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Research article

Spectral discrimination of wild oat and canary grass in wheat fields for less herbicide application

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Abstract – Wheat, *Triticum durum* L, is a major cereal crop in Spain with over five million ha grown annually. Wild oat, *Avena sterilis* L., and canary grass, *Phalaris* spp., are distributed only in patches in wheat fields but herbicides are applied over entire fields, thus leading to over-application and unnecessary pollution. To reduce herbicide application, site-specific management techniques based on weed maps are being developed to treat only weed patches. Intensive weed scouting from the ground is time-consuming and expensive, and it relies on estimates of weeds at unsampled points. Remote sensing of weed canopies has been shown to be a more efficient alternative. The principle of weed remote sensing is that there are differences in the spectral reflectance between weeds and crops. To test this principle, we studied spectral signatures taken on the ground in the visible and near-infrared windows for discriminating wheat, wild oat and canary grass at their last phenological stages. Late-season phenological stages included initial seed maturation through advanced maturation for weeds, and initial senescence to senescent for wheat. Spectral signatures were collected on eight sampling dates from April 28 through May 26 using a handheld field spectroradiometer. A stepwise discriminant analysis was used to detect differences in reflectance and to determine the accuracy performance for a species classification as affected by their phenological stage. Four scenarios or classification sets were considered: wheat-wild oat-canary grass, with each species represented by a different group of spectra; wheat and grass weeds, combining the two weed species into one spectral group; wheat and wild oat with each represented as a single group, and finally, wheat and canary grass. Our analysis achieved 100% classification accuracy at the phenological stages of initial seed maturation, and green and advanced seed maturation and partly green for weeds and wheat, respectively, between the dates of April 28 and May 6. Furthermore, we reduced the number of hyperspectral wavelengths to thirteen out of 50. Multispectral analysis also showed that broad wavebands corresponding to those of QuickBird satellite imagery discriminated wild oat, canary grass and wheat at the same phenological stages and dates. Our findings are very useful for determining the timeframe during which future multispectral QuickBird satellite images will be obtained and the concrete wavelengths that should be used in case of using airborne hyperspectral imaging. Accurate and timely mapping of the spatial distribution of weeds is a key element in achieving site-specific herbicide applications for reducing spraying volume of herbicides and costs.

hyperspectral / multispectral / remote late-season weed detection / precision agriculture / vegetation indices

1. INTRODUCTION

Wheat is the most important cereal crop in Spain, with over five million ha grown annually. Wild oat (*Avena sterilis* L.), canary grass (*Phalaris* spp.) and ryegrass (*Lolium rigidum* L.) are the most common grass weeds in cereal crops and have been found, respectively, in 65%, 34% and 32% of the arable fields in Southern Spain (Saavedra et al., 1989). Although patchy distribution of wild oat and ryegrass in winter cereals has been previously observed (Barroso et al., 2004b; Blanco-Moreno et al., 2006), grass herbicides are usually applied to entire fields, leading to the risk of over-application. Patch spraying of grass weeds in winter cereals (Timmermann et al., 2003; Barroso et al., 2004a; Ruiz et al., 2006) has demonstrated the feasibility of using Site-Specific Weed Management (SSWM) to control these worldwide weeds. A key aspect of SSWM is that accurate, appropriate and timely weed maps are required in order to take full advantage of site-specific herbicide applications.

Discrete sampling and intensive scouting in different grid sizes, together with spatial interpolation techniques, have been used to study the spatial distribution of weeds and to estimate weed density at unsampled points (Jurado-Expósito et al., 2003, 2005). Rew and Cousens (2000) concluded that mapping weed patches based on ground survey techniques

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(discrete sampling) on a large scale is time-consuming and expensive. They also argued that continuous sampling methods such as remote sensing are more appropriate and cost-effective for SSWM. Remote sensing of weed canopies may be more efficient than time-consuming field measurements, and interest in using this technology for developing weed distribution maps has increased in recent years. The importance of remote sensing in site-specific weed control has been widely reviewed by Felton et al. (2002), Radhakrishnan et al. (2002), Thorp and Tian (2004), and Brown and Noble (2005).

The spectral response of a plant species at the canopy or the single leaf level is unique, and this response is referred to as the spectral signature. A defining characteristic of the spectral signature is that it varies according to phenological stage. The basic principle of using ground-acquired spectral signatures for remote sensing is that if differences in reflectivity based on the distinctive phenological stage can be measured or recognized, then weed detection may be possible. Several weed species have been identified in crops by exploiting their distinctive phenological stages (Brown and Noble, 2005; Peña-Barragán et al., 2006; Kavdir, 2004; Girma et al., 2005; Lass and Callihan, 1997). Differences in the weed-crop life cycle at advanced phenological stages, before crops and weeds are both yellow, may allow for the detection of spectral differences. Therefore, the detection of a late-season grass weed infestation may be particularly useful when spectral differences between cereal crops and grass weeds are at their highest because weeds senesce at a different time than crops (Rew et al., 1996; Koger et al., 2003; Thompson et al., 1991). In addition, considering the fact that weed infestations can be relatively stable in location from year to year (Barroso et al., 2004b; Jurado-Expósito et al., 2004, 2005), late-season weed detection maps could be used to design site-specific control methods in subsequent years, or to apply in-season post-emergence herbicides if adequate pre-emergence control was not achieved. For example, post-emergence site-specific application can be useful in the control of grass weed (e.g., *Avena* spp.) patches in cereals with very specific and expensive herbicides. It has been demonstrated that by locating weed patches in the most spectrally suitable season, a site-specific herbicide treatment program could be designed for the next season in corn and sunflower crops (Goel et al., 2003; Peña-Barragán et al., 2007).

Technological advances have produced innovative handheld hyperspectral sensors that offer an improvement over multispectral sensors. Hyperspectral sensors have hundreds of very narrow and contiguous wavelengths that are usually less than 10 nm wide, whereas multispectral sensors collect data over several (3 to 7) broad bands. Therefore, because the band widths are narrower in hyperspectral scanner systems, small or local variations in absorption features can be detected that might otherwise be masked within the broader bands of multispectral scanner systems (Schmidt and Skidmore, 2003; Koger et al., 2004). Hyperspectral data have been successfully used for spectral discrimination of 27 salt-marsh vegetation types in a coastal wetland (Schmidt and Skidmore, 2003), for the detection of pitted morning glory (*Ipomea lacunosa* L.) in soybean fields (Koger et al., 2004), and to determine the ability to separate five weeds and two crop species (Smith and Blackshaw, 2003; Peña-Barragán et al., 2006).

As mentioned above, the use of hyperspectral scanner systems involves analyzing hundreds of wavelengths. In order to reduce the amount of hyperspectral data used to predetermine a subset of narrow wavelengths without loss of important information, several statistical methods have been used. For instance, artificial neural networks have been used in corn (Yang et al., 1999; Goel et al., 2003) and wheat (Wang et al., 1999; López-Granados et al., 2008); decision tree technology has been applied in corn (Goel et al., 2003) and land cover (Friedl and Brodley, 1997; Friedl et al., 1999); and multivariate data analysis methods such as principal components and discriminant analysis have been performed in tomato and corn (Slaughter et al., 2004; Karimi et al., 2005a, b). Girma et al. (2005) studied optical spectral signatures for detecting cheat (*Bromus secalinus* L.) and ryegrass in winter wheat under greenhouse conditions. The authors concluded that spectral measurements differed with plant growth stage, but suggested that it would be necessary to assess whether spectral identification is robust under field conditions.

Some authors have also tried to discriminate weed and crop species using hyperspectral rather than multispectral data using stepwise discriminant analyses to test whether fine spectral detail is actually required (Smith and Blackshaw, 2003; Brown and Noble, 2005). This information is essential because discrimination of hyperspectral signatures may allow for the use of airborne hyperspectral sensors (e.g., Compact Airborne Spectrographic Imager, CASI), whereas discrimination among multispectral signatures can be used for high spatial resolution satellite imagery (e.g., QuickBird).

Spectral reflectance differences can be enhanced by using vegetation indices, which are mathematical (ratio and lineal) combinations of selected wavelengths, or wavebands when hyperspectral or multispectral data are used, respectively. 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; Hatfield and Pinter, 1993). The most widely used indices in multispectral remote sensing are the normalized difference vegetation index (NDVI) = (NIR − R/NIR + R), where NIR stands for near-infrared and R stands for red multispectral bands (Rose et al., 1973), and the ratio vegetation index (RVI) = (NIR/ R) (Jordan, 1969). The NDVI and RVI are commonly used to differentiate between types of vegetation because the latter usually shows high reflectance in NIR and low reflectance in the red range, and both indices enhance these differences (Hansen and Schjoerring, 2003; Elmore et al., 2000; Koger et al., 2003). The NDVI was also used in some reports to discriminate between weeds and crops (Lamb et al., 1999; Lass and Callihan, 1997; López-Granados et al., 2006; Peña-Barragán et al., 2006), and between weed-free and weed-infested areas in soybean (Chang et al., 2004) and sunflower fields (Kavdir, 2004).

As part of a broader research program to investigate the possibilities and limitations of remotely-sensed imagery in mapping late grass weeds in wheat, it is essential to analyze the variations in their hyper- and multispectral signatures at distinct mature phenological stages in field conditions. This approach will allow for identification of suitable wavelengths or wavebands for species discrimination and classification. In addition, assuming that the sampling date must be chosen when the phenological differences are maximal, it is necessary to obtain time series data late in the season in order to determine the best opportunity for the identification of crops and weeds. Thus, the objectives of this study were (1) to evaluate the potential of using a time series of field spectroradiometry data in the visible and near-infrared domains to discriminate between late-season wheat, wild oat and canary grass on the basis of hyperspectral and multispectral characteristics, and (2) to compare the performance accuracy of the discrimination at every sampling date. The results obtained will facilitate determination of the optimal timeframe and the suitable wavelengths or wavebands for hyperspectral airborne or multispectral satellite imagery for mapping these weeds in wheat.

2. MATERIALS AND METHODS

The study was conducted in Andalusia, southern Spain, during the spring of 2006 in Santa Cruz (25.6 ha of land, Universal Transverse Mercator [UTM] coordinates 361,076 E; 4,185,313 N). The winter wheat crop was planted in mid-November and harvested in mid-June. Consistent natural weed infestations were made up of wild oat and canary grass. The farm was regularly visited every week from late April onwards to collect phenological stage data and spectral signatures of crops and weeds, as indicated below. Four phenological stages of weeds and wheat were considered (adapted from Lancashire et al., 1991) corresponding to three periods within the sampling dates: April 28th through May 6th, when wheat plants were at the advanced seed maturation stage and partly green, and wild oat and canary grass were at the initial seed maturation stage and green; May 14th through May 22nd, when wheat plants were at the initial senescence stage and yellowing and weeds were at an advanced seed maturation stage and partly green; and on May 26th, when wheat plants were senescent and yellow and weeds were at the initial senescence stage and yellowing.

2.1. Spectral readings and data analysis

The spectral signatures of weed-free wheat and grass weed species patches were taken from April 28th to May 26th 2006 every four days. A total of eight sampling dates were recorded. Each weed species patch had about 20–25 spikes/panicles per m^2. Twenty vertical measurements under cloudless conditions were collected for each plant species at random using an ASD HandHeld FieldSpec spectroradiometer (Analytical Spectral Devices, Inc., 5335 Sterling Drive, Boulder, CO 80301, USA) placed at a height of 60–80 cm above each plant species canopy. The spectral data were converted into reflectance, which is the ratio of energy reflected off the target to the energy that is incident on the target. Every spectral signature was calibrated using a barium sulfate standard reflectance panel as a reference (Spectralon, Labsphere, North Sutton, NH, USA) before and immediately after each measurement. Spectroradiometer readings were taken under sunny conditions between 12:00 h and 14:00 h (Salisbury, 1999) using a 25° field-of-view optic, measuring an area of about 0.15 to 0.20 m^2. Hyperspectral measurements were collected between 325 and 1075 nm with a bandwidth of 1.5 nm, although the reflectance spectra were very noisy at the ends of the range and only the measurements between 400 and 900 nm were analyzed. Previous studies have shown that neighboring wavelengths can frequently provide similar information. Thus, the hyperspectral measurements collected were averaged to represent 50 10-nm-wide measurements between 400 and 900 nm (Peña-Barragán et al., 2006; Thenkabail et al., 2004), and these were then statistically analyzed. Reflectance measurements on the canopy scale were also averaged to represent similar multispectral broad wavebands, blue (B): 450–520 nm, green (G): 521–600 nm, red (R): 630–690 nm and near-infrared (NIR): 760–900 nm available on the commercial satellite QuickBird, which currently has the highest spatial resolution. The vegetation indices normalized difference vegetation index (NDVI) = (NIR − R/NIR + R), ratio vegetation index (RVI) = (NIR/R), R/B (R ratio B, Everitt and Villarreal, 1987), NIR − R, and (R − G)/(R + G) were also calculated and analyzed.

Discriminant analysis (DISCRIM) of the hyperspectral and multispectral data and the vegetation indices was done using SPSS software (SPSS 13.0, Inc., Chicago; Microsoft Corp., Redmond, WA). The DISCRIM procedure permitted the establishment of a predictive model of group membership based on characteristics observed in each case. The DISCRIM procedure generated a discriminant function (or a set of functions for more than two groups) because the number generated corresponded to the number of groups minus one based on the linear combinations of the predictor variables that provided the best discrimination between groups (Karimi et al., 2005b). 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. To discriminate between weeds and wheat crops, a set of suitable hyperspectral wavelengths, multispectral bands or multispectral vegetation indices was selected using the stepwise discriminant method (STEPDISC) of SPSS. The STEPDISC procedure is a combination of the forward selection and backward elimination of the variables. Forward selection was used for the inclusion of a variable and backward elimination was used for the removal of variables that were no longer significant in the model (Karimi et al., 2005a). For this study, the Wilks lambda test was used to determine the significance of each discriminant function. The values of the Wilks lambda were indicative of the separability or discriminatory power of spectral wavelengths (i.e., the lower the Wilks lambda value, the greater the spectral differentiation between groups; Thenkabail et al., 2004). At each step, the variable that minimized the overall Wilks lambda was entered. In addition, the minimum partial F established to enter a variable was 3.84, and 2.71 was the maximum partial F for removing a variable (more details in Visauta and Martori, 2003).

Four scenarios or classification sets were considered. The stepwise discriminant model (STEPDISC) was calculated considering set (1) wheat, wild oat and canary grass, each representing a different discrimination group; set (2) wheat and grass weed with the two weed species considered to be one group; set (3) wheat and wild oat; and set (4) wheat and canary grass. The functions were generated from a sample of cases, hyperspectral wavelengths, multispectral wavebands or multispectral vegetation indices for which group membership (wheat, wild oat or canary grass) was known (count data). 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 involves the calculation of misclassification matrices by determining the number of wrongly classified groups in any single class. The "leave-one-out" approach for cross-validation was selected as the classification option for the STEPDISC analysis in order to assess the accuracy of the model. In the development of STEPDISC models, the data were divided into two parts. The first was used to develop and construct the model, while the second was used to validate its classification accuracy (Karimi et al., 2005a). This method was applied to both reflectance values and spectral indices to construct a classification rule to discriminate between wheat and grass weed species.

3. RESULTS AND DISCUSSION

3.1. Hyperspectral and multi-temporal analysis

Between April 28th and May 6th, the spectral signatures of wild oat, canary grass and wheat exhibited a characteristic peak in the green region of the spectrum at 550 nm wavelength, known as the "green peak", and the highest reflectance values in the near-infrared domain from 760 to 900 nm, of the green vegetation (Fig. 1). For example, on May 2nd, when weeds were at the phenological stage of initial seed maturation and green, and wheat was at the advanced seed maturation and partly green stage, reflectance values were 10%, 12% and 17% in the green peak, and 63%, 78% and 90% in the near-infrared plateau for wheat, wild oat and canary grass, respectively. This demonstrates that weed species and wheat were still in an active living phase. However, on May 26th, when weeds were at the phenological stage of initial senescence and yellowing, and wheat was at senescent and yellow, wheat, wild oat and canary grass, respectively, showed reflectance values of 18%, 22% and 20% in the green peak, and values of 46%, 50% and 49% in the near-infrared plateau. Reflectance values on this date steadily increased as the wavelengths increased and did not exhibit any reflectance peaks or increases within the green and near-infrared regions of the spectrum. Thus, late phenological stages of the species consistently affected the magnitude and amplitude of spectral reflectance values. These data

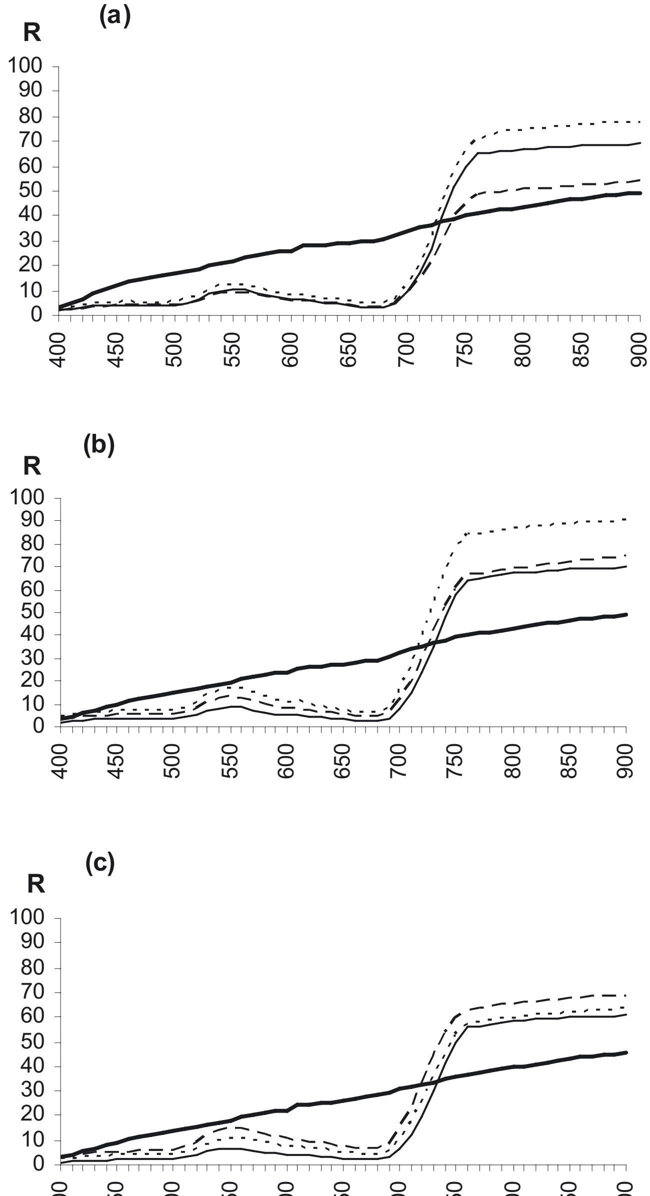

Figure 1. Mean reflectance percentage of wild oat (a), canary grass (b) and wheat (c) according to crucial sampling dates: April 28th (–), May 2nd (...), May 6th (- - -) and May 26th (**–**). Axis X shows the hyperspectral wavelengths (every 10 nm).

are in agreement with data obtained previously by other researchers (Koger et al., 2003; Rew et al., 1996) who studied late-season weed infestation discrimination when spectral differences between crops and weeds prevailed, e.g., when a still green weed is present in a senescent cereal crop or before crops and weeds are simultaneously senescent and turning yellow.

Hyperspectral differences between wheat, wild oat and canary grass may be attributed to variations in the relative amounts of chlorophyll content, water content and the cell-to-air space ratio, which are variables that influence the spectral

Table I. Hyperspectral stepwise discriminant results for wavelengths selected for wild oat, canary grass and wheat according to different classification sets.

Classification sets	Sampling dates		Wavelength (nm)	Wilks' Lambda	Exact-F	Overall classification	Cross validation
Wheat-Wild Oat-Canary grass	April	28	450, 420, 620, 400, 700, 580	0.003	72.7	100	100
	May	2	730, 740, 760, 770, 610, 620, 700, 420, 560, 450, 430	0.007	77.1	100	100
		6	460, 470, 740, 420, 580, 650	0.019	54.8	100	100
		10	550, 570, 690, 530, 480, 470, 730, 420	0.044	23.6	98.3	96.7
		14	460, 680, 900, 490, 780, 520, 420, 720	0.027	31.8	98.3	95
		18	790, 550, 530, 750, 470, 630, 420	0.123	25	98.3	88.3
		22	690, 650, 680, 900	0.086	33	91.8	90.2
		26	450, 500, 420, 520	0.142	22.4	86.7	83.3
Wheat-Weeds	Apr	28	420, 660, 690	0.175	42.5	100	96.8
	May	2	770, 760, 620, 700, 470, 420	0.100	79.7	100	100
		6	680, 460, 760, 420	0.122	98.1	100	100
		10	680, 460, 740, 450, 730	0.266	29.8	93.3	91.7
		14	410, 680, 690, 740	0.429	18.3	88.3	85
		18	460, 540, 400, 410	0.230	46	96.7	93.3
		22	680, 640, 760, 600	0.208	53.2	100	98.4
		26	680, 650, 610	0.399	28.1	91.7	86.7
Wheat-Wild Oat	April	28	450, 420, 620, 510, 700, 400	0.007	336.5	100.	100
	May	2	770, 800	0.243	57.6	90	90
		6	690, 470, 890, 420, 610	0.065	97.3	100	100
		10	550, 690, 730, 510, 760, 480, 490, 870, 400	0.065	47.6	100	100
		14	500, 430, 490, 460, 900, 730, 410	0.064	67.2	100	100
		18	700, 710	0.161	96.2	100	100
		22	680, 650, 810	0.269	32.6	95	90
		26	450, 500, 530, 420	0.159	46.2	100	95
Wheat-Canary grass	April	28	400, 670, 680, 410, 500, 660	0.035	64.9	100	100
	May	2	420, 890, 850	0.078	140.9	100	100
		6	680, 460, 780, 420	0.115	67.1	100	100
		10	420, 680, 400, 870, 760	0.258	19.5	97.5	92.5
		14	680, 510, 440, 560	0.202	34.5	97.5	95
		18	460, 540, 450	0.222	42	97.5	97.5
		22	710, 580	0.333	38	97.6	95.1
		26	760, 800, 610, 720	0.477	9.6	87.5	82.5

properties of vegetation (Price, 1994; Zwiggelaar, 1998; Smith and Blackshaw, 2003). Schmidt and Skidmore (2003) demonstrated that differences in the green peak are important for discriminating vegetation types characterized by variations in chlorophyll content, while differences in the near-infrared plateau are important for distinguishing vegetation types characterized by differences in canopy structure or geometry. The pigment content in leaves of green plants contributes to the reflectance values at the green peak of 550 nm. Therefore, the presence or absence of a green peak and high or low reflectance values in a near-infrared spectral window could provide a means for remote detection, allowing for mapping these species at different phenological stages (Peña-Barragán et al., 2006). These reflectance percentage variations could be due to differences in the timing and duration of every phenological stage among the different grass species, which increases in the order of wheat > wild oat = canary grass.

The classification results given in Table I were obtained from the discriminant analysis model for a different set of wavelengths that were chosen on the basis of their order of entry into the stepwise discriminant procedure selection to discriminate between crop and weeds. A number of wavelengths ranging from 11 to 2 were selected to develop every discriminant function for separating the spectra in the different scenarios considered. When wheat, wild oat and canary grass were included in the classification set (set 1), a correct discrimination percentage of 100% was obtained during the interval from April 28th to May 6th. On these dates, the most frequently selected wavelength was 420 nm. Wavelengths within the blue and near-infrared regions were selected nine and seven times, respectively, and 800–900 nm was not chosen for any of the discrimination models or dates. This first classification set was the most difficult and challenging (Cussans, 1995) and is of interest in cases where both weed species are present in the field and the precise recognition of wild oat from canary grass and wheat is important. This scenario occurs when a selective and more expensive herbicide against only wild oat has to be applied. The discrimination model corresponding to May 26th performed the worst, misdiscriminating at around 13.3% of the spectra, and correctly discriminating 86.7% of the spectra.

When the discrimination set was reduced to weeds and crops (set 2), 100% discrimination was achieved during the interval from April 28th to May 6th, and also for May 22nd, with 420 and 760 nm being the wavelengths most often selected. A total of 12 wavelengths were chosen, and again the 800–900 nm interval was not chosen in any of the discrimination models. The discrimination model corresponding to May 14th performed the worst, misdiscriminating around 11.7% of the spectra, and correctly discriminating 88.3%. Discrimination between weeds and crops was effective, assuming that a mixed population of wild oat and canary grass was present in the field and could be controlled by a given herbicide treatment (Borregaard et al., 2000).

When considering only spectra from wild oat and wheat (set 3), the highest performance was obtained, with six out of the eight sampling dates exhibiting 100% classification. These dates were April 28th and May 6th, 10th, 14th, 18th and 26th. Due to this larger number of favorable sampling dates, the number of wavelengths chosen was also greater, with 400, 420, 450, 490, 500, 510, 690, 700 and 730 nm being the wavelengths most often selected. A total of 23 wavelengths were chosen. Regardless of the input spectra, wavelengths in the 690–760 nm range have been reported as being decisive for vegetation discrimination (Smith and Blackshaw, 2003; Cochrane, 2000). This interval falls within the region of the spectrum known as the "red edge", defined by the boundary between the chlorophyll absorption process in the red wavelengths and leaf scattering in the near-infrared wavelengths. The exact wavelength of the red edge depends on the chlorophyll concentration (Munden et al., 1994). When wheat-canary grass spectra were taken into account (set 4), no classification errors occurred from April 28th to May 6th. On these sampling dates, the wavelengths most frequently selected were located in the blue range, from 400 to 460 nm, and in the red range, from 660 to 680 nm. A total of 11 wavelengths were chosen.

Several researchers have reported similar results in discrimination studies of different weed and crop species (Vrindts et al., 2000; Borregaard et al., 2000; Girma et al., 2005; Goel et al., 2003; Peña-Barragán et al., 2006; López-Granados et al., 2006). Thus, the number of significant wavelengths varied with time (Karimi et al., 2005a). Additionally, it has been shown that the exact wavelength depends on the chlorophyll concentration (Munden et al., 1994), which corresponds to the phenological stage (Girma et al., 2005; Peña-Barragán et al., 2006).

In all of the sets studied, a smaller Wilks lambda (nearest to 0) was obtained when there was a higher separability between spectra, indicating the discriminatory power of every set of selected wavelengths. Generally, the latter were within the visible and near-infrared spectral ranges, although those in the visible region (blue, green and red) were selected more frequently than those in the near-infrared region. Taking the four classification scenarios into account, the three most appropriate dates in decreasing order were April 28th = May 6th > May 2nd, when weeds were at the phenological stage of initial seed maturation and wheat was at the advanced seed maturation and partly green phenological stage. On these sampling dates, several ranges of wavelengths were crucial and most often selected for correct discrimination of wheat, wild oat and canary grass. Thus, wavelengths in the blue range from 420 to 460 nm, the green range from 560 to 580 nm, the red range from 620 to 650 nm, and the near-infrared (NIR) range from 700 to 740 nm were the most frequently selected to discriminate wheat, wild oat and canary grass. Generally, there were no consistent differences between the overall correct classification results from the stepwise discriminant analysis and those from cross-validation, indicating that the classification models were validated.

These results reveal that there were significant spectral differences between wild oat, canary grass and wheat in late phenological stages. Hyperspectral study may lead to opportunities for the use of airborne hyperspectral sensors. At present, airborne hyperspectral sensors such as the Compact Airborne Spectral Imager (CASI) are capable of acquiring data covering up to 288 wavelengths over a spectral range of 400 to 1000 nm, and moreover, CASI is user-programable. Therefore, once discriminant analysis of data collected from the ground has been shown to be a promising approach for the classification of the spectral signatures of wild oat, canary grass and wheat, future investigations will be required in order to determine the potential for analysis of CASI imagery taken when weeds and wheat are at the correct phenological stages. For this purpose, CASI should be programed with 13 wavelengths in the spectral range intervals of blue (420–460 nm), green (560–580 nm), red (620–650) nm and near-infrared (700–740 nm), rather than the 288 available wavelengths. However, this kind of imaging remains prohibitively expensive due to operating costs. Lack of aerial companies providing a cost-effective product could make this type of analysis too high priced for farmers or consultants for individual fields.

3.2. Multispectral vegetation indices and multi-temporal analysis

Mean reflectance curves of wild oat, canary grass and wheat obtained over time according to the four multispectral bands currently available on the commercial satellite QuickBird are shown in Figure 2. There were apparent reflectance differences in all of the four multispectral bands for wild oat, canary grass and wheat on different sampling dates, demonstrating that there was a potential for separating the grass plants studied. Figure 2 shows that certain visible and near-infrared bands could be useful in discriminating wheat, wild oat and canary grass at corresponding phenological stages or sampling dates. This graph also shows that it might occasionally be necessary to use vegetation indices to enhance these small spectral differences when they are not consistent. As indicated by the hyperspectral study, several works have shown that weeds are more

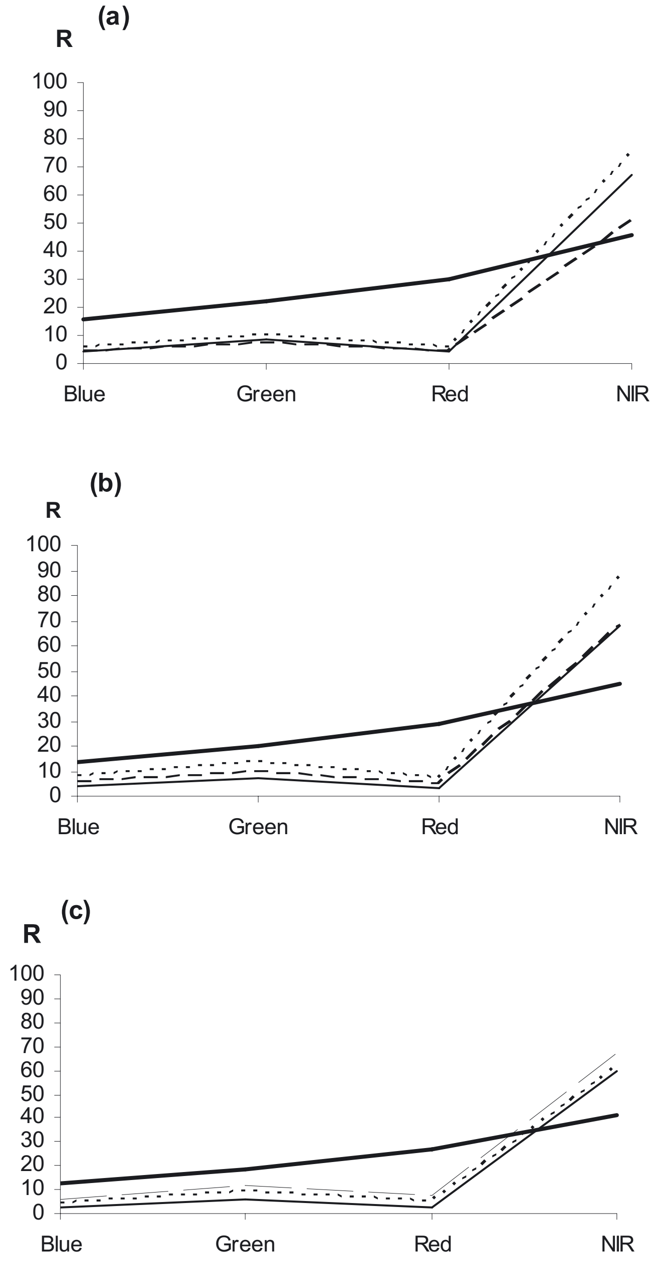

Figure 2. Mean reflectance percentage of wild oat (a), canary grass (b) and wheat (c), according to crucial sampling dates: April 28th (–), May 2nd (...), May 6th (- - -) and May 26th (━). Axis X shows the reflectance data averaged to represent similar multispectral broad wavebands (Blue: 450–520 nm; Green: 521–600 nm; Red 630–609 nm and Near Infrared: 760–900 nm) available on the commercial satellite QuickBird.

detectable if they senesce at different times compared with the crop because these changes in the weed life cycle may cause reflectivity differences (Curran, 1985; Thompson et al., 1991). These differences in the classification percentages on different sampling dates may be due to changes in height and canopy coverage, as well as texture features related to different maturity levels or phenological stages that produce significant differences in the reflectance pattern of weeds (Noble et al., 2002; Burks et al., 2002). Thus, Peña-Barragán et al. (2007) reported that discrimination efficiency of *Ridolfia segetum* in sunflower crops was consistently affected by the phenological stages in the following order: flowering > senescence > vegetative. The authors reported classification percentages ranging from 85 to 98%. As happened when using hyperspectral data, stepwise discriminant analysis was able to identify the restricted multispectral bands or vegetation indices that were useful for identifying the variations in spectral signatures from every grass species. Table II shows the multispectral bands and vegetation indices selected for each of the four classification sets considered. A number of bands or vegetation indices ranging from 7 to 1 was selected to develop every discriminant function for separating the spectra in the different scenarios studied.

Correct classification percentages of 100% were reached for April 28th and May 6th, when individual species were included in the classification set (set 1). On these two dates, weeds and wheat were at the phenological stage of initial seed maturation and green, and advanced seed maturation and partly green, respectively. The four multispectral bands, blue, green, red and near-infrared, and also the near-infrared – red vegetation index, were selected on these sampling dates. Spectral reflectance differences can be enhanced by using vegetation indices because they are able to detect the vegetation active living phase based on vegetation reflectance contrast between different wavebands. The fact that 100% correct classification was achieved from April 28th to May 6th could be due to the detection of the differences in the phenological stage from the two weed species and wheat. These differences were based on the fact that weeds were still in their active living phase at the phenological stage of initial seed maturation and green, but wheat was at the advanced seed maturation and partly green stage. The sampling dates from May 10th to May 18th performed worse, with May 10th being the worst, misclassifying 30.0% of the spectra and correctly classifying 70.0%. As mentioned for the hyperspectral study, this set is the most interesting and challenging approach because individual species were included in the classification set. In set 1, every grass species was discriminated on most of the sampling dates, showing the highest percentages of classification of 100%, or at least, over 95%, with the exception of May 10th and May 18th. Similar results were obtained in the discrimination of wild oat, canary grass and ryegrass in wheat crops when neural networks were applied to multispectral data from one sampling date (López-Granados et al., 2008).

When considering the classification of set 2, which was comprised of weeds and wheat, the discrimination percentage was higher than 98% on all sampling dates. The data sets collected between April 28th and May 6th and also between May 10th and May 18th were the best, discriminating the spectra with 100% accuracy. The four multispectral bands, and also four of the five spectral indices including red/blue, normalized difference vegetation index (NDVI) = (near-infrared – red/ near-infrared + red), ratio vegetation index = (near-infrared/ red) and near-infrared – red, were selected from April 28th to May 6th. However, from May 10th to May 18th, only blue, green and near-infrared bands, and the normalized difference

Table II. Multispectral stepwise discriminant results for wavebands and multispectral vegetation indices selected for wild oat, canary grass and wheat according to different classification sets. See abbreviations in Materials and Methods (Sect. 2.1).

Classification sets	Sampling dates		Multispectral bands and vegetation indices	Wilks' lambda	Exact-F	Overall classification (%)	Cross validation (%)
Wheat-Wild Oat-Canary grass	April	28	B, G, NIR, R	0.002	16.4	100	86.7
	May	2	NDVI, G, NIR, RVI, B	0.047	48.7	98.3	98.3
		6	NIR-R, R, B, NIR, G	0.003	196	100	100
		10	R, G, NIR	0.351	12.625	70	70
		14	R/B, R	0.030	133.5	95	96.7
		18	NDVI, NIR, RVI	0.195	23.2	83.3	81.7
		22	NIR-R, R, B, NIR	0.002	274.2	98.3	98.3
		26	R/B	0.003	8421.7	98.3	98.3
Wheat-Weeds	April	28	R/B, G, NIR, R	0.000	14578	100	100
	May	2	R/B, NDVI, NIR, RVI	0.003	5294.1	100	100
		6	R/B, NIR-R, B, R, NIR, G, RVI	0.096	70.1	100	100
		14	(R–G)/(R+G), NIR-R	0.071	370.5	98.3	100
		10	R/B, NIR	0.036	758.026	100	100
		18	(R–G)/(R+G), B, G, NIR, NDVI	0.023	22.8	100	100
		22	R/B, NDVI, R	0.060	295	98.3	100
		26	NIR-R, R/B	0.071	370.5	98.3	100
Wheat-Wild Oat	Apr	28	B, R	0.123	60.5	100	95
	May	2	NDVI	0.297	89.1	92.5	92.5
		6	NIR-R, R	0.027	677.6	100	100
		10	RVI	0.882	5	57.5	57.5
		14	R/B	0.070	507.5	97.5	100
		18	RVI, B, G, NIR, NDVI	0.143	40.9	97.5	95
		22	NIR-R	0.007	5179.6	100	100
		26	R/B	0.004	9956.6	100	100
Wheat- Canary grass	April	28	B, R	0.124	60.2	100	100
	May	2	B, RVI	0.089	188.3	100	100
		6	B, R, NIR, G, RVI	0.112	54.2	100	97.5
		10	NDVI	0.774	11.121	75.0	75.0
		14	R/B	0.095	361	97.5	100
		18	NDVI	0.478	41.4	87.5	85
		22	R/B, R	0.078	219.6	97.5	100
		26	(R–G)/(R+G)	0.095	361	97,5	100

vegetation index, red/ blue and (red – green)/ (red + green) vegetation indices were chosen. Generally, the discrimination between wheat and weeds performed slightly better than between individual species. According to Yang et al. (2002) and López-Granados et al. (2008), the observation that the discrimination percentage is generally higher when the classification set is comprised of weeds and crops may be due to the fact that, with two weed species grouped into one class, there are many more weed spectra than wheat spectra included in the discrimination process.

When only wheat and wild oat spectral signatures were included in the classification of set 3, correct classification percentages of 100% were obtained on four sampling dates, i.e., April 28th, and May 6th, 22nd and 26th. A smaller number of bands and vegetation indices was necessary to discriminate accurately between wheat and wild oat. This could be the result of having high contrast in the mean multispectral reflectance values between wheat and having only one weed species because the differences in their phenological stages were more evident than when the two weed species were grouped as a single discriminatory class (set 2). Thus, on April 28th, blue and red bands, but no vegetation indices, were essential for separating wheat from wild oat. On May 6th the red band and near-infrared – red index were selected. On May 22nd and May 26th, only one vegetation index was required to successfully discriminate weeds and crops with no misclassification error, near-infrared – red and red/ blue, respectively.

When the classification set was comprised of wheat and canary grass (set 4) the best overall classification of 100% was recorded from April 28th to May 6th. The bands falling within the visible part of the spectrum (blue, green and red and near-infrared) were chosen, as well as the ratio vegetation index.

During this period of time, wheat was at the phenological stage of advanced seed maturation and partly green and canary grass was at the initial seed maturation and green stage.

In all of the sets studied, a smaller Wilks lambda (nearest to 0) was achieved when a higher separability between spectral data was obtained, indicating the discriminatory power of every set of multispectral bands or multispectral vegetation indices chosen. In general, considering the four classification sets, the wavebands selected were within the visible and near-infrared spectral range, although those in the visible region, blue, green and red, were selected more frequently than those in the near-infrared one. Similarly to the hyperspectral analysis, the three most appropriate dates in decreasing order were again April 28th = May 6th > May 2nd, when weeds were at the initial seed maturation and green phenological stage, and wheat was at the advanced seed maturation and partly green stage. Generally, at the latest phenological stages, the power of discrimination decreased. There were no consistent differences between the overall correct classification results from the stepwise discriminant analysis and those from cross-validation, indicating the high degree of accuracy of the classification models.

Multispectral analysis showed that several vegetation indices and broad wavebands corresponding to those of QuickBird satellite imagery discriminated wild oat, canary grass and wheat according to phenological stage, as did the hyperspectral study. Our results suggest that these weeds might be discriminated using high spatial resolution satellite images such as those obtained from QuickBird. Thus, the timeframe of nine days between April 28th and May 6th would be ideal for future remote image acquisition under Mediterranean conditions.

Because airborne hyperspectral sensors such as the Compact Airborne Spectral Imager (CASI) are high priced, a less expensive alternative could be to use QuickBird satellite imagers for large-scale weed infestations.

4. CONCLUSION

Our study reveals that there were significant spectral differences between wild oat, canary grass and wheat in late phenological stages. A hyperspectral study showed that wavelengths in the blue (420 to 460 nm), green (560 to 580 nm), red (620 to 650 nm) and near-infrared (700 to 740 nm) regions of the spectrum were the most frequently selected to discriminate wheat, wild oat and canary grass. Thus, reducing the number of wavelengths to thirteen out of 50 allowed for 100% spectral classification at phenological stages of initial seed maturation and green for wild oat and canary grass, and at advanced seed maturation and partly green for wheat. Phenological differences were significant at these stages. Multispectral analysis showed that several vegetation indices and broad wavebands corresponding to those of QuickBird satellite imagery discriminated wild oat, canary grass and wheat at the same phenological stages as hyperspectral study. Therefore, we would recommend a timeframe of nine days from April 28th to May 6th, in our Mediterranean conditions, for future hyperspectral or multispectral remote image acquisition. It is essential to have this wide a timeframe for proper mapping of these weeds using remotely-sensed data, especially taking into account that cloudy days in spring are very frequent and no remote images can be taken under these circumstances. These maps may contribute to more efficient and sustainable weed management, allowing for site-specific herbicide application decisions that will reduce spray volume and costs for agro-ecological and economic benefit.

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