Classifying Irrigated Crops as Affected by Phenological Stage Using Discriminant Analysis and Neural Networks

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ABSTRACT. In Spain, water for agricultural use represents about 85% of the total water demand, and irrigated crop production constitutes a major contribution to the country's economy. Field studies were conducted to evaluate the potential of multispectral reflectance and seven vegetation indices in the visible and near-infrared spectral range for discriminating and classifying bare soil and several horticultural irrigated crops at different dates. This is the first step of a broader project with the overall goal of using satellite imagery with high spatial and multispectral resolutions for mapping irrigated crops to improve agricultural water use. On-ground reflectance data of bare soil and annual herbaceous crops [garlic (*Allium sativum*), onion (*Allium cepa*), sunflower (*Helianthus annuus*), bean (*Vicia faba*), maize (*Zea mays*), potato (*Solanum tuberosum*), winter wheat (*Triticum aestivum*), melon (*Cucumis melo*), watermelon (*Citrullus lanatus*), and cotton (*Gossypium hirsutum*)], perennial herbaceous crops [alfalfa (*Medicago sativa*) and asparagus (*Asparagus officinalis*)], deciduous trees [plum (*Prunus* spp.)], and non-deciduous trees [citrus (*Citrus* spp.) and olive (*Olea europaea*)] were collected using a handheld field spectroradiometer in spring, early summer, and late summer. Three classification methods were applied to discriminate differences in reflectance between the different crops and bare soil: stepwise discriminant analysis, and two artificial neural networks: multilayer perceptron (MLP) and radial basis function. On any of the sampling dates, the highest degree of accuracy was achieved with the MLP neural network, showing 89.8%, 91.1%, and 96.4% correct classification in spring, early summer, and late summer, respectively. The classification matrix from the MLP model using cross-validation showed that most crops discriminated in spring and late summer were 100% classifiable. For future works, we would recommend acquiring two multispectral satellite images taken in spring and late summer for monitoring and mapping these irrigated crops, thus avoiding costly field surveys.

Crop irrigation is the principal water use in many countries and regions of the world (Shiklomanov, 2000). In Europe, agriculture is a significant consumer of water resources, accounting for around 30% of total water use. In Spain, water for agricultural use represents about 85% of the total water demand, and irrigated crop production constitutes a major proportion of the country's economy (Montesinos and Bea, 2008). Strategic management of crop irrigation has relevant agro-environmental repercussions as the constantly rising demand and excessive use of irrigated water in Mediterranean countries has deteriorated groundwater resources by depleting aquifers and accelerating saltwater intrusion. For this reason, a variety of European policies, especially the Water Framework Directive and the Common Agricultural Policy, have been created to regulate the supply of water to agriculture and to promote the employment of sustainable agricultural practices to ensure environmental safeguards and future yields (Alexandridis et al., 2008). To encourage the sustainable use of water resources, it is essential to develop advanced and accurate tools to classify and monitor irrigated crops and to estimate the surface occupied by each irrigated crop, each of which usually has different water requirements (Martínez and Calera, 2001).

The continuously changing character of agricultural zones at various spatial and temporal scales in response to management decisions, agricultural policies, prices, irrigation water availability, and environmental factors among others makes remote sensing technology a helpful tool for updated land-cover information and assessing and monitoring vegetation changes (Martínez-Casasnovas et al., 2005). Remotely sensed data can significantly improve reliability compared with ground visits. The basis of discriminating crops using remote sensing is that the spectral response of a plant species at the canopy is unique and known as a spectral signature. This is based on the behavior of reflected electromagnetic radiation according to external factors of every species and is usually expressed as reflectance. A defining characteristic of the spectral signature is that it varies according to sampling date or phenological stage, and it can be measured by on-ground or remote sensors. In fact, plant species have been discriminated by exploiting reflectance differences based on their canopy structure (Brown et al., 1994; Jurado-Expósito et al., 2003) or distinctive phenological stages (Brown and Noble, 2005; Girma et al., 2005; Kavdir, 2004; Lass and Callihan, 1997; Peña-Barragán et al., 2006). Mapping crops using remote sensing data may be particularly useful for applications such as land management or irrigation monitoring (Bastiaanssen and Bos, 1999), and deciphering crop water requirements (Alexandridis et al., 2008). Several authors have reported that the majority of studies to discriminate or inventory irrigated crops have involved discrete broadband remote sensing (multispectral sensors) (Bastiaanssen et al., 2000; Clarke and

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Moran, 1995; Trout et al., 2008). One of the main characteristics of Mediterranean horticultural irrigated areas is the spatial fragmentation in terms of crop diversity (annual and perennial herbaceous crops, and deciduous and non-deciduous trees) and the small size of fields (Campbell, 2002). There are several reports on estimating irrigated crop areas in northern and central Spain by medium spatial resolution satellite [e.g., Landsat Thematic Mapper, pixel size 30×30 m (Martínez and Calera, 2001; Martínez-Casasnovas et al., 2005; Serra and Pons, 2008)]. Nevertheless, in horticultural irrigated areas of southern Spain (Andalusia) where small farm plots (<0.5 ha) are frequent, irrigation is on demand and the main parameter to estimate costs is the surface occupied by each class of irrigated crop. Crop discrimination and classification can be extremely difficult when using sensors with high temporal resolution, but medium spatial resolution. Thus, higher spatial resolution satellites such as QuickBird (spatial resolution of 0.70×0.70 m in panchromatic and 2.8×2.8 m in multispectral; DigitalGlobe, Longmont, CO) would be highly advantageous as the accuracy of the thematic map is very important. This map could be used as a tool to facilitate to the public authority in Andalusia the monitoring necessary to estimate and rebound costs or to predict possible restrictions or modify behavior in case of water scarcity.

As part of an overall research program to investigate the opportunities and limitations of QuickBird satellite in mapping irrigated crops, it is crucial first to explore the potential for identifying variations in their spectral signatures using handheld spectroradiometry. The reasoning behind the spectral characterization of data taken on-ground is quite straightforward: if differences in reflectance of different crops can be measured or recognized, there is potential for discriminating and mapping them using remotely sensed data. Such an approach should indicate the wavebands suitable for irrigated crop species discrimination and classification.

Spectral reflectance differences can be enhanced by using vegetation indices, which are mathematical (ratio or linear) combinations between bands. Data from two or more wavebands are often combined to create multispectral vegetation indices, which are useful for characterizing plant growth and development because they take advantage of the vegetation reflectance contrast between different wavebands (Jackson and Huete, 1991). The most widely used indices in multispectral remote sensing are the normalized difference vegetation index [$NDVI = (NIR - R) / (NIR + R)$, where NIR is near-infrared and R is red (Rouse et al., 1973)] and the ratio vegetation index [$RVI = NIR / R$ (Jordan, 1969)]. NDVI and RVI are commonly used to provide a good indicator of the type of vegetation and the phenological evolution of crops because the latter usually shows high reflectance in NIR and low reflectance in the R range, and both indices enhance these differences (Koger et al., 2003; Trout et al., 2008). NDVI has also been used to discriminate irrigated crops at different growth stages (Martín de Santa Olalla et al., 2003).

Distinguishing irrigated crops requires not only the detection of significant spectral differences, but also an algorithm that can successfully classify crops (i.e., to categorize a spectrum as the specific group or species to which it belongs). Several multivariate methods and neural networks have been investigated for spectral classification of nitrogen and potassium deficiencies in olive orchards (Gómez-Casero et al., 2007), and crops and weeds (Gómez-Casero et al., 2010; López-Granados et al., 2008; Yang et al., 2002), among others. However, no information has been found regarding applications of neural networks

and other multivariate analyses to spectral discrimination and classification of irrigated crops under field conditions. Thus, the objectives of this study were two-fold. First, to evaluate the potential of classic methods of discriminant analysis, as well as more sophisticated algorithms, for the classification of bare soil, annual/perennial herbaceous, and deciduous/non-deciduous tree irrigated crops using a time series of field spectroradiometry based on multispectral data and vegetation indices in the visible and NIR domains. Second, to compare the accuracy performance for spectrum classification into the plant species to which it belongs. Three methods were applied: discriminant analysis, and two artificial neural networks: multilayer perceptron (MLP) and radial basis function (RBF). This is the first step of a project with an overall goal of using high spatial resolution and multispectral satellite imagery for mapping irrigated crops for the improvement of irrigation management.

Materials and Methods

STUDY SITE. The study was conducted within the irrigation community on the left bank of the Guadalquivir River, in an irrigated area of 70 km² located near Córdoba (Andalusia, southern Spain; lat. $37^{\circ}47'36''$ N, long. $5^{\circ}05'22''$ W) in WGS84 (World Geodetic System) Zone 30N, which does not exceed 180 m above sea level. This irrigation network receives water from April to September on demand and farmers pay according to the irrigating surface. The dominant climatic regime is typically Mediterranean, with mild winters and dry summers. According to the U.S. Department of Agriculture Keys to Soil Taxonomy (USDA, 1998), the soil was classified as Typic Xerofluvent. The irrigated crops of the study were grouped as annual herbaceous crops [garlic, onion, sunflower, bean, maize, potato, winter wheat, cotton, and cucurbits (melon and watermelon)], perennial herbaceous crops (alfalfa and asparagus), deciduous trees (plum), and non-deciduous trees (citrus and olive). Sowing and harvest dates, and phenological stages at sampling times for every crop are shown in Table 1.

SPECTRAL READINGS. Canopy spectral reflectance of bare soil and every crop was taken at a specified date in three periods of the year: Spring 2007 (on 15 May: alfalfa, asparagus, bean, early maize, garlic, onion, potato, sunflower, wheat, citrus, olive, and plum), early summer (on 28 June: alfalfa, asparagus, cotton, cucurbits, early maize, sunflower, citrus, olive, and plum), and late summer (on 7 Sept.: alfalfa, asparagus, cotton, early and late maize, citrus, olive, and plum). On each date, 30 spectral measurements were collected for bare soil and every canopy of irrigated crop using a spectroradiometer (ASD Handheld FieldSpec; Analytical Spectral Devices, Boulder, CO). Thus, the total number of spectral data obtained and processed varied as follows: 390 in spring (30 from each crop sampled on 15 May, plus 30 from bare soil), 300 in early summer (30 from each crop sampled on 28 June, plus 30 from bare soil), and 270 in late summer (30 from each crop sampled on 7 Sept., plus 30 from bare soil). Spectroradiometer readings were taken under sunny conditions between 1200 and 1400 hr (Salisbury, 1999). The sensor was placed in a telescopic pole above each plant canopy or soil at 60 to 80 cm using a 25° field-of-view optic that resulted in ≈ 0.13 to 0.18 m spatial resolution for each spectral measurement. This was previously calculated to ensure that only the object of interest was included in each measurement. The spectral data were converted into reflectance, which is the ratio of energy reflected off the target to the energy incident on

Table 1. Sowing and harvest dates, and phenological stages for every irrigated crop in spring, early summer, and late summer.

Land use	Sowing date	Harvest date	Sampling date		
			Spring	Early summer	Late summer
Alfalfa ^z	Early March	Perennial	Pre-flowering and green	Flowering and green	Full flowering and green
Asparagus	February	March next season	Fruit development and green	Ripening and green	Fully ripe and green
Bare soil	—	—	—	—	—
Bean	Early December	Early June	Development of fruit and green	Harvested ^y	—
Citrus		Late November	Leaf development and partially yellowing	Ripening and green	Ripening and green
Cotton	End of April	Mid-October	Cotyledon ^x	Leaf development	Ripening of fruits and seeds, and green
Cucurbits	End of April	Mid-August	Cotyledon	Development of fruit	Harvested
Garlic	Early January	Late May	Growth completed	Harvested	—
Maize	Early March	Early September	Leaf development	Full flowering and green	Fully ripe and yellow
	Late June	Mid-October	Not sown yet ^w	Leaf development	Full flowering and green
Olive		Late December	Flowering and green	Ripening and green	Ripening and green
Onion	Early January	Late May	Growth completed and yellowing	Harvested	—
Plum		Early July	Flowering and green	Ripening and green	Fruit harvested and green
Potato	Early January	Late May	Full flowering and green	Harvested	—
Sunflower	Mid-March	Late July	Leaf development	Ripening	Harvested
Wheat	Early December	Mid-June	Full flowering and green	Harvested	—

^zAlfalfa was harvested three or four times during the year.

^yWhen crop was harvested, no spectral signatures were taken.

^xCrops in cotyledon stage. No spectral signatures were taken.

^wNo spectral signatures were taken.

the target; with reference to a barium sulfate standard reflectance panel (Spectralon, Labsphere, North Sutton, NH) before and immediately after each measurement. Therefore, every spectral signature was individually calibrated against the Spectralon white reflectance standard to minimize the potential noise from external factors such as illumination. Measurement replications ensured representative spectral variation within crops. Hyperspectral measurements were between 325 to 1075 nm (1.5-nm bandwidth). However, the reflectance spectra were very noisy at the extremes of the range and only the measurements between 400 and 900 nm were analyzed. Reflectance data at the canopy scale were averaged to represent similar multispectral broad wavebands [blue (B) = 450–520 nm, green (G) = 521–600 nm, red (R) = 630–690 nm, and NIR = 760–900 nm] available on the commercial satellite QuickBird. The following multispectral vegetation indices were also calculated from the B, G, R, and NIR wavebands: NDVI, RVI, NIR/G, NIR/B; B/G; B/R, and G/R. In addition, each crop was georeferenced using a submeter differential global positioning system (PRO-XRS; Trimble, Sunnyvale, CA) for future QuickBird satellite imagery analysis.

DISCRIMINANT ANALYSIS. Multispectral and vegetation indices data were subjected to discriminant analysis using SPSS software (version 16.0; SPSS, Chicago). The fundamental problem inherent to the discriminant analysis lies in assigning an unknown subject to one of two or more groups on the basis of a multivariate observation. The discriminant analysis procedure permitted the development of a predictive model of group membership based on characteristics observed in each case. The procedure originated a discriminant function (or a set of them for more than two groups) because the number generated corresponded to the number of groups minus one, based on linear combinations of the independent variables. The number of discriminant functions providing a statistically significant among-group variation essentially defined the dimensionality of the discriminant space. This test also measured the difference between groups (Karimi

et al., 2005a). To determine if the set of wavebands selected could be used to separate the different crops, the stepwise discriminant model was performed using SPSS software. Forward selection was employed for the inclusion of a variable and backward elimination was used for the removal of variables no longer significant in the model (Karimi et al., 2005b). A Wilk's lambda test was used to determine the significance of each discriminant function. Wilk's lambda statistic ranges from 0 to 1 and is indicative of the discriminatory power of spectral wavebands [i.e., the lower the Wilk's lambda value, the greater the spectral differentiation between groups; in contrast, the higher value, there are minimum differences between classes (Thenkabail et al., 2004)]. At each step, the variable that minimized the overall Wilk's lambda was entered. In addition, the minimum partial F necessary to enter a variable was 3.84, and 2.71 maximum partial F for removing a variable (Visauta and Martori, 2003).

The stepwise discriminant model was calculated considering every land use and sampling date (i.e., nine herbaceous plus three fruit tree crops, and bare soil for spring; six herbaceous plus three fruit tree crops, and bare soil for early summer; and five herbaceous plus three fruit tree species, and bare soil for late summer) as a different predictor variable or class. The functions were generated from a sample of cases for which group membership (each crop species and bare soil) was known. These functions could then be applied to new cases with measurements for the predictor variables but an unknown group membership. The suitability of the discriminant functions for a given classification was compared using a cross-validation method, which is the technique widely used for the validation of an empirical model. It involves the calculation of misclassification matrices by determining the number of wrongly classified groups in any single class. The "one data out" approach for cross-validation was selected as the classification option for the stepwise discriminant analysis to assess the accuracy of the model. This approach works by leaving out one spectrum; the model is then

trained with the remaining spectra and, finally, the developed model is used for the classification of the spectrum left out (Gómez-Casero et al., 2007; Karimi et al., 2005a). Thus, as the data set available in spring, early summer, and late summer contained 390, 300, and 270 spectra, respectively; 389, 299, and 269 spectra were used for every sampling data for training and one spectrum for testing, and the percentage of correct classification was calculated. This procedure was applied to both spectra and vegetation indices.

ARTIFICIAL NEURAL NETWORKS. Two artificial neural networks, the MLP and RBF, were used to the data set to identify the test crops. These procedures are mathematical models that perform a computational simulation of the behavior of neurons in the human brain by replicating, on a small scale, the brain's patterns, to form results from the events perceived (i.e., is a model based on learning a set of training data). The main characteristic of artificial neural networks is their capacity for learning by example. This means that by using a neural network, there is no need to program how the output is obtained, given certain input; rather, examples are shown of the relationship between input and output, and the neural network will learn the existing relationship between the two by means of a learning algorithm. This learning will materialize in the network's topology and in the value of its connections. Once the neural network has *learned* to carry out the desired function, it can be used (i.e., input values for which the output is unknown can be entered) and the neural network will calculate the output. The neural network is composed of a number of interconnected processing elements (similar to biological neurons) that are joined by weighted connections (analogous to synapses). Supervised learning in neural network typically occurs through training or exposure to a known set of input and corresponding output data. The training algorithm adjusts the connection weights through an iterative procedure in which the error is minimized (Ashish et al., 2004). The amount of training data required for successful classification increases exponentially with increased dimensionality of the input data (Dixon and Candade, 2008).

The MLP neural model is a fully connected multilayer feed-forward supervised learning network with symmetric sigmoid activation functions, trained by the back-propagation algorithm to minimize a quadratic error criterion. *Fully connected* means that the output from each input and hidden neuron is distributed to all of the neurons in the following layer; *feed-forward* means that the values only move from input to hidden to output layers—no values are fed back to earlier layers. The size of the MLP is described as the size of input layer $\times$ size of hidden layer $\times$ size of output layer (Burks et al., 2005; Këranen et al., 2003). In our study, the size of the input layer is the number of spectral measurements taken from the spectroradiometer for every land use and sampling date. The number of neurons in the hidden layer and the number of hidden layers are selected during the training process. They are generally minimized to reduce the number of computations necessary to obtain the desired output accuracy. In this study, one hidden layer of four, seven, and four neurons were used for spring, early summer, and late summer, respectively. When testing an unknown sample, each output neuron of the network gets a score value in the range $[-1 + 1]$, and the network appropriates the sample to the class that has the highest score. One output layer containing as many neurons as classes to which the samples are classified was used for every sampling date.

The RBF is also a fully connected feed-forward neural network with a simple three-layer topology: an input layer, a hidden layer, and an output layer. As a result, the input layer is fixed by the number of variables in the input vector and the output layer is fixed by the number of classes to be discriminated. The hidden layer is variable in size, with the number of neurons determined by the training algorithm. For the input of each neuron, the distance between the neuron center and the input vector is calculated. For the neurons in the hidden layer, a Gaussian density function serves as activation function, with outputs inversely proportional to the distance from the center of the neuron (Martín del Brío and Sanz-Molina, 2006). In our study, the variables of the input and output layers for the RBF method were the same as for the MLP method. One hidden layer of 13 neurons for spring, and 12 neurons for both early summer and late summer.

The suitability of MLP and RBF for a given classification model was determined by a hold-out cross-validation procedure, where the size of training set was $\approx 3n/4$ and $n/4$ for the test set, n being the size of the full dataset at every sampling date. Consequently, the full dataset was randomly split in two datasets, and after training, the network is run on the test set that provides an unbiased estimate of the generalization error, provided that the test set was chosen randomly. The main differences between MLP and RBF networks are that, in the latter, the connections between the input and hidden layers are not weighted, and the transfer functions on the hidden layer nodes are radially symmetric (Martín del Brío and Sanz-Molina, 2006). The main difference between the stepwise discriminant procedure and the neural networks is that the discriminant analysis originates a discriminant function (or a set of them) based on linear combinations of the independent variables, whereas the neural networks present a fitted function in an analytical form where the parameters are weights, biases, and network topology. The MLP and RBF neural network SPSS application were used. We evaluated the classification performance of the stepwise discriminant analysis, and the MLP and RBF neural networks.

Results

Mean multispectral reflectance curves for each crop and bare soil from the three sampling dates, according to the four multispectral bands currently available on the commercial satellite QuickBird, are presented (Fig. 1). Soil presented its characteristic spectral signature, and reflectance increased as wavelength increased. The overall shapes of reflectance curves for herbaceous and tree crops were similar, exhibiting the characteristic peak in the G waveband produced by green vegetation and the highest reflectance in the NIR range of 750 to 900 nm. However, sampling dates of the different horticultural crops consistently affected the magnitude and amplitude of spectral reflectance values. There were apparent reflectance differences in any of the multispectral bands for the different irrigated crops and bare soil on the three sampling dates which showed that there was a potential for discrimination. In spring and early summer, all of the crops showed the typical high reflectance value in the green peak and higher reflectance in the NIR part of the spectrum, indicating that they were at the vegetative or flowering phenological stage. In late summer (Fig. 1C), early maize was at its latest growth stage and its mean reflectance curve steadily increased as wavelength increased without the green peak for photosynthetically active vegetation,

Fig. 1. Mean reflectance curves of bare soil and every irrigated crop for multispectral bands [blue = 450–520 nm, green = 521–600 nm, red = 630–609 nm, and near-infrared (NIR) = 760–900 nm] and different sampling dates: spring (A), early summer (B), and late summer (C).

indicating that this crop was in a partly desiccated and yellowing phenological stage.

Discriminant functions obtained from a stepwise selection technique, based on a specific multispectral waveband or vegetation index, were useful for identifying the variations in spectral measurements from every crop species at each sampling date. Individual multispectral wavebands and vegetation indices

selected to develop the discriminant functions for separating the spectra of bare soil, and the different herbaceous and tree crops for every sampling date, using the stepwise discriminant procedure, are shown in Table 2. Wilk's lambda values indicate the discriminatory power of every waveband or vegetation index (i.e., smaller values, near to 0, indicate a higher spectral separability between herbaceous crops, tree crops, and bare soil). Classification results from the discriminant analysis model for different sets of multispectral wavebands and vegetation indices chosen on the basis of their entry order in the stepwise discriminant procedure are also given in Table 2. The four multispectral bands and all the indices used in the model were selected in spring, early summer, and late summer, but with a different order of entry. The first variable entered into the discriminant function in all the sampling dates was the NDVI index, being crucial in classifying bare soil and the fourteen crops studied. The NIR multispectral band, as well as the vegetation indices created from the combination of this band with others, B/G, B/R, RVI, and NIR/B, also showed great potential for crop discrimination, as they were preferably selected at the beginning of the discrimination equation. The best classification percentage was 95.4%, obtained in late summer, and the worst percentage (81.7%) was obtained in spring, when the highest number of crops was sampled (Table 1).

Table 3 lists the percentage of correct classification for stepwise discriminant models, and MLP and RBF from bare soil, and herbaceous and tree crops when individual irrigated crop species were included at every sampling date for the whole interval (450–900 nm) and selected indices, and for every multispectral waveband and individual vegetation index. The best classification percentage was obtained when an MLP classification model was used, showing 89.8%, 91.1%, and 96.4% correct classification at spring, early summer, and late summer, respectively. Stepwise discriminant classification results were better than those from the RBF for any of the dates. The RBF model performed the worst, showing success rates ranging from 76.2% to 86.8%. All three models exhibited the best classification accuracy in late summer.

For clarity in the results, only a classification matrix using cross-validation for the

MLP model (the most accurate) is shown (Table 4). The values in the table provide the percentage of both correctly classified classes (classification accuracy) and misclassified classes (error percentage) for each sampling date. For example, Table 4 shows that citrus was correctly classified at every sampling date and also informs that 30% of plum tree spectral measurements were misclassified as citrus. Bare soil was correctly classified at all

Table 2. Stepwise discriminant results for multispectral bands and vegetation indices selected for bare soil, herbaceous crops, and tree crops at every sampling date.

Land use	Sampling date	Multispectral bands and vegetation indices ^z	Wilks' lambda	Exact F	Overall classification (%)	Cross -validation (%)
Herbaceous: tree crops ^y and bare soil	Spring	NDVI, B/G, RVI, NIR/B, NIR, B/R, B, NIR/G, G, G/R, R	0.036	633.9	81.7	79.7
Herbaceous: tree crops ^x and bare soil	Early summer	NDVI, B/R, NIR/B, NIR/G, RVI, R, B, NIR, G, G/R, B/G	0.021	1124.9	83.5	82.3
Herbaceous: tree crops ^w and bare soil	Late summer	NDVI, RVI, B/R, NIR/B, B, R, NIR, G, NIR/G, G/R, B/G	0.013	1885.5	95.4	93.3

^zMultispectral bands (B = blue, G = green, R = red, NIR = near-infrared), and vegetation indices [NDVI = (NIR- R/NIR+ R); RVI = (NIR/R)].

^yHerbaceous crops (alfalfa, asparagus, bean, garlic, early maize, onion, potato, sunflower, and wheat); tree crops (olive, citrus, and plum).

^xHerbaceous crops (alfalfa, asparagus, cotton, cucurbits, early maize, and sunflower); tree crops (olive, citrus, and plum).

^wHerbaceous crops (alfalfa, asparagus, cotton, and early and late maize); tree crops (olive, citrus, and plum).

Table 3. Percentage of correct classification of bare soil, herbaceous crops, and tree crops at every sampling date obtained from the stepwise discriminant analysis (SDA), and from multilayer perceptron (MLP) and radial basis function (RBF) neural networks.

Sampling date	Classification method	Wavebands and vegetation indices ^z (% correct classification)											
		All bands (450–900 nm) and vegetation indices	450–520 nm B	521–600 nm G	630–690 nm R	760–900 nm NIR	NDVI	RVI	NIR/G	NIR/B	B/G	B/R	G/R
Spring	SDA	81.7	29.7	28.7	30.3	31.7	26.0	28.7	32.0	33.7	41.3	26.0	29.0
	MLP	89.8	35.1	34.5	37.5	33.4	37.3	32.5	36.4	40.0	37.0	28.1	31.9
	RBF	76.2	39.4	36.4	38.5	42.1	34.6	35.5	40.7	43.3	47.0	30.5	33.8
Early summer	SDA	83.5	40.4	32.7	37.3	29.6	35.4	44.2	52.7	48.5	40.8	45.4	35.0
	MLP	91.1	49.7	46.7	34.4	31.4	33.9	36.9	48.3	50.5	44.8	51.1	43.1
	RBF	80.0	49.1	48.3	43.3	37.1	41.7	45.4	56.1	47.9	50.3	50.0	47.3
Late summer	SDA	95.4	36.3	30.0	47.9	31.7	50.0	57.1	56.3	60.4	57.5	62.5	63.8
	MLP	96.4	40.2	41.1	48.5	36.8	60.9	49.4	60.6	61.3	59.4	66.7	72.8
	RBF	86.8	38.4	38.7	50.3	36.2	61.5	59.6	61.2	64.2	60.6	66.1	72.8

^zMultispectral bands (B = blue, G = green, R = red, NIR = near-infrared), and vegetation indices [NDVI = (NIR- R/NIR+ R); RVI = (NIR/R)].

dates (100% classification accuracy). The majority of the irrigated crops (alfalfa, asparagus, citrus, garlic, onion, potato, sunflower, and wheat) were correctly classified (100% classification accuracy) in spring. Citrus, cotton, cucurbits, and sunflower were correctly classified in early summer. In late summer, the correct classification was 100% for alfalfa, citrus, early maize, and olive. Generally speaking, the misclassification percentage between herbaceous crops and tree crops was lower than that between herbaceous crops and herbaceous crops.

Discussion

Spectral signatures of the irrigated crop species exhibited differences in magnitude of reflectance (Fig. 1), supporting its use as an identification method. These spectral differences may be attributed to variation in the relative amounts of chlorophyll content, water content, and cell-to-air space ratio, which influence the spectral properties of vegetation (Price, 1994; Smith and Blackshaw, 2003). In our stepwise discriminant study, the NDVI index was crucial in discriminating irrigated crops at the three sampling dates. The NDVI index has been used in numerous studies related to monitoring natural and cultivated vegetation, as well as irrigated system inventories, due to its strong correlation with vegetation parameters such as green plant cover (Bastiaanssen, 1998; Lass and Callihan, 1997; López-Granados et al., 2006; Peña-Barragán et al., 2004; Sillescu et al., 2006). Gopal et al. (1999) discriminated crops and natural

vegetation by means of the temporal evolution of NDVI based on differences in phenological development because it has been shown that temporal monitoring of this index provides a good indicator of phenological evolution as it is often measured as a greenness index because it is considered an approximation to chlorophyll activity (Moran et al., 1997; Serra and Pons, 2008). Previous work has shown that wavelengths in the visible and NIR regions of the spectrum exhibit great power in multitemporal discrimination of plant species (Peña-Barragán et al., 2006). The NIR multispectral band, as well as the vegetation indices created from the combination of this band with others, also showed great potential for crop discrimination. Smith and Blackshaw (2003) suggested that, regardless of the input samples, wavelengths in the NIR domain are always selected as being important for plant species discrimination. The cross-validation percentages were lower than those yielded by overall classification (Table 2). Karimi et al. (2005b) also found greater accuracy in overall classification than in cross-validation when using a set of selected wavebands.

The best overall classification was obtained in late summer, when a smaller number of crop species was available. The results of the three classification methods showed that the highest percentage of classification accuracy was achieved with MLP for all dates, followed by stepwise discriminant analysis and RBF. This is in agreement with results obtained by Burks et al. (2005) when comparing the classification capabilities of three neural network models and the discriminant statistical model.

Table 4. Classification matrix obtained from the multilayer perceptron neural network for cross-validation using multispectral bands and vegetation indices for bare soil, herbaceous crops, and tree crops at every sampling date.

		Land use													
		Predicted													
Sampling date	Observed	Bare						Maize							
		Alfalfa	Asparagus	soil	Bean	Citrus	Cotton	Cucurbits	Garlic	early, late	Olive	Onion	Plum	Potato	Sunflower
(% correct classification)															
Spring	Alfalfa	100	0	0	0	0			0	0	0	0	0	0	0
	Asparagus	0	100	0	0	0			0	0	0	0	0	0	0
	Bare soil	0	0	100	0	0			0	0	0	0	0	0	0
	Bean	10	0	0	35	0			0	10	45	0	0	0	0
	Citrus	0	0	0	0	100			0	0	0	0	0	0	0
	Early maize	12	12	0	12	0			12	40	0	0	12	0	0
	Garlic	0	0	0	0	0			100	0	0	0	0	0	0
	Olive	0	0	0	0	0			10	0	80	0	0	0	10
	Onion	0	0	0	0	0			0	0	0	100	0	0	0
	Plum	0	0	0	0	30			0	0	0	0	50	20	0
	Potato	0	0	0	0	0			0	0	0	0	0	100	0
	Sunflower	0	0	0	0	0			0	0	0	0	0	0	100
	Wheat	0	0	0	0	0			0	0	0	0	0	0	100
Early summer	Alfalfa	50	50	0		0	0	0		0	0		0		0
	Asparagus	0	85	0		0	0	0		0	15		0		0
	Bare soil	0	0	100		0	0	0		0	0		0		0
	Citrus	0	0	0		100	0	0		0	0		0		0
	Cotton	0	0	0		0	100	0		0	0		0		0
	Cucurbits	0	0	0		0	0	100		0	0		0		0
	Early maize	0	20	0		0	0	0		35	45		0		0
	Olive	0	0	0		0	0	0		20	80		0		0
	Plum	0	0	0		35	0	0		0	0		65		0
	Sunflower	0	0	0		0	0	0		0	0		0		100
Late summer	Alfalfa	100	0	0		0	0			0	0		0		
	Asparagus	0	75	0		0	0			0, 0	25		0		
	Bare soil	0	0	100		0	0			0, 0	0		0		
	Citrus	0	0	0		100	0			0, 0	0		0		
	Cotton	0	0	0		0	80			0, 0	20		0		
	Maize														
	Early	0	0	0		0	0			100, 0	0		0		
	Late	0	0	0		0	0			0, 85	0		15		
	Olive	0	0	0		0	0			0, 0	100		0		
	Plum	10	0	0		0	0			0, 10	0		80		

These authors showed that the back-propagation neural network provided 97% classification performance, which exceeded the 93% and the 91% classification accuracies obtained using discriminant analysis and RBF, respectively. This could be because a discriminant analysis originates a discriminant function based on linear combinations of the independent variables, whereas the neural networks present a fitted function where the parameters are weights and biases, and network topology. The difference between both neural networks is that a back-propagation neural network like MLP achieves high output accuracy, but can be difficult to train, requiring longer training times than the RBF network. The RBF model is very simple in topology, with relatively high accuracy and superior trainability. However, this model required significantly greater computations for a feed-forward output solution compared with the MLP network, whereas the MLP model achieved higher classification accuracy with less computational requirements in spite of its training requirements.

Considering the classification matrix from the MLP model, most irrigated crops were correctly classified according to sampling dates. Thus, very high classification accuracy was obtained in spring and late summer, when most crop species exhibited 100% classification accuracy. The misclassification percentages were lower when discriminating herbaceous from tree crops than when discriminating herbaceous from herbaceous crops. In spite of these problems with spectral discrimination and for future works with remote sensed imagery, it can be assumed that there will not be major problems in distinguishing herbaceous from tree crops (e.g., cotton from olive, or late maize from plum in late summer) due to their very different cropping patterns. Some authors have reported a large number (a total of 36) of Landsat-7 and Landsat-5 satellite images (30-m spatial resolution and six multispectral bands) taken at different timeframes to classify Mediterranean irrigated crops (Serra and Pons, 2008). They consider that satellites such as QuickBird have a high spatial resolution, but not especially powerful spectral resolution.

However, our results suggest that the QuickBird multispectral window, in combination with sampling dates chosen at the timing when the spectral differences between crop canopy reflectance are maximal, should be adequate for the successful identification of the main irrigated Mediterranean crops, thus avoiding extensive time series data collection and analysis. One optimal scenario might involve collecting only two QuickBird images to map irrigated crops. A first image could be taken in spring and potentially would classify most of the irrigated crops (alfalfa, asparagus, citrus, garlic, onion, potato, sunflower, and wheat); and a second one taken in late summer would classify those remaining (early and late maize, cotton, plum, and olive). This strategy for image acquisition would allow considerable savings, preventing a high number of redundant images and unnecessary image processing. QuickBird has already been proven a useful data source that accurately determines agronomic variables such as invasive plant species (Tsai and Chou, 2006; Yang et al., 2006). Successful bare soil discrimination is also important for further image analysis because irrigation constraints can render some land temporarily uncultivated.

Currently, Andalusian farmers and authorities have made considerable investments to obtain modern irrigation systems. Portable sprinkler systems are the most common for herbaceous crops such as garlic and alfalfa, center pivots for sunflower or maize, and drip irrigation is usually used for trees and herbaceous crops such as asparagus. However, comparatively little attention was paid to assess irrigation performance for improving of irrigation management. The district supervisor usually provides field information and irrigation system characteristics by visiting each parcel at least once a year to confirm the information regarding crop and method of irrigation. Remote sensing has several advantages over these field measurements because data derived from remote imagery are timely, objective, systematic, accurate, covers a wide area with difficult access, and information is represented through thematic maps and not in tabular form. Every thematic map obtained at every date can be used for cataloguing the type of crop and its phenological canopy evolution, and to follow up of changes in land use, e.g., garlic, onion and potato are harvested on late May (or early June) and, afterward, late maize can be sown on late June in the same parcels. Thus, the surface previously occupied by onion or garlic is not bare soil during the summer, the most important irrigation season, but rather it is being used by another irrigated crop with different water requirement. These changes in land use can be useful for in-season water estimation or to assess surface occupied by each crop to derive corresponding costs. Every organization responsible for the corresponding irrigation network could have its own remote sensing division or, alternatively, the consultancy sector could perform the analysis and provide the service to government and general board of irrigation users. Our current investigations are addressed to map these irrigated crops using QuickBird images collected in the same study area.

The spectral information herein presented can be a guide for creating a multitemporal spectral library of the main Mediterranean horticultural irrigated crops. Documented crop spectral libraries according multitemporal canopy development are very useful for facilitating information for canopy radiation models and as reference for crop phenological stage identification and classification in remote sensed imagery (Price, 1994; Rama Rao et al., 2007; Verhoef, 1984). In addition, spectral libraries of different phenological stages can help to determine appropriate

waveband sensitivity for the remote sensors used to discriminate a given crop species by maximizing the timing and cost of detection for each sensor according to spatial, spectral, and temporal resolution (Hunt et al., 2004).

Conclusion

To conclude, our results show that the MLP model identified and recognized the differences between spectral signatures of bare soil and the most important horticultural irrigated herbaceous and tree crops at spring and late summer. They also indicate that the MLP neural network model should be considered for a future successful classification of remote sensed data. Results suggest the importance of B, G, R, and NIR bands and NDVI vegetation index in the discrimination and classification of irrigated crops. Therefore, spring and late summer would be the recommended dates for using satellite imagery such as QuickBird with high spatial resolution and these four bands for potential discriminating and mapping these crops in our conditions where small fields are frequent. This would be of value for improved water utilization in horticultural zones experiencing water shortages because efficient estimations of the surface occupied by each irrigated crop will correspond to a different water requirement.

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