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Optimization of supervised classification procedure for irrigated crop discrimination using Landsat TM images

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RESUMEN

En este artículo se evalúan varios modos de clasificación supervisada con objeto de optimizar el proceso de clasificación y poder así agilizar y mejorar la estimación de superficies de cultivos. Para ello se han utilizado cuatro imágenes Landsat TM del regadío de Flumen (Huesca), dos de 1993 y dos de 1994, y se han ensayado doce clasificaciones supervisadas diferentes por año con firmas espectrales obtenidas de imágenes unitemporales y multitemporales para las ocupaciones de primavera y verano, aplicándose también tres formas diferentes de toma de áreas de entrenamiento (automática, semiautomática y manual).

La bondad de las clasificaciones se ha evaluado con varias medidas de exactitud. La clasificación multitemporal automática ha resultado la más idónea. Además se ha constatado la influencia de la fecha de las imágenes en la discriminación de cultivos, indicándose cuáles son las imágenes más adecuadas para su discriminación.

PALABRAS CLAVE: clasificación supervisada, exactitud, teledetección, cultivos.

ABSTRACT

In this article different supervised classifications modes were evaluated in order to optimize the classification procedure for ease and improve the crop hectarage estimations. Four Landsat TM images from the irrigated district of Flumen (Huesca, Spain), two dated from 1993 and another two from 1994, were used. Twelve supervised classifications for each year were applied using spectral signatures of spring and summer land cover, obtained from unitemporal and multitemporal images, with three different kinds of training area selection (automatic, semiautomatic, and manual).

After applying several accuracy indices, the automatic multitemporal classification was found to be the most sound. The influence of the image date on the crop classification was also studied, and this article shows, which images were the most suitable in crop discrimination.

KEY WORDS: supervised classification, accuracy, remote sensing, crops.

INTRODUCTION

Crop extent estimates in different areas of Aragón (Spain), based on supervised classification of Landsat 5 TM images, were obtained for years in the Centro de Investigación y Tecnología Agroalimentaria de Aragón (CITA). Classification and ground data were combined for crop hectarage estimation by the method of frame area sampling and regression estimator with satellite data (Casterad *et al*., 1992; Barbosa *et al*. 1996; Casterad, 1996).

The precision of the estimates obtained by the above mentioned method is conditioned by the classification quality, in addition to other factors, so that the interest is on optimizing the classification procedure. Among supervised and unsupervised classification methods, the supervised ones usually give the highest classification accuracy being the most suitable to our purposes because they tend to discriminate informational categories (Campbell, 1996). The maximum likelihood classifier, by far the most widespread among supervised classification methods, was used in this work.

Cover type, growth stage and phenology of crops, spectral bands used, training fields extraction type, satellite image date acquisition, use of multitemporal data, etc. are some factors that influence on the classification procedure. Too many tests are required in order to know the influence of these factors in the classification. The majority of works cannot tackle such tests using predetermined classification methodology. In Spain, Lobato and Moreiras (1991) analyzed different choices and variables (preselection of more representatives pixel, size of training pixels, number of bands used, multitmeporality, sectorization, clustering + classification, etc.) to be taken into account in the classification process.

Following in this way, Barbosa *et al*. (1996) compared crop hectarage estimates of the irrigated district of Flumen (Huesca, Spain) obtained by the method of frame area sampling and regression estimator with satellite data of four different supervised maximum likelihood classifications: (i) manual classification of a spring image from 20 May 1991; (ii) manual classification of a summer image from 24 August 1991; (iii) manual-multitemporal classification of both images; and (iv) automatic-multitemporal classification of both images. In results, for crop hectarage estimation using regression estimator with satellite data, the precision improvements produced for each crop are different depending on the used classification procedure. However, no classification showed to be better than the others in terms of global classification accuracy. Complementing studies will be required to ratify these results obtained by Barbosa *et al*. (1996) and to determine the best classification method to discriminate the main crops in different irrigated areas.

In the present work, unitemporal and multitemporal supervised maximum likelihood classifications, using three different kinds of training area selection (automatic, semiautomatic, and manual), were evaluated and compared for the 332 km^2 irrigated district of Flumen (Huesca, Spain) in 1993 and 1994. The influence of the image date on crop discrimination was also analyzed.

The irrigation district of Flumen is located in the middle Ebro Basin, (Aragón, north-eastern Spain). Basin and border irrigation is applied to plots typically size from 0.8 ha to 1 ha. However, groups of adjacent fields have often the same crop. The main crops in the area are alfalfa, maize, rice, sunflower and winter cereals (barley and wheat).

MATERIAL AND METHODS

Supervised classification

One spring and one summer Landsat 5 TM scene per year (6 March and 12 July in 1993, and 28 May and 29 June in 1994), corresponding to the study area, were individual and jointly classified using the maximum likelihood method described in ERDAS (1994). The pre-processing consisted of: (i) visualization and enhancement of the image, (ii) cutting of sub-scenes containing the study area, and (iii) radiometric and geometric corrections of these sub-scenes. Training fields were selected by manual, automatic and semiautomatic techniques from ground truth data (Figure 1), which were obtained from a systematic random sampling by blocks (Casterad, 1996). The sampling units were squares of 500 m of side.

In the manual selection, the analyst chooses the pixels to be used as training fields based on the available ground truth data. In automatic selection, the mixed pixels that are in the border of the plot-used (adjacent plots with the same used) were eliminated, and the remaining pixels were used for training. In semiautomatic selection, the signature's frequency histograms obtained in the automatic selection were displayed (band by band) and visually inspected by the analyst. When a particular signature is present a multi-peaked histogram, different homogenous spectral subclasses were created within this class, if there are sufficient number of training subclasses pixels. The correspondence of these peaks to some crop characteristics (development stage, kind of management, etc.) was analyzed, with the help of the RGB composite image and the ground data annotations.

Combining the three techniques of training area selection and the different images, twelve classifications per year were tested. Six ones were unitemporal classifications (three using the spring image, and three using the summer image); another three were multitemporal classifications (spring and summer images) using spectral signatures of spring land covers (land covers present in the spring images); and, finally, three ones were multitemporal classifications using spectral signatures of summer land covers (land covers present in the summer image).

Classification accuracy

Confusion matrices were used in classification accuracy assessment (Story and Congalton, 1986; Congalton, 1991). They were obtained from comparison between ground truth and classified data in the sampling units, once the border pixels were eliminated. The overall accuracy percentage (OA%) and the Kappa statistic (k) were calculated in each classification results. The OA is the simplest descriptive statistic derived from the confusion matrix and reports the overall proportion of correctly classified pixels in the sampling units.

$$OA = \frac{\sum_{i=1}^{n} X_{ii}}{\sum_{i=1}^{n}\sum_{j=1}^{n} X_{ij}} \times 100$$

where, n is the number of rows and columns in error matrix, X_{ii} are the diagonal entries or correctly classified pixels (observed number in row i column i) and X_{ij} is every element of the confusion matrix (number of observations in row i column j).

The k estimate can be obtained by the following formula (Bishop *et al.*, 1975; Hudson and Ramm, 1987):

$$= \frac{N\sum_{i=1}^{n} X_{ii} - \sum_{i=1}^{n} X_{i+}X_{+i}}{N^2 - \sum_{i=1}^{n} X_{i+}X_{+i}}$$

where, X_{i+} are the marginal total of row i, X_{+i} are the marginal total of column i, and N is the number total of pixels or observations.

Unlike OA, Kappa considers all the elements of the confusion matrix providing a measure of agreement that is adjusted for chance agreement (Campbell, 1996).

Both measures indicate the overall classification accuracy but they do not reflect what happens with every specific class. Therefore, the following indices were computed for every class:

(i) The User's accuracy (Ua) or the probability that a classified pixel actually represents that category on the ground, and the producer's accuracy (Pa) or the probability of a reference pixel (ground category) being correctly classified (Congalton, 1991).

$$Ua = \frac{X_{ii}}{X_{+i}} \times 100$$

$$Pa = \frac{X_{ii}}{X_{i+}} \times 100$$

(ii) The Hellden (HI) and Short (SI) indices that report the relationship between the correctly classified pixels and the marginals of the confusion matrix (Rosenfield and Fitzpatrick-Lins, 1986)

$$HI = \frac{2X_{ii}}{X_{i+} + X_{+i}} \times 100$$

$$SI = \frac{X_{ii}}{X_{i+} + X_{+i} - X_{ii}} \times 100$$

(iii) The Kappa statistic which estimate is (Bishop *et al.*, 1975; Rosenfield and Fitzpatrick-Lins, 1986)

$$\hat{\kappa}_i = \frac{N X_{ii} - X_{i+}X_{+i}}{N X_{i+} - X_{i+}X_{+i}}$$

Fitzgerald and Lees (1994) have suggested three ranges of agreement for the Kappa statistic, being adopted in this article. These were: bad ($\kappa<0.4$), good ($0.4\leq\kappa\geq0.75$) and excellent classification ($\kappa>0.75$).

Comparisons between classifications were made from a hypothesis test that allows determining whether two confusion matrices are significantly different (H_0: $\kappa_1=\kappa_2$). The test is:

$$Z = \frac{\kappa_1 - \kappa_2}{\sqrt{V\kappa_1 + V\kappa_2}}$$

where, Z is the standard normal deviation (Congalton and Mead, 1983; Rosenfield and Fitzpatrick-Lins, 1986), $\hat{\kappa}$ is the estimator of Kappa for every matrix to be compared, and V $\hat{\kappa}$ is the variance of Kappa as defined by Bishop *et al*. (1975) and Hudson and Ramm (1987).

The Z value and the normal distribution table determine whether to accept or refuse the null hypothesis, depending on the chosen significance level.

RESULTS AND DISCUSSION

The classes discriminated in each classification were: alfalfa+forage, rice, winter cereal sunflower, maize, pines, uncropped and other classes (composed by unclassified pixels). The only exception is the unitemporal classification of 6 March 1993 image. This date is too early for rice discrimination.

Global classification accuracy

Table 1 presents two measures of global classification accuracy, overall accuracy (OA) and estimated Kappa ($\hat{\kappa}$). The variance of $\hat{\kappa}$ is also included. In general, multitemporal classifications were more accurate than unitemporal, presenting greater values for OA and $\hat{\kappa}$, and smaller values for V $\hat{\kappa}$.

When the comparisons among the classifications of the two years were analyzed, those from 1994 were found to be better than those from 1993 (greater values for OA and $\hat{\kappa}$). That means that, image dates in 1994 were found more suitable than those from 1993. At any rate, the accuracy difference between one and another year was greater when comparing spring images than summer images. This can be explained by the difference of date between the two spring images (6 March and 28 May). At these particular dates the development stage of the crops is completely different.

In general, manual training area selection provided the smallest values for OA and , while semiautomatic selection provided the greatest values. Nevertheless, differences between semiautomatic and automatic selection were small.

	Unitemporal			Mulitemporal		
	OA%	$\hat{\kappa} \times 100$	$V\hat{\kappa} \times 10^{-6}$	OA%	$\hat{\kappa} \times 100$	$V\hat{\kappa} \times 10^{-6}$
1993						
Automatic						
Spring land covers	65.14	44.59	49.45	71.70	61.18	37.47
Summer land covers	68.62	54.43	40.14	72.53	61.56	35.77
Semiautomatic						
Spring land covers	65.69	44.84	50.21	73.35	63.69	35.79
Summer land covers	69.43	55.51	39.73	73.44	62.83	35.07
Manual						
Spring land covers	63.57	43.31	48.54	64.49	53.72	36.53
Summer land covers	65.52	52.83	37.04	63.23	51.95	34.55
1994						
Automatic						
Spring land covers	73.83	64.53	37.58	77.09	69.62	32.70
Summer land covers	69.54	56.32	39.65	75.53	66.38	34.27
Semiautomatic						
Spring land covers	73.32	63.67	38.25	77.35	70.03	32.13
Summer land covers	70.20	57.26	39.60	76.62	68.06	33.24
Manual						
Spring land covers	70.26	61.22	36.48	71.06	63.13	33.35
Summer land covers	63.05	50.98	36.87	68.18	58.72	34.33

Tabla 1. Overall accuracy (OA), estimated kappa ($\hat{\kappa}$) and variance of kappa ($V\hat{\kappa}$) for different supervised classifications in the irrigated district of Flumen (Huesca).

Table 2 shows Z values in the significant difference test between classifications. Z values were smaller than 7.5 in the comparisons among unitemporal classifications. No differences caused by training area selection techniques were found in seven of the twelve comparisons (at the 95 percent confidence level). In the comparisons among multitemporal classifications, only two ones were not significantly different, and Z values for eight comparisons were greater than 7.5.

Comparison among unitemporal classifications and comparison among multitemporal classifications showed the greatest Z values for the cases where the manual classification was implied. In general, no significant differences, at the 95 percent confidence level, were observed among semiautomatic and automatic training area selection methods, while the manual training selection method was significantly different from the automatic and the semiautomatic method. In contrary, on unitemporal-multitemporal comparisons, the smallest Z values were observed in the pairs where the manual classification was implied. In the classifications of 1994, the automatic-unitemporal and the manual-multitemporal for spring land covers, and the semiautomatic-unitemporal and the manual-multitemporal, both spring and summer land covers, were not significantly different.

The automatic-multitemporal classification appears be the most suitable for the global discrimination of classes. The semiautomatic-multitemporal method provided slightly better results than the automatic method, but, in general, it was not significantly different from the automatic-multitemporal method (Table 2). In addition, the semiautomatic-multitemporal method was much more time-consuming and tedious.

	1993		1994	
	Spring land covers	Summer land covers	Spring land covers	Summer land covers
Unitemporal-Unitemporal				
Automatic-Semiautomatic	0.25 ns	1.21 ns	0.99 ns	1.06 ns
Automatic-Manual	1.29 ns	1.82 ns	3.94 **	6.10 **
Semiautomatic-Manual	1.54 ns	3.06 **	2.83 **	7.18 **
Multitemporal-Multitemporal				
Automatic-Semiautomatic	2.93 **	1.51 ns	0.51 ns	2.04 *
Automatic-Manual	8.67 **	11.46 **	7.99 **	9.25 **
Semiautomatic-Manual	11.72 **	13.04 **	8.53 **	11.36 **
Unitemporal-Multitemporal				
Automatic-Automatic	17.79 **	8.18 **	6.07 **	11.70 **
Automatic-Semiautomatic	20.69 **	9.69 **	6.59 **	13.75 **
Automatic-Manual	9.85 **	2.87 **	1.66 ns	2.79 **
Semiautomatic-Automatic	17.45 **	6.96 **	7.06 **	10.61 **
Semiautomatic-Semiautomatic	20.33 **	8.46 **	7.58 **	12.65 **
Semiautomatic-Manual	9.53 **	4.13 **	0.64 ns	1.79 ns
Manual-Automatic	19.27 **	10.23 **	10.10 **	18.26 **
Manual-Semiautomatic	22.19 **	11.78 **	10.64 **	20.40 **
Manual-Manual	11.29 **	1.04 ns	2.29 *	9.17 **

ns: not significant different.
**: significantly different at 95 percent confidence level.
*: significantly different at 99 percent confidence level.

Tabla 2. Comparison between supervised classifications by Z test of kappa statistic in the irrigated district of Flumen (Huesca).

Specific class accuracy

Comparison between different accuracy measures by class showed that the SI obtained the lowest values tending to underestimate the classification accuracy, while the percent correct (user's accuracy) tended to overestimate it. The HI reflects the user's and the producer's accuracy as a whole, being the harmonic mean of them. The classes with HI > $\hat{\kappa} \times 100$ are predominant. The results agree with those of Rosenfield and Fitzpatrick-Lins (1986). At any rate, these authors show that the applied coefficients depend on relative value and location of pixel frequency in the confusion matrix. HI and $\hat{\kappa}$ were considered, among the tested accuracy measures, the most representative and suitable way to express and analyze the class accuracy.

In general, multitemporal classifications showed higher accuracy than unitemporal, although in some cases, as like rice and uncropped, the difference observed was small. Also, semiautomatic training area gives the best results, although minimum differences were found with the automatic selection. Automatic-multitemporal classification was confirmed as the most suitable for crop hectarage in the irrigated district of Flumen (Huesca). HI and $\hat{\kappa}\times 100$ obtained in the automatic-multitemporal classifications are presented in Table 3.

Classes	Unitemporal				Multitemporal			
	1993		1994		1993		1994	
	HI (%)	$\hat{\kappa}\times 100$	HI (%)	$\hat{\kappa}\times 100$	HI (%)	$\hat{\kappa}\times 100$	HI (%)	$\hat{\kappa}\times 100$
Alfalfa+forage								
Spring land cover	52.09	45.51 g	77.63	83.46 e	65.02	65.77 g	80.06	83.83 e
Summer land cover	66.64	56.66 g	71.79	63.41 g	72.17	69.21 g	81.28	84.01 e
Rice								
Spring land cover			93.16	96.55 e	86.64	84.98 e	92.52	97.82 e
Summer land cover	83.65	79.78 e	86.28	81.79 e	85.93	83.99 e	92.68	98.44 e
Winter cereal								
Spring land cover	58.43	52.12 g	68.27	56.68 g	75.76	68.96 g	79.34	73.79 g
Sunflower								
Summer land cover	41.99	45.41 g	14.88	25.77 b	59.26	57.89 g	48.58	50.47 g
Maize								
Summer land cover	0.00	-	19.24	28.33 b	37.35	34.30 b	53.11	53.98 g
Pines								
Spring land cover	52.34	79.57 e	21.34	66.74 g	72.22	79.00 e	70.86	69.68 g
Summer land cover	48.21	63.58 g	43.70	53.11 g	69.63	69.65 g	70.05	71.50 g
Uncropped								
Spring land cover	76.76	44.94 g	75.43	54.87 g	74.02	54.28 g	77.05	63.50 g
Summer land cover	79.05	52.86 g	79.96	52.59 g	81.08	65.12 g	83.17	66.41 g
Other classes								
Spring land cover	5.00	1.84 b	9.17	5.20 b	16.80	9.52 b	10.17	4.62 b
Summer land cover	8.53	4.59 b	15.51	10.20 b	8.02	3.62 b	11.60	5.43 b

e: excellent; g: good; b: bad

Tabla 3. Hellden INdex (HI) and Kappa ($\hat{\kappa}$) for the main land cover in automatic supervised classifications of the irrigated district of Flumen (Huesca).

These results disagree with those presented by Barbosa *et al*. (1996), where manual-multitemporal classification was found, in general, to be the best. Probably, this disagreement results from to the criterion adopted by the analyst on the selection of the training areas.

The highest values of HI and $\hat{\kappa}$ for alfalfa+forage were obtained, both in 1993 and 1994, in the summer (land cover) multitemporal classification, being the best-classified crop after rice. The spring image of 1993 was too early to discriminate alfalfa+forage, and confusions with winter cereal were observed (at this particular time, beginning of March, alfalfa+forage and winter cereal presented a similar development stage). Also confusion with uncropped was observed at the areas where the crop was poorly developed. However, an image from this date can be useful if other images are not available. Barbosa *et al.* (1996) noted that the cutting date conditions the image selection to discriminate this crop. In this study results confirm this, observing a substantial variation of accuracy between dates.

Rice was the best-discriminated crop, presenting HI and $\hat{\kappa}\times 100$ values greater than 75 percent for all tested classifications, except for $\hat{\kappa}$ in summer (land cover) manual-unitemporal classification in 1993 (67 percent). These excellent results are explained because rice is inundated during a long time of its cycle causing its spectral response to be very different from the rest of the crops (basically the rice spectral response is a water spectral response). Discrimination becomes more difficult as the rice grows and gradually covers the water, and the spectral response becomes more similar to other crops. These results obtained for rice are in agreement with Barbosa *et al.* (1996). The greatest values of HI and $\hat{\kappa} \times 100$ in the unitemporal classifications were obtained with the image of 28 May (spring 1994), following of 29 June (summer 1994) and presenting the smallest values in 12 July (summer 1993). Very good rice discrimination will be obtained just with a unique spring image.

Behind alfalfa+forage and rice, winter cereal was the best-discriminated crop. Good accuracies were obtained in multitemporal classifications: HI bigger than 75 percent and $\hat{\kappa} \times 100$ around 70 percent. However, worse results were observed in unitemporal classification due to unfavourable image acquisition dates. As occurred with alfalfa+forage, the image from March 1993 was too early and winter cereal was scarcely developed, being confused with alfalfa+forage and uncropped. However, this image showed that an acceptable discrimination could be possible with an early image in default of a better one.

Results obtained for winter cereal with the image from 28 May 1994 (unitemporal and spring land covers in all the Tables) were good, in spite of being a little late date in the season, and were similar to those obtained by Barbosa *et al*. (1996) who used an image from 20 May 1991. We also assayed winter cereal discrimination with the image of 29 June 1994. At this particular time, winter cereal is about to harvest, even some plots have been already harvested, being spectrally confused with uncropped. A more detailed analysis from unitemporal classifications, where barley and wheat were separately discriminated instead of being grouped as winter cereal, showed that barley was the most confused with the uncropped category (about 75 percent in automatic and semiautomatic selection, and 56 percent in manual), while this confusion was smaller for wheat (40-45 percent and 28 percent, respectively). At this date, the differences in the cycle of the two species were noted: barley ripens before wheat does.

The same analysis from the 28 May 1994 image noted that the confusion between barley and the uncropped category was 53 percent in automatic selection, 46 percent in semiautomatic, and 21 percent in manual. The confusion between wheat and the uncropped category was 19 percent in automatic and semiautomatic and 5 percent in manual selection. The utility of an appropriated late image to discriminate barley from wheat was corroborated. Moreover, manual training area selection was the most suitable for this purpose.

Sunflower and maize were the crops that presented the worst results with HI and $\hat{\kappa} \times 100$ less than 60 percent (Table 3). An acceptable discrimination for both crops was not possible in the unitemporal classifications. Due to an extensive sowing period (from the end of April to the beginning of June), sunflower presents a very heterogeneous spectral response; in addition, in 1993 no care was applied in many plots because the main interest on sunflower was to obtain the subvention conceded by the European Union for sunflower sowing. The worst results were obtained with the unitemporal classification of 1994. The date of this image was too early to discriminate sunflower, because the crop is not yet developed. Unitemporal classification from 1993 was better than that from 1994, due to a more adequate date and a main availability of training areas caused by a larger representation of this crop in the irrigated district. The results obtained by Barbosa *et al*. (1996) confirm the difficulties to discriminate this crop, although a visual analysis over the classification of the image from 12 July 1993 showed that plots with a good development were well discriminated.

The poor representation of maize in 1993 (just a little more than 2 percent of the sample) does not allow obtaining acceptable results in any of the tested classifications. Even in the automatic and semiautomatic-unitemporal classification no selected training areas of maize were classified. In 1994, multitemporal classification allowed its discrimination in spite of the early dates of the images, but poor results were obtained again with the unitemporal classification. Barbosa *et al*. (1996) using an image of a later date and a multitemporal classification, obtained slightly better results for maize classification than those obtained for 1994. It would be interesting, both for sunflower and maize, to test an image from the end of July to the middle of August, time of their maximum development.

When small acreage was taken as training areas in a unitemporal classification, as in the maize case, the manual selection provided more user's and producer's accuracy and, then, better HI, although $\hat{\kappa} \times 100$ was worse.

Pine class corresponds to low-density woods of *Pinus halepensis*, Mill. located on slopes or in small recreation areas. A good discrimination was achieved by multitemporal classifications, whose accuracies are similar to the winter cereal. Good results were obtained by the unitemporal classification of the spring image of 1993, because pine is a perennial species that, at which time, points up from uncropped areas and shortly developed crops. HI and $\hat{\kappa} \times 100$ were substantially different in unitemporal classifications.

This difference was also observed for the uncropped category, although in this case HI was bigger than $\hat{\kappa} \times 100$ in all the classifications. The uncropped areas were well discriminated and the accuracy indices were similar for all classifications. Results for summer classifications were slightly better.

The applied classification procedure has established a miscellaneous class named *other classes*. This class is formed by the unclassified pixels that correspond to pixels with the least probability of belonging to a class. This probability was established by means a threshold. This group obviously presented the worse accuracy's values: HI and $\hat{\kappa} \times 100$ smaller than 17 percent and 10, respectively.

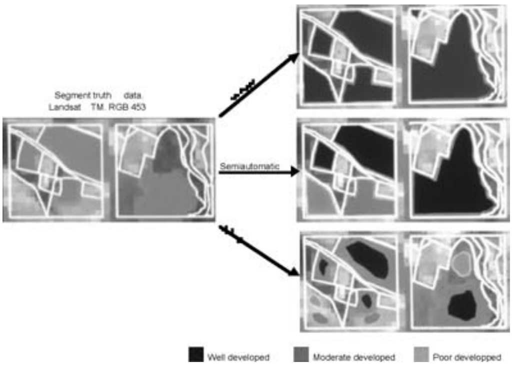

***Figura 1.** Example of results of three selection training areas by three methods (automatic, semiautomatic and manual) for a couple of ground truth area samples.

CONCLUSIONS

The multitemporal classification with automatic training area techniques has been found the most suitable to obtain crop hectares in the irrigation district of Flumen (Huesca, NE Spain).

In general, the semiautomatic training area techniques provided more accurate classifications than the automatic technique, although no significance differences have been found. The manual training area technique was worse, showing significance differences with the other two procedures; however, the manual classification is influenced by the analyst subjectivity on taking training areas, so that the extrapolation of the results obtained for manual classification is limited.

In 1994, imagery dates were more suitable than in 1993, as shown by the higher accuracy of the classifications in 1994.

In this irrigation district, results in discriminating all the classes were similar to those obtained in our previous studies.

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BIBLIOGRAPHY

BARBOSA, P.M., CASTERAD, M A., and HERRERO, J. 1996. Performance of several Landsat TM images classification methods for crop extent estimates in an irrigation district. *International Journal of Remote Sensing*. 17 (18): 3665-3674.

BISHOP, Y.M.M., FIENBERG, S.E., and HOLLAND, P.W. 1975. *Discrete multivariate analysis. Theory and practice*. The Massachusetts Institute of Technology, 552 pp.

CAMPBELL, J.B. 1996. *Introduction to remote sensing*, 2nd Edition. London: Taylor & Francis. 622 pp.

CASTERAD, M A. 1996. Cuestiones de diseño y ejecución en la estimación de superficies de cultivos en pequeñas demarcaciones. *Investigación Agraria. Producción y Protección Vegetales*. 11 (2): 255-279.

CASTERAD, M.A., ARÁN, M., HERRERO, J., and ALBIZUA, L. 1992. Estimación de superficies de cultivos en pequeños regadíos mediante encuesta de terreno y datos de satélite. *Agronomie*. 12: 661-668.

CONGALTON, R.G. 1991. A review of assessing the accuracy of classifications of remotely sensed data. *Remote Sensing of Environment.* 37:35-46.

CONGALTON, R.G., and MEAD, R.A. 1983. A quantitative method to test for consistency and correctness in photointerpretation. *Photogrammetric Engineering and Remote Sensing.* 49(1):69-74.

ERDAS. 1994. *ERDAS field guide*, Version 8.1. (Atlanta: ERDAS Inc.). 394 pp.

FITZGERALD, R.W., and LEES, B.G. 1994. Assessing the classification accuracy of multisource remote sensing data. *Remote Sensing of Environment*. 47:362-368.

HUDSON, W.D., and RAMM, C.W. 1987. Correct formulation of Kappa coefficient agreement. *Photogrammetric Engineering and Remote Sensing*. 53 (4):421-422.

LOBATO, A., y MOREIRAS, J.M. 1991. Análisis metodológico y de resultados de diferentes alternativas de clasificación de imágenes de satélite para la obtención de estadísticas agrarias. IV Reunión Científica de la Asociación Española de Teledetección, Sevilla, pp. 287-294.

ROSENFIELD, G.H., and FITZPATRICK-LINS, K. 1986. A coefficient of agreement as a measure of thematic classification accuracy. *Photogrammetric Engineering and Remote Sensing.* 52 (2):223-227.

STORY, M., and CONGALTON, R.G. 1986. Accuracy assessment: a user's perspective. *Photogrammetric Engineering and Remote Sensing*. 52 (3):397-399.

Todas las figuras precedidas de asterisco se incluyen en el cuadernillo anexo de color