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Field spectroscopy for weed detection in wheat and chickpea fields

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Weed control is commonly performed by applying selective herbicides homogeneously over entire agricultural fields. However, applying herbicide only where needed could have economical and environmental benefits. The objective of this study was to apply remote sensing to the detection of grasses and broadleaf weeds among cereal and broadleaf crops. Spectral relative reflectance values at both leaf and canopy scales were obtained by field spectroscopy for four plant categories: wheat, chickpea, grass weeds, and broadleaf weeds. Total reflectance spectra of leaf tissues for botanical genera were successfully classified by general discriminant analysis (GDA). The total canopy spectral classification by GDA for specific narrow bands was 95 ± 4.19% for wheat and 94 ± 5.13% for chickpea. The total canopy spectral classification by GDA for future Vegetation and Environmental Monitoring on a New Micro-Satellite (VENμS) bands was 77 ± 8.09% for wheat and 88 ± 6.94% for chickpea, and for the operative satellite Advanced Land Imager (ALI) bands was 78 ± 7.97% for wheat and 82 ± 8.22% for chickpea. Within the critical period for weed control, an overall classification accuracy of 87 ± 5.57% was achieved for >5% vegetation coverage in a wheat field, thereby providing potential for implementation of herbicide applications. Qualitative models based on wheat, chickpea, grass weed, and broadleaf weed spectral properties have high-quality classification and prediction potential that can be used for site-specific weed management.

1. Introduction

Weeds are the most acute pest in agriculture, with an estimated annual global damage of around 40 thousand million US dollars (USD) per year (Monaco, Weller, and Ashton 2002). Weeds reduce crop yield and quality by competing with crops for water, sunlight, and minerals (Pinter et al. 2003; Slaughter, Giles, and Downey 2008); producing allelopathic substances (Moran et al. 2004); hosting diseases and insects (Pikart et al. 2011; Papayiannis, Kokkinos, and Alfaro-Fernandez 2012); and disturbing tilling and harvesting (Monaco, Weller, and Ashton 2002). One increasing problem is weed resistance to herbicides (Mallory-Smith, Thill, and Dial 1990; Jones et al. 2005; Marshall and Moss 2008). In Australia alone, herbicide resistance is estimated to impose an additional annual cost of more than a thousand million USD (Gibson, Kingwell, and Doole 2008).

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More than 60% of the pesticides developed worldwide are herbicides (Monaco, Weller, and Ashton 2002). Thus, it is not surprising that herbicides are also the most common pesticide found in groundwater (Manh et al. 2001). Herbicides can be an environmental hazard to fauna as well as humans (Dhawan, Bajpayee, and Parmar 2009; Brent and Schaeffer 2011). Consequently, the amount of herbicide that can be applied per unit area unit is restricted in some countries (Biller 1998; Timmermann, Gerhards, and Kuehbauch 2003; Slaughter, Giles, and Downey 2008). Herbicide-use regulations, consumer concerns, and growing interest in organically produced foods limit the long-term acceptability of herbicide application (Slaughter, Giles, and Downey 2008).

Weed distribution in fields is non-uniform and confined to patches of varying size along field borders (Gerhards et al. 1997; Lamb and Brown 2001; Vrindts, De Baerdemaeker, and Ramon 2002; Gerhards and Christensen 2003; Moran et al. 2004; Slaughter, Giles, and Downey 2008; Weis et al. 2008). Application of herbicides on a field is often based on the previous year's weed problems and information obtained from field scouting (Manh et al. 2001; Moran et al. 2004). By significantly reducing the quantity of herbicide applied (Gerhards et al. 1997; Gerhards and Christensen 2003; Timmermann, Gerhards, and Kuehbauch 2003; Eddy et al. 2006; Slaughter, Giles, and Downey 2008; Weis et al. 2008), site-specific weed control and management could economically benefit farmers and consumers, as well as the environment, without diminishing weed control efficacy (Pinter et al. 2003; Slaughter, Giles, and Downey 2008; Weis et al. 2008). Reducing the amount of herbicide applied should reduce the probability of weeds building resistance to herbicides and increase herbicide effectiveness.

According to Lindquist et al. (1998), it is possible to reduce the quantity of herbicide applied by applying herbicides only where weeds are located. Site-specific weed management has reduced herbicide use by 11–90% without affecting crop yield (Brown, Steckler, and Anderson 1994; Brown and Steckler 1995; Johnson et al. 1995; Lindquist et al. 1998; Feyaerts and van Gool 2001; Gerhards and Christensen 2003). Weed distribution and competition with crops are influenced by spatial variability in topography, drainage, soil type, and microclimate. There is significant variation in weeds within and between different fields (Moran et al. 2004), emphasizing the need for site-specific weed management.

Real-time (on-the-go) nonselective weed detection and control can be implemented by means of tractor-mounted, optical sensors that trigger a spray nozzle valve to open briefly upon detection of green vegetation (Bennett and Pannell 1998; Biller 1998; Blackshaw, Molnar, and Lindwall 1998). This approach can be applied to entire fields before crop emergence or between crop rows after emergence (Moran, Inoue, and Barnes 1997; Alchanatis et al. 2005; Slaughter, Giles, and Downey 2008). Other ground-based, on-the-go sensing methods are designed to detect the shape of weed leaves against a light-toned soil background, and can thus be applied only in the early growing stages (Gerhards and Christensen 2003; Weis et al. 2008). In addition, remote sensing from air or space has been used to identify and map weeds prior to herbicide application (Gerhards et al. 1997; Weis et al. 2008). Remote-sensing techniques can provide fast and cost-effective mapping of weed populations over large areas, which otherwise would be impractical to cover by manual ground survey methods (Zwiggelaar 1998; Hamouz et al. 2008). Remote-sensing applications also allow early- and late-season, and spatial and spectral methods for site-specific weed detection and management (Zwiggelaar 1998; Moran et al. 2004; Alchanatis et al. 2005).

Few studies have dealt with ground-level spectral classification of crops and weeds over multiple growing seasons. Lopez-Granados et al. (2008) classified ground-level spectral reflectance of wheat, four grass weeds (GW), and soil, and concluded that one sampling date per growth season, when phenological distinction is maximal, can provide high-quality classification. However, relying upon phenology as a basis for spectral differences will likely be ineffective if the optimal time for herbicide application precedes the date of maximal phenological variability among crops and weeds. In their extensive review, Gray, Shaw, and Bruce (2009) determined that short-wave infrared (SWIR) bands are important for classifying ground-level spectral reflectance of soybean, six broadleaf weeds (BLW), and soil. Likewise, Slaughter, Giles, and Downey (2008) found many reports in the literature in which studies were conducted in ideal conditions with no spatial overlap of crops and weeds, and which resulted in classification accuracies of 65–95%. Zwiggelaar (1998) mentions in his review that the use of selected wavelengths for the discrimination between row crops and weeds has not been demonstrated to date, and imaging using a limited number of wavelengths might not be sufficient. The first step required to distinguish between crops and weeds is to obtain continuous spectra of pure plants of each species, which can be done by means of data with high spatial and spectral resolutions. Vrindts, De Baerdemaeker, and Ramon (2002) employed such data and found that relative reflectance values were needed to classify crops and weeds, and to minimize the effect of different lighting conditions on spectral data. In addition, their use of several wavebands resulted in high classification accuracy.

A dicotyledonous leaf has more air spaces within its spongy mesophyll tissue than a monocotyledonous leaf (Raven, Everet, and Eichhorn 2005) of the same thickness and age, resulting in higher reflectance in the NIR region (Gausman 1985). The red-edge region is the slope connecting the red (R) and near infrared (NIR) regions in the reflectance spectra of plants, and is an important element in spectral separation of different plant species, including weeds and crops (Vrindts, De Baerdemaeker, and Ramon 2002; Smith and Blackshaw 2003; Herrmann et al. 2011).

The Advanced Land Imager (ALI) is a multispectral sensor with nine bands, including two in the red-edge region, onboard the Earth Observing-1 (EO1) satellite that provides spatial resolution of 30 m, a swath of 37 km, and revisit frequency of 16 days (Chander, Markham, and Helder 2009). Vegetation and Environmental Monitoring on a New Micro-Satellite (VENμS) is a future satellite with a super-spectral sensor (12 bands in visible, red edge, and NIR regions). VENμS will provide excellent spatial resolution of 5.3 m, a 27.5 km swath, and revisit frequency of 2 days (Herrmann et al. 2011). These specifications of VENμS are highly suitable for site-specific weed management and other precision agricultural applications.

In this research, remote sensing was used to detect annual grasses and BLW amongst broadleaf and cereal crops. Specific objectives were twofold: (1) the use of leaf spectral reflectance to distinguish between wheat, chickpea, GW, and BLW; and (2) to examine the potential of using canopy spectral reflectance from the field and band-equivalent reflectance of VENμS and ALI to predict categories of crops and weeds.

2. Methodology

2.1. Study sites

Field measurements and sampling were performed in both rainfed and irrigated wheat and chickpea experimental plots in winter 2007 and 2008 at the Gilat Research Center (31° 20′ N, 34° 40′ E) and Kibbutz Saad (31° 28′ N, 34° 33′ E) in the northwestern Negev, Israel. The climate is semi-arid with a short rainy season (November–April) that yields an average annual precipitation of 230 mm at Gilat and 385 mm at Kibbutz Saad (Har Gil, Bonfil, and Svoray 2011). Soils are Calcic Xerosols with sandy loam texture formed from alluvium and loess on shallow hills of average elevation 80–150 m above sea level (Kafkafi and Bonfil 2008).

2.2. Field measurements and sampling design

An Analytical Spectral Devices (ASD, Inc., Boulder, CO, USA) FieldSpec Pro FR spectrometer was used to measure the spectral reflectance from plants at leaf and canopy scales in the early growth stages. The ASD instrument operates over a range of 400–2400 nm with a spectral sampling resolution of 1.4 nm for 400–1000 nm and 2 nm for 1000–2400 nm. Spectra were resampled to 5 nm bands by means of linear interpolation. Atmospheric water absorption spectral regions (1350–1420 nm and 1800–1960 nm) were then eliminated from the resampled spectra. This range of 400–2400 nm is defined hereafter as all wavebands. Spectral measurements were taken at leaf and canopy scales. The high-intensity contact probe of the ASD radiometer was used to obtain leaf-scale spectra as required to determine the feasibility of spectral separation between crops and BLW or grasses. The total number of leaf spectral samples obtained by the contact probe was 608, with the following distribution: wheat 63, chickpea 57, GW 136, and BLW 352. All leaf spectral samples were acquired 30–40 days after emergence (DAE) of the crops.

The bare fibre adaptor of the ASD instrument was also used to collect canopy reflectance data at solar noon ± 1 h, under clear sky conditions with a bare fibre adaptor that was levelled in a nadir angle. Reference measurements of spectral reflectance were obtained periodically using a standard white reference panel (Spectralon Labsphere Inc., North Sutton, NH, USA). At a viewing angle of 25°, the field of view (FOV) was a circle with radius of $\sim$32 cm when the bare fibre optic adaptor was held 1.4 m above ground. This radius was large enough to include a few plants in the FOV while being small enough to select only one category of plants (e.g. wheat, chickpea, BLW, or GW). Since canopy spectral measurements were obtained during the early growing stages of crops and weeds, and the height of the probe was fixed, it was assumed that changes in the FOV between different measurements were negligible. Wheat or chickpea crops, GW, and BLW were separately measured as sole targets in the FOV against a soil background. Soil was also measured as a sole target.

To explore the spectral feasibility and limitations of satellites, the ground spectral data were resampled to VENμS bands by averaging these spectra in the range of each of the bands (Herrmann et al. 2011) and to EO1-ALI bands by averaging with respect to the spectral response in the range of each of the bands (Mendenhall, Lencioni, and Evans 2000). At ground level, a pixel or FOV could be obtained containing one target (e.g. wheat, BLW, GW, or soil) as opposed to airborne or spaceborne sensors, where it is likely that each pixel will contain number of targets. Mixed pixels will be a combination of the spectra of the targets they contain (Biewer et al. 2009). Spectral measurements of wheat with BLW, and wheat with GW, both with soil background, were acquired to examine the effect of a mixed pixel of crop and weeds on the classification quality for wheat fields.

The spectral data from each season were randomly divided into calibration (50%) and validation (50%) data sets. Validation statistics were computed to assess the accuracy of the calibration. The number of samples changed with crop, DAE, and relative coverage of vegetation. Canopy spectral sampling sites were distributed in the crop fields based on the presence or absence of weeds. The canopy spectral samples were acquired 8–57 DAE in wheat fields and 10–79 DAE in chickpea fields.

Vegetation coverage (Deardorff 1978) was assessed at each spectral measurement. To do this, a 50 $\times$ 60 cm rectangular frame (the same area as the FOV) was placed in the centre of the FOV. The rectangular frame was then divided to 20 equal size squares.

Assessment was done for each of the squares and accumulated, with 5% weight per square, to include the entire area surrounded by the frame. All assessments were performed by the same person. Since herbicides are intended to be applied before closure of the crop canopy (Thorp and Tian 2004), the spectral samples were obtained in the early growth stages of crops and weeds. The classification analysis was mainly limited to plots with >30% vegetation coverage in order to reduce the negative effect of soil background on crop canopy reflectance, while classification of data with both 0–100% and >5% vegetation cover was applied for specific cases, as shown in the results.

2.3. General discriminant analysis

Qualitative classification analysis was applied by the general discriminant analysis (GDA) method (Wastell 1987; Baudat and Anouar 2000; Shen, Bai, and Fairhurst 2007). GDA applies the general linear model to the discriminant function analysis problem. The general linear model is a generalization of the linear regression model that tests for effects of categorical and continuous predictor variables, and accommodates experimental designs with either a single dependent variable or multiple dependent variables. Discriminant function analysis involves the prediction of a categorical dependent variable by one or more continuous or binary independent variables, and is used to determine which variables discriminate between two or more naturally occurring groups. There can be as many classification functions as there are groups. For each group it is possible to determine the location of the centroid. A case would be classified as belonging to a group in which the Mahalanobis distance to the group's centroid is the least (Mahalanobis, Bose, and Roy 1937). These classifications are determined not only by the most influential wavelengths but also by all the spectra. Therefore, to discriminate between different crops and weeds, as well as to determine the most important wavelengths for the separation, GDA forward stepwise models were created and validated by Statistica v. 9 software (StatSoft, Inc., Tulsa, OK, USA).

The quality of classification of the validation data sets was assessed by Cohen's Kappa coefficient, overall accuracy, user's accuracy, and producer's accuracy for each confusion matrix. Cohen's Kappa, as defined by Cohen (1960), is a unitless value ranging from 1 for perfect agreement to –1 for complete disagreement. Cohen's Kappa is presented in the following equation:

$$\text{Kappa} = \frac{d - q}{N - q}, \tag{1}$$

where d is the sum of ground truth pixels that were correctly classified, q is the product of total ground truth and total classification values summed and divided by the total number of samples, and N is the total number of samples. The 95% confidence limit (CL) was calculated for overall accuracy as shown by Foody (2008):

$$\text{CL} = \pm t_{N,d-1}\sqrt{\frac{p\,(1-p)}{N-1}}, \tag{2}$$

where p is the overall accuracy, $t_{N,d-1}$ is the statistical value of 95% two-tailed testing for d samples, N is the total number of samples, and d is the sum of ground truth pixels that were correctly classified. The CL of total accuracy allows comparison between models based on significance, and thus indicates whether there is any model that is significantly better or worse than the others (Foody 2008).

3. Results and discussion

Leaf spectra obtained by contact probe are pure, without any mixed-category spectra (Figure 1(*a*)). Plant species differ in levels of reflectance, but otherwise have similar spectral features. Differences in spectral reflectance can be observed in the NIR region (700–1200 nm) and may be attributed to variation in internal leaf structure between cereals (GW and wheat) and broadleaf plants (BLW and chickpea). Conversely, plant canopy spectra obtained by bare fibre probe (Figure 1(*b*)) are influenced by >60% vegetation cover with soil as background. The various plant categories differ in regard to level of reflectance and possess similar spectral features between 700 and 2400 nm. Besides soil background, canopy spectra are influenced by canopy structure and thickness, as well as by other external parameters (e.g. plant age, sun angle, and wind). These parameters can influence reflectance values in the visible (400–700 nm), NIR, and SWIR (1200–2400 nm) regions. These differences in the level of reflectance and features for both leaf and canopy scales form the basis for the use of GDA to classify categories.

Very high overall accuracy for classification was obtained from the GDA model of pure leaf spectra by general category (wheat, chickpea, BLW, and GW, Table 1), thus indicating that GDA is capable of detecting features that consistently appear in pure leaf spectra of general vegetation categories. The overall accuracy was excellent for classification by plant species (Table 2), where 20 samples of unknown genera that could not be related to any of the 13 weed species were excluded from the data set. These results indicate that classification by genera would be as efficient as that by category. Using hyperspectral data, Smith and Blackshaw (2003) obtained perfect results when classifying leaves but the quality of classification was less when species of crops and weeds were classified. Gibson et al. (2004) applied multispectral (i.e. yellow, red, and infrared wide bands) aerial imagery to identify the presence of GW and BLW in soybean, but were unable to discriminate between weed species. Therefore, this simple classification scheme is deemed suitable for discriminating among these general plant categories.

General DA model results for samples with over 30% vegetation coverage are shown for wheat in Table 3 and chickpea in Table 4. In both cases the user's and producer's accuracy for each of the classes is >91% and >87%, respectively. The overall accuracies are 95% and 94% for wheat and chickpea, respectively, with 95% CI that reduces total accuracy to not less than 90% and 88%, respectively. In both cases, the BLW class has perfect user's accuracy and GW perfect user's accuracy. The producer's accuracy of wheat is greater than for chickpea, which might be related to the biomass density of the crop (Thorp and Tian 2004), since the FOV of the fibre optic adaptor can cover five or six rows of wheat compared with only one row of chickpea. In both cases the soil is classified with high success. GDA-based classification results for wheat are based on 11 narrow bands: sorted in order of importance, these are 675, 715, 705, 745, 690, 875, 850, 1090, 750, 760, and 1070 nm. For chickpea, eight narrow bands are important: 675, 725, 705, 730, 690, 715, 685, and 680 nm. Included in each series are several highly ranked red-edge bands (e.g. 675, 715, and 705 nm for wheat, and 675, 725, and 705 nm for chickpea). Therefore, optical sensors with four or more red-edge bands might be required for implementing the proposed GDA classification scheme. Another interesting result is that out of the five most important bands, red-edge bands occupy the first, third, and fifth places in both models' narrow-band lists. These findings indicate that the NIR and red-edge regions contain information that is important for detection of categories and species of vegetation, which is in agreement with previous studies (Vrindts, De Baerdemaeker, and Ramon 2002; Jurado-Exposito et al. 2003; Smith and Blackshaw 2003). Thenkabail et al. (2004) presented a list of 22 narrow wavebands in the range 350–2500 nm ideal for discriminating natural and agricultural

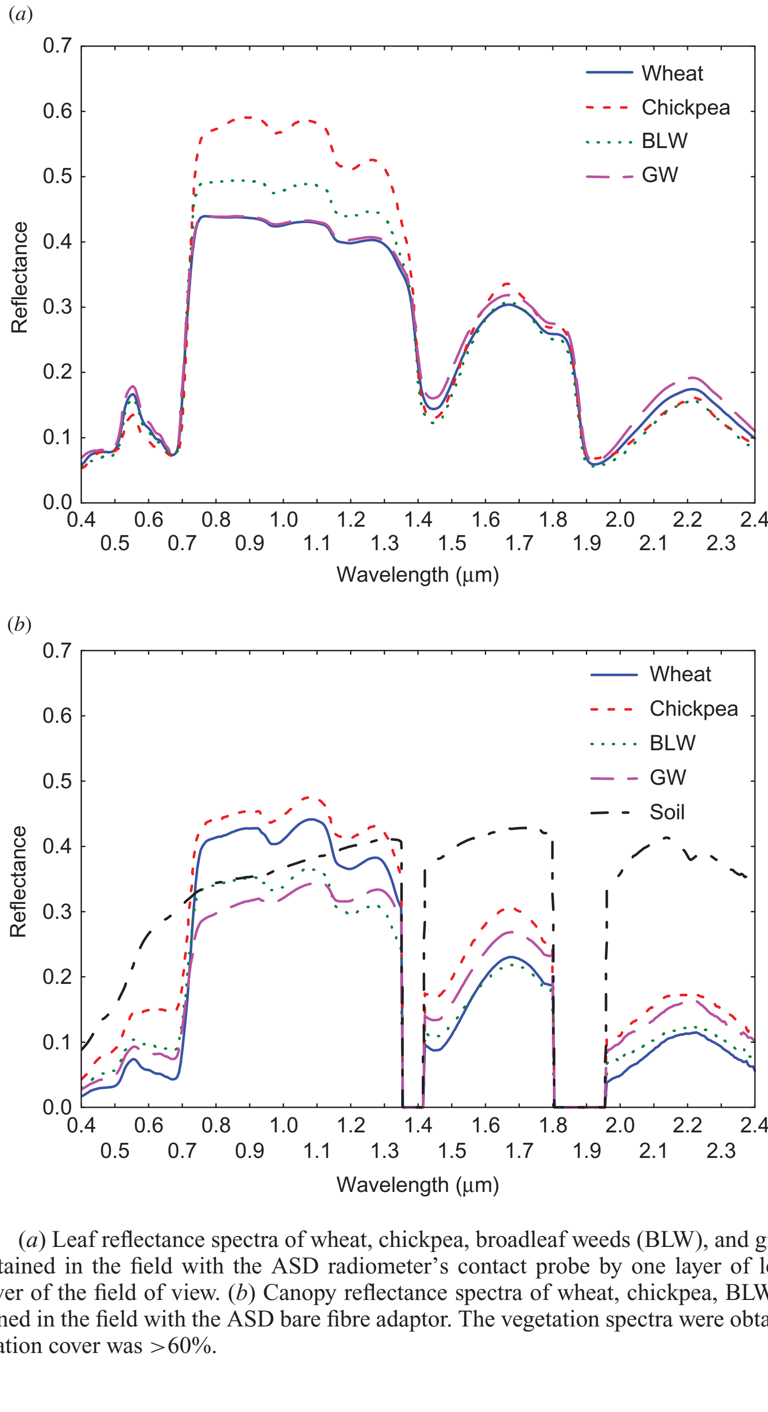

Figure 1. (*a*) Leaf reflectance spectra of wheat, chickpea, broadleaf weeds (BLW), and grass weeds (GW) obtained in the field with the ASD radiometer's contact probe by one layer of leaves with 100% cover of the field of view. (*b*) Canopy reflectance spectra of wheat, chickpea, BLW, GW, and soil obtained in the field with the ASD bare fibre adaptor. The vegetation spectra were obtained when the vegetation cover was >60%.

vegetation and weeds. The six red-edge bands (i.e. 675, 680, 685, 690,705, and 730 nm) found to be important for classification in the current study were in accordance with this list. Gray, Shaw, and Bruce (2009) reported that the most important bands for classification of soybean, soil, and six BLWs are in the SWIR region. Reflectance in the SWIR region

Table 1. Confusion matrix of the classification of pure leaf spectra by vegetation category using all wavebands.

	Ground truth classes				Total # of classified samples	User's accuracy % correct
	Wheat	Chickpea	BLW	GW		
Map classes						
Wheat	**32**	0	0	1	33	**97**
Chickpea	0	**28**	0	0	28	**100**
Broadleaf weeds (BLW)	0	0	**174**	0	174	**100**
Grass weeds (GW)	0	0	0	**66**	66	**100**
Total # of ground truth samples	32	28	174	67		
Producer's accuracy % correct	**100**	**100**	**100**	**99**		**99.7***

Note: *95% confidence interval = ±0.6% for the overall classification accuracy and Kappa = 0.99.

Table 2. Classification by GDA of pure leaf spectra by genus, all wavebands.

Genera	% Correct	Number of validation samples
Wheat	100	32
Chickpea	100	28
Hordeum	100	10
Hirschfeldia	100	20
Malva	100	40
Sinapis	96	24
Ipomoea	100	11
Avena	100	12
Solanum	100	11
Setaria	100	17
Silybum	100	11
Chrysanthemum	100	29
Sonchus	100	13
Lolium	100	9
Beta	100	14
Total	99.6	281

Table 3. Canopy classification model for wheat fields based on 11 narrow bands (sorted by importance: 675, 715, 705, 745, 690, 875, 850, 1090, 750, 760, and 1070 nm) and homogeneous sample with vegetation cover >30%.

	Ground truth classes				Total # of classified samples	User's accuracy % correct
	Wheat	BLW	GW	Soil		
Map classes						
Wheat	**36**	0	1	1	38	**95**
Broadleaf weeds (BLW)	0	**24**	0	0	24	**100**
Grass weeds (GW)	0	2	**22**	0	24	**92**
Soil	1	0	0	**20**	21	**95**
Total # of ground truth samples	37	26	23	21		
Producer's accuracy % correct	**97**	**92**	**96**	**95**		**95***

Note: *95% confidence interval = ±4.19% for the overall accuracy and Kappa = 0.94.

Table 4. Canopy classification model for chickpea fields, based on 8 narrow bands (sorted by importance: 675, 725, 705, 730, 690, 715, 685, and 680 nm) and homogeneous sample with vegetation cover >30%.

	Ground truth classes				Total # of classified samples	User's accuracy % correct
	Chickpea	BLW	GW	Soil		
Map classes						
Chickpea	**13**	1	0	0	14	**93**
Broadleaf weeds (BLW)	0	**24**	0	0	24	**100**
Grass weeds (GW)	0	1	**23**	1	25	**92**
Soil	2	0	0	**20**	22	**91**
Total # of ground truth samples	15	26	23	21		
Producer's accuracy % correct	**87**	**92**	**100**	**95**		**94***

Note: *95% confidence interval = ±5.13% for the overall classification accuracy and Kappa = 0.92.

is influenced by plant water content, whereas that in the visible region is influenced by chlorophyll pigments (Gausman 1985).

Classification results based on resampled VENμS and ALI bands, for samples with over 30% vegetation coverage, are shown in Table 5 for wheat and Table 6 for chickpea. The BLW class has the highest user's accuracy for wheat in VENμS data, and 3% greater than soil in ALI data (Table 5). BLW has the highest user's accuracy together with soil for chickpea in VENμS data, and second after soil in ALI data (Table 6). Since chickpea is a broadleaf and wheat is a grass, it may be that BLW could be classified with higher accuracy against a crop that is not a broadleaf. By the same logic, the GW class obtained higher user's accuracy values in chickpea than in wheat, but as mentioned above the BLW class user's accuracy values are still greater than the GW class, even in chickpea. This relatively high user's accuracy of BLW agrees with Vrindts, De Baerdemaeker, and Ramon (2002), who classified BLW against GW using three to nine selected bands. Red-edge narrow bands were highly important for classification, as mentioned above. There is no advantage in four red-edge bands (i.e. VENμS) over two (i.e. ALI), since both Cohen's Kappa values and user's accuracies are similar and overall classification accuracies overlap when considering confidence intervals. Nevertheless, VENμS would be better suited for site-specific weed management than ALI due to its greater spatial resolution (5.3 m vs 30 m). The chickpea models provided better classification results than the wheat models, but this advantage is not significant based on 95% CI.

The total accuracy is 79 ± 6.74% for all ASD wavebands in wheat fields for six categories: wheat, BLW, and GW with soil as background, and soil and two categories of mixed vegetation in the FOV (Table 7). To simulate a situation where the decision to spray or not is to be made, the results of GDA classification for three options of herbicide application (no spray, spray BLW, or spray GW) are presented in Table 8 for all wavebands. No herbicide would be applied if only wheat and soil were detected in the FOV of the sensor, whereas herbicide would be applied if BLW or GW with wheat, or only BLW or GW were detected. This scenario is based on heterogeneous spectra with >5% vegetation cover 25–40 DAE of wheat, which is the optimal time for herbicide application. Spectral data obtained at ground level by Lopez-Granados et al. (2008) resulted in high classification, but no relation to an optimal time for herbicide application was mentioned. For the application window in wheat fields, the overall classification accuracy was 87 ± 5.57% for all ASD wavebands (Table 8). The user's accuracy for no herbicide application indicates that 79% of the decisions not to

Table 5. Canopy classification models for wheat fields based on resampled VENμS and ALI broadbands, with vegetation cover >30%.

	VENμS						ALI					
	Ground truth classes				Total # of classified samples	User's accuracy % correct	Ground truth classes				Total # of classified samples	User's accuracy % correct
	Wheat	BLW	GW	Soil			Wheat	BLW	GW	Soil		
Map classes												
Wheat	**30**	7	5	3	45	**67**	**29**	3	5	0	37	**78**
Broadleaf weeds (BLW)	0	**16**	0	0	16	**100**	1	**18**	2	0	21	**86**
Grass weeds (GW)	4	3	**18**	0	25	**72**	3	5	**16**	1	25	**64**
Soil	3	0	0	**18**	21	**86**	4	0	0	**20**	24	**83**
Total # of ground truth samples	37	26	23	21			37	26	23	21		
Producer's accuracy % correct	**81**	**62**	**78**	**86**		**77***	**78**	**69**	**70**	**95**		**78****

Notes: *95% confidence interval = ±8.09% for the overall classification accuracy and Kappa = 0.68.
**95% confidence interval = ±7.97% for the overall classification accuracy and Kappa = 0.70.

Table 6. Canopy classification models for chickpea fields based on resampled VENμS and ALI broadbands, with vegetation cover >30%.

	VENμS						ALI					
	Ground truth classes				Total # of classified samples	User's accuracy % correct	Ground truth classes				Total # of classified samples	User's accuracy % correct
	Chickpea	BLW	GW	Soil			Chickpea	BLW	GW	Soil		
Map classes												
Chickpea	**14**	2	0	1	17	**82**	**13**	4	0	1	18	**72**
Broadleaf weeds (BLW)	0	**19**	1	0	20	**95**	0	**16**	2	0	18	**89**
Grass weeds (GW)	0	5	**22**	0	27	**81**	0	6	**21**	0	27	**78**
Soil	1	0	0	**20**	21	**95**	2	0	0	**20**	22	**91**
Total # of ground truth samples	15	26	23	21			15	26	23	21		
Producer's accuracy % correct	**93**	**73**	**96**	**95**		**88***	**87**	**62**	**91**	**95**		**82****

Notes: *95% confidence interval = ±6.94% for the overall classification accuracy and Kappa = 0.84.
**95% confidence interval = ±8.22% for the overall classification accuracy and Kappa = 0.76.

Table 7. Herbicide application model for wheat fields with vegetation cover of 0–100%, restricted to 25–40 days after emergence, for all wavebands.

	Ground truth classes						Total # of classified samples	User's accuracy % correct
	Wheat	Wheat & BLW	Wheat & GW	BLW	GW	Soil		
Map classes								
Wheat	**24**	6	4	2	1	2	39	**62**
Wheat & broadleaf weeds (BLW)	1	**20**	0	5	1	0	27	**74**
Wheat & grass weeds (GW)	0	1	**13**	0	1	0	15	**87**
BLW	0	3	0	**18**	0	0	21	**86**
GW	0	0	1	0	**11**	0	12	**92**
Soil	0	0	0	1	0	**26**	27	**96**
Total # of ground truth samples	25	30	18	26	14	28		
Producer's accuracy % correct	**96**	**67**	**72**	**69**	**79**	**93**		**79***

Note: *95% confidence interval = ±6.74% for the overall classification accuracy and Kappa = 0.75.

Table 8. Herbicide application model for wheat fields with vegetation cover >5%, restricted to 25–40 days after emergence, for all wavebands.

		Ground truth classes			Total # of classified samples	User's accuracy % correct
	Herbicide application	Wheat & soil	BLW & wheat or BLW	GW & wheat or GW		
Map classes						
Wheat & soil	No	**52**	9	5	66	**79**
Broadleaf weeds (BLW) & wheat or BLW	Yes (spray BLW)	1	**46**	1	48	**96**
Grass Weeds (GW) & wheat or GW	Yes (spray GW)	0	1	**26**	27	**96**
	Total # of ground truth samples	53	56	32		
	Producer's accuracy % correct	**98**	**82**	**81**		**87***

Note: *95% confidence interval = ±5.57% for the overall classification accuracy and Kappa = 0.81.

spray are indeed correct. Basing site-specific herbicide application on a map derived from remote sensing and the GDA method would be highly effective, as indicated by the user's accuracy of 96% for spraying both BLW and GW.

4. Summary and conclusions

Classification of crops and weeds was applied by GDA models at both leaf and canopy scale. The leaf scale resulted in almost perfect classification by both genus and category. The canopy scale was applied for several spectral resolutions, hyperspectral and resampling to current and forthcoming satellites included, as well as different vegetation coverage percentage. GDA is negatively affected by a non-uniform number of samples among classes (Fraley and Raftery 2002), and it has difficulty in separating classes that are spectrally similar (Zhao and Maclean 2000). In the current study, the GDA results were influenced by an unequal number of samples among classes. The classes were of different vegetation types that may have included soil characteristics in many spectral samples, in addition to soil as a class on its own. Nevertheless, the results of this study indicate that differentiation between crops and weeds is possible using GDA, thus potentially contributing to practical site-specific herbicide application. Specific conclusions are:

- the spectral characteristics of pure leaf spectra enable precise classification of different plant categories and genera;
- the red-edge region is highly important for crop and weed classification; and
- spectral separation of crops and weeds is potentially useful for wheat fields, with $>5\%$ vegetation cover in the critical period for weed control.

Ground-level sensors offer very high spatial resolution, and therefore the potential ability to apply classification to classes comprising only one plant species. In contrast, satellite sensors offer synoptic, map-like views that cover large regions at lower spatial resolution and therefore the potential ability to apply classification to classes comprising only one plant species is smaller. If a space platform is to be chosen, VENμS would be a better option than ALI because of its greater spatial resolution and revisiting frequency. Ground sensors are less affected by atmospheric effects on vegetation reflectance measurements. Further research is needed to determine what level of ground truth data is needed to adjust the GDA model to sensor spatial and spectral resolutions, and to determine the effect of mixed pixels.

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