Quickbird image segmentation for mapping crops and their agro-environmental associated measures

Clasificación de cultivos y de sus medidas agro-ambientales mediante segmentación de imágenes QuickBird

F. López-Granados[1], I.L. Castillejo-González[2], J.M. Peña-Barragán[1], M. Jurado-Expósito[1], M. Sánchez de la Orden[2], L. García-Torres[1] y A. García-Ferrer[2]
flgranados@ias.csic.es

[1]*Instituto de Agricultura Sostenible, CSIC, Apdo. Correos 4084, 14080-Córdoba (España)*
[2]*Departamento de Ingeniería Gráfica y Geomática, Universidad de Córdoba, Campus de Rabanales, Edificio Gregor Mendel, 14071-Córdoba (España)*

RESUMEN

En la últimas décadas han ido creciendo considerablemente los conocimientos y la sensibilización sobre la protección al medioambiente en muy diversas áreas, entre las que se encuentra la Agricultura. El uso intensivo del laboreo ocasiona graves daños medioambientales como la erosión del suelo, la contaminación de las aguas superficiales (escorrentía y colmatación de embalses), el descenso del contenido de la materia orgánica y de la biodiversidad de los suelos labrados, y el aumento de la emisión de CO_2 del suelo a la atmósfera. Actualmente, la Unión Europea sólo subvenciona a los agricultores que cumplen lo que se conoce como "*Medidas Agroambientales o de Condicionalidad*" cuyo diseño ha estado dentro de las competencias de las Políticas Agrarias Autonómicas, Nacionales y Europeas. Estas medidas consisten en alterar el perfil y la estructura del suelo lo menos posible, dejando éste sin labrar y permanentemente protegido por cubiertas vegetales (rastrojo) en el caso de cultivos herbáceos (ej. trigo, maíz, girasol), o por cubiertas vegetales vivas o inertes (restos de poda) en el caso de cultivos leñosos (principalmente cítricos y olivar). El seguimiento del cumplimiento de estas medidas se re-

ABSTRACT

Soil management in crops is mainly based on intensive tillage operations, which have a great relevancy in terms of increase of atmospheric CO_2, desertification, erosion and land degradation. Due to these negative environmental impacts, the European Union only subsidizes cropping systems which require the implementation of certain no-tillage systems and agro-environmental measures, such as keeping the winter cereal residues and non-burning of stubble to reduce erosion, and to increase the organic matter, the fertility of soils and the crop production. Nowadays, the follow-up of these agrarian policy actions is achieved by ground visits to sample targeted farms; however, this procedure is time-consuming and very expensive. To improve this control procedure, a study of the accuracy performance of several classification methods has been examined to verify if remote sensing can offer the ability to efficiently identify crops and their agro-environmental measures in a typical agricultural Mediterranean area of dry conditions. Five supervised classification methods based on different decision rule routines, Parallelepiped (P), Minimum Distance (MD), Mahalanobis Classifier Distance (MC), Spectral Angle

aliza a través de visitas presenciales a un 1% de los campos susceptibles de recibir ayudas. Este método es ineficiente y provoca muchos errores con la consiguiente presentación de un ingente número de reclamaciones. Para subsanar esta problemática, en este artículo presentamos los resultados obtenidos en la clasificación de los cultivos y las medidas agroambientales asociadas a éstos en una imagen multiespectral QuickBird tomada a principios de Julio de una zona típica de cultivos en régimen de secano de Andalucía. Se aplicaron 5 métodos de clasificación (Paralelepípedos, P; Mínima Distancia, MD; Distancia de Mahalanobis, MC; Mapeo del Ángulo Espectral, SAM; y Máxima Probabilidad, ML) para la discriminación de rastrojo de trigo quemado y sin quemar, arbolado, carreteras, olivar, cultivos herbáceos de siembra primaveral y suelo desnudo. Además, la imagen es segmentada en objetos para comparar la fiabilidad obtenida aplicando los métodos anteriores partiendo tanto de píxeles como de objetos como Unidades Mínimas de Información (MIU). El análisis de los resultados permite concluir que las clasificaciones de todos los usos de suelo basadas en objetos claramente mejoraron las basadas en píxeles, obteniéndose precisiones (overall accuracy) mayores al 85%. La elección de un método de clasificación u otro influye en gran medida en la precisión de los mapas obtenidos.

Debido a que la precisión del mapa temático que necesitamos obtener ha de ser muy elevada para tomar decisiones sobre Conceder / No conceder las ayudas, sería interesante estudiar si el incremento de la resolución espacial que se obtenga gracias a la fusión de imágenes multiespectral y pancromática de QuickBird para obtener una imagen fusionada con resolución espacial de la pancromática (0.7 m) y espectral de la multiespectral (4 bandas) mejora la precisión de cualquiera de los métodos de clasificación estudiados.

PALABRAS CLAVE: Inventario de cultivos; Rastrojo quemado y sin quemar; Segmentación de imágenes

Mapper (SAM), and Maximum Likelihood (ML), were examined to determine the most suitable classification algorithm for the identification of agro-environmental measures such as winter cereal stubble and burnt stubble areas and other land uses such as river side trees, vineyard, olive orchards, spring sown crops, roads and bare soil. An object segmentation of the satellite information was also added to compare the accuracy of the classification results of pixel and object as Minimum Information Unit (MIU). A multispectral QuickBird image taken in early summer was used to test these MIU and classification methods. The resulting classified images indicated that object-based analyses clearly outperformed pixel ones, yielding overall accuracies higher than 85% in most of the classifications. The choice of a classification method can markedly influence the accuracy of classification maps.

KEYWORDS: Burnt and non-burnt crop stubble; Crop inventory; Image segmentation.

INTRODUCTION

Soil management in the Mediterranean basin is mostly based on intensive tillage agricultural practi-

ces, which have serious agro-environmental implications and consequences in terms of increase of atmospheric CO_2, desertification, land erosion and degradation, and sediment transport (Schlesinger,

2000; Hill *et al*., 1995). Due to these negative environmental impacts, the European Union (E.U.) only subsidizes cropping systems which require the implementation of certain agro-environmental measures such as crop cover in olive orchards and non-burning of crop stubble to keep the crop residues after harvesting (Anonymous, 2007). Nowadays, around 45% (4.3 M ha) of the whole Andalusian (Andalusia, southern Spain) surface is devoted to intensive agricultural production and to control these agrarian policy actions, a precise follow-up of crop inventories and cropping systems by the E.U. and local administrations is required. Current methods to follow-up of cropping systems and to map agricultural practices by the Andalusian administration consist of both, ground visits at least to 1% of the whole surface and drive-by to sample fields on a country-by-country basis. This drive-by method consists of designing transects, from which the results are used to estimate or extrapolate the agriculture system used in the entire country. Obviously, these procedures are time-consuming, very expensive and deliver inconsistent results due to it covers relatively small areas or only very few target fields.

Remote sensing has demonstrated to efficiently identify and map crops, cropping methods, and vegetation inventories over large areas (South *et al*., 2004; Yu *et al.*, 2006). These techniques can signify lower costs, faster work and better reliability than ground visits. But, particularly for this purpose, the accuracy of the thematic map is extremely important because this map could be used as a tool to help the administrative follow-up to make the decision on Concede/Not to concede the subsidy. Medium spatial resolution satellite imagery such as Landsat TM and SPOT has often proven to have an insufficient or inadequate accuracy for detailed vegetation studies (Harvey and Hill, 2001). However, higher spatial resolution satellite imagery such as IKONOS and QuickBird has already been considered to be a useful data source for accurately classifying agronomic and forest variables such as forest inventory (Chubey *et al*., 2006) and sorghum yield (Yang *et al*., 2006).

South *et al*. (2004) summarize most supervised classification algorithms into three main categories: distance-based, probability-based and angular-based decision rules. Distance-based classifiers rely primarily on mean spectral values of distinct classes, ignoring variance within classes. Probability classification routines incorporate both the mean and variance of the data set into the classification decision rule. Finally, angular-based classifiers use a classification decision rule based on spectral angles formed between a referenced spectrum and an unclassified pixel. There is no one ideal classification routine. The best one depends on all the needs and requirements of each study.

Most remote sensing land use classification studies are based on pixel information. However, the increase in spatial resolution causes an increase in intraclass spectral variability and a reduction in classification performance and accuracy when pixel-based analyses are used. To overcome this problem, it could be useful to group the adjacent pixels into spectral and spatially homogeneous objects. These objects are created from a segmentation process. Object merging/growing algorithms take some pixels as seeds and grow the regions around them based on certain homogeneity criteria (Yu *et al*., 2006). Thereafter, the classification is not based on the pixel but on objects such as Minimum Information Unit (MIU). This idea involves an image segmentation to delineate homogeneous objects in the same way that human vision tends to generalize images into homogeneous areas (Laliberte *et al*., 2004). While the information of the pixel-based image analysis is only the spectral response information of all pixels in each band, the object-based analysis obtains additional information derived from an image object by the calculation of descriptive statistics of spectral information such as mean and standard deviation from all the pixels aggregated in each object. Therefore, objects are not characterized by a uniform reflectance value but by a distribution of a certain spatial autocorrelation (Lobo, 1997).

This spatial information is based on object size, shape and context and can be calculated as information pertaining to an object's sub- or super-object if a multilevel image object hierarchy has been created (Chubey *et al*., 2006). Thus, these discrete objects are homogeneous as regards spectral or spatial characteristics and according to Benz *et al*., (2004) can contribute to powerful automatic and semi-automatic analysis for most remote sensing applications. However, there is no information about object-based classifications in typical agricultural dryland Mediterranean areas to mapping cropping systems and key agro-environmental measures with high spatial resolution image satellite.

Therefore, the main objective of this paper was to examine five supervised classification routines applied to pixel and object data as MIU to analyze the

potentiality of each method for the identification and mapping of cropping systems and their agro-environmental associated measures using a multispectral QuickBird image.

MATERIALS

Land covers and data acquisition

The study area is about 87.21 km^2 (15.3 x 5.7 km) located around Montilla, province of Córdoba (Andalusia, southern Spain, Fig. 1). This agricultural area is representative of Andalusian dryland crops and has a typical continental Mediterranean climate, characterized by long dry summers and mild winters, and a relatively flat relief with an average height of 380 m above sea level.

In this scene, ten land uses were considered: 1) spring-sown sunflower (*Helianthus annuus* L.), 2) olive (*Olea europaea* L.) orchards, 3) vineyards (*Vitis vinifera* L.), 4) burnt crop stubble (of winter cereal: wheat, *Triticum durum* L., generally), 5) winter cereal stubble, 6) urban soil, 7) roads, 8) river side tree areas made up of mulberry-trees (*Morus alba* L.), eucalyptus (*Eucalyptus globules Labill*) and poplar (*Populus nigra* L.), 9) dark agricultural bare soil, and 10) light agricultural bare soil. The latter two land uses provided radiometric signals contrasting enough to separate the agricultural bare soil into two categories: light and dark bare soil. Ground-truth land use was randomly defined to substantiate and validate the classification procedures. The study area was visited to determine actual land uses. Over 127 ha were georeferenced using the sub-meter differential GPS TRIMBLE PRO-XRS provided with TDC-1. Each land cover class was shared out proportionally. Thirty hectares of this surface were used to collect the spectral signature in the training process. The remaining 97 ha were used to assess the accuracy of the classifications.

Satellite data and preprocessing

Digital image data were acquired over the study area by QuickBird satellite on 10th July 2004. QuickBird data set consisted of 4-bands multispectral image (blue: 450-520 nm; green: 521-600 nm; red: 630-690 nm; and near-infrared: 760-900 nm) with a spatial resolution of 2.8 m and a radiometric resolution of 8 bit. Radiometric and geometric corrections were previously carried out by the distri-

butor. The radiometric corrections included: relative radiometric response between detectors, non-responsive detector fill and a conversion for absolute radiometry. Geometric corrections removed spacecraft orbit position and attitude uncertainty, Earth rotation and curvature, and panoramic distortion. Additionally, a coarse DEM was used to normalize for topographic relief with respect to the referenced ellipsoid (information available in: http://www.eurimage.com/products/quickbird.html#standard). The image showed a spatial displacement and it was georeferenced for superimposing of cadastral information. Cadastre ancillary data were superimposed to provide useful information in order to improve the segmentation process. Pixels and objects as MIUs were used in the classifications (Fig. 2a and 2b, respectively).

Segmentation

Segmentation subdivides images into separate regions. Each segmentation image can show a large number of possible solutions but the best one is that which shows meaningful image-objects that correspond to real entities. The segmentation algorithm used in this study, the Fractal Net Evolution Approach, has been carried out by the software Definiens Developer 7. It is used to produce image object primitives as a first step for a further classification and other processing procedures (Baatz and Shäpe, 2000). The image has been processed by a multiresolution bottom up region-merging approach, in which the smallest image object contains one pixel. Objects have been generated based upon several adjustable criteria: scale (control size parameter), colour (spectral information) and shape (smoothness and compactness information). Multiresolution segmentation is an optimization procedure that minimizes, for a given number of image objects, the average heterogeneity (Definiens, 2007a) and produces highly homogeneous image objects in an arbitrary resolution on different types of data (Baatz and Shäpe, 2000). This segmentation approach allows, for different scale segmentation, to represent the image information in different spatial resolutions simultaneously by a hierarchical network. Information about adjacent objects on the same level (horizontal neighbours) and objects on different hierarchical levels (vertical neighbours) are allowed by this network. Although it generates a large amount of information, this study has used only two types of information: the mean spectral value of each
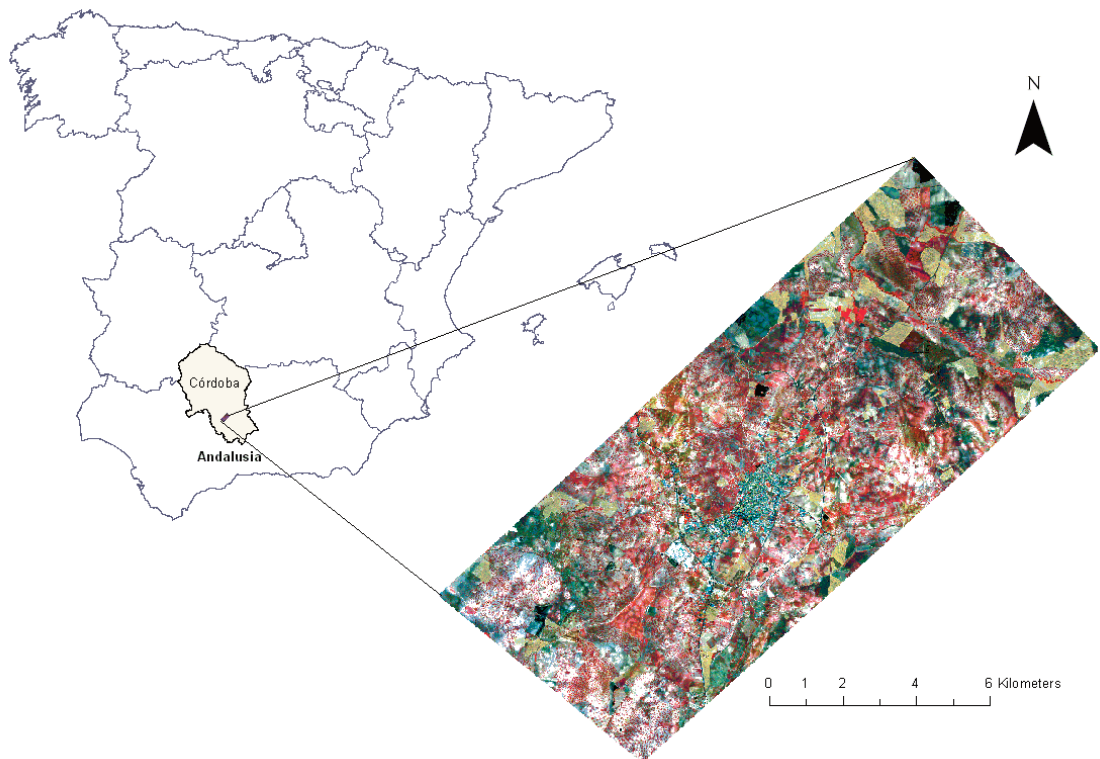
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55

Figure 1. Location of study area in Córdoba Province (Andalusia, Spain).
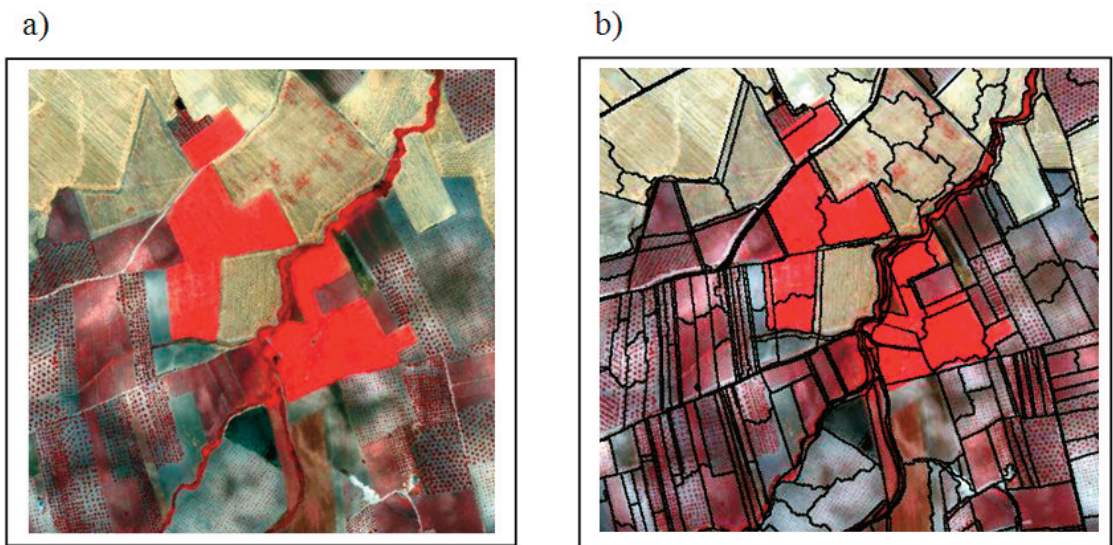
a)

b)

Figure 2. a) QuickBird image, b) QuickBird image with superimposed limits of objetcs.

object in each layer and some textural parameters of each layer that detect the local differences between objects in lower levels or subobjects: contrast, entropy and homogeneity (Table 1). These textural parameters have been calculated based on the co-occurrence matrix of Haralick. This is a tabulation of how often different combinations of pixel gray levels occur in an image (Definiens, 2007b). Homogeneity and contrast measure the concentration levels of elements along the diagonal of the gray level co-occurrence matrix (GLCM), meaning, the amount of local variation. The entropy studies the likeness of the elements in the matrix.

Classification and accuracy

Five supervised classification methods were selected to examine their suitability for classification: Parallelepiped (P), Minimum Distance (MD), Mahalanobis Classifier Distance (MC), Maximum Likelihood (ML) and Spectral Angle Mapper (SAM). The first three methods, P, MD and MC are distance-based classifiers, while ML and SAM are probability and angular-based ones, respectively. The QuickBird image was independently classified by each of these methods, applying the decision rules to pixels and objects as MIU.

A key concern in remote sensing is to quantify the coincidence between the estimated map and the ground-truth map. To avoid any subjective estimation, a numerical confusion matrix analysis was used to indicate its correct assessment and the errors between the classes studied (Congalton, 1991). The confusion matrix provides the Overall Accuracy (OA) of the classification, which indicates the percentage of correctly classified pixels; the producer's accuracy (PA) and omission error, which indicates the probability that a classified pixel actually represents that category in reality; and the user's accuracy (UA) and commission error which indicate how well training set pixels were classified (Rogan *et al.*, 2002). Overall classification accuracy indicates the overall success of classification and has been standardized at 85% for the minimum accepted value. Data not reaching this level will require a re-classification or class aggregation (Foody, 2002). On the other hand, the Kappa test determines whether the results presented in the error matrix are significantly better than random or chance classification indicating a more conservative estimation than simple percent agreement value (Congalton, 1991; Rogan *et al.*, 2002). Landis and Kock (1977) suggested than Kappa coefficient (Kc) of over 0.8 strongly indicates that a given classification is unlikely to have been

Categories	Description	
Spectral features	Mean	$$\frac{1}{\#P_v}\sum_{i,j\in P_v}c_{i,j,k}$$
Texture features	GLCM_Homogeneity	$$\sum_{i,j=0}^{N-1}\frac{P_{i,j}}{1+(i-j)^2}$$
	GLCM_Contrast	$$\sum_{i,j=0}^{N-1}P_{i,j}(i-j)^2$$
	GLCM_Entropy	$$\sum_{i,j=0}^{N-1}P_{i,j}(-\ln P_{i,j})$$

$\#P_v$: total number of pixels contained in an image object v, i: row number, j: column number $c_{i,j,k}$: intensity value of an image layer k in the cell i,j, N: numbers of rows and columns, $P_{i,j}$: normalized value in the cell i,j.

Table 1. Object-based features

obtained by chance alone. OA, PA, UA and Kc were calculated for every final thematic map to validate and assess the accuracy of the classification procedures and imagery considered.

Because high resolution satellite data classification generates noise, especially salt and pepper noise, the classification errors can be important. To improve classification methods and obtain better results, a majority filter of 5x5 (MF 5x5) was also applied to all classifications to decrease land use heterogeneity. ENVI 4.3 (Research Systems Inc. 2006) was the software used for image processing.

RESULTS

OA and Kc results with and without the majority filter applied for every classification method according to the different MIU studied and considering the ten land uses are shown in Table 2. When the majority filter was applied, best results in OA and Kc were obtained for pixel as MIU, whereas hardly perceptible differences were reached for the object-based analysis. Taking into account the classification methods, consistent differences (over 55%) in OA and Kc for the worst (P) and best (ML) classification methods were obtained. Thus, the OA and Kc were 46.9% and 0.39, and 90.6% and 0.89, respec-

tively, for P pixel and ML object-based classification. With objects as MIU in the classification, four of the five classification algorithms achieved OA of over 85%. Thus, OA was 86.7%, 89.0%, 89.9% and 90.6% for MD, SAM, MC and ML, respectively, with Kc values of over 0.85. Figure 3 shows a piece of image for the less (a, b) and most accurate (a', b') land use classifications for pixels and objects as MIU.

Table 3 summarizes the PA for every individual land use for the different MIU and classification methods considered. PA varied considerably according to the land use classified. A general examination of the individual land cover classifications shows that mixed covers (*e.g.* olive orchard, spring sown crops and urban soil) presented high intraclass spectral variability and lower PA for pixel-based analyses as MIU than for object-based analyses. For example, the greatest differences in PA can be observed in the olive orchard category, which showed PA values greater than 92% in all the object-based classifications. By contrast, river side trees and roads, which usually exhibit a lower intraclass spectral variability, showed higher PA for all the pixel-based classifications than for the object-based ones, except for ML for river side trees, where a higher PA was found for object-based classifications.

	P[1]		MD		MC		SAM		ML	
MIU[2]	OA[3]	Kc	OA	Kc	OA	Kc	OA	Kc	OA	Kc
Pixel	46.9	0.39	59.2	0.54	72.3	0.69	61.8	0.56	89.6	0.88
	(44.3)	(0.36)	(55.5)	(0.5)	(65.0)	(0.6)	(57.5)	(0.5)	(79.2)	(0.76)
Object	69.9	0.66	86.7	0.85	89.9	0.88	89.0	0.87	90.6	0.89
	(69.8)	(0.66)	(85.1)	(0.8)	(89.9)	(0.88)	(88.9)	(0.87)	(90.5)	(0.89)

[1] Method of classification: P: Parallelepiped, MD: Minimum Distance, MC: Mahalanobis Classifier Distance, SAM: Spectral Angle Mapper, ML: Maximum Likelihood.
[2] MIU: Minimum Information Unit; (3) Accuracy values: OA: overall accuracy, Kc: Kappa coefficient.

Table 2. Accuracy results of the classifications carried out. Results with the majority filter in regular font. Results without the majority filter between brackets and in italic font
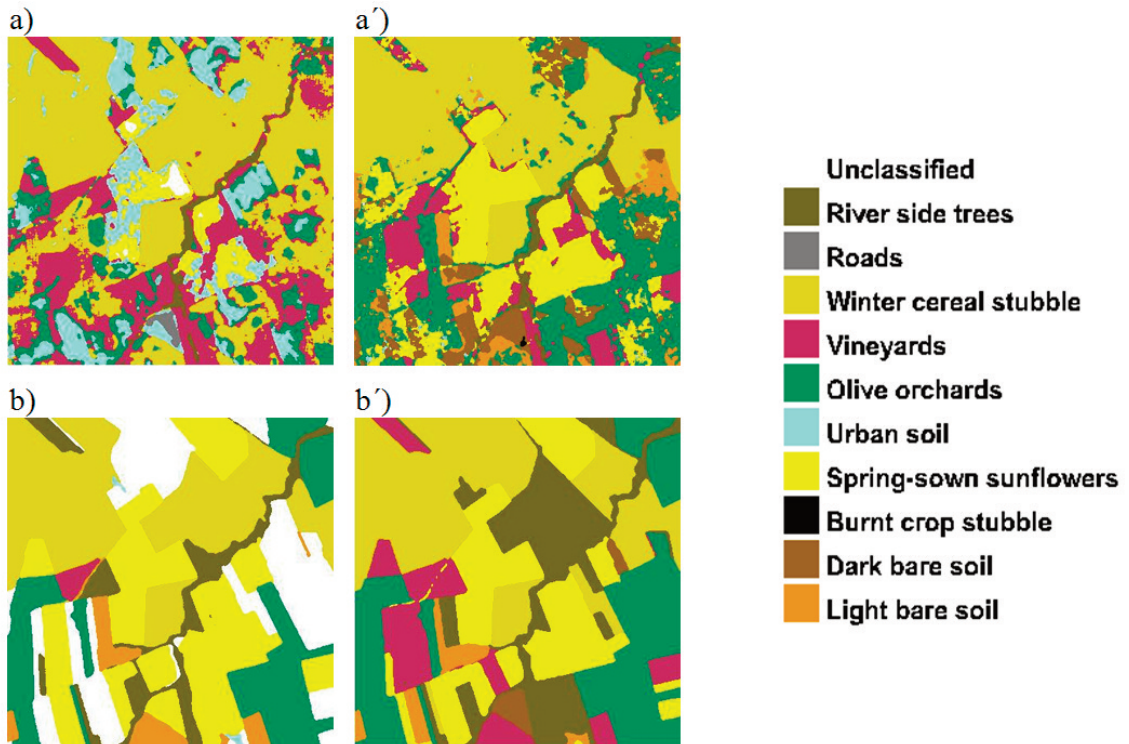
Figure 3. Result of the Parallelepiped (a, b) and the Maximum Likelihood (a´, b´) classifiers using pixels (a, a') and objects (b, b'), as Minimum Information Unit in a QuickBird image.

Discrimination of burnt crop stubble land use was very successful applying the MC and ML methods for any MIU considered in the image with PA higher than 92.69%. Similarly, winter cereal stubble discrimination was very accurate with PA of over 96.98% or even of 100% for any MIU considered and applying SAM, ML or MC classifications. In dark bare soil, light bare soil and spring sown crops categories, the PA was higher than 89% for both MIU in ML classifications. By contrast, for roads category the PA was higher in pixel-based analysis than in the object one, showing values higher than

86.1% in any of the pixel classifications.

Table 4 shows the UA for every individual land use for both MIU and classification methods considered. As stated before for PA, two of the most successful classified land uses were burnt crop stubble and winter cereal stubble areas. For instance, for burnt crop stubble, UA was usually higher than 97% in most of the classifications, and even 100% success in many of them. Winter cereal stubble also presented high accuracy showing UA values from 97% to 100% in all the object-based classifications.

	MIU[1]	River side trees	Roads	Winter cereal stubble	Vineyard	Olive orchards	Urban soil	Spring-sown crops	Burnt crops stubbe	Dark bare soil	Light bare soil
P[2]	P	81.44	92.28	95.56	71.59	25.68	49.54	28.92	78.43	0.00	0.00
	O	73.22	82.31	86.26	2.70	94.45	30.35	97.91	85.91	14.79	87.55
MD	P	86.03	86.11	73.46	49.64	28.20	45.20	70.21	90.66	58.41	93.38
	O	72.28	71.13	95.53	87.44	92.76	88.77	84.37	97.10	79.84	69.28
SAM	P	89.42	89.70	99.87	66.14	44.46	25.45	22.93	68.35	71.06	57.79
	O	68.81	76.01	96.98	91.89	92.49	75.65	84.29	98.23	89.15	83.78
MC	P	83.49	90.07	100.00	80.33	35.68	59.28	82.63	92.69	63.97	94.97
	O	73.42	74.68	100.00	93.30	93.44	92.30	90.35	98.38	93.22	67.83
ML	P	87.58	93.32	99.29	80.02	84.38	84.12	89.70	96.77	93.70	93.09
	O	97.00	45.31	99.84	83.87	99.64	61.57	95.38	99.36	90.29	89.92

[1] MIU: Minimum Information Unit: P: Pixel; O: Object
[2] Classifier Abbreviations: P: Parallelepiped, MD: Minimum Distance, MC: Mahalanobis Classifier Distance, SAM: Spectral Angle Mapper, ML: Maximum Likelihood.

Table 3. Producer's accuracy (%) of the five classifications (Results with the majority filter applied)

	MIU[1]	River side trees	Roads	Winter cereal stubble	Vineyard	Olive orchards	Urban soil	Spring-sown crops	Burnt crops stubbe	Dark bare soil	Light bare soil
P[2]	P	85.99	50.72	46.03	52.31	38.20	19.55	90.66	100	0.00	0.00
	O	75.28	31.68	100.00	100.00	94.34	66.39	39.59	100	100	73.89
MD	P	67.56	68.41	61.23	67.72	55.31	43.85	60.05	100	39.99	62.16
	O	86.06	99.42	97.97	81.42	94.12	90.10	65.73	100	66.38	88.79
SAM	P	52.90	31.59	80.09	67.26	78.56	28.31	47.40	97.83	45.33	58.46
	O	93.43	55.70	98.24	77.26	94.05	93.64	87.17	97.87	78.74	91.32
MC	P	85.87	77.69	76.67	91.30	80.18	42.30	80.89	100	51.55	67.69
	O	99.53	65.52	98.04	89.93	97.33	95.48	83.70	99.11	66.61	81.59
ML	P	99.05	86.01	94.57	82.85	94.25	77.07	76.71	100	91.82	87.07
	O	80.58	100	99.78	97.49	92.35	96.90	86.88	100	77.81	80.08

[1] MIU: Minimum Information Unit: P: Pixel; O: Object
[2] Classifier Abbreviations: P: Parallelepiped, MD: Minimum Distance, MC: Mahalanobis Classifier Distance, SAM: Spectral Angle Mapper, ML: Maximum Likelihood.

Table 4. User's accuracy (%) of the five classifications. (Results with the majority filter applied).

DISCUSSION

The first result to note is that the poorest and best classifiers were P and ML considering all the land uses. More specifically, P and pixel-, and ML and object-based analyses were the worst and best choices, respectively. MD, MC and SAM in the object-based study also performed well and all of them fulfilled the commonly accepted requirements of at least 85% overall classification accuracy (Foody, 2002), and a range of 0.75 (Montserud and Leamans, 1992) to 0.80 (Landis and Koch, 1977) for Kappa coefficient. When considering individual land uses, accuracy was higher since very low omission errors or a maximum PA (even 100%) occurred for winter cereal stubble and burnt crop stubble for MC and ML for any MIU. A great number of land use classifications were efficient whatever the classifier, some of them exhibiting a PA of over 70%. These results support the findings of Thomlinson *et al.* (1999) who reported that the criterion for a successful land cover categorization was not only 85% minimum overall, but also with no class with less than 70% accuracy. Recently, according to Yu *et al.* (2006), an overall classification accuracy surpassing 60% could be considered satisfactory when mapping complex vegetation classification with more than 13 alliances constructed by 52 vegetation land uses. Thus, although there is no standard estimation of accuracy, there is a reasonable consensus that a greater accuracy is necessary if the number of land use categories is low. A greater accuracy is also essential if thematic map results can help environmental policy and decision-making to address sustainable agricultural practices. Similarly, an important achievement in this research was the good results of PA in many of the classes studied. This was especially noticeable for winter cereal stubble and burnt crop stubble, which are two of the main agro-environmental measures for reducing erosion in E.U. They were the most accurately classified land uses. This, together with the discrimination of cover crops in olive orchards reported by Peña-Barragán *et al.* (2004), permits the undertaking of the three fundamental agro-environmental measures approved for winter cereals and olive groves, two of the main crops in Mediterranean dryland conditions.

For olive orchards, which was one of the land uses with the highest intraclass variability, consistent increases in PA and UA were obtained when comparing pixel- and object-based analyses. This is in agreement with the basic reason for using image segmentation due to the object-based analysis overcoming the problems of reduction in statistical separability between classes caused by the increase in intraclass spectral variability in traditional pixel-based classification approaches (Yu *et al.*, 2006). Conversely, for burnt crop stubble and winter cereal stubble, the increases in the PA for object- comparing to pixel-based analyses were not so outstanding probably because these land uses can be considered as being more homogeneous covers with a lesser intraclass spectral variability.

With regard to recommending the use of pixel or object-based analysis two considerations should be made: the improvement in accuracy obtained and the expertise requirements involved in the process. Considering the whole land use classification, object-based analysis and ML as the best classifier (Table 2), the Kc achieved a 1% improvement in performance relative to ML and pixel classification (Kc from 0.88 to 0.89 with the majority filter applied). However, the improvements were higher than 20% for object-based analysis and of the other classification methods. By other hand, when individual land uses were considered, for example, for burnt crop stubble, the omission errors of classifications based on objects were lower than those based on pixel ones. This indicates that, whereas improvements in accuracy of 1% for the general land use classification and ML method cannot really be considered as remarkable, for classifying crucial individual land uses involved in reception of the subsidy, the improvements in decreasing omission errors were in fact considerable. Therefore, to use one or other MIU in the classification will depend on the emphasis on achieving the maximum accuracy and the ratio cost/efficiency that we wish to obtain in our objectives. If we desire to produce a high accuracy map of a given land use that is ready to use for decision-making procedures by the EU or local administrations, *e.g.* classification of burnt crop stubble, then ML and object analysis would be highly recommended, although this approach requires more expertise. If we aim to create a crop inventory for all the land uses, then ML for pixel method would offer enough detailed vegetation classification and would be the best choice. Thus, a hybrid decision could be adopted: ML with pixel-based classification could be suggested for crop inventories and ML with object-based as MIU for decision-making and for follow-up of agrarian policy actions.

Our results indicate that early July, the timing for taking imagery for agro-environmental measure

classification, was optimum since in an image recorded before, for example, in May or June, winter cereal stubble and burnt crop stubble would not have been able to be classified. Peña-Barragán *et al*. (2004) studied different dates and also concluded that early July was the best moment for discriminating cover crops in olive orchards, the other most important agro-environmental measure. The QuickBird 8 bit image offered enough radiometric detail for the successfully identification and mapping of crops and their agro-environmental associated measures. However, 11 bit image could probably increase the overall accuracy of some of the classification methods due to its higher radiometric resolution.

CONCLUSIONS AND FUTURE WORK

The accuracies obtained noticeably reveal that the choice of different classifiers and MIU cause high variations of the performance for crops and their agro-environmental measures classification. Thus, a hybrid decision could be adopted: ML with pixel-based classification could be suggested for crop inventories and the ML with object-based parameters for decision-making for a follow-up of agrarian policy actions.

Future work could address the evaluation of pan-sharpened QuickBird imagery (from panchromatic and multispectral images) to test the improvements in accuracy of overall and individual land use classification. This could be particularly useful when the accuracy of the thematic map is extremely important because this map could be used as a tool to help the administrative follow-up to make the decision on Concede / Not to concede the subsidy.

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63