFTER THE BIG FIRE OF 1997 USING IKONOS IMAGERY

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ABSTRACT

This paper compares a pixel-based *vs*. an object-based classification (OBIA) of a multi-spectral IKONOS image for mapping Mediterranean forests after fire. The study area was a part of the aesthetic, peri-urban forest of Thessaloniki, Greece (Seich-Sou forest) after the big fire of 1997. The IKONOS image was acquired in 2001 and was classified with Maximum Likelihood Classification (MLC, per-pixel method) and with the Membership Function classifier (per-object method). The latter relies on the development of rules, which have the potential to support objective and standardised mapping. Five land use/cover classes were recognised in the forest according to the national legislation. Verified by visual photointerpretation and ancillary ground truth data, OBIA seems to give more realistic results than MLC, especially for grasslands, agricultural land and reforested areas. Future work will focus on testing OBIA in the entire extent of the forest towards an operational use of the rule-set for monitoring Mediterranean forests after fire.

INTRODUCTION

Forest is a natural resource with multifaceted and incalculable importance for man and nature. Forests are typically ranging over wide areas, and cover rough terrain. In the peri-urban forest of Seich-Sou in Thessaloniki, Greece a disastrous wildfire occurred in 1997. About 1,664 hectares were burnt, an area representing 55% of the forest. Such large events usually have a significant impact on the ecology of a forest, since many physical, chemical, mineralogical, and biological soil properties could be affected by the fire (1); some of the effects may even be permanent.

Immediately after the forest fire, emergency measures were taken to counter the effects of the fire. The Forest Agency of Thessaloniki and the Directorate of Reforestation of the Region jointly launched a series of projects for rainwater management and burned area mapping. There was also a study for the extended reforestation. The largest reforestations were those of 1998 and 2000 (personal communication with the Region).

When a forest area is affected by fire, it is necessary to map the burned area in order to assess the economic, ecological and aesthetic impacts. Among the most reliable methods and techniques for studying burnt forest areas are remote sensing and Geographical Information Systems (GIS) (2). GIS provide the digital environment for analysing spatial data and mapping regions of interest (3,4). With the combination of these two sciences equal results as in a field survey can be achieved. Furthermore, specialised techniques can be used in order to produce rapid and precise series of the digital thematic maps for comparison and monitoring (5,6,7).

Among different remote sensing methodologies, object-based image analysis is a fast growing technique and very promising for the future of image analysis. Object-based image analysis (OBIA) is considered to have great potential in multi-scale mapping, and as a result has been receiving increased attention during the last decade (8). OBIA, which focuses on analysing groups of pixels (called ‘image objects’ or simply ‘objects’) rather than processing single pixels alone, comprises two steps: a) image segmentation for creation of objects linked through a spatial and hierarchical network and b) classification of these objects (9).

Object-based classification succeeds to manage the inherent heterogeneity of a class, for instance, individual trees in a meadow. Furthermore, object-based classification succeeds to avoid the sensitivity of noise of pixel-based classification. In addition, it gives the opportunity to develop a hierarchical classification and to use criteria (rules) beyond the spectra: shaped objects, neighbourhood, and texture (10). Rules can support objective and standardised mapping and monitoring.

According to (10) there are also disadvantages of object-based classification. Classification accuracy depends on the quality of image segmentation. Classification error could be accumulated due to the error in both image segmentation and classification process and finally, once an object is misclassified, all pixels in this object will be misclassified. To sum up, advantages overcome the disadvantages and bring the process close to the classic photo-interpretation, but in a way more objective and stable, based on the creation of rules.

A lot of research in different fields has been conducted for comparison of OBIA with pixel-based methods and particularly with the Maximum Likelihood Classification (MLC). In general for satellite images with very high spatial resolution (1-5 m) the MLC technique gives a strong misclassification which is due to spectral variability within land cover types (i.e., the within-class variability is very high) (10).

The main goal of this paper is the comparison of OBIA with MLC on very high resolution satellite imagery for post-fire mapping of Mediterranean forests. Furthermore, the target is to examine the potential of OBIA for automated classification of IKONOS imagery, which is essential for forest monitoring.

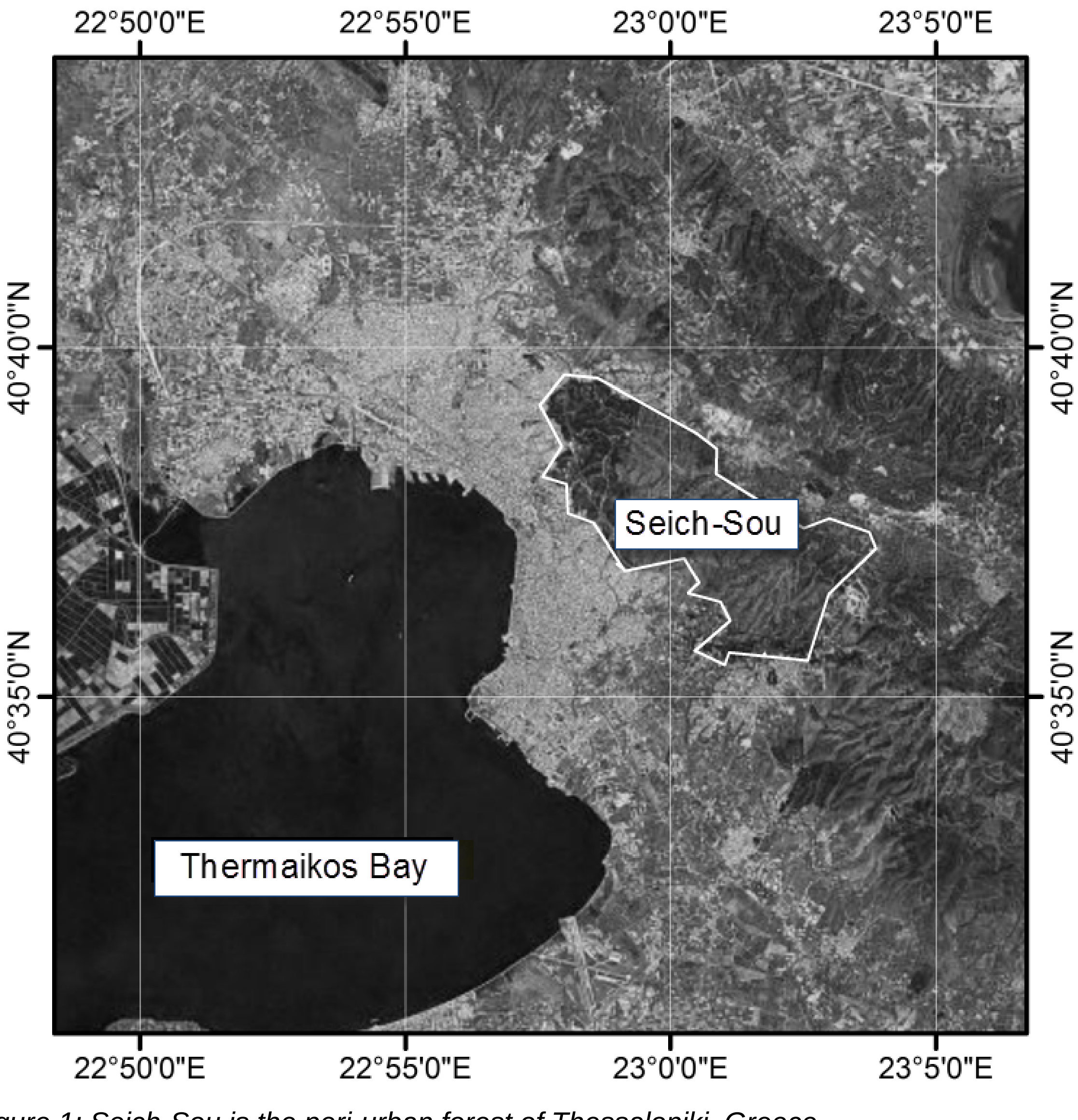

Figure 1: Seich-Sou is the peri-urban forest of Thessaloniki, Greece.

METHODS

Study area

The peri-urban forest of Seich-Sou extends to the NE side of the city of Thessaloniki (22°55' ÷ 23°05' E and 40°35' ÷ 40°40' N) (Figure 1). The total area of the forest is 3,014 hectares.

The forest hosts 277 plant species, with pine *trees (Pinus brutia Ten, Pinus pinea L. and Pinus halepensis Mill)* being dominant. There are also scattered cypress *(Cupressus sempervirens),* plane trees *(Platanus orientalis)* and many species of populus (11).

From the available digital geodata, it is derived that the average height of the area is 302 m while the minimum and maximum elevation (a.s.l.) is 80 m and 550 m, respectively. Also, the average slope of the area is estimated to be 16.7%, while the standard deviation of the slope is at 8.5%. These figures indicate a mild and fairly uniform terrain. The slopes of the forest are mainly southern, which means that the forest is visible from the city of Thessaloniki and Thermaikos bay, giving the forest a great aesthetic value.

For mapping the area, 5 categories of land use/cover were selected. The nomenclature was based on the current forest legislation of the country. The classes were the following:

- urban areas,
- forest,
- agricultural land,
- bare land,
- grasslands.

As the object-based classification is very time consuming, the analysis was limited to a sub-area abstracted from Seich-Sou forest which, however, included burnt and non-burnt patches with all targeted categories (Figure 2).

Dataset description

The geodata were collected from various sources and organised into a common geographic database, according to the Greek Geodetic Reference System (EGSA87). More specifically, the data used in this work included:

- a topographic map of the burned area by the Forest Service of Thessaloniki, which was scanned and digitised. This provides a detailed definition on study area boundaries and the burnt area perimeter.
- a multi-spectral IKONOS satellite image (4 m pixel size), acquired on 23rd of May 2001 (see Figure 2)
- agricultural land use outlines derived from the Land Parcel Identification System (LPIS) database.

Mapping methods

The methods implemented for the mapping of the area were:

- a pixel-based classification and more specifically: the Maximum Likelihood Classification (MLC) of the IKONOS image.
- an object-based classification of the IKONOS image and more specifically: the development of a classification rule set.

The MLC was implemented as a pixel-based algorithm on the IKONOS image (12,13). The training sites were selected with random stratified sampling. More specifically, six samples were selected for each category, represented by 40 to 400 pixels. The choice of the number of pixels per class was based on (14), i.e., the number of pixels per selected area of interest must be over 10 times and less than 100 times the number of channels of satellite images. ERDAS Imagine was used for the classification.

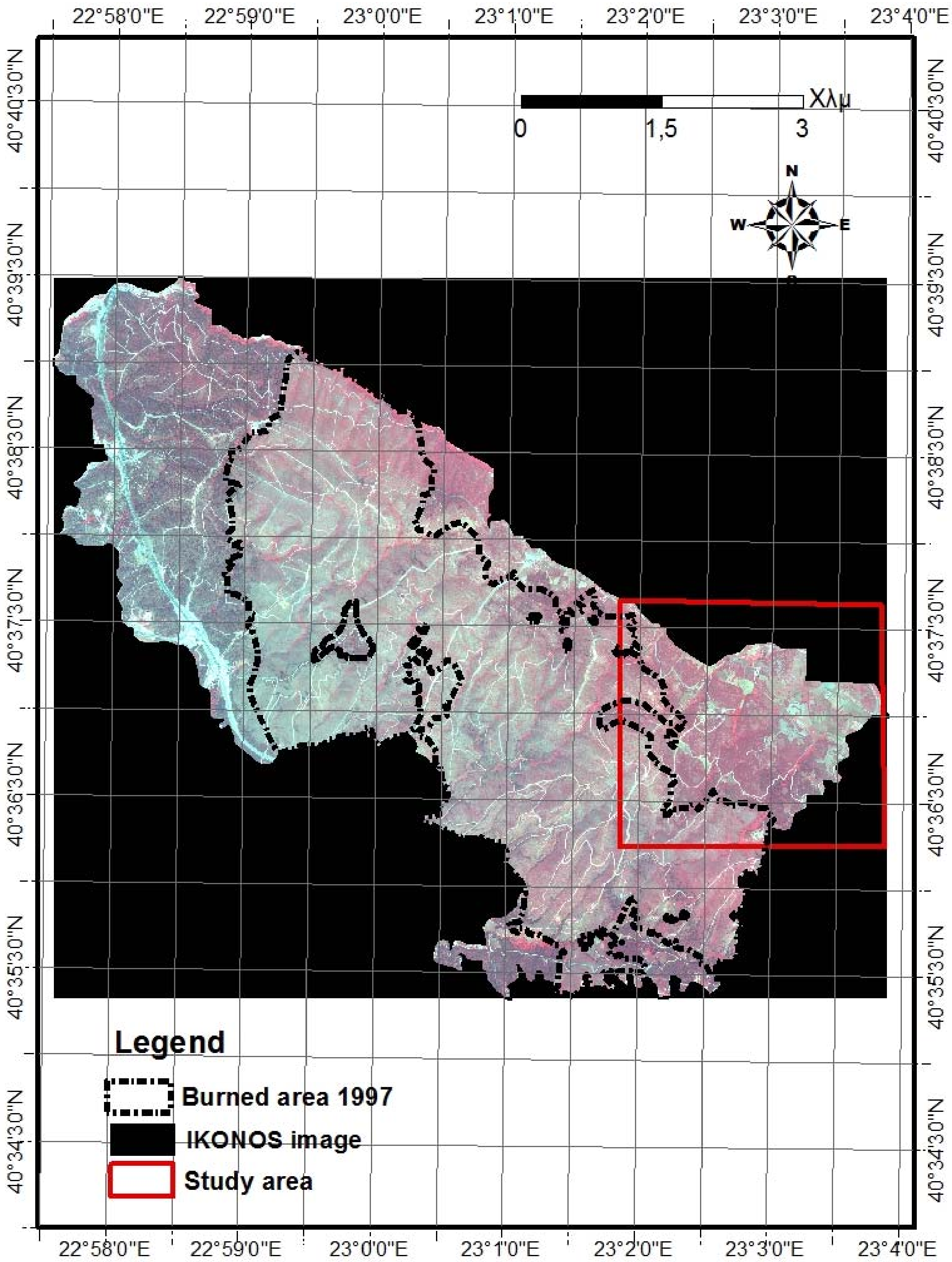

Figure 2: The study area (inset) is a subset of the Seich-Sou forest.

Using eCognition Definiens (version 7), an object-based classification was implemented on the same image. A 2-level class hierarchy was designed in top-down approach. Three semantic classes were denoted at the 1st hierarchical level, i.e., ‘Agricultural’, ‘Not vegetated’ and ‘Vegetated’, while five classes were denoted at the 2nd hierarchical level, i.e., ‘Bare land’, ‘Roads’ and ‘Urban’ under the ‘Not vegetated’ class and ‘Forest’ and ‘Grassland’ under the ‘Vegetated’ class (Figure 3).

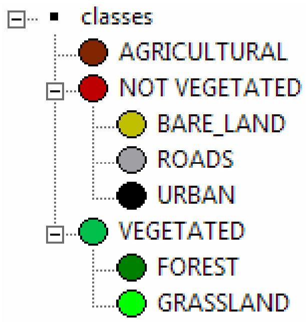

Figure 3. The class hierarchy.

A trial-and-error approach showed that for the designed hierarchy a single segmentation level would be adequate. Multiresolution segmentation, an algorithm embedded in eCognition software, was employed for the extraction of image objects (15). The specific segmentation parameters selected were:

- image layer weights: 1 for each channel of the image
- scale parameter: 25.

The composition of the homogeneity criterion was weighted 40% for shape against 60% for colour and 50% for compactness against 50% for smoothness. In addition to the above parameters, the vector layer from the LPIS database was utilised as a thematic layer. This assisted in accurately isolating forest from agricultural land and roads from bare land patches.

The ‘Membership Function’, a non-parametric classifier, was implemented for the classification of the objects. Membership Function calculates class probabilities using logical and algebraic combinations of fuzzy sets. In order to select appropriate features for feeding the classifier, a feature space optimisation process was implemented. This tool assists in finding optimum combinations of features that are particularly suitable for separating classes in conjunction with a nearest neighbour classifier (15). Table 1 shows the membership functions for all classes.

Table 1: Set of rules developed for classification.

Class hierarchy		**Logical Function**	**Membership function***		
Level-1	Level-2		Feature	Value	Type
“Agricultural”			Thematic information from LPIS		
“Not vegetated”		Intersection (AND)	Brightness	400÷752	Full range
			Not max difference	1.0÷0.5	Full range
	“Urban”		Mean BLUE	480÷565	Full range
	“Roads”		Thematic information from LPIS		
	“Bare land”		Similarity to class	Not “Urban”	
“Vegetated”		Intersection (OR)	Similarity to class	not “Not vegetated”	
	“Forest”		NDVI	>0.315	Larger than (Boolean, Crisp)
	“Grassland”		NDVI	<0.315	Smaller than (Boolean, Crisp)

**terminology adopted from Definiens Professional 7 software*

RESULTS

The mapping results from the implementation of MLC and OBIA are demonstrated in Figure 4. The tabular results are provided in Table 2.

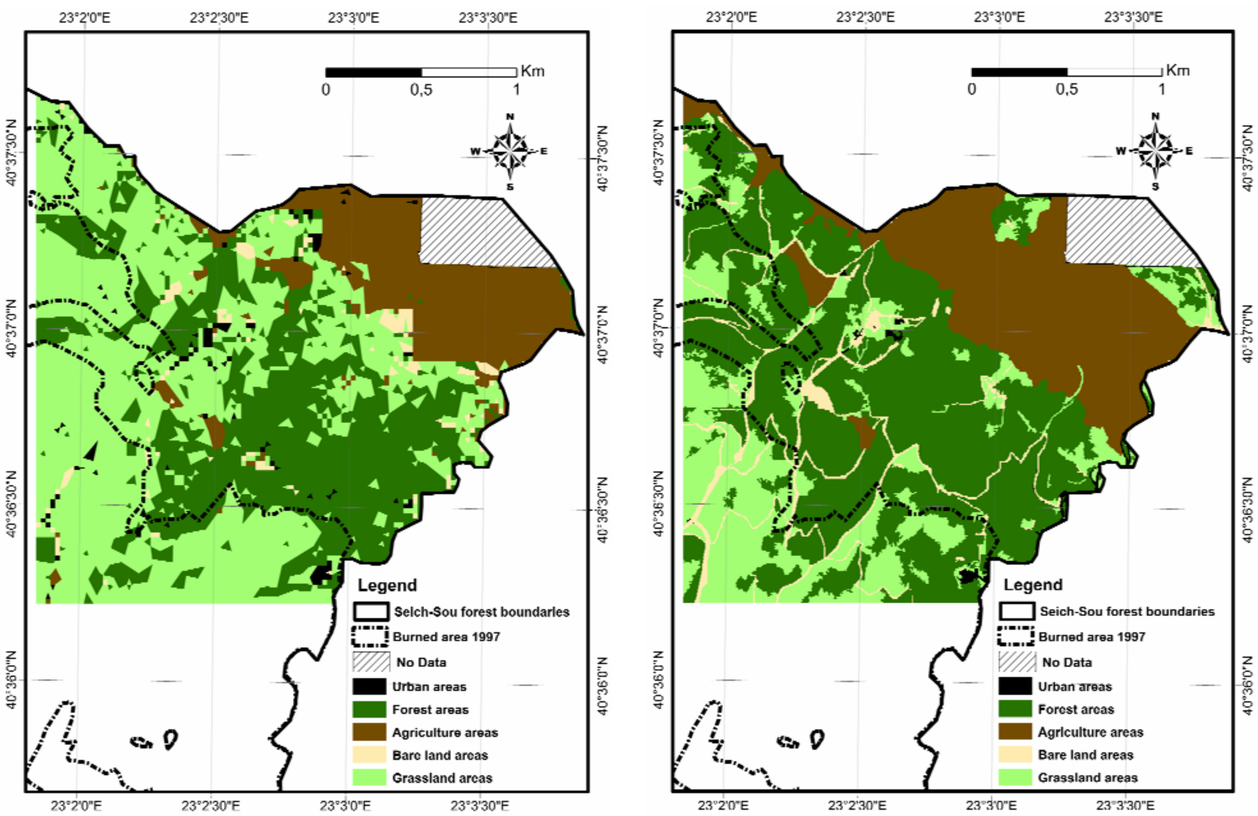

Figure 4: The results of the IKONOS classification (left: MLC; right: OBIA).

Table 2. The results of area (ha and %) of the MLC and OBIA.

Categories	MLC Area (ha)	MLC %*	OBIA Area (ha)	OBIA %
Urban areas	6.53	1.31	3.00	0.60
Forest	159.63	32.11	248.52	49.98
Agricultural land	79.12	15.91	114.55	23.04
Bare land	10.50	2.11	24.82	4.99
Grasslands	241.43	48.56	106.30	21.38

**Percentages refer to the entire mapped area*

The nomenclature of the two classifications was slightly different: in that of MLC the class 'Bare land' contained bare land and roads, which are represented by separate classes in OBIA. In order to compare the two methods, these two classes were merged in the OBIA classified image. Comparison results are demonstrated through two thematic maps: a map of similarities (Figure 5, left) and a map of differences (Figure 5, right). In the map of differences, the classes illustrate areas as they have been classified with OBIA.

The results were checked by visual photointerpretation complemented by ancillary ground truth data from a field survey. Classification patterns derived from OBIA seem more realistic in comparison to those taken from MLC. For example, roads and other small or linear objects are apparent in the OBIA classified image, whereas there is no distinction of the same objects in the MLC one. Also, changes using OBIA are smooth, whereas changes are quite abrupt with MLC. However, ground truth data were quite limited and only supportive to visual photointerpretation and therefore not adequate for a statistically robust quantitative accuracy assessment.

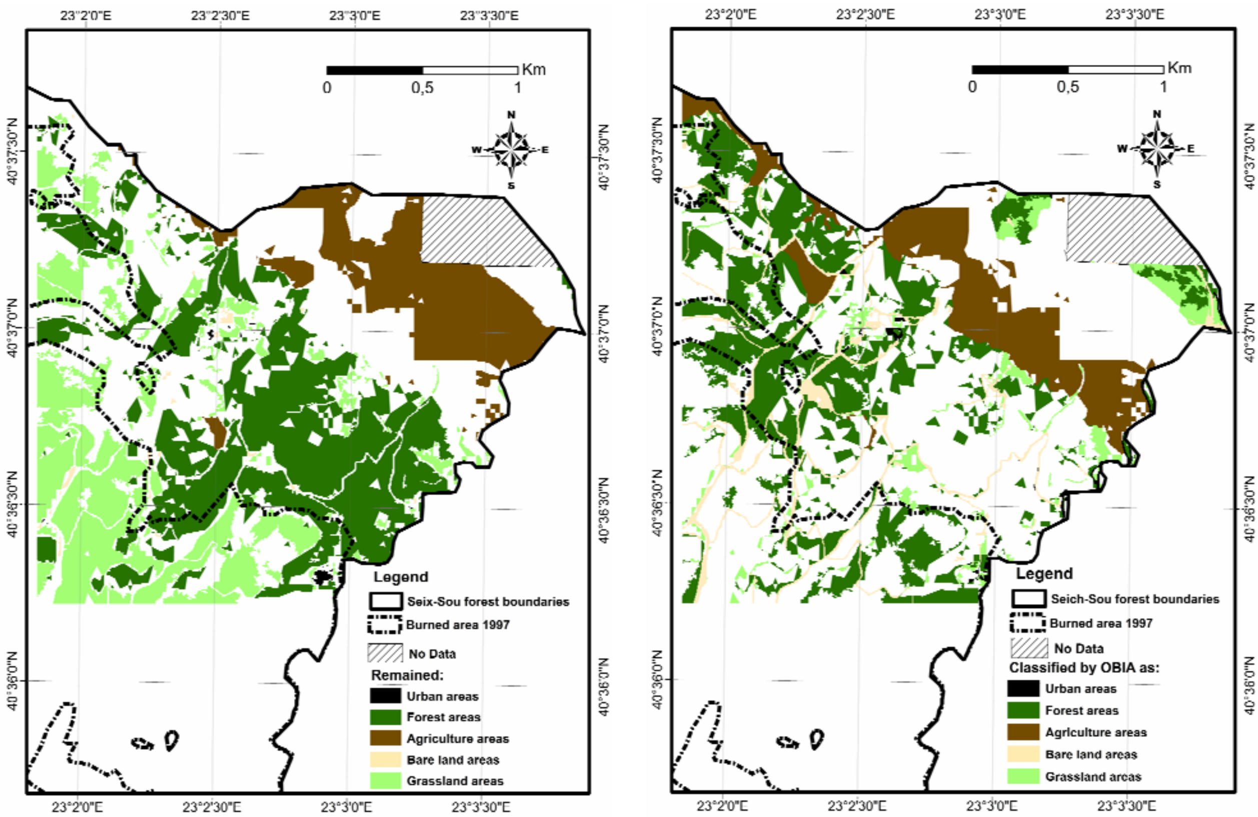

Figure 5: Left side: areas classified in the same category by both methods; right side: areas classified in different categories by each of the methods.

By comparing the results of the two implemented classification methods, the following points are derived (Table 3):

- The biggest differences from MLC to OBIA are observed in grasslands; more specifically, 21% of grasslands in MLC were classified as forest in OBIA, while 7% of the grassland in MLC were classified as agricultural land in OBIA.
- Judging from the whole area classified as forest by the two methods, OBIA rule-set demonstrated a better performance.
- With regard to the reforestation areas, the two methods behaved differently, with OBIA again more accurate, as it classified the majority of these patches in the (correct) forest class.

Table 3. Comparison of gathered results using MLC and OBIA

OBIA	Urban areas		Bare land		Forest		Agricultural land		Grasslands	
MLC	ha	%*	ha	%	ha	%	ha	%	ha	%
Urban areas	0.690	0.139	1.631	0.328	0.924	0.186	1.788	0.360	1.494	0.300
Bare land	0.396	0.080	1.493	0.300	1.222	0.246	6.243	1.256	1.141	0.229
Forest	0.661	0.133	5.609	1.128	134.129	26.977	10.537	2.119	8.693	1.748
Agricultural land	0.300	0.060	2.816	0.566	7.581	1.525	60.351	12.138	8.070	1.623
Grasslands	0.956	0.192	13.270	2.669	104.663	21.051	35.633	7.167	86.906	17.479

**Percentages refer to the entire mapped area*

CONCLUSIONS

The goal of this paper was to examine differences of implementing MLC and OBIA on an IKONOS image of the peri-urban forest of Seich-Sou, after the fire of 1997. A long-term objective was to explore the potential of using OBIA for regular monitoring of Mediterranean ecosystems affected by fire. The results, verified by limited ground true data, showed that OBIA performed significantly better and even more realistically than MLC, specifically for agricultural land, grasslands and forest. OBIA was better also in mapping reforestation patches correctly, i.e., as ‘forests’. Future research will focus on testing the OBIA rule-set in the entire forest of Seich-Sou and on setting the basis for transferring the rule-set in different study areas.

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