

Forest cover mapping in Central Spain with IRS-WiFS images and multi-extent textual-contextual measures

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Abstract. An area of 95 200 km² in central Spain was mapped using IRS-WiFS data to test the potential use of this imagery for regional cover type mapping. In addition to the original WiFS red and NIR spectral bands, textural-contextual images were computed as means and variances of the NDVI and the NIR and red bands over windows of different sizes (3 × 3 to 50 × 50 pixels) and included in the analysis. An iterative classification of the imagery was performed using a maximum likelihood classifier with feature selection by spectral separability indices. Results obtained in this study show that IRS-WiFS is a valuable source of information for forest cover mapping at regional scales. Semi-natural areas (comprising forests, shrubs and grasslands) and forests were classified with 93% and 83% mean accuracy, respectively. The classification accuracy of most cover types increased when textural-contextual information computed over large windows (larger than those reported in the literature) were used for classification in combination with spectral data.

1. Introduction

The IRS-1C Wide Field Sensor (WiFS) is a relatively new sensor that has provided data since 1996. WiFS has a swath width of 810 km, ground spatial resolution of 188 m and two spectral bands in the range of the red (R, 620–680 μm) and the near-infrared (NIR, 770–860 μm) wavelengths (NRSA 1995). These spatial and spectral resolutions make WiFS a potentially useful data source for regional forest cover analyses.

Previous remote sensing studies used contextual and textural information to increase image classification accuracy. Accuracy was found to increase when low pass filter images, which reduce image noise and take into account the characteristics of the neighbourhood pixels (context), were combined with non-filtered spectral data (Atkinson *et al.* 1985) for image classification. Contextual information derived using majority filters, probabilistic label relaxation, and other similar techniques (Richards 1993, Kartikeyan *et al.* 1994, Kwang 1996) have also been used for post-classification refinement. Small windows (3 by 3 pixels) were used to extract the contextual

information. Textural measures, such as variances, have also been used in the classification of remotely sensed data to increase the classification accuracy (Kushwaha *et al.* 1994, San Miguel-Ayanz and Biging 1996, Chica-Olmo and Abarca-Hernández 2000). Small windows, up to a maximum of 9 pixels by 9 pixels, were used to compute texture variables (Hodgson 1998). However, as noted by Hodgson (1998), human interpreters of satellite sensor images gain useful information for the classification by analysing the pattern in much larger windows than those commonly considered by digital classifiers. In fact, human interpreters may use a hierarchy of windows of different extents to extract the useful information for the classification (Hodgson 1998).

This study shows the potential of using IRS-WiFS imagery for cover type mapping at the regional scale. It also demonstrates that the inclusion of textural and contextual information extracted from windows of different sizes (including much larger sizes than those commonly used for satellite sensor imagery classification) along with per-pixel spectral data results in increased image classification accuracy.

2. Methods

2.1. Data

An IRS-1C-WiFS image acquired on 9 September 1998 was geometrically rectified to the CORINE European Land Cover Database (CEC 1993) with sub-pixel accuracy. The 95200 km² study area selected on the image comprised both typically Mediterranean vegetation types (e.g. *Quercus ilex*, *Pinus halepensis*) and others that are characteristic of more humid areas (e.g. *Quercus pyrenaica*).

Independent classification training and accuracy assessment polygons were selected on CORINE, which included non-natural classes (irrigated land, olive groves, vineyards, urban areas, etc.) to ensure the data normality required by the maximum likelihood classifier (MLC). CORINE does not differentiate between evergreen and deciduous broad-leaved forests, but the latter presented a much greater NIR response in the analysed image, which allowed defining two independent cover classes with the aid of the Natural Vegetation Map of Europe (NVME) (CEC 1987). The heterogeneous class 'mixed forest', composed both of coniferous and broad-leaved species, was not considered as a separate forest type, and was merged with the other

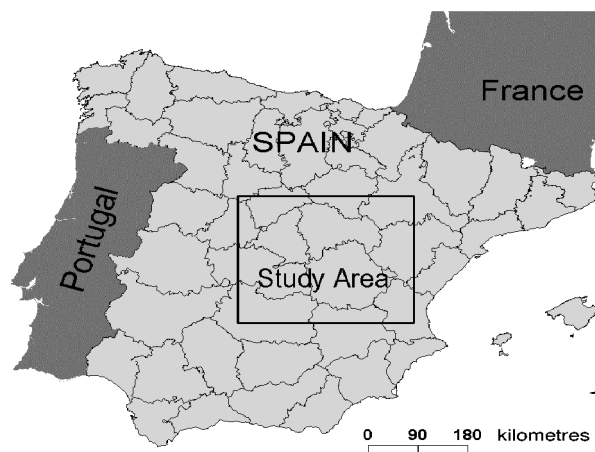


Figure 1. Location of the study area, delimited by the square on the map of Spain.

forest classes. The two CORINE shrub classes ('sclerophyllous vegetation' and 'transitional woodland and shrub') were merged in a unique class.

2.2. Derivation of new images

A new set of textural-contextual images was generated and included in the analysis. The images were computed as means and variances of the NDVI and the R and NIR bands in windows of 3×3 , 7×7 , 15×15 , 20×20 , 30×30 , 40×40 and 50×50 pixels to total 42 new images. The mean or variance of the spectral values of all the pixels in the window was computed and assigned to the central pixel. To make the classification feature selection process computationally affordable, the 42 textural-contextual images were reduced to their 10 first principal components, which accounted for more than 99% of the variance of this new information.

Deciduous broad-leaved forests and irrigated agricultural areas were not spectrally separable with the original WiFS bands, as both are characterised by a high NIR and relatively low red radiance (figure 2). However, the use of textural-contextual information permits the separation of these classes. Irrigated lands are usually located next to other non irrigated agricultural areas with high red radiance, while deciduous forests are located on natural surroundings, typically with fairly low

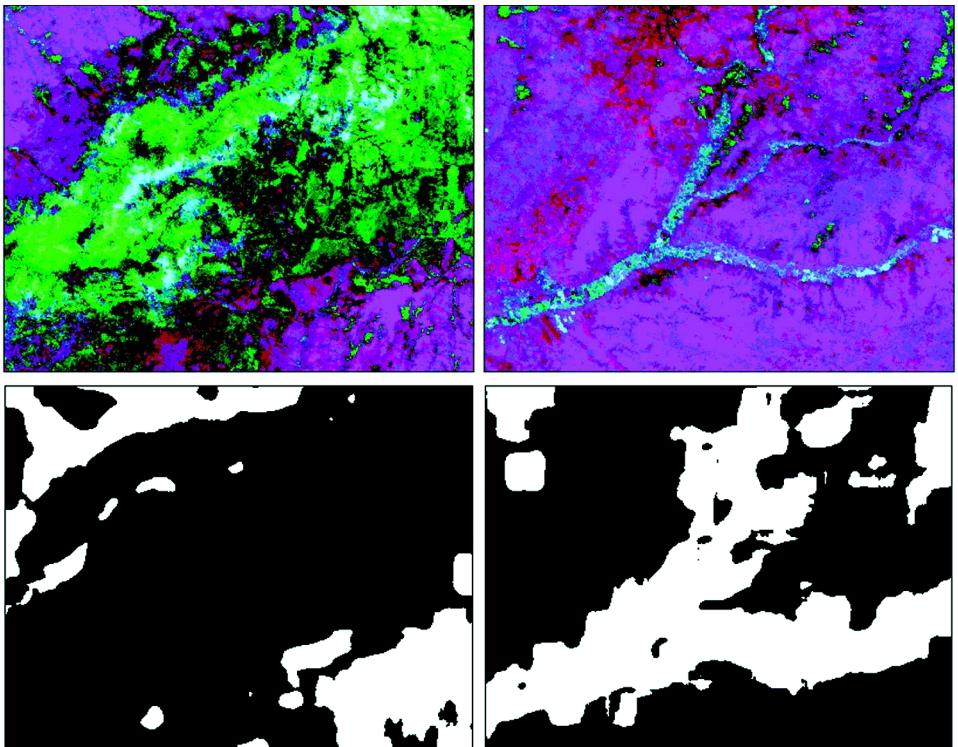


Figure 2. Two zones of the study area presenting deciduous broad-leaved forest (left) and irrigated agricultural land (right). The upper images (400 by 311 pixels) are colour composites with the red and NIR bands and the NDVI displayed respectively as the RGB components, where both cover types present a blue-cyan colour. Below them, and for the same zones, are shown in white the areas with a high variance in the red band in 30 pixel \times 30 pixel windows.

red radiance. The variance of the red band computed over a large extent (a 30×30 pixel window) captures this information (figure 2) and enables one to appropriately discriminate these spectrally similar cover types on the basis of their degree of contrast with neighbourhood cover types.

In addition to the two original red and NIR WiFS bands and the textural-contextual information, also the NDVI, the NIR/R ratio, and the first principal component of the WiFS bands were included in the analysis. These have been used by some authors to increase cover type classification accuracy (San Miguel-Ayanz and Biging 1996). Signatures corresponding to all these images were extracted from the training polygons selected on CORINE.

2.3. Classification

An iterative classification method based on the MLC was applied in this study. In this approach, one cover type is classified in each iteration, allowing the selection of a different number and set of features for the classification of each of the remaining unclassified cover types. The process results in an increase in classification accuracy when compared to that obtained by single step classifiers (San Miguel-Ayanz and Biging 1996). The Transformed Divergence, the Jeffries-Matusita, and the weighted versions of these spectral separability indices, which include class prior probabilities, were used to select the features that best classified each of the forest classes (Richards 1993). Classifications with the set of features that presented the best minimum and mean separability provided by each of these indices were performed. The set that provided the highest accuracy for each of the cover types was selected. The number of features was varied from 2 to the number in which a significant decrease in classification accuracy was reported. The cover type that presented the highest accuracy was classified and masked, so that the iterative classification method would continue with the remaining unclassified portion of the image. The first step was the classification of non-natural areas, in which the NIR and red bands were used. Then the iterative classification proceeded with the forest and semi-natural cover types. Only one of the non-natural classes (irrigated agricultural areas) was classified using textural-contextual information, since it results in a great reduction of the confusion between that class and deciduous broad-leaved forests, as described earlier (figure 2).

3. Results and conclusion

Accuracy analysis was performed through the comparison of the classified image with a reference data set obtained from the intersection of CORINE and the NVME. Neither CORINE nor NVME can be considered as ground truth data, since they are the result of two different mapping procedures, one mainly based on remote sensing (CORINE) and the second based on ground sampling techniques. No rigorous accuracy assessment of either data set is available. However, they constitute the only European reference maps for comparison with an eventual regional classification using WiFS imagery. The classification accuracy results are presented in table 1. These include also the accuracy of a classical single-step classification with a MLC using only the per-pixel spectral information of the two original WiFS bands. Significant increases in classification accuracy were obtained for all the classes when including textural-contextual information in the classification (except shrubs). Mean accuracy (mean of producer and user accuracy) increased noticeably for evergreen (14%) and deciduous broad-leaved (35%) forests. Confusion of this latter class with irrigated agricultural lands was diminished (table 2) by including large window-size

Table 1. Accuracy assessment for the iterative classification (columns 2, 3) and the single step classification (columns 3, 4). Producer accuracy is the percentage of reference areas of a given type classified correctly, while user accuracy is the percent of correctly classified areas within those labelled in a certain cover type by the classifier.

	Textural-contextual iterative classification		R and NIR single step classification		Mean accuracy increase (5)
	User accuracy (%)	Producer accuracy (%)	User accuracy (%)	Producer accuracy (%)	
Deciduous broad-leaved forest (DBF)	91.87	98.48	46.02	74.68	+ 34.83
Evergreen broad-leaved forest (EBF)	49.21	57.18	50.00	27.87	+ 14.26
Coniferous forest (CF)	54.42	75.93	42.84	77.73	+ 4.89
Shrubs (SH)	67.14	48.20	66.55	55.06	- 3.14
Natural grassland (NG)	56.94	45.18	32.77	45.99	+ 11.68
Water bodies (WB)	100	99.64	100	98.20	+ 0.72
Non natural areas (NN)	94.50	92.16	95.15	86.53	+ 2.49

Table 2. Confusion matrix for the iterative classification of WiFS data. Main diagonal elements are percentage of the reference data correctly labelled by the classifier for each cover type (producer accuracy). See table 1 for the description of class acronyms.

Classification	Reference data (%)						
	DBF	EBF	CF	SH	NG	WB	NN
DBF	98.48	0.82	0.36	0	0	0	0
EBF	0	57.18	16.12	20.61	1.46	0	0.70
CF	1.01	34.45	75.93	18.19	8.01	0	0.46
SH	0	4.77	7.43	48.20	36.70	0	4.13
NG	0	0	0	3.24	45.18	0	2.55
WB	0	0	0	0	0	99.64	0
NN	0.51	2.78	0.16	9.76	8.65	0.36	92.16

contextual information in the classification (figure 2). Shrubs and natural grasslands were confused with several other forest cover classes and particularly among themselves (table 2). The overall map classification accuracy was 72%. If the three types of forests are merged in a single forest class 83% accuracy is achieved.

These results show that WiFS is a valuable source of information for forest cover mapping and land stratification for forest inventory at the regional scale. In addition, the multi-extent textural-contextual information helped in discriminating spectrally similar classes, especially when computed over larger windows than those previously used in satellite sensor image classification.

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