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A semi-operational approach for land cover mapping in the Mediterranean

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ABSTRACT: Classification of remotely sensed imagery is considered an appropriate technique to obtain land cover information. Recent improvements in the spatial resolution of sensors make possible the extraction of detailed thematic maps. However, high spatial resolution may reduce the accuracy of per-pixel classification methods, as the spectral within class variability increases. Similar spectral characteristics of Mediterranean land cover types and high land fragmentation make the discrimination of land cover categories difficult. An object-oriented classification approach is thought to be a solution.

The aim of this study was to develop a methodology for the semi-operational land cover mapping in the Mediterranean to support policy-making and planning, carried out in the framework of the Geoland project (SIP3-CT-2003-502871), in the context of ‘‘Global Monitoring for Environment and Security’’ (GMES) initiative.

A two-step approach was developed on the basis of object-oriented classification to exploit the potential of the different available data. In the first step only QuickBird multi-spectral data were used to extract land cover classes at coarse level, while in the second step the categorization of the vegetated areas was refined using both multi-spectral and panchromatic images, as well as DEM data.

The developed methodology was implemented to map a heterogeneous, highly fragmented area in Crete (Greece). The analysis of the confusion matrix revealed some patterns of common misclassifications, mainly due to the high spatial resolution of the imagery. The overall accuracy shows an acceptable performance of the developed object-oriented approach, given the heterogeneity of the environment and the complex classification needs.

1 INTRODUCTION

The use of accurate information about the land is considered to be crucial for environmental policy-making and planning. With the CORINE Land Cover programme, the European Council admits the usefulness of land cover data to provide with territorial dimension the formulation, implementation, monitoring and evaluation of policy-making. Since then, different initiatives, (e.g. INSPIRE directive) have highlighted the need for the 'territorialisation' of the information and its representation by means of Geographic Information in the European territory including Land Cover as an essential data set. (E.E.A., 2005, Weber & Hall, 2001).

Remote sensing image classification is generally thought to be an appropriate technique to obtain land cover information, since it provides a map-like continuous representation of the Earth's surface at a wide range of temporal and spatial scales (Foody, 2002). Recent improvements in spatial resolution make feasible the extraction of more detailed thematic maps. Nevertheless, the high spatial resolution of advanced sensors may reduce the accuracy of per-pixel classification methods, as the spectral within class variability is increased. In addition, when dealing with Mediterranean land covers, since many of them exhibit similar spectral characteristics, the separation by simple per-pixel classifiers becomes difficult. In these cases, the use of textural attributes as a potential solution for the classification of land cover in Mediterranean regions is recommended, given that different categories can exhibit different textures where the spectral values are similar (Lloyd *et al*. 2004). Thus, a region-based approach for the classification is thought to be a solution to these problems. (Schiewe *et al*. 2001).

The aim of this study was to develop a methodology for the semi-operational land cover mapping in the Mediterranean to support policy-making and planning. Within the framework of the Geoland project objective of utilizing Earth Observation resources focusing on "Land Cover Change in Europe", "Environmental Stress in Europe", and "Global Vegetation Monitoring", a two-step approach was developed on the basis of object-oriented classification. The developed methodology was implemented to map a typical human intervened Mediterranean area in Crete (Greece), characterized by an extreme landscape fragmentation. The output land cover map was assessed for its accuracy against ground truth data from an extensive field survey and aerial photo interpretation.

2 STUDY AREA AND DATASET

The agricultural area of the municipality of Kolymvari, which is located in the NW part of Crete (Figure 1), was selected as a typical example of a human-intervened complex Mediterranean landscape. The landscape of the area is characterized as roughly flat, mountainous and semi-mountainous, containing areas which enjoy special protection under the NATURA 2000 programme (Directive 92/43/EEC, Greek Habitat Project Natura 2000). Tree crops cover an area of about 4,500 ha, the most extensive part of which are olive plantations.
The data set used in this study included

- one QuickBird scene (16.5 km $\times$ 16.5 km approx.) with a spatial resolution of 0.639 meters in panchromatic band and 2.5 meters in VNIR bands. The image, acquired on November 16, 2002, with a 14° off-nadir angle, was provided as Basic Imagery Level 1B and was orthorectified using orthophotos (1m pixel resolution) and DGPS-acquired ground control points. The accuracy achieved for both the multi-spectral and panchromatic modes was less than one pixel.

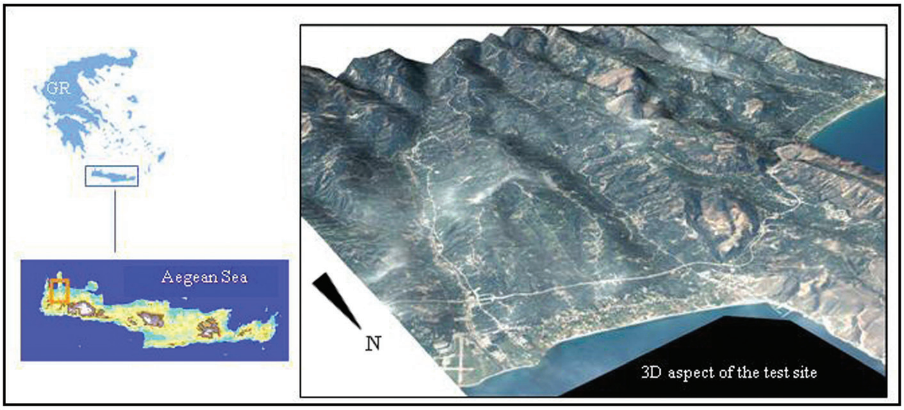

Figure 1. Study area (location and 3D aspect by overlaying the QuickBird scene on the DEM).

- a Digital Elevation Model derived from available point raster files (20m resolution), which were interpolated using the non-linear rubber sheeting interpolation method and resampled to a pixel size of 4m, was also used to orthorectify the satellite imagery and later on for the classification of the scene.

The preprocessing of the image was carried out in ERDAS LPS suite by Sekuloska (2006) and Sarakiotis (2006), and the classification was carried out in eCognition Professional 4.0. Resulting shape files and an accuracy assessment sampling plan were processed with ESRI ArcMap 9.1.

3 METHODS

The representation of image information by objects directly connects these objects within a topological network, thus allowing the efficient use of different kinds of relational operations. The underlying algorithm of eCognition joins the neighbouring regions that show a degree of fitting— related to their spectral variance and shape properties—smaller than a user-defined threshold, called 'scale parameter', into image segments. This parameter determines the number and size of resulting segments. Applying various scale parameters as well as different weights to the various layers of input data, a multi-scale, and hierarchical scene representation can be obtained (Schiewe *et al*. 2001). Features for classification are computed based on image objects, so, classification can address, beyond spectral information, texture and shape information, as well as relational or context features (Baatz *et al*. 2004). The classification of the extracted segments is performed using fuzzy membership functions.

3.1 *Classification Scheme*

The land cover classes used in this study were imposed by the Geoland Project, being a slightly modified version of the CORINE land cover classification scheme (Figure 2).

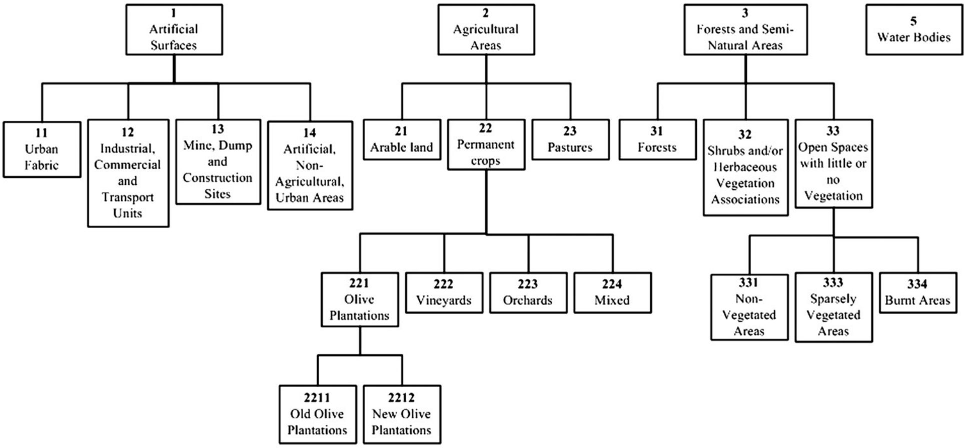

Figure 2. Classification scheme – Modified CORINE land cover.

3.2 *Approach development*

To facilitate the classification process and to exploit the potential of the different data available, a two-step approach was developed (Figure 3). In the first Step, the extraction of the most evident land cover classes using only multi-spectral data was carried out. In the second Step, the classification in the vegetated areas was refined in order to assign all land cover segments to the appropriate land cover class using both multi-spectral and panchromatic images, as well as the DEM data.

The best parameters for the segmentation of the image were identified after comparing different segmented images with various scale parameters, band weights, and homogeneity criteria. The parameters were selected by visual examination regarding the final categories to be extracted. One level of segmentation was used in the first Step while a hierarchical network of three levels was created in the second Step (Table 1).

3.2.1 *Step 1*

The resultant objects were classified in an initial level using a hierarchical scheme of classification with different parent and child classes. The categorization was made using as few as possible features by manual definition of the fuzzy membership functions (Table 2). The scheme, resulted on the repetition of several classes belonging to the same land cover standing for the high variability of appearance in the VHR imagery and the effort to assign every object to a land cover category.

In order to reduce the fragmentation of the resulted map, the classified objects were merged, producing a new level via ‘‘classification based segmentation’’. Thus, the high number of polygons generated in the first segmentation was fused by creating groups that contain all the classes belonging to the same definitive land cover category. The resultant classification (Figure 4) was exported into a shape file used as a thematic layer in Step 2.

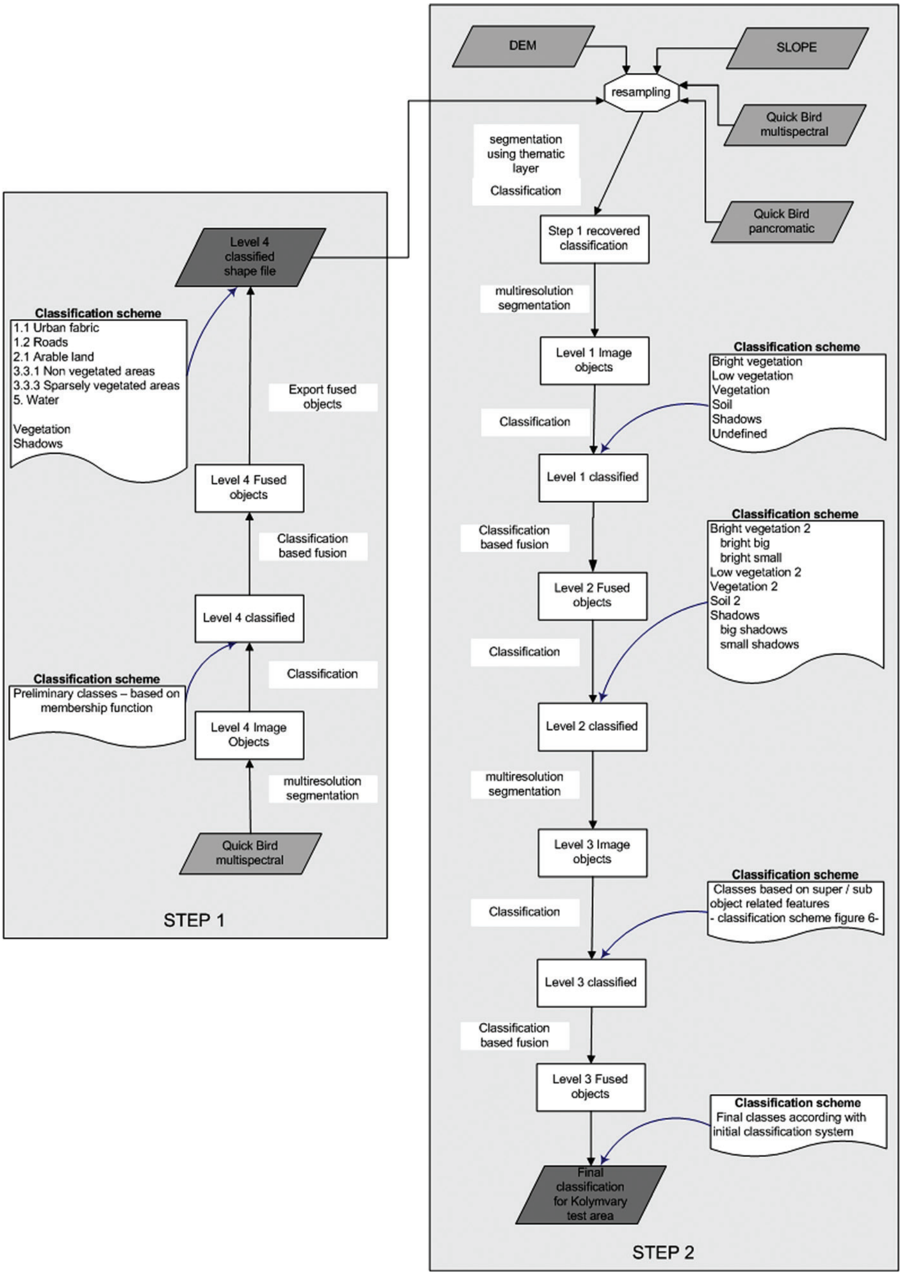

Figure 3. Classification workflow sequence.

Table 1. Image segmentation parameters used in both Steps 1 and 2.

<table>
<tr><th></th><th>Level</th><th>Scale Parameter</th><th colspan="2">Band weights</th><th colspan="2">Homogeneity Criterion</th></tr>
<tr><td rowspan="4">STEP 1</td><td rowspan="4">1</td><td rowspan="4">35</td><td>Band 1</td><td>3</td><td rowspan="4">Shape factor-0.2</td><td rowspan="4">Compactness-0.5
Smoothness-0.5</td></tr>
<tr><td>Band 2</td><td>3</td></tr>
<tr><td>Band 3</td><td>3</td></tr>
<tr><td>Band 4</td><td>1</td></tr>
<tr><td rowspan="11">STEP 2</td><td rowspan="5">1</td><td rowspan="5">20</td><td>Band 1</td><td>0</td><td colspan="2" rowspan="5">Shape factor - 0</td></tr>
<tr><td>Band 2</td><td>0</td></tr>
<tr><td>Band 3</td><td>0</td></tr>
<tr><td>Band 4</td><td>0</td></tr>
<tr><td>Panchromatic</td><td>1</td></tr>
<tr><td rowspan="5">2</td><td rowspan="5">60</td><td>Band 1</td><td>0.5</td><td rowspan="5">Shape factor - 0.6</td><td rowspan="5">Compactness - 0.6
Smoothness - 0.4</td></tr>
<tr><td>Band 2</td><td>1</td></tr>
<tr><td>Band 3</td><td>0.5</td></tr>
<tr><td>Band 4</td><td>1</td></tr>
<tr><td>Panchromatic</td><td>0</td></tr>
<tr><td>3</td><td>10000</td><td>Thematic layer (Classification result in step 1)</td><td>1</td><td colspan="2">Shape - 0</td></tr>
</table>

3.2.2 *Step 2*

The previously obtained classification was used as an input (thematic layer) to create a new project, where mainly different kinds of vegetation remained to be classified. The parameters for the first level of segmentation were tuned to recover the objects classified during Step 1. The classification in Step 2 was mainly based on the extraction of basic elements from the panchromatic imagery, at a very fine level of segmentation, and the use of class-related features to categorize super-objects at a coarser level. The process was carried out only in those polygons previously classified as "vegetated areas".

The basic elements classified at the finest segmentation level (Level 1) consisted of three different kinds of vegetation elements (low vegetation, bright vegetation due to light effects on the image, and other vegetation objects), soil, shadows and unidentified objects (Figure 5). All of them were extracted by means of spectral information and class-related features, as shown in Table 3.

Table 2. Main features used for the discrimination of the Land Cover classes – Step 1.

Class	Used Features
Arable Land	Band 1–Band 3, NDVI (Normalized Difference Vegetation Index), Std. Deviation Band 4, Area, Distance to Neighbouring objects.
Artificial Covers	Area, Brightness, Length/Width, NDVI, Shape Index, Rectangular Fit.
Roads	Band 4–Band 1, NDVI, Length/Width, Compactness.
Vegetated areas	NDVI, Ratio Band 1, Band 4–Band 1, GLCM Entropy All Directions Bands 3 and 4, GLDV Entropy All Directions Band 4
Water	Band 4–Band 1, Inverted Similarity to Artificial Covers

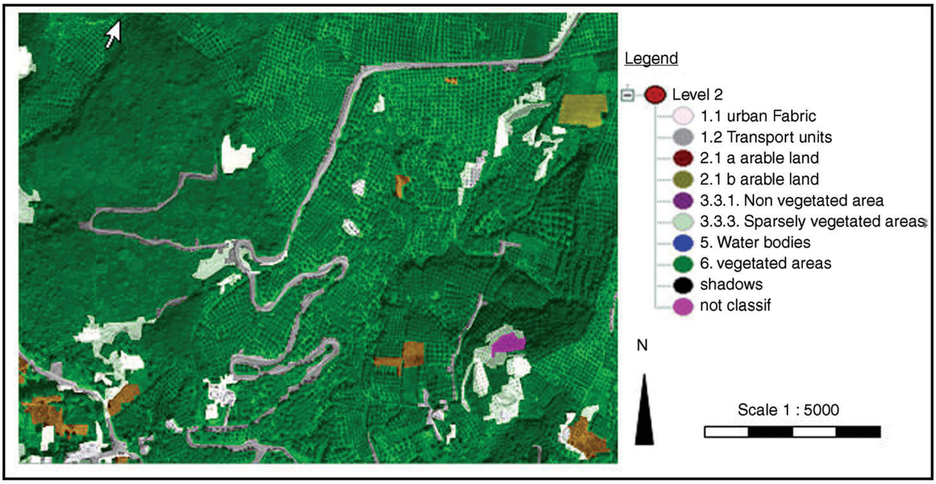

Figure 4. Outcome of the classification carried out in Step 1 (subset).

Table 3. Features used for the extraction of basic elements in Level 1.

Class	Used Features
Bright vegetation	Relative Border to Brighter Neighbours in Panchromatic
Low vegetation	Band 3/Panchromatic
Shadows	Relative Border to Brighter Neighbours in Panchromatic Area
Soil	Band 4/Panchromatic
	ARVI (Atmospherically Resistant Vegetation Index)
Vegetation	Band 3/Panchromatic
Unidentified	Not classified

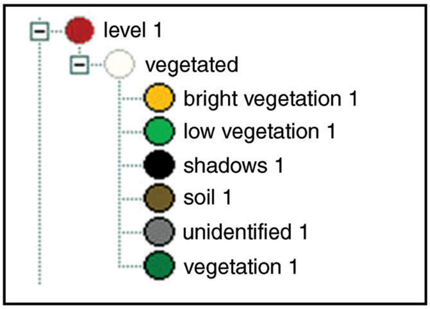

Figure 5. Basic elements identified at the finer level of segmentation.

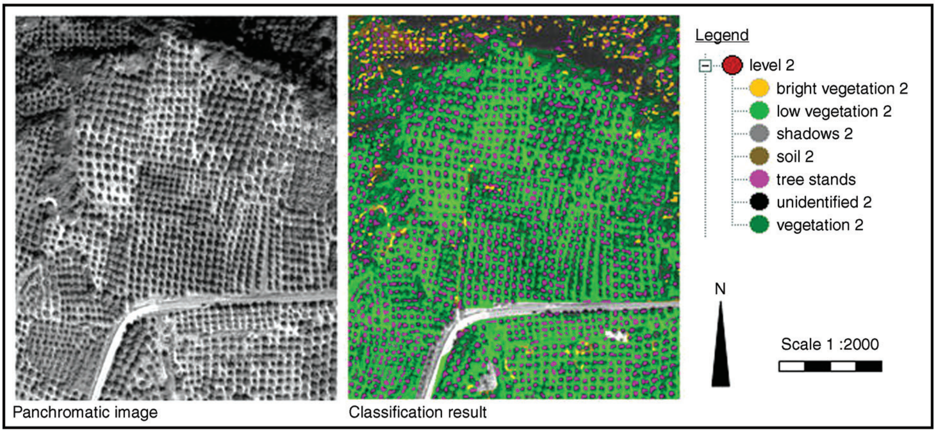

Figure 6. Basic elements extracted in Level 2.

The finest classified level (Level 1) was fused via classification-based segmentation into a new second level (Level 2) (Figure 6). Thus, the high fragmentation of the map was reduced, and valuable shape information of sub-objects was made available for the classification of the next higher level.

At the third coarser level (Level 3), the desired classes were categorized by means of class-related features, which referred to existing class assignments of image objects on the sub-object level. Relative areas of basic elements, densities (number of elements divided by area) or distances between them were used for the categorization of the different vegetation classes. DEM and slope features were also useful for the classification.

The final land cover map was generated by classification-based segmentation of the third level. Small spot polygons resulting from the classification were merged with neighbouring/surrounding polygons, and the classification obtained in Step 1 was integrated to finalize the thematic map.

Due to software/ hardware computation performance limitations nine subsets of the whole study area were generated. The classification protocol was then applied to each one of them. Results were exported and processed in ArcMap obtain the final land cover map.

3.3 *Accuracy assessment*

A key concern of using land cover information from remotely sensed data is that these thematic land cover maps are of insufficient quality for operational applications. Many methods of accuracy assessment have been discussed in the remote sensing literature. Currently the most widely used are being based on an error matrix (Congalton, 1991; Foody, 2002). Since the amount of data classified is usually in the range of millions of pixels in any given satellite imagery, the error matrix is based on a limited set of samples. Usually a combination of random and systematic sampling would provide the best balance between statistical validity and practical application (Congalton, 1991). Therefore, the reference data were obtained mainly by visual interpretation of a computer-generated point grid on the QuickBird scene and the orthophotographs available. Following Congalton (1991), a base sample size of 50 points per class was established. Further stratification was applied for each class depending on the area covered by each class. A maximum of 100 and a minimum of 5 points per class were allowed in order to keep the number of samples within a reasonable limit. Finally, 500 points were sampled for all classes.

The validation of the actual land cover was made at each sample point by extending the observation in a radius around it of approximately 10 meters within the boundaries of the evaluated polygons. The assignment of the class at each sample point was carried out according to the predominant category, which must cover more than 60% of the buffered area. Whenever visual identification of the ‘‘ground truth’’ on the imagery or the aerial photo was not possible, the point was identified later on by field assessment on site.

The ‘water bodies’ class was excluded from the overall accuracy computations, since (i) the purpose of the classification was the extraction of land cover classes, and (ii) due to the fact that the high number of properly classified points in this class would have led to an overestimation of the total accuracy of the classification.

Based on the confusion matrix, the overall, producer’s and user’s accuracy were calculated. To accommodate the effect of chance allocation, Cohen’s Kappa coefficient was also computed (Cohen, 1960).

4 RESULTS AND DISCUSSION

Commonly associated with an increase in spatial resolution is a decrease in classification accuracies of land cover types that are characterized by a high degree of internal variability (e.g. Cushnie 1987). In a land cover classification of a Landsat Thematic Mapper image of a Mediterranean area in the Curcova Deltas (Turkey), Lloyd *et al.* (2004) already reported misclassifications attributed to the degree of internal variability within the categories to be extracted. Higher spatial resolution imageries (e.g. QuickBird) emphasize even more the within-class heterogeneity of the Mediterranean land cover classes. As a result, for classification purposes, it has been necessary to develop extensive class hierarchies to identify all possible appearances of a specific class. Thus, the probability of having classes with overlapping spectral characteristics increases.

The rather complex class hierarchy is also a consequence of the applied classification scheme, designed for political decision-making and not considering the physical background of remote sensing applications. The extraction of these categories from satellite imagery in some cases is quite complex, since the scheme increases the feature variance of certain classes (Gitas *et al.* 2003).

The low spectral resolution of QuickBird did not allow the identification of the desired classes of vegetation based just on the pixel values from the multi-spectral imagery. Thus, a two-step approach was chosen while attempting to separate different vegetated land covers based mainly on textural characteristics. Aplin *et al.* (1999), in a per-field classification of a United Kingdom area with rural and urban land cover types, follow a similar integration approach. In this case, proportions of land cover classes obtained by pixel-based classification were successfully used to characterize polygons at a higher level.

The methodology was developed and tested on small subsets and then implemented to map the entire study area. Subsequently, the accuracy of the resulting final land cover map was tested using an error matrix. The analysis of the error matrix (Table 4) revealed some patterns of common misclassifications, which may guide the users for possible applications of the resulted land cover map. These misclassifications appeared between the following classes:

– Land cover classes with high relative area of basic elements classified as bare soil: Urban fabric (11), Non-vegetated areas (331), Sparsely vegetated areas (333), Arable land (21) and very young new olive plantations (2212).
– Land cover classes with high vegetation density: Forest (31), some kinds of shrub and/or herbaceous vegetation associations (32), Old olive plantations (2211), Orchards (223) and Vineyards (222).

To some extent, the implemented approach, based on the characterization of super-objects by their sub-object composition, may have led to the aforementioned misclassifications. Nevertheless, Gitas *et al*. (2003), in the land cover classification of a similar area, located 25 km south of the Kolymvari municipality, reported similar misclassifications due, again, to the high spatial resolution of the sensor (IKONOS) and the characteristics of the CORINE classification scheme.

Other observed misclassifications are attributed to operational limitations. The classification at once of the whole extension of the study area (185 km^2) required an enormous computation time. Therefore, it was eventually necessary to subset and classify the image in smaller subsets. As a consequence of this, some misclassifications appeared in the areas where the edges of the subsets were merged.

In addition, the big extent of the area resulted also in noticeable spectral variability between different parts of the image, which contributed to the increased within-class variability, and the consequent difficulties to classify the land covers.

Currently, no general agreement on the evaluation of success in land cover mapping has been stated by the scientific community. Foody (2001) cites the target of an overall accuracy of 85%, set by Thomlinson *et al*. (1999). However, he also points out that this target is rarely achieved. Tanase (2006) achieves an overall accuracy of 80% in the Anopolis area (40 km south-east of Kolymvari) using a similar dataset and approach (object-oriented classification of a QuickBird scene). Such high accuracy was possible due to the much less fragmented landscape of the study area and the use of a classification scheme specially adapted to the objective of the study. In contrast, Gitas *et al*. (2003), in a pixel-based classification of their study area, achieved, for a CORINE land cover classification scheme, an overall accuracy of 52%. Thus, the overall accuracy of 68.4% achieved in the present work (Table 4) is considered to be an acceptable performance, taking into account the high fragmentation of the landscape and the complex class hierarchy required for the classification.

Nevertheless, the overall accuracy computation ignores error matrix off-diagonal elements (the omission and commission errors). Those errors are incorporated by the Kappa analysis. Landis and Koch (1977) considered the Kappa statistic value of 0.62

Table 4. Accuracy assessment results: error matrix, overall accuracy and class accuracy.

	Classified data												
	Class code	**11**	**12**	**21**	**31**	**32**	**222**	**223**	**331**	**333**	**2211**	**2212**	total
Reference data	11	7							4	1			12
	12		12							1			13
	21			3				1	1	1	1		7
	31				7	4				1	4	1	17
	32				5	10		1	1	5	15	11	48
	222			1		1	4				3		9
	223							1			3	2	6
	331		1						44			3	48
	333								13	47	3	3	66
	2211				1	2		1		1	71	13	89
	2212			1			2		3	4	11	75	96
	Total	7	13	5	13	17	6	4	66	61	111	108	411
	User's accuracy	100.0	92.3	60.0	53.8	58.8	66.7	25.0	66.7	77.0	64.0	69.4	
	Producer's accuracy	58.3	92.3	42.9	41.2	20.8	44.4	16.7	91.7	71.2	79.8	78.1	
	KHAT statistic	0.62											
	Overall accuracy	68.4											

(Table 4) calculated for this study, an indicator of a moderate agreement as opposition to a chance agreement.

5 CONCLUSIONS AND OUTLOOK

A two step object oriented approach was developed for semi-operational land cover mapping in the Mediterranean. Results indicate better performance by implementing object-oriented than pixel-based classification, a fact which coincides with Gitas *et al*. (2003) suggestion, based on a comparable classification. Still, the high fragmentation of Mediterranean landscapes comprises a difficult issue to address, at least with available methodologies and low spectral resolution/ very high spatial resolution imageries.

The obtained accuracy is assigned not only to the limitations of the imagery, but also to the applied classification scheme, designed for political decision-making and not considering the physical background of remote sensing applications. In addition, hardware and software limitations forced the sub setting of the study area, creating discontinuities in spatial features that contributed to accuracy reduction.

Higher class discrimination and better accuracy results may be achieved combining high spatial and spectral resolution imagery. Moreover, image acquisition in a time season, within which the phenology differences of the plants are more evident, or the parallel use of more than one image acquired within the same year, might improve the land cover discrimination potential. Finally, another issue for future studies is to set the level of detail needed, to conclude to the most adequate spatial resolution, to map Mediterranean landscapes.

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