A Hybrid approach for land cover mapping based on the combination of soft classifiers outputs and uncertainty information

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Abstract

In this article, the authors present a hybrid approach to produce more accurate land cover maps of diverse landscapes representing Mediterranean environments. The innovation of the proposed methodology is to use, in the combination of soft classifiers outputs, information about the classification uncertainty associated with each pixel and its neighbourhood.

The hybrid combined classification method developed includes the following steps: 1) definition of the training areas; 2) pixel-based classification using several soft classifiers; 3) computation of the classification uncertainty; 4) application of rules to combine the outputs of the pixel-based soft classifications and the uncertainty information obtained with uncertainty measures, on a pixel and neighbourhood based approach; 5) image segmentation; and 6) object classification based on decision rules that include the results of the combined soft pixel-based classification and its uncertainty. The proposed methodology was applied to an IKONOS and a SPOT-4 multispectral image with, respectively, 4m and 20m spatial resolution.

The overall accuracy of the hybrid classification obtained with the proposed methodology was higher than the one obtained for the individual pixel-based classifications, which shows that this approach may increase classification accuracy. The approach showed to be particularly powerful to obtain Land Cover Map for landscapes representing Mediterranean environments.

Keywords

Soft classifiers, uncertainty, land cover, IKONOS, SPOT

I INTRODUCTION

The use of a hybrid classification approach, which combines pixels and objects, has been shown to be suitable for the identification of Landscape Units that contain a variety of land cover objects using Very High Spatial Resolution images. With the combination of a set of classifiers outputs it is possible to obtain a classification that is often more accurate than the individual classifications (Gonçalves et al., 2010; Gonçalves, 2011). Although several approaches have been proposed for combining hard classifications, the development of methods to combine soft classifications and their integration in a hybrid pixel and object based approach is still a field of research. This study tests whether the combination of the outputs of a set of soft classifiers in a hybrid classification approach using uncertainty and contextual information can improve the accuracy of the results. In the proposed hybrid classification method, the uncertainty information was used in two phases. First, for combining the outputs of three pixel-based soft classifications. This was done through the development of rules that incorporate the information provided by the pixel-based soft classifications and the results given by the application of an uncertainty measure. Second, in the classification of the obtained segmented objects, which represent the Land Units. These are classified through decision rules which include the results of the combined soft pixel-based classification and its uncertainty. The main objective of integrating uncertainty in the classification process is to avoid the use of misclassified pixels in the classification. The first step of the method was applied to different kinds of images, namely to two IKONOS multispectral images and a SPOT-4 multispectral image, with 4m and 20m of spatial resolution respectively, with different Mediterranean landscapes characteristics, to evaluate the outputs reliability. The second step was only applied to an IKONOS multispectral image to obtain a Land Unit Map (LUM).

II DATA

The study was conducted using three multispectral satellite images with High Spatial Resolution (HSR) from two regions of Portugal (Figure 1), two located in the Alentejo region and one in the Central region. An image of the Alentejo region near Alcácer was used, obtained by the IKONOS sensor, having 4 spectral bands namely (1) blue (0.45-0.52 μm), (2) green (0.52-0.60 μm), (3) red (0.63-0.69 μm) and (4) near infrared (0.76-0.90 μm), with a spatial resolution of 4m and a dimension of 11.8 km by 8.7 Km. The two other images were obtained by the SPOT 4 sensor, having 4 spectral bands, namely (1) green (0.50-0.59 μm), (2) red (0.61-0.68 μm), (3) near infrared (0.78-0.89 μm) and (4) short-wavelength infrared (1.58-1.75 μm), with a spatial resolution of 20m and a dimension of 16.4 km by 15.1 Km.

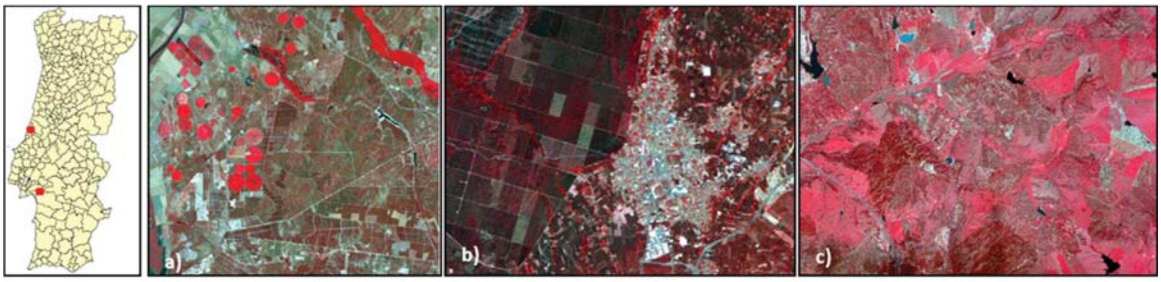

Figure 1: Multispectal images (false color) : a) SPOT-4 image of the Alentejo region, located in the municipal district of Setubal; b) SPOT-4 image of the Central region located in the municipal district of Marinha Grande; c) IKONOS image of the Alentejo region located in the municipal district of Alcácer.

The locations of the images chosen to carry on the study are representative of the main forest species and Mediterranean landscapes in Portugal. The SPOT-4 image is located in the municipal district of Marinha Grande, in the Central region, near the coast, and includes areas with different characteristics, such as: built-up areas; agricultural fields and forest. The dominant forestry species in the region are eucalyptus and coniferous trees.

The SPOT-4 image is located in the municipal district of Setubal, in the Alentejo region, is occupied mainly by agriculture, pastures, forest and agro-forestry areas. The dominant forest species are eucalyptus, coniferous and cork trees.

The IKONOS image is located in the municipal district of Alcácer, in the Alentejo region. It is also occupied mainly by agriculture, pastures, forest and agro-forestry areas, where the dominant forest species are eucalyptus, coniferous and cork trees.

III METHODOLOGY

The main goal of the classification is to obtain a LUM, where the objects that represent Landscape Units (LU) have a mean area of 0.5 ha and are classified using a hybrid classification approach that integrates the combination of the outputs of pixel-based soft classifications and their uncertainty. The combination of the pixel-based soft classification is made through the application of rules that incorporate the information provided by the pixel-based classifications and the results given by the uncertainty measures on a pixel and neighbourhood based approach. This approach considers not only each pixel-based classification and its uncertainty information but also the classification and uncertainty of its neighbourhood. Three soft classifiers were used in this application: 1) the neural network Multi-Layer Perceptron Classifier (MLPC); 2) a pixel-based supervised fuzzy soft classifier based on the underlying logic of Minimum-Distance-to-Means (FC); and 3) Maximum Likelihood Classifier (MLC). The classifiers were trained using the same sampling protocol that included 100 pixels per-class. The classes used in this study to identify Surface Elements (SE), which are the basic elements of landscape, are: Eucalyptus Trees (ET), Cork Trees (CKT), Coniferous Trees (CFT), Shadows (S), Shallow Water (SW), Deep Water (DW), Herbaceous (H), Sparse Herbaceous (SH), Non Vegetation Area (NVA), Irrigated Herbaceous (IH) and Non Irrigated Herbaceous (NIH). These classification methods assign to each pixel and to the each class under consideration, in the case of MLPC, different degrees of assignment, in the case of FC, different degrees of possibility and in the case of MLC, different degrees of probabilities. This extra data provides additional information at the pixel level that allows the assessment of the classification uncertainty. To analyze if the use of an output combination of a set of soft classifiers in a hybrid approach classification can improve the accuracy of the results, a similar method, where the combination of the three classifiers and the classification uncertainty was not considered, is also presented. The hybrid classification method that was developed includes the following steps: 1) definition of the training areas; 2) pixel-based soft classification using several soft classifiers; 3) computation of the classification uncertainty; 4) development and application of rules to combine the soft classifications, incorporating the information provided by the pixel-based classifications the results given by the uncertainty measures, on a pixel and neighbourhood based approach; 5) image segmentation; and 6) object classification based on decision rules that include the results of the combined soft pixel-based classification and its uncertainty. The second method that does not take into consideration the output combination of the pixel-based classifications and their uncertainty includes three steps: 1) pixel-based classification of the image; 2) image segmentation and 3) object classification based on decision rules. This article focuses only on the first methodology since the second one was already presented in (Gonçalves et al., 2009a).

Combination of pixel-based soft classifications

The first phase of the algorithm developed to combine pixel-based soft classifications checks whether the same class is assigned to each pixel by all classifiers. If this condition is satisfied, the class is accepted. If the output classes for each individual pixel differed, the uncertainty information is compared and the class assigned with the lower value of uncertainty is chosen to be the one assigned to the pixel. In this approach the uncertainty measure E, developed by (Chow, 1970), was used to quantify the uncertainty at each spatial unit. This measure is given by

$$\mathrm{E} = 1 - p(x_1) \qquad (1)$$

where $p(x_1)$ is the largest degree of possibility or probability of the possibility distributions or probability distributions assigned to the pixel corresponding to the several classes. This measure is also called ambiguity measure.

If the classifiers have different results for a certain pixel but the ambiguity values are equal the results of the neighborhood classification is used to make a judgment.

To evaluate if the combined classification improves the results, the accuracy assessment was made with the same protocol used with the single classifiers and the results were compared.
One of the classifiers used was the MLP neural network, which is a non-parametric method and is the most commonly used in remote sensing. Details of the MLP can be found in Atkinson and Tatnall (1997) and in Brown et al. (2009). The MLP provides an activation level for every output class of each pixel, and for hard classifications each pixel is allocated to the class with the largest activation level. A soft classification may be derived from this classifier by considering the activation levels of the network output units for each pixel. These activation levels range from 0 to 1, and may be used as indicators of the uncertainty associated with the pixel allocation to the classes. The other classifier used was a pixel-based supervised fuzzy classifier based on the underlying logic of the Minimum-Distance-to-Means classifier. Details of the fuzzy classifier can be found in (Gonçalves *et al.*, 2009b). The third was a supervised Bayesian classifier similar to the maximum likelihood classifier. The maximum likelihood classifier is based on the estimation of the multivariate Gaussian probability density function of each class using the classes statistics (mean, variance and covariance) estimated from the sample pixels of the training set. Details can be found in (Gonçalves et al., 2009b).
To evaluate the classification accuracy of the individual soft classifications and the combined results, a stratified random sampling with about 100 pixels per class was selected considering the entire image scene, which also included mixed pixels. The number of pixels was chosen to obtain a standard error of 0.05 for the estimation of the accuracy indexes of each class. Each land cover class was sampled independently and the accuracy assessment was made with an error matrix.

Hybrid Classification to obtain a Landscape Unit Map

The LUM was built using the combined output of the pixel-based classification, its ambiguity information and the objects obtained with the segmentation algorithm. In the segmentation stage the whole image was partitioned into a series of closed objects, corresponding to the spatial patterns. The extraction of the objects was driven using the "Fractal Net Evolution Approach" (FNEA) segmentation method, implemented in eCognition software, which can be described as a region merging technique (Baatz and Schape, 2000).
In this study only one segmentation level was considered, chosen from a series of experiments done with different parameters, the results of which were visually analyzed. The criterium that led to their choice was the identification of meaningful image-objects i.e., groups of pixels that represented the LU existing in the study area, with a mean area of 0.5 ha. The next step was the development of rules that incorporate the information provided by the combined pixel-based classification within each object and the results given by the ambiguity measure E. The classification of the LU is similar to a decision tree which, for geographical objects, is a hierarchical structure consisting of several levels. At each level a test is applied to one or more attribute values. The application of a rule results either in a leaf, allocating an object to a class, or a new decision node, specifying a further decision rule. In this study eight LU classes were used: Water Bodies (WB), Agriculture and Pasture Areas (A), Non-Vegetated Areas (NVA), Broad-Leaved Forest (BF), Coniferous Forest (CFF), Cork Forest (CF), Agro-Forestry Areas (AFA) and Mixed Forest (MF). Table 1 shows the classification rules, based on the SE identified in the previous phase. The structure of the rules is based on the ones used on the study performed by (Gonçalves *et al.*, 2009a).
For the accuracy assessment, the sampling unit to assess the accuracy of the LUM was a fixed-area square plot sampling unit with an area of 0.5 ha. A stratified random sampling of about 50 samples per class was chosen, which guarantees a standard error of 0.07 for the Conditional

Probability of the Map (CPM) and Conditional Probability of Reference (CPR) estimates for each class, assuming that the classification accuracy is superior to 50%, which is acceptable because the construction of the LUM already involved a prior pixel-based classification and an analysis of the terrain. The accuracy assessment was made with an error matrix, where the p_{ij} entry is the proportion of area that is class *i* in the map and class *j* in the reference within the square areas with 0.5 ha. The CPM and CPR accuracy parameters were then derived from the error matrix.

Rules	Test	Class if true
Rule 1	Objects which have more than 10% of SE classified as tree crowns, regardless of species, with ambiguity of less than 0.5	Forest
	Objects which do not satisfy the previous test	Non-Forest
Rule 2	The mode of the SE, inside the object, with ambiguity of less than 0.5 is Deep Water or Shallow Water	Water Bodies
	The mode of the SE, inside the objects, with ambiguity of less than 0.5 is Herbaceous Vegetation or Sparse Herbaceous Vegetation	Agriculture
	The mode of the SE, inside the objects, with ambiguity of less than 0.5 is Non-Vegetated Area or Shadow	Non-Vegetated Areas
Rule 3	Eucalyptus Trees represent more than 75% of the trees or objects that have only Broad- Leaved Trees inside	Broad-Leaved Forest
	Coniferous Trees represent more than 75% of the trees or objects that have only Coniferous Trees inside	Coniferous Forest
	Cork Trees represent more than 75% of the trees or objects that have only Cork Trees inside and the percentage of Herbaceous or Sparse Herbaceous is inferior to Cork Trees	Cork Forest
	Objects that do not satisfy the previous test	Mixed or Non-
Rule 4	The percentage of trees is less than 50%; the percentage of Herbaceous or Sparse Herbaceous is superior to Cork Trees and 80% of trees are Cork Trees with ambiguity of less than 0.5	Agro-Forestry Areas
	Objects that do not satisfy the previous test	Mixed Forest

Table 1. Object's classification rules.

IV RESULTS

Combined Pixel Classifications

The accuracy assessment of the combined classification was made with the same testing datasets used to evaluate the individual classifications. Table 2 shows the Global Accuracy (GA) results.

Regions / Classifiers	Marinha Grande (SPOT-4)	Setubal (SPOT-4)	Alcacer (IKONOS)
FC	73.8%	70.4%	65.5%
MLPC	75.6%	72.4%	64.5%
MLC	86.9%	73.7%	66.9%
Combined	89.2%	82.7%	72%

Table 2. Global Accuracy of the classifications.

The GA of the combined classification of the Marinha Grande, Setubal and Alcácer regions was 89% , 82% and 72% respectively which represents a higher value than that of the most accurate individual classification. Figure 2, Figure 3 and Figure 4 show the classification results when each pixel is assigned to the class with a higher degree of probability for the MLC classifier, higher degree of possibility for the FC classifier, and with the largest activation level for the MLPC classifier for the three areas classified. The spatial distribution of the ambiguity measure E is also presented in the same figures, below the classification results. The regions with the larger ambiguity (darker zones) are the ones where the assignment degrees were lower.

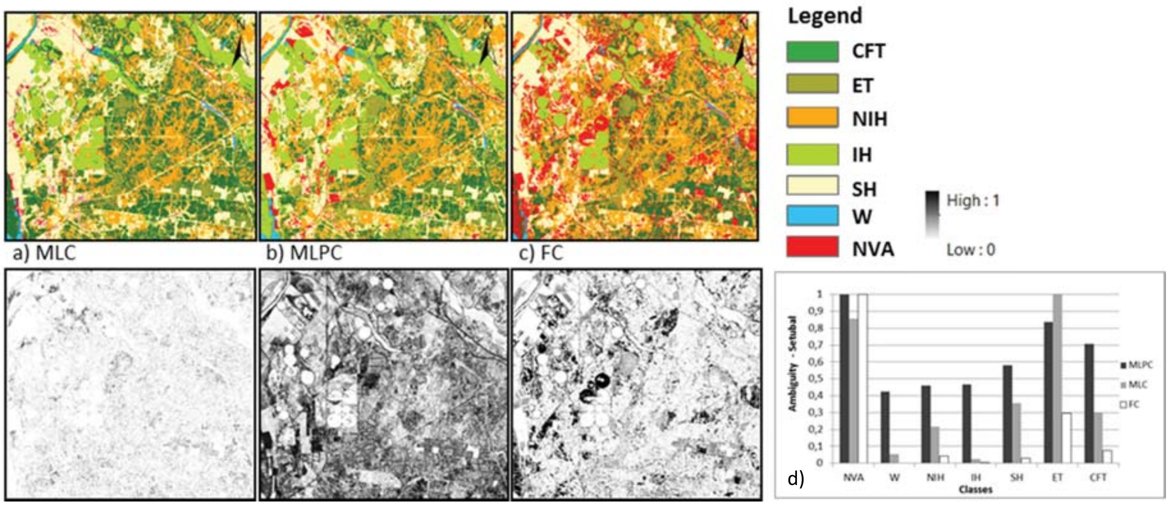

Figure 2: Hard version of the classification results of the Setubal area (above) and spatial distribution of ambiguity (below) with: a) MLC classifier b) MLPC classifier and c) FC classifier. Graph d) shows the mean ambiguity per class.

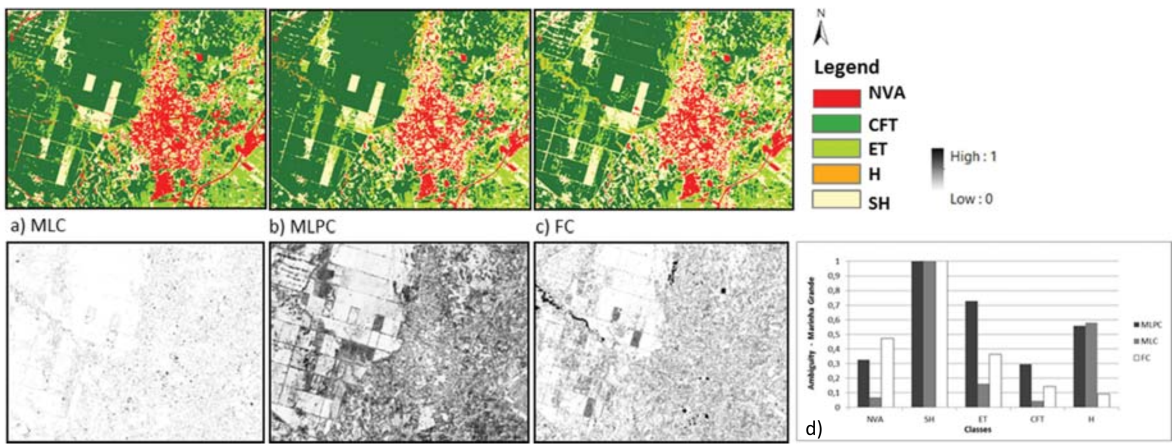

Figure 3: Hard version of the classification results of the Marinha Grande area (above) and spatial distribution of ambiguity (below) with: a) MLC classifier b) MLPC classifier and c) FC classifier. Graph d) shows the mean ambiguity per class.

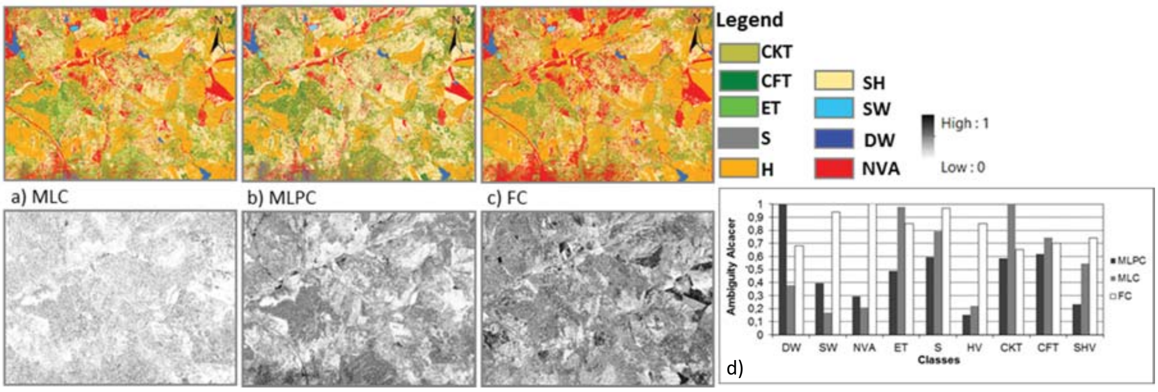

Figure 4: Hard version of the classification results of the Alcacer area (above) and spatial distribution of ambiguity (below) with: a) MLC classifier b) MLPC classifier and c) FC classifier. Graph d) shows the mean ambiguity per class.

The comparison of the mean ambiguity per class shows that for the Setubal area, almost all the classes were assigned with lower ambiguity with the FC classifier. The only exception was the Non-Vegetation Area which was assigned to the pixels with lower ambiguity by the MLC classifier. For the Marinha Grande area, SH was the class assigned to the pixels with more uncertainty by all classifiers, almost all the classes were assigned with lower ambiguity by the MLC classifier. The only exception was Herbaceous (H) that was assigned with lower mean ambiguity by the FC classifier.

For the Alcácer area, the comparison of the mean ambiguity per class shows that forest species, such as CKT and CFT, were assigned to the pixels with lower ambiguity with MLPC classifier. The class DW, SW and NVA classes were assigned to the pixels with lower ambiguity with MLC. The FC classifier presents the higher values of ambiguity. The mean ambiguity presented by the classifiers depends essentially on the characteristics of the image.

Land Unit Map

The Global Probability (GP) classification accuracy for the LUM, obtained with the hybrid approach which classifies the LU (segmented objects) using the combined classification and the ambiguity information, was 72%. The best result for the GP classification with the hybrid approach, using an individual classification (the ones that had the best GA results) and without the ambiguity information, was 59%. This shows that the accuracy increased significantly with the combined classification and the inclusion of the ambiguity information.

Figure 5 allows the comparison between the results of the CPR and CPM accuracies for the LUM obtained with both hybrid classification approaches. These show that the classification results obtained with the method using uncertainty are considerably better for almost all LU classes and this improvement is more evident for the forest classes. Figure 5 shows the final results of the classification with the proposed hybrid classification method.

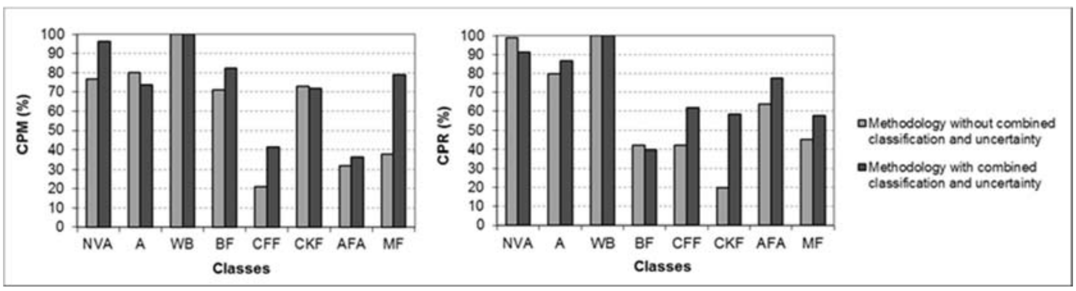

Figure 5: Conditional probability of reference (CPR) and Conditional probability of the map (CPM) obtained with the hybrid approach (LUM) with and without combined classification and uncertainty.

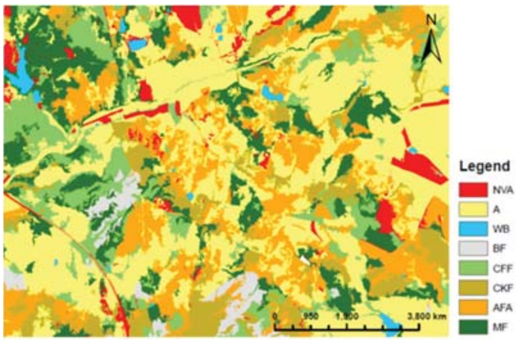

Figure 6: Land Unit Map.

V CONCLUSIONS

The goal of this study was to evaluate if the proposed hybrid combined classification method, using uncertainty information associated with the pixel-based soft classification, produces more accurate land cover maps of diverse landscapes representing Mediterranean environments. Another goal was to investigate if the proposed method that combines the outputs of different soft classifications, using the uncertainty information to choose the best class to assign to each pixel, when applied to different multispectral satellite images always produces more accurate Land Units. The method was applied to IKONOS and SOPT-4 multispectral satellite images with 4m and 20m spatial resolution and the results have shown that with the combined method the accuracy results in both cases were higher. With the proposed hybrid pixel-object classification, the global accuracy of the classification of Mediterranean Landscape Unit classes increased by 11% when compared to a similar classification method that does not use combined classification and ambiguity information. These results have confirmed that the information provided by the uncertainty measure was useful for the combined classification process and in the construction of the Landscape Unit Map because it allowed the determination of the best class to assign to the pixels.

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