Comparing pixel vs. object based classifiers for land cover mapping with Envisat-MERIS data

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Abstract
The work presented in this paper is part of SatStat project, which is being developed in e-Geo – Geography and Regional Planning Research Centre of the Universidade Nova de Lisboa, under the framework of the European Space Agency (ESA) Announce of Opportunities for Portugal. The main goal of SatStat is to annual monitor forest areas using low resolution images. The imagery dataset includes an Envisat-MERIS multitemporal set of images for Portugal. In order to monitor the forest areas, 2003 was consider as the reference year and several classification techniques were tested to map the land cover of Portugal in that year, using a 2 level nomenclature. A pixel-based classifier was tested against an object-oriented classifier and an accuracy assessment was preformed to identify the best method.

1. Introduction

The different classification approaches applied to the imagery and its comparison are the object of this paper. Two techniques are tested, a pixel-based and an object-based classification. While the traditional pixel-based classification classifies each pixel according to certain statistical values, the object-based classification first sorts pixels into object primitives, builds so called segments and then assigns each segment to a class.

There is little work on object-oriented (OO) classifiers applied to low resolution images. A bibliographic review on this issue reveled some studies with Landsat data (30m resolution) (e.g., Erasmi *et al*., 2004; Mitri and Gitas, 2004; Scmidt, 2003; Wong *et al*., 2003; Mansor *et al*., 2002; Civco *et al*., 2002), but only few studies used OO classification in lower resolutions (>200m).

Lewis (2004) constructed an OO classification model based on change detection for MODIS (pixel of 250m) imagery to delineate fire scars in Australia. The segmentation of 2 MODIS image dates, using different weights for each band (Red and NIR band), was applied. Afterwards, a difference function was calculated for change detection purposes. The subsequent object classification took place in several steps. A series of decision rules based on thresholds were applied. A first classification regarding only the object characters (i.e., without class related features) identified all the fire scar objects and any other feature that could be confused with them. Then a classification with class related features removed more misclassified objects, and two manual classifications subsequently produced the final fire map. The author concluded that the constructed model was relatively robust, efficient and provided a product suitable for operational fire information.

Gitas *et al*. (2004) developed an OO model for mapping a recently burned area in the Mediterranean on a regional scale. The methodology included segmentation of the NOAA-AVHRR image (spatial resolution of 1.1km) into 2 different levels before its final classification, using different spectral as well as contextual object features. The burned area map resulting from the image classification was compared with the fire perimeter produced by the Forest Service in terms of spatial overlap. The results of the comparison indicated a high degree (90%) of spatial agreement. It was concluded that the OO approach can accurately map large recently burned areas on a regional scale using the low spatial resolution data of NOAA-AVHRR.

Gottsche and Olesen (2002) tested the OO classification in low resolution images (AVHRR), to detect clouds and weather situations. Due to the required pixel accuracy for cloud detection, this approach showed no advantage over conventional detection schemes nevertheless, it was shown that the OO classifier can readily mimic such schemes using its Nearest Neighbor classification.

2. Data set

The imagery investigated in this study consists of an Envisat Medium Resolution Imaging Spectrometer (MERIS) multitemporal data set. The chosen imagery was MERIS Full Resolution Level 2 data that consists of geolocated, calibrated surface reflectances ("top of aerosol") in 13 spectral channels from visible to near infrared wavelengths (412.5 to 890nm), with a 300m pixel. For classification proposes, the selected set was composed by the 13 spectral bands and the Top-of-Atmosphere (ToA) and Bottom-of-Atmosphere (BoA) bands, performing a 15 band dataset.

Three image dates from 2003 were selected: 14 May 2003, 18 September 2003 and 7 October 2003.

3. Methodology

The applied nomenclature for the land cover mapping of Portugal with Envisat was adapted from the 1995 National Forest Inventory of the Portuguese Forest Services. This classification scheme identifies 5 broad land cover classes in the 1st level and 8 on the 2nd level (Table 1).

Table 1. Nomenclature applied for land cover mapping with Envisat-MERIS images

1st Level	2nd Level
Urban	
Agriculture	
	Irrigated land
	Non-irrigated land
	Permanent crops
Forest	
	Forest stands and young plantations
	Forest burnt areas
	Clear cut areas
Uncultivated	
	Shrubland
	Fallow
Inland Waters	

The three seasonal images were chosen due to specific land cover dynamics: irrigated and non-irrigated areas in agriculture class and burnt areas on forest class. For the agriculture land cover characterization, spring and summer images were selected, while for burnt areas mapping, an autumn image was used.

The land cover mapping stage is organized in 3 stages that can be broadly named pre-processing, classification and analysis of results. The pre-processing stage includes geometric correction of the imagery dataset. The image processing phase foresees the test of different image classifiers. Then, the selection of the best methodology for land cover mapping with Envisat-MERIS data is preformed in the third stage.

3.1 Pre-processing

A geometric correction was performed, and all 3 images were co-registered. The image from May 2003 was then selected as the reference image and all others were registered to it using Ground Control Points (GCP) selected both in the reference and raw images. GCP were well distributed over the image, with individual Root Mean Square Errors (RMSE) less than 1 pixel, and a global RMSE less than 0.5 pixel. The geometric transformation applied was a 2nd order polynomium, and the resampling algorithm was the Nearest Neighbor (Santos *et al*., 2005).

3.2 Classification techniques

Classification is the process and operations used to assign pixels of a continuous raster image to predefined classes. This process can be done traditionally in a pixel-basis or, using a more recent technique that operates at the object level. The principal goal of this study is to test these two different classification techniques in Continental Portugal with Envisat-MERIS data. In both classifications – pixel and object based –, due the seasonal dynamics of the land cover classes, all 3 image dates from 2003 – spring, summer and autumn scenes – were classified independently, producing 3 land cover seasonal maps. Afterwards, map algebra operations where applied to the 3 maps in order to obtain the final land cover classification for 2003, with 10 land cover classes identified. For this task, we used several sources of ancillary data to help on land cover identification: the 2000 Corine land cover map, annually burnt area maps, and Landsat ETM+ images. The land cover nomenclature (Table 1) derives from a seasonal nomenclature that mixes level 1 and level 2 classes. Each seasonal image is classified into 9 seasonal classes: urban, agriculture, forest stands, forest burnt area, shrubland, fallow, inland waters, smoke/cloud, and nodata (that represents the Atlantic Ocean). The final annual land cover map is then produced with map algebra expressions that use these seasonal classes to achieve the annual classes.

3.2.1 Pixel-based classification

The chosen supervised classifier was the Maximum Likelihood (ML), which is a standard, pixel based approach that classifies pixel according to the multivariate probability density functions of the classes of interest. Statistical properties of training data sets from ground reference data are typically used to estimate the probability density functions of the classes. Each unknown pixel is then assigned to the class with the highest probability at the pixel location.

The supervised classification occurred for the 3 dates independently. For each class, a significant number of training areas were collected. Some classes requested more samples then others due to its spectral diversity and seasonal differencing (e.g., urban>130 areas, forest stands>2500 areas). After collecting the training areas, a ML classification was preformed in the 15 spectral bands dataset. The ML parameters applied, in ENVI 4.1 software, were:

- Probability threshold: none (all pixels are classified)
- Scale factor: 10000 (since the image units are reflectances)

3.2.2 Object-Oriented classification

The object oriented (OO) image analysis is applied with the main purpose of exploring the potential of this new approach for MERIS image dataset classification and comparing it with other per pixel classification methodologies. This approach required the construction of image objects, which was preformed in eCognition software. The development of the OO model involved two steps, namely segmentation and object's classification.

The first step implied a multi-resolution segmentation of each image date. The segmentation was applied to the 15 spectral bands in order to create pixel based objects using the following parameters: 0 for scale factor, 0.5 for shape, 0.5 for compactness, 0.5 for smoothness and a diagonal pixel neighborhood.

The classification process in eCognition is supervised, allowing system training by introducing sample objects (nearest neighbor) or classification concepts (membership functions and logic combinations), in order to build up a knowledge base for the classification of the image objects generated in the segmentation phase. A combination of both approaches was applied on the initial feature dataset (15 spectral bands) along with an additional set of 6 vegetation indexes, performing 21 features. The object's classification occurred in the following steps:

1. Class hierarchy creation.
The class hierarchy is the framework of the knowledge base for the image object classification in eCognition, and contains all the classes of the classification schema. In this study, a parent class was created for the level 1, and the 9 seasonal classes were created as child classes.

2. Samples collection for each class, using a nearest neighbor classifier.
For each class, several samples were collected, using the spectral information available in the feature space (21 spectral bands).

3. Selection of the features that best separate the classes.
Using the sample information, a feature space optimization is preformed. The analysed feature space was composed by the 15 spectral bands and 6 vegetation indexes. From this group, only few features were selected (varying from 3 to 5 features depending on the image date) and used in the classification process. The optimization is based on choosing the features that best separate the image objects into the indicated samples (i.e., that maximize the separation distance).

4. Membership functions definition.
All classes were defined as being in level 1. This feature is needed when performing classification on different image objects levels, because it defines which class description is valid for each level.

For the agriculture, forest stands and shrubland classes, the NDVI feature was applied: the vegetation classes are characterized by a positive NDVI. This rule was implemented in the membership function "Larger than (boolean)", with the condition value of 0. For the water class, the NDVI feature was also applied but with the function form "Smaller than (boolean)", in order to limit the water classification to those image objects with NDVI less than 0.

5. Image objects classification.
After constructing the knowledge base described in the previous steps, the nearest neighbor classifier was applied to the whole image in order to produce a land cover map. This classification produces a level 1 of image objects, at the pixel level, that have a land cover associated.

After classifying level 1 with the sample information, the map was improved by applying fuzzy rules to the misclassified image objects.

6. Image objects improved classification.
A structure group is created for each class of objects and a segmentation based classification is applied to form a second level of classification. This process merges all objects in the same class, eliminating the pixel level information, and calculates all contextual relations between them. In this second level, several rules using contextual and expert information were developed in order to reclassify some objects. The multiresolution segmentation into two levels, allows using the pixel level information that is on level 1, along with the contextual information that is presented in level 2.

For the urban class, all fallow objects that were totally surrounded by urban objects (feature relative border to urban neighbor-objects) and that had an area less than 4 pixels were reclassified as urban objects. For the burnt class, all shrubland and fallow objects that were not in the border of water objects, that had a relative border to burnt neighbor-objects, and that had an area less than 4 pixels, were reclassified as burnt objects. The smoke class, identified only in the spring and autumn images, was also improved by reclassifying those urban and fallow objects that had more than 1 pixel border to smoke objects. In the Inland water class, some confusion was detected between shrubland and burnt objects near the water. The reclassification rule was applied to every shrubland objects that had a relative border to water neighbor-objects greater than 1 pixel (information from level 1) and to every burnt objects that had a border to water objects.

After these rules were constructed for the class objects, the level 2 was then reclassified using the class-related feature option, in order to incorporate the contextual and expert information.

3.3 Map Algebra

After producing the three seasonal maps, using a both classification approach, the annual map - Land Cover Map for 2003 (LCM 2003) - is obtained in the 3 following steps:

1. The urban, agriculture, forest, uncultivated and water classes are obtained using the 10 map algebra expressions described in Table 2.
   These map algebra expressions are knowledge-based, and make use of the land cover identified in the 3 seasonal maps. The separation of the agriculture class into irrigated land, non-irrigated land and permanent crop is only possible in this stage. The same applies to the forest class. This is because of the seasonal development of these classes that can only be mapped when all dates are analyzed
2. The remaining unclassified pixels are labeled using more thematically relaxed map algebra expressions, as described in Table 3.
3. The remaining ones are labeled as in the autumn map. Note that the agriculture pixels are reclassified as permanent agriculture and burnt pixels are reclassified as fallow.

The map algebra expressions make use of expert knowledge on land cover dynamics. For example, in Portugal, the irrigated crops are cultivated in the spring and harvested in late summer, while the non-irrigated crops are cultivated and harvested earlier, producing land cover dynamics nearly inverse. The dynamic behavior is also applied for redefine other classes like the Fallow class. In fact, when using seasonal information the Fallow class can be easily distinguished from the Agriculture class. The seasonal maps allow also the identification of clear cuts in forest areas.

Table 2. Map algebra applied to the seasonal maps for the Land Cover Map for 2003 production.

Land Cover class	**Map Algebra Expression**
Water	Spring=water or Summer=water or Autumn=water
Urban	Spring=urban and Summer=urban and Autumn=urban
Irrigated land	Spring=fallow and Summer =agriculture and Water=0
Non-irrigated land	Spring=agriculture and Summer=fallow and Water=0
Permanent crop	Spring=agriculture and Summer=agriculture and Water=0
Burnt forest areas	(Spring=forest and Summer=burnt) or (Summer=forest and Autumn=burnt) and Water=0
Forest	Spring=forest and Summer=forest and (Autumn=forest or Autumn=agriculture or Autumn=shrub)
	(Spring=agriculture or Spring=shrub) and Summer=forest and Autumn=forest
	Spring=forest and (Summer=agriculture or Summer=shrub) and Autumn=forest
Shrubland	Spring=shrub and Summer=shrub and Water=0
Clear Cut	(Spring=forest and Summer=fallow and Autumn=fallow) or (Spring=forest and Summer=forest and Autumn=fallow)
Fallow	Spring=fallow and Summer=fallow and Autumn=fallow

Table 3. Map algebra applied to the remaining unclassified pixels/objects in the seasonal maps, to produce the final Land Cover Map for 2003

Land Cover class	**Map Algebra Expression**
Urban	((Spring=urban and Summer=urban and Autumn=fallow) or (Spring=urban and Summer=fallow and Autumn=urban) or (Spring= fallow and Summer=urban and Autumn=urban)) and unclassified
Irrigated land	Summer =agriculture and Autumn=agriculture and unclassified
	Spring=fallow and (Summer=forest or Summer=shrub) and Autumn=fallow and unclassified
Permanent crop	Spring=agriculture and Summer=shrub and Autumn=fallow and unclassified
	Spring=shrub and Summer=agriculture and Autumn=fallow and unclassified
Forest	Spring=forest and Summer=shrub and Autumn=agriculture and unclassified
Shrubland	Spring=shrub and Summer=forest and Autumn=agriculture and unclassified
Fallow	(Spring<>urban and Spring<>fallow) and (Summer<>urban and Summer<>fallow) and Autumn=urban and unclassified
….	The remaining unclassified pixels are labeled with the class of the Autumn map but, the burnt areas area reclassified as Fallow and the agriculture as Permanent crop

When applying the map algebra expressions listed in table 2, approximately 70% of the pixels/objects are classified into one of the 10 land cover classes. The remaining unclassified pixels/objects are subjected to other thematically more flexible map algebra expressions (Table 3) that make use of some already expected land cover spectral confusions: the shrubs are better distinguished from the forest in the summer image, because they are at the top of their growth stage. When a pixel/object is classified as Fallow-Vegetation-Fallow in the 3 maps, this is typically an irrigated land trend, so if the vegetation is forest or shrub, it is being misclassified and should be agriculture. Regarding the urban class, one can assume that if a pixel/object is classified as urban in 2 maps and fallow in the other, than it is an urban pixel/object. Figure 1 shows the Land Cover Map 2003 obtained from the supervised and the object-oriented classifications, after applying the map algebra expressions.

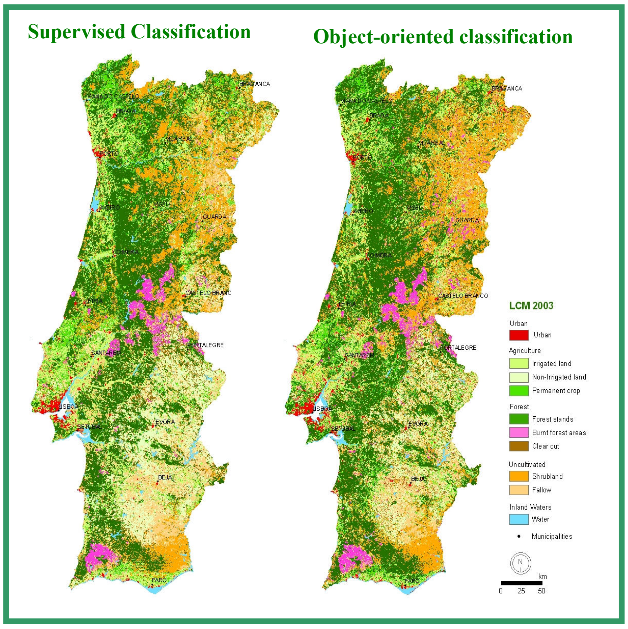

Figure 1. Land Cover Maps for 2003 obtained by supervised and object-oriented classification of seasonal Envisat-MERIS data

3.4 Pixel vs Object - Classification accuracy

To access the quality of the LCM2003 an accuracy assessment was produced. The selected sample unit was the pixel. The sample size comprised 1860 pixels, and all individual classes had more than 50 samples. The samples were selected in a random stratified sampling.

After selecting the samples, they were labelled using several sources of ancillary data to help on land cover identification: the 2000 Corine map, annually burnt area maps, and Landsat ETM+ images. After sample labeling, and to access the efficiency of the pixel-based and object-oriented classifications, an error matrix was designed. Several quality measures like user's and producer's accuracy, overall accuracy and Kappa analysis were calculated from the error matrix (Tables 5 and 6). From the error matrix analysis, the following considerations can be taken:

- The map that best describes the land cover for 2003, using the 10 classes (Table 1), and a multitemporal seasonal dataset of Envisat-MERIS images, is the one produced with the pixel-based approach (Maximum Likelihood classifier). The ML classifier rated a KHAT of 85% (strong agreement) against the 63% (poor agreement) of the OO classifier. The highest producer's accuracy was 100% and 94% in the inland waters and forest stand classes, respectively, and the lowest was 76% in the permanent crop class.
- The clear cut class was the one that presented more problems, in both maps, from the user's point of view. In fact, this class is mainly misclassified as non-irrigated land due to similar seasonal dynamics: both are vegetation classes in spring time and fallow class in the summer. The vegetation classes that are being confused in the spring map are forest and agriculture because after the raining season (winter time), both classes look very similar in the spring.
- The uncultivated classes presented some confusion. Some shrubland samples were misclassified as forest stands and fallow. These were expected confusions because where the shrub is very abundant it is easily confused with more open forest stands, where the background is generally composed by some shrub species. However, when the shrub is very sparse it can be identified as fallow land.
- The quality results of the OO classifier were inferior to the one produced by the ML classifier. The urban, forest stand, fallow and inland classes were well identified, from the producer's point of view, but agriculture classes had poor performance and the clear cut class had the lowest accuracies.

4. Conclusions

In low spatial resolution satellite images, distinct land cover classes may produce similar spectral responses turning more difficult their discrimination. On the other hand, pixel-based classifications of such resolutions always face the problem of mixed-pixels. The present study considered these drawbacks and tested a new approach – OO classification – that is similar to visual interpretation, taking into account the variation in the texture, color and form of image objects.

However, the classification assessment presented in this paper concludes that, the traditional pixel-based classification produces better land cover mapping, with the seasonal dataset of Envisat-MERIS images, than the object-oriented classification. In fact, in a spatial resolution of 300m pixel, land cover characteristics such as texture or form that can be of great use in an object-oriented context, were not very explicit and, therefore, could not be explored. We concluded that in objects with a minimum mapping unit of 9ha, the form is not clearly present.

Table 5. Error matrix and quality indexes of the map produced with the Maximum-Likelihood Classifier

MAP	REFERENCE										
	Urban	Irrigated Land	Non-Irrigated Land	Permanent crop	Forest stands	Burnt forest	Clear cut	Shrubland	Fallow	Inland Water	User's Accuracy
Urban	**50**	0	0	0	0	0	0	0	1	0	0.98
Irrigated Land	1	**120**	5	8	5	0	0	2	4	0	0.86
Non-Irrigated Land	0	0	**200**	1	0	1	4	3	1	0	0.95
Permanent crop	2	7	9	**91**	8	0	1	7	0	0	0.73
Forest stands	0	1	3	6	**408**	0	0	13	0	0	0.95
Burnt forest	0	0	0	0	0	**98**	0	0	4	0	0.96
Clear cut	0	0	24	0	0	3	**49**	2	3	0	0.60
Shrubland	0	6	6	10	15	0	0	**159**	0	0	0.81
Fallow	6	1	9	3	0	3	9	15	**133**	0	0.74
Inland Water	0	0	0	0	0	0	0	1	0	**57**	0.98
Total	59	135	251	119	436	105	63	202	146	57	**1365**
Producer's Accuracy	0.85	0.89	0.80	0.76	0.94	0.93	0.78	0.79	0.91	1.00	
Sample size = 1573 pixels **KHAT** = 0.85 **Overall Accuracy** = 0.87											

Table 6. Error matrix and quality indexes of the map produced with the Object-Oriented Classifier

MAP	REFERENCE										
	Urban	Irrigated Land	Non-Irrigated Land	Permanent crop	Forest stands	Burnt forest	Clear cut	Shrubland	Fallow	Inland Water	User's Accuracy
Urban	**49**	0	0	0	0	0	1	0	16	0	0.74
Irrigated Land	2	**91**	3	15	5	0	1	11	8	1	0.66
Non-Irrigated Land	0	0	**143**	4	0	1	13	2	12	0	0.82
Permanent crop	0	19	17	**62**	6	0	2	10	6	1	0.50
Forest stands	0	6	8	24	**394**	3	10	44	2	2	0.80
Burnt forest	0	0	2	0	5	**76**	0	3	5	2	0.82
Clear cut	0	0	39	1	0	0	**15**	0	1	0	0.27
Shrubland	0	15	25	9	26	6	10	**123**	14	1	0.54
Fallow	8	4	14	4	0	19	11	9	**82**	4	0.53
Inland Water	0	0	0	0	0	0	0	0	0	**46**	1.00
Total	59	135	251	119	436	105	63	202	146	57	**1081**
Producer's Accuracy	0.83	0.67	0.57	0.52	0.90	0.72	0.24	0.61	0.56	0.81	
Sample size = 1573 pixels **KHAT** = 0.63 **Overall Accuracy** = 0.69											

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