A Method to Incorporate Uncertainty in the Classification of Remote Sensing Images

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Abstract. The authors analyze in this paper whether the introduction of the uncertainty associated to the classification of surface elements in the classification of landscape units can improve the results accuracy. To this end, a hybrid classification method is developed, incorporating uncertainty information in the automatic classification of very high spatial resolution multispectral satellite images to obtain a map of landscape units. The developed classification methodology includes the following steps: 1) a soft pixel-based classification; 2) computation of the classification uncertainty; 3) image segmentation; and 4) object classification based on decision rules.

The first step of the proposed methodology is the soft pixel-based classification performed with the maximum likelihood classifier, aiming to identify the surface elements (e.g., tree crown, shade, bare soil, buildings). Subsequently the posterior probabilities are computed to all pixels of the image. This information enables the computation of the classification uncertainty. An image segmentation is then made to obtain image-objects. The classification of the resulting objects into landscape units is performed considering a set of decision rules that incorporate the probabilities assigned to the several classes at each pixel and the degree of uncertainty associated to these assignments.

The proposed methodology was tested on the classification of an IKONOS satellite image. The accuracy of the classification was computed using an error probabilistic matrix. The comparison between the results obtained with the proposed approach and those obtained without considering the classification uncertainty revealed a considerable improvement in the classification accuracy. This shows that the information about uncertainty can be valuable when taking decisions and can actually increase the accuracy of the classification results.

Keywords: soft classification, maximum likelihood classifier, hybrid classification, uncertainty.

1. Introduction

Very High Spatial Resolution (VHSR) images opened some new problems to the Remote Sensing Community and lead to the development of new studies to improve the identification of land cover features. These images allow the identification of smaller objects, and therefore more fine landscapes can be delineated. Since the pixel area on the ground is smaller, the problem of capturing distinct elements in each pixel decreased, increasing the percentage of pure pixels. However, VHSR images also present drawbacks and limitations. Since the spectral resolution of these images is lower than that of sensors with smaller spatial resolution, some limitations occur, for example, in the characterization of forest cover (Goetz et al. 2003). Furthermore, the increase of the spectral variability and the amount of shadows, as well as the enormous
amounts of data, created a strong need for new methods to exploit these data efficiently and the necessity of a closer integration of remote sensing and Geographic Information Systems (GIS) (Blaschke et al. 2004). In addition, the complexity of the relationships between pixels and objects as well as the presence of land units that are mosaics of single entities or spatial arrangements of classes, like Agro-Forestry areas, require the development of new methods that incorporate shape and context, which are some of the main clues used by a human interpreter (e.g. Wang et al. 2004, Plantier and Caetano 2007).

In this study, a hybrid classification method that incorporates uncertainty information in the soft automatic classification of VHSR multispectral satellite images is presented, to obtain a map of Landscape Units (LU). The results are compared with the ones obtained with a similar method where classification uncertainty is not considered.

2. Study area and data

The study was conducted in a rural area with approximately 9 km x 12 km, occupied mainly by agriculture, forest and agro-forestry areas, representing Mediterranean environments. The dominant forestry species in the region are eucalyptus, coniferous and cork trees.

An image obtained by the IKONOS sensor was used, with a spatial resolution of respectively 1m in the panchromatic mode and 4m in the multi-spectral mode (XS). The product acquired was the Geo Ortho Kit and the study was performed using the 4 multi-spectral bands. The geometric correction of the multi-spectral image consisted of its orthorectification. The average quadratic error obtained for the geometric correction was of 1.39 m, inferior to half the pixel size, which guarantees an accurate geo-referencing. Pixels in the image are recorded in 16 bits to keep the 11 bits original image information. Since, in unitemporal studies carried out in regions with no significant topographic effect and a uniform atmosphere on the image data, the radiometric corrections do not improve the results (Caetano 1995), no radiometric corrections were applied to the image.

3. Methodology

The main goal of the classification is to obtain a Landscape Units Map (LUM). However, VHSR images like IKONOS, with 4m spatial resolution, do not allow the identification of LU at the pixel level, and therefore LU classes, such as Urban or Agro-Forestry, can not be classified only with pixel information. The identification of these classes requires the analysis of arrangement, quantity and context information of elementary entities, called Surface Elements (SE), like crown trees and parts of buildings. For this reason, the classification methodology consists in the preliminary identification of the elementary entities that are the basic units of landscape, constructing a Surface Elements Map (SEM) based on a soft probabilistic pixel classification. This classification method assigns, to each pixel, different degrees of probability to several classes. This extra data also provided additional land cover information at the pixel level which allowed the assessment of the classification uncertainty. The LU were subsequently obtained with an object-segmentation method. At this stage the LU becomes the basic units rather than the individual pixels. The identification of the land cover classes within each LU was performed considering a set of rules that included: the arrangement of the pixel classification; the probabilities assigned to the several classes at each pixel and the degree of uncertainty associated to these assignments.

To analyze whether the introduction of the uncertainty associated to the classification of SE in the classification of LU can improve the results accuracy, a similar method, where classification uncertainty is not considered, was performed. For this reason, two classification methods are presented in this study. The first method introduces uncertainty in the classification process itself and includes the following steps: 1) soft pixel-based classification; 2) evaluation of the classification uncertainty; 3) image segmentation and 4) object classification based on decision rules (see Fig. 1). The second classification method does not have uncertainty into consideration and includes three steps: 1) hard pixel based classification of the image; 2) image segmentation and 3) object classification based on decision rules. This pixel/object combined approach was initially presented in Plantier and Caetano (2007). Since the goal is to evaluate if the introduction of the uncertainty in the classification of LU can improve the results accuracy, the paper focuses mainly on this methodology.
3.1. Classification with uncertainty

3.1.1 Surface elements map
To identify and map the SE a soft Maximum Likelihood Classifier (MLC) based on Bayesian modelling was used. The MLC is the most widely used image classifier, but it has been mainly used in its crisp version. However, the output can be in the form of posterior class probabilities providing a soft classification. Unlike traditional hard classifiers, the output is not a single classified map, but rather a set of images (one per class) that express the probability that each pixel belong to the class in question.

Before the classification itself, various preliminary processing steps were carried out. First, an analysis of the image by a human interpreter was made, to define the most representative classes and their SE. The SE classes used in this study are the following: Eucalyptus Trees (ET); Cork Trees (CKT), Coniferous Trees (CFT); Shadows (S); Shallow Water (SW), Deep Water (DW), Herbaceous Vegetation (HV), Sparse Herbaceous Vegetation (SHV) and Non-Vegetated Area (NVA).

The second step was the establishment of the protocol to select the training and test sample elements. The training dataset consisted on a semi-random selection of sites. A human interpreter designed twenty five polygons for each class and a stratified random selection of 120 samples per class was performed. The sample unit of the training set was the pixel and the sample size was 5% of the pixels inside the polygons. Only pixels representative of pure SE were considered (Plantier and Caetano, 2007).

To evaluate the soft classification accuracy a stratified random sampling of 100 pixels per class was selected. The number of pixels was chosen to obtain a standard error of 0.05 for the estimate user’s accuracy of each class (Stehman, 2001). Each land cover class was sampled independently. The accuracy assessment was made with a probabilistic error matrix, where the (i,j) entry is the proportion of area that is class i in the map and class j in the reference. These proportions are estimated from the sample data, and the overall accuracy of the map is derived from the diagonal elements of the error matrix. The Conditional Probability of the Map (CPM) and the Conditional Probability of the Reference (CPR) were also calculated.

3.1.2 Uncertainty
The uncertainty of the probabilistic soft classification was evaluated using an indicator of the classification uncertainty $CU$, available in the commercial software IDRISIS, given by

$$CU = 1 - \frac{\max_{i=1,...,n}(p_i) - \sum_{i=1}^{n} p_i}{1 - \frac{1}{n}}$$

where $p_i$ (i=1,…,n) are the posterior probabilities associated to the several classes and n is the number of
classes under consideration. This indicator takes values in the interval \([0,1]\) and only depends upon the maximum probability, the sum of all probabilities assigned to the class and the total number of classes. CU evaluates until which point the classification is dispersed over more than one class and the degree of compatibility with the most probable class, providing information about the classifier difficulty in assigning only one class to each pixel.

### 3.1.3 Landscape units map

The LUM was built through the combination of the SEM, their uncertainty information and the objects obtained with the segmentation algorithm. The objects extraction was made 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).

This method starts with the assumption that each pixel is an object, and proceeds with the aggregation of neighbour objects. The decision to fuse adjoining objects depends on the criteria of local homogeneity. The adjoining objects are fused into one if the spectral heterogeneity of the object resulting from the fusion does not exceed a certain maximum value, which determines the maximum heterogeneity. As a consequence, the size of the objects resulting from the fusion depends upon the value given to that parameter, called, for this reason, scale parameter (Baatz and Schape, 2000). The drawback of this approach is that the final decision about the scale parameter is made by visual inspection of the image rather than by quantitative criteria. In this study only one segmentation level was considered. The parameters used are shown in Table 1. The criteria 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 medium area of 0.5 ha.

#### Table 1 - Segmentation Parameters

<table>
<thead>
<tr>
<th>Red</th>
<th>Blue</th>
<th>Green</th>
<th>Nir</th>
<th>Scale</th>
<th>Color</th>
<th>Shape</th>
<th>Smoothness</th>
<th>Compactness</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.5</td>
<td>1</td>
<td>1</td>
<td>250</td>
<td>0.9</td>
<td>0.1</td>
<td>0.9</td>
<td>0.1</td>
</tr>
</tbody>
</table>

The next step corresponds to the development of rules that incorporate the information about the probabilities assigned to the several classes at each pixel in the previous soft classification and the degree of uncertainty associated to these assignments. The rules construction requires a preliminary analysis of the probabilities assigned to the SE classes and their uncertainty in order to choose the appropriate thresholds. The transformation of a SEM into a LUM is similar to a decision tree. A decision tree classifier 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 LU classes used in this study are: Non-Vegetated Areas (NVA), Agriculture (A), Water Bodies (WB), Broad-Leaved Forest (BF), Coniferous Forest (CFF), Cork Forest (CKF), Agro-Forestry Areas (AFA), and Mixed Forest (MF).

![Fig. 2: Landscape Unit Classes classification workflow](image-url)
Fig. 2 shows the LU classes classification workflow and Table 2 shows the used rules. The aim of rule 1 is to make a distinction between ‘Forest Areas’ and ‘Non-Forest Areas’. Rule 2 assigns the objects considered ‘Non-Forest Areas’, to one of the three LU classes: Water Bodies, Agriculture, and Non-Vegetated Areas. Rule 3 classifies the Forest regions into ‘Dense Forest’ and ‘Non-Dense Forest’. Rule 4 assigns the objects classified as ‘Dense Forest’ to one of four possible LU classes, namely Broad-Leaved Forest, Coniferous Forest, Cork Forest and Mixed Forest. Finally, rule 5 assigns the objects considered ‘Non-Dense Forest’ to one of two possible LU classes: Agro-Forestry Areas and Mixed Forest.

Table 2 - Classification Rules

<table>
<thead>
<tr>
<th>Rules</th>
<th>Test</th>
<th>Class if true</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rule 1</td>
<td>Objects have more than 10% of SE classified as tree crowns with a probability higher than 0.75, regardless the species, and uncertainty less than 0.25</td>
<td>Forest</td>
</tr>
<tr>
<td></td>
<td>Objects do not satisfy the previous test</td>
<td>Non-Forest</td>
</tr>
<tr>
<td></td>
<td>The mode of the SE, inside the object, with a probability higher than 0.75 and uncertainty less than 0.25 is Deep Water or Shallow Water</td>
<td>Water Bodies</td>
</tr>
<tr>
<td>Rule 2</td>
<td>The mode of the SE, inside the objects, with a probability higher than 0.75 and uncertainty less than 0.25 is Herbaceous Vegetation or Sparse Herbaceous Vegetation</td>
<td>Agriculture</td>
</tr>
<tr>
<td></td>
<td>The mode of the SE, inside the objects, with a probability higher than 0.75 and uncertainty less than 0.25 is Non-Vegetated Area or Shadow</td>
<td>Non-Vegetated Areas</td>
</tr>
<tr>
<td>Rule 3</td>
<td>Objects have more than 75% of trees with a probability higher than 0.75 and uncertainty lower than 0.25, regardless the species</td>
<td>Dense Forest</td>
</tr>
<tr>
<td></td>
<td>Objects do not satisfy the previous test</td>
<td>Non-Dense Forest</td>
</tr>
<tr>
<td>Rule 4</td>
<td>Eucalyptus Trees represent more than 75% of the trees</td>
<td>Broad-Leaved Forest</td>
</tr>
<tr>
<td></td>
<td>Coniferous Trees represent more than 75% of the trees</td>
<td>Coniferous Forest</td>
</tr>
<tr>
<td></td>
<td>Cork Trees represent more than 75% of the trees</td>
<td>Cork Tree Forest</td>
</tr>
<tr>
<td></td>
<td>Neither Eucalyptus nor Coniferous species predominates</td>
<td>Mixed Forest</td>
</tr>
<tr>
<td>Rule 5</td>
<td>The percentage of trees is less than 50%; the percentage of Herbaceous or Sparse Herbaceous is superior than Cork Trees and 80% of trees is Cork Trees with probability higher than 0.75 and uncertainty less than 25%</td>
<td>Agro-Forestry Areas</td>
</tr>
<tr>
<td></td>
<td>Objects do not satisfy the previous test</td>
<td>Mixed Forest</td>
</tr>
</tbody>
</table>

To evaluate the accuracy of the LUM a stratified random sampling of 40 samples, selected per class, was chosen. The sample unit used was a square area with 0.5 ha. The accuracy assessment was made with a probabilistic error matrix.

3.2. Classification without uncertainty

To evaluate if the use of uncertainty in the classification improves the results, a classification method very similar to the previously described, but where the uncertainty is not considered, was applied to the same image. The identification and mapping of the SE were made with the crisp MLC. The SE classes and the sampling design were the ones used for the previous method and described in section 3.1.1. The rules developed to transform the SEM into a LUM are similar to the ones explained in section 3.1.3. but without considering the posterior probabilities and the uncertainty. The accuracy assessment was made with the same protocol used in the classification method explained above.

4. Results and discussion

The accuracy of the SEM produced is the same for both classification methodologies and presented a global probability of 63.24%. The accuracy values of the CPR and CPM of the SEM are presented in Fig. 3.

The CPR and CPM accuracies per class show that water classes (DW and SW) and Herbaceous Vegetation (HV) were very well identified and that non forestry classes presented better results than forestry classes. Forestry species were often confounded with several other SE, but mainly with Herbaceous Vegetation. Significant confusion was also observed between Cork Trees and Sparse Herbaceous and between Eucalyptus and Coniferous. This confusion was due to the proximity of their spectral signatures.
Fig. 3: Conditional Probability of the Reference (CPR) and Conditional Probability of the Map (CPM) accuracy of the Surface Elements Map.

Fig. 4 shows the average uncertainty per class. The comparison of these results with Fig. 3, shows that the results are consistent, since forestry species present higher values of uncertainty than non forest species and lower values of accuracy. The forest species that shows higher uncertainty and lower accuracy is the Eucalyptus Trees.

Fig. 4: Average Classification Uncertainty (CU) per class of the Surface Elements Map.

The correlation between the CU and the classification accuracy was evaluated. The correlation coefficient between CU and CPM was 0.71 and between CU and CPR was 0.39. These results reveal that there is a good agreement between the CU measure and CPM accuracy, and therefore the CU may be used to estimate CPR accuracy.

The global probability classification accuracies for the LUM obtained with the classification method that used the uncertainty information was 66%, and the global probability classification with the classification method without the uncertainty information was 54%. This shows that the accuracy increased significantly with the inclusion of the uncertainty information.

Fig 5 and Fig. 6 allow the comparison between the results of the CPR e CPM accuracies for the LUM obtained with both classification methods. 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.

Fig. 5: Conditional Probability of Reference obtained with the hybrid approach (LUM) with and without uncertainty.
A comparison between Fig. 4, Fig. 5 and Fig. 6, shows that the LU classes which showed more improvement with the use of the uncertainty information, were the ones formed through the arrangement of the SE that presented higher values of uncertainty. This new classification method proved that the uncertainty information allowed the identification of the misclassified SE and avoided their use in the transformation from a SEM to a LUM.

5. Conclusions

The obtained results show that the hybrid pixel-object classification integrating the SE classification uncertainty improved significantly the overall classification of LU classes in a Mediterranean environment, when compared with a similar classification method that does not take classification uncertainty into consideration. The use of uncertainty proved to be valuable in the classification process within this context and therefore this approach seems promising and worthy of further studies. From a methodological viewpoint, the hybrid approach revealed to be adequate for the transformation of a SEM, with detailed land cover features, in a LUM with a format well suited to be integrated in a GIS.

6. Acknowledgements

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7. References


