AN OBJECT ORIENTED APPROACH FOR THE DISCRIMINATION OF FOREST AREAS UNDER THE CRITERIA OF FOREST LEGISLATION IN GREECE USING VERY HIGH RESOLUTION DATA.

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KEY WORDS: **Object-oriented, Forest ecosystems, Image fusion, Logistic regression, Nearest neighbor, Segmentation**

ABSTRACT:

The accurate discrimination of forest from natural non-forest areas in Greece presents great interest, since nowadays there is an ongoing effort to develop a Forest Cadastre system. We evaluated the possibility to extract forest areas according to the legislation criteria, in a mountainous area in the Northern-central part of Greece, using an object oriented approach and a very high resolution image. The 240 hectares study area is occupied from deciduous and evergreen forest species, shrublands and grasslands. The segments were classified using two different algorithms, namely Nearest Neighbor, built-in the software *eCognition* and a logistic regression approach. Furthermore we evaluated for the same task the usefulness of a fused image with the Gram-Schmidt method, classified after the segmentation with the NN algorithm. After the classification of the first level we proceed with a classification based segmentation approach resulting to a second upper level. The later was classified using class and hierarchy related features of the software to quantify the criteria of the Forest law.
Logistic regression classification of the original multispectral image proved to be the best method in terms of absolute accuracy reaching around 85% but the comparison of the accuracy results based on the Z statistic indicated that the difference in the results between the three approaches was non-significant.
Overall the object oriented approach followed in this work, seems to be promising in order to discriminate in a more operational manner and with decreased subjectivity the extent of the forest areas in Greece.

1. INTRODUCTION

The accurate discrimination of forest from natural non-forest areas (woodlands, shrublands, grasslands) in Greece presents great interest, since nowadays there is an ongoing effort to develop a Forest Cadastre system.
The Greek forest law contains certain criteria in order to determine eligibility of land as “forest” or “woodland”, relating to the canopy cover, the vertical structure of the forest canopy and the shape of the patches.
Specifically in order for a patch to be characterized as “forest” or “woodland”, its size should exceed 0,3 hectares or unless so, it should be at least 30 meters wide or in close interdependence and interaction with other forest areas. Furthermore the forest canopy cover should exceed 30 percent. The distinction among the two categories is based on criteria relating to the existence of stratums of forest canopy and the canopy cover of each layer. In general woodlands correspond mainly to areas covered with a discontinuous tree layer, shrubs and herbaceous vegetation.
So far this discrimination has been accomplished on the basis of manual photo interpretation of aerial photographs at scale of 1:30.000. However it is common that this approach results in great degree of subjectivity and a lot of disputes among the civilians and the Forest Service.
Therefore it is obvious that a development of new more objective approaches, in order to delineate and characterize the land under dispute is necessary, especially in areas under pressure for residential expansion since areas characterized as “forest” are protected from being built.
A methodology was developed based on an object oriented classification approach and the exploitation of very high resolution Quickbird data. Apart from the use of a nearest neighbor classifier embedded within eCognition environment, a logistic regression model was developed and compared to the NN classifier for the assignment of the segments to classes.

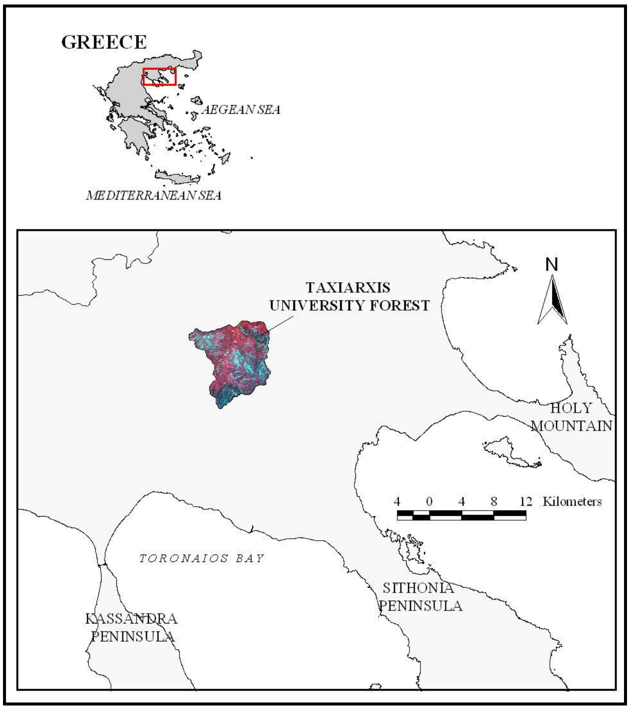

Figure 1 Location of the study area

Furthermore the spatial information of the multispectral image was enhanced through a merging procedure with the panchromatic image, and the resulted image was classified with a NN classifier, an approach that seemed to operate well in forest environments (Kosaka et al., 2005) Prior to the classification step, the landscape of the scene was explored through the utilization of the local variance method.

2. STUDY AREA

The 240 hectares study site, is located in the upper north region of Greece and it is part of the Aristotle's University Forest (Figure 1) which has a total of 5800 ha area. The altitude in the University Forest ranges from 320 to 1200 meters. The main forest species of importance and abundance are Oak (*Quercus conferta*), Pine (*Pinus nigra*), Beech (*Fagus moesiaca*). Pinus nigra areas originate from extensive reforestation plantations during 1950 decade. These areas are under the pressure of the deciduous species of the forest which are favored furthermore from selective thinning.
The study site is located in the upper Northeastern part of the University Forest and it was selected since it presents the maximum variability in terms of species composition and the highest fragmentation due to the anaglyph.

3. MATERIALS AND METHODOLOGY

3.1 Data acquiring and pre-processing

A Quickbird image was acquired on June 2004. Both the multispectral and the panchromatic images were geometrically pre-processed in order to compensate some of the errors present. For the process a DTM was used with 10 meter cell size and ground control points identified over existing orthophotographs. The total RMS error did not exceeded 1.1 meters for neither of the images.
The original image was subject to the IHS transformation along with the calculation of a vegetation index, namely NDVI as means to enhance the available spectral information.
Furthermore the Gram-Schmidt technique (Laben and Brower 2000) was used in order to fuse the multispectral with the panchromatic image, enhancing the spatial information present in the first one.
Finally a ground survey was conducted in the study site (as part of a larger one covering the total extent of the University Forest) and 10 plots were accurately located using a GPS handheld device and print outs of the panchromatic image with a scale 1:2000. Detailed forest parameters within each plot were recorded in detail.

3.2 Segmentation

Segmentation algorithm embedded in eCognition is a bottom-up region merging technique. Within eCognition environment some important decisions have to be made regarding the number of the segmentation levels as well as the appropriate parameters used to derive them (information layers to be considered, scale factor, color/shape heterogeneity). In order to determine if it was possible to construct a level depicting individual trees the local variance method (Woodcock and Strahler, 1987) was used (Curran and Atkinson, 1999):

$$\sigma_v^2 = \frac{1}{L \times M} \sum_{l=1}^{L} \sum_{m=1}^{M} \frac{1}{9} \sum_{j=-1}^{+1} \sum_{k=-1}^{+1} \left[\bar{z}_v(l+j, m+k) - z_v(l+j, m+k)\right]^2 \quad (1)$$

where σ_v^2 is the mean local variance, $\bar{z}_v$ is the mean value within a 3 x 3 window, in the center of which there is a pixel z_v.
The mean local variance is estimated over a series of multiplies of the original pixel with size v and it is expressed in relation to pixel size in a form of a diagram.

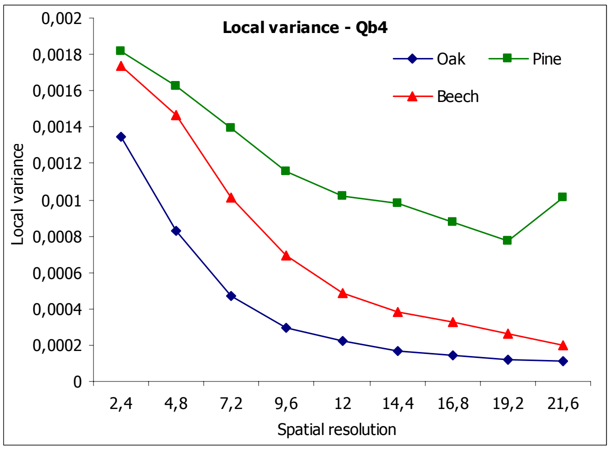

Figure 2 Local variance graphs for the main tree species

Subsets of the image corresponding to pure patches of the main species were selected and the local variance was estimated for successive image pyramids. As it was observed (Figure 2), the peak in the local variance corresponds to pixel sizes smaller than the available pixel size. Despite the fact that pixel size is almost the half from the mean canopy diameter, it seems that segmenting the image in purpose of delineating individual crowns is not feasible. Instead the scale of the first segmentation level was set so that to extract clumps of crowns and/or very large individual trees (deciduous). Developing a second level of segments did not considered to be necessary since no other phenomena seemed to be recognized operating within the extent of the scene under investigation.
After a trial and error procedure the red band of the original image as well as the hue and saturation bands, were used for the segmenting the image, whilst the scale parameter was set to 70 and no shape heterogeneity was considered. The positive contribution of the former two bands can be explained by the fact that they segregate the spectral information during the IHS transformation.

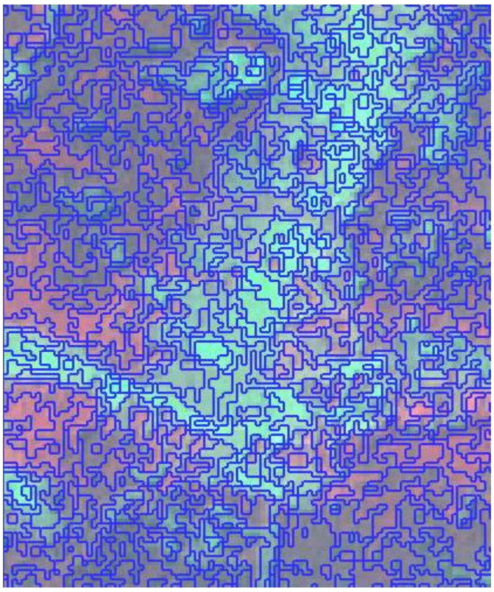

Figure 2 Segmentation results for a subset of the original image

Respectively for the fused image the red and near-infrared bands were used and the scale parameter was set to 40, with the resulted segments having an overall smoother appearance in comparison with the ones resulted from the original image.
A note to be made in this point is about the extra amount of time needed for segmenting the fused image. Specifically for the original the time needed was 30 seconds while for the fused the time raised to 3 minutes.

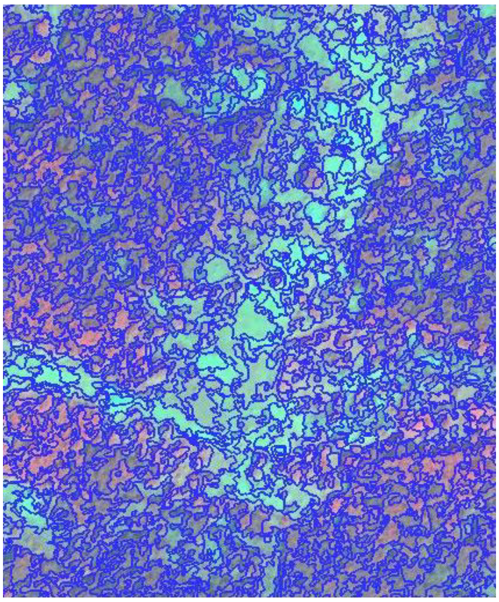

Figure 3 Segmentation results for a subset of the fused image

3.3 Classification

3.3.1 Nearest neighbor classifier

Within eCognition there is a constellation of features providing information among the others about the spectral, shape, textural and class memberships attributes of image objects themselves as well as features in relation to their context describing the relations that exists with other networked objects operating on the same semantic network (Baatz and Shape, 1999). For the assignment of the objects to classes there are two different strategies.
The first one of the procedures is the so called membership functions which are "manually" defined conditions/rules to describe classification categories based on a kind of expert knowledge.
The other alternative is the use of a single nearest neighbor (1-NN) classifier. The nearest neighbor algorithms belong to the non-parametric classifiers, meaning no assumption is needed that the data follows the Gaussian distribution (Hubert-Moy et al., 2001). Within eCognition the use of the nearest neighbor classifier automatically generates multidimensional membership functions and a multidimensional feature space where the distinction of classes operates. In this study we selected to use the nearest neighbor approach mode since it allows greater transferability of the classification model to other areas needing only the re-selection of new sample objects each time (Ivits and Koch 2002). Furthermore when the classes are not well separated from each other by just a few features or only one feature the nearest neighbor is suggested (Definiens, 2004), a situation which is expected when the subject of the classification is the ambiguous nature of forest ecosystems.

3.3.1.1 Level 1

Two categories were inserted for classifying the segments namely *Trees* and *Non-Trees*. Both spectral and textural features were considered as potential variables for the discrimination of the categories. Most suitable features proved to be the mean value of red band and the mean value of hue. Preliminary tests to augment the classification categories (shrubs, bare land, low vegetation) seemed to have negative influence in the classification result. After finalizing the classification, an upper level was created based on a classification-based segmentation, in order to fuse adjacent segments assigned to the same category.
The same processes described so far was adopted for classifying the first level of the fused image. Again a note has to be made about the time needed for the procedure of feature space optimization, which for the fused image was almost as double (twenty two minutes instead of eleven).

3.3.1.2 Level 2

The new level was classified based on a projection of the first level classification and other class-related features. Different classes where developed in accordance to the national Forest law. In example class *Forest retained*, included objects with size larger than 0.3 hectares (fuzzy expression with lower and upper limits 0.2 and 0.4 hectares respectively) and with existence of sub-objects classified as *Trees*. Class *Forest in NonForest_Forest* which included objects having a considerable size and being in interdependence and interaction with *Forest retained*, was described according to the following conditions:

- Sub-objects of the class *Tree*
- Relative border to *Forest retained* less than 0.1
- Area larger than 0.1 hectare
- Existence within 30 meters, of objects classified as *Forest retained*

In the other hand class *Forest in NonForest_NonForest* included the first two of the conditions above plus a feature indicating non-similarity with class *Forest in NonForest_Forest.* After defining classes the final classification based fusion took place, merging objects or part of objects belonging to the same structure group. Two structure groups where formed, the first one including classes *NonForest retained* and *Forest_in_NonForest_NonForest*, and the second one engulfing all the others.

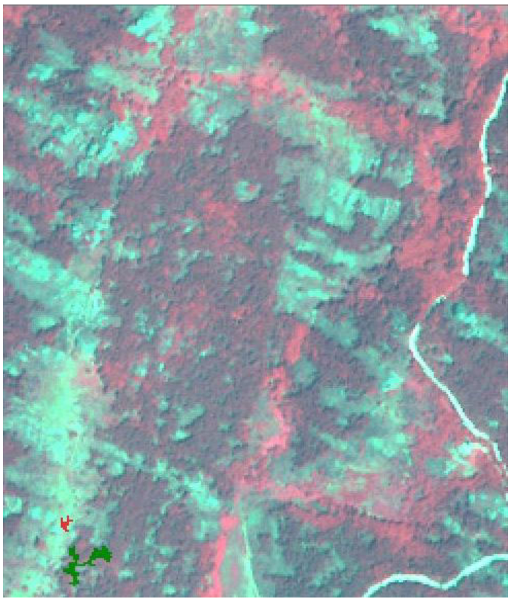

Figure 4 Part of the scene under investigation

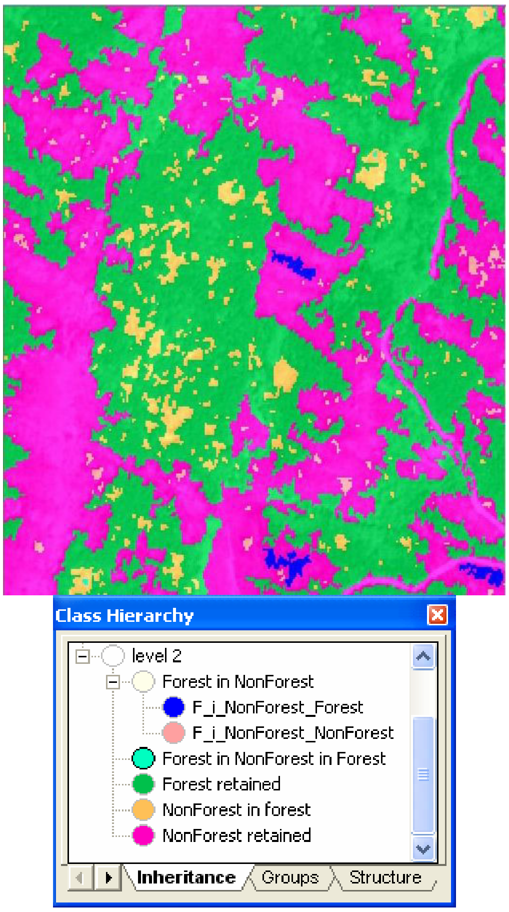

Figure 5 Classification result of the second level for the subset of the image corresponding to Figure 4. The lower image depicts the class hierarchy followed in the classification.

3.3.2 Logistic regression

Multiple logistic regression modeling is used to predict a binary dichotomous variable using a set of independent explanatory variables by estimating the probability of the event's occurrence.

Logistic regression may be proved useful for the classification of satellite remotely sensed data, especially when the independent variables (spectral observations) do not follow the normal distribution. The main consideration for implementing the logistic regression modeling into classification process is to express the classification problem in a binary dichotomous way, i.e. to consider the classification categories by two each time (Koutsias and Karteris, 1998). In terms of the probabilities for either of the two outcomes of the event the equation for the multiple logistic regression can be expressed as:

$$p_i = \frac{\exp\left(a + \sum_{g=1}^{m} \beta_g x_g\right)}{1 + \exp\left(a + \sum_{g=1}^{m} \beta_g x_g\right)} \tag{2}$$

while the parameters α and β_g (g= 1,2,3..m) of the x_g variables, are computed usually using the maximum likelihood method.

3.3.2.1 Level 1

For the implementation of this method, the segments delineated were exported to a GIS environment along with their features and samples were selected for the two classification categories. Through a statistical process (forward stepwise procedure based on Wald criterion) the most appropriate variables where selected. The goodness of fit of the developed logistic model proved to be satisfying as it can be observed in Table 1

Measure	Value	Signif.
Hosmer and Lemeshow's Chi-square	8.601	.377
-2LL	124.528	
Cox & Snell R Square	0,672	
Nagelkerke R Square	0,897	

Table 1 Statistical measures for assessing overall fit of the logistic model

After the development the probability image was derived and this image was converted to binary (Trees/Non-Trees) after determining the most appropriate threshold (Vasconcelos et al., 2001).

Figure 6 Prediction for the existence or non-existence of the dependent variable. Lighter tones indicate greater probability for a segment to be assigned to the category Trees.

3.3.2.2 Level 2

The binary image was re-imported within eCognition environment. In the following step a classification based fusion approach was used for producing the second level which was afterwards classified following the same semantics and concept previously described.

4. RESULTS AND DISCUSSION

The accuracy estimation of the three different approaches, was carried out according to the manual delineation of the classification categories from two experienced photo-interpreters after selective field visits. Based on this information 6 different sets of 600 random points were selected. The logistic regression approach seems to be the most accurate (Table 2) in terms of overall accuracy, according to both photo-interpreters. Regarding the other two approaches (original image classified with NN algorithm and fused image classified with NN algorithm), no clear inference can be made.

	NN	Log	Merge
1st photointerpreter	83,17	85,67	84,17
2nd photointerpreter	83,17	84,17	81,33

Table 2 Overall accuracy for the three classification approaches, after the two independent photo-interpreters

The fact that the fused image proved to be not better from the original one was somehow unexpected considering also the appealing segmentation results. After careful examination of the results it seemed that some errors where induced in the classified fused image across the borders of the stands. This can be probable attributed to the effect of shadowing and the distortion caused to the values of the corresponding segments after the fusion process.

To test if the error matrices from all approaches were significantly different the Z test statistic was used (Cohen, 1960):

$$Z = \left|\mathrm{Khat}_1 - \mathrm{Khat}_2\right| / \sqrt{\mathrm{varKhat}_1 - \mathrm{varKhat}_2} \qquad (3)$$

where Khat1, Khat2, denote the estimates of the kappa statistic and VarKhat1,VarKhat2, be the corresponding estimates of their variance

At the 95% confidence level, the critical value for determining if two error matrices area significantly different, is 1,96. According to the results of the pairwise test (Table 3), none of the matrices were significantly different.

Classification1	Classification2	Z
	1st photointerpreter	
NN	Log	0,597
NN	NN-Merged	0,344
Log	NN-Merged	0,336
	2nd photointerpreter	
NN	Log	0,361
NN	NN-Merged	1,118
Log	NN-Merged	1,437

Table 3 Significance results after the comparison of the matrices resulting from different classification approaches.

From the results above it seems that the selection of the classification algorithm did not influence significantly the classification result. The most important issue was the object-oriented approach which allowed the establishment of relationships between the objects. Adopting the object oriented approach in an operational manner seems promising but accuracy should be further improved before such an initiative.

A potential solution could be the coupling of the presented object-oriented approach with individual tree delineation methods, an approach similar to the work of Burnett and Blasckhe (2003). However the implementation of automated methods for individual tree crown recognition seems to be complicated in areas covered with deciduous forest species (Wulder 1998). Probably the most hopeful approach under an operational context seems to be the incorporation in the classification process, of remotely sensed data providing information about the vertical structure of the forest stands (i.e. Radarsat-2).

5. CONCLUSIONS

An object oriented methodology for forest areas discrimination in Greece has been implemented in this work. Three different classification approaches were assessed, with neither of them been significantly different in terms of absolute accuracy. The exploitation of the fused Quickbird image did not proved to be advantageous, especially considering the extra amount of time needed for its processing. Logistic regression proved to be slightly better from nearest neighbor algorithm in the classification of the segments from the first level, but the difference was not found to be statistically significant. The object oriented approach, regardless the classifier used, seems to be seems a very promising approach for forest mapping and characterization in Mediterranean ecosystems.

ACKNOWLEDGMENTS

This work has been supported by the General Secretariat for Research and Technology, in the framework of the Operational Programme *Competitiveness 2000-2006*.
Furthermore the primary author would like to thank Dr. Geoffrey Hay and Dr. Guillermo Castilla, for their time and patient in answering to all his questions relating object oriented analysis.

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