Hybrid Segmentation – Artificial Neural Network Classification of High Resolution Hyperspectral Imagery for Site-Specific Herbicide Management in Agriculture

P.R. Eddy, A.M. Smith, B.D. Hill, D.R. Peddle, C.A. Coburn, and R.E. Blackshaw

Abstract

Site-Specific Herbicide Management (SSHM) in Precision Agriculture (PA) requires weed detection in crop fields for directed herbicide application instead of spraying entire fields. This has significant economic and environmental advantages for improved agricultural practices that are essential given forecast increases in global population and food production needs. In this study, a new hybrid segmentation - Artificial Neural Network (HS-ANN) method was compared to standard Maximum Likelihood Classification (MLC) for improving crop/weed species discrimination in SSHM/PA. Very high spatial resolution (1.25 mm) ground-based hyperspectral image data were acquired over field plots of canola, pea, and wheat crops seeded with two weed species (redroot pigweed, wild oat) in southern Alberta, Canada. The very high spatial and spectral resolution image data required development of a simple yet efficient vegetation index (Modified Chlorophyll Absorption in Reflectance Index (MCARI)) threshold segmentation to separate vegetation from soil for classification. The HS-ANN consistently outperformed MLC in both single date and multi-temporal classifications. Higher class accuracies were obtained with multi-temporally trained ANNs (84 to 92 percent overall), with improvements up to 31 percent over MLC. With advancements in imaging technology and computer processing speed, this HS-ANN method may constitute a viable farm option for real-time detection and mapping of weed species for SSHM in agriculture.

Introduction

Site-Specific Herbicide Management (SSHM) involves selectively applying herbicides to an agricultural field based on identified zones of weed density rather than spraying an entire field (Thompson *et al.*, 1991). As a key component in Precision Agriculture (PA), SSHM can provide substantial benefits through reducing the amount of herbicide required for weed control and crop protection since the weed-controlling chemical is only applied where it is actually needed (Brown and Steckler, 1995; Medlin *et al.*, 2000; Blackshaw *et al.*, 2006). Techniques for implementing SSHM strategies are of increasing importance for compliance with strict environmental regulations and are also advantageous economically. SSHM techniques may result in a 30 to 72 percent reduction in herbicide requirements (Mortensen *et al.*, 1995) and considering that global herbicide product sales totalled $14.8 billion (USD) in 2006 (Crop Life, 2007), could constitute a substantial savings to producers. This reduction of chemicals applied also reduces the risk of environmental contamination as a result of ground-water leaching and introducing less chemicals into the atmosphere (Lindquist *et al.*, 1998; Radhakrishnan *et al.*, 2002; Smith and Blackshaw, 2003). With projections of global population increases in the coming years and the associated increased reliance on agriculture to meet challenging food production demands (Tweeten, 1998; FAO, 2007), effective and efficient agricultural practices such as SSHM/PA will be crucial to reducing environmental impacts and helping ensure the economic viability of agricultural systems.

Operational implementation of real-time SSHM requires on-board image acquisition and processing systems and precise control of herbicide spray applicators (Tang *et al.*, 1999; Brown and Noble, 2005). The image acquisition and processing system must rapidly differentiate weeds from crop (Hutto *et al.*, 2006; Grey *et al.*, 2007) and provide the sprayer control with a map of weed location and density in near real-time. This map is built up in the field with immediate herbicide application dependant on Artificial Intelligence (AI) system decision making. Such a system requires accurate species recognition as well as computational efficiency (Tian *et al.*, 1999; Tang *et al.*, 2000; Burks *et al.*, 2000b).

The rich information provided by hyperspectral sensor systems requires efficient data processing and interpretation tools, such as AI methods, for practical application to real-time SSHM. Artificial Neural Networks (ANNs) are uniquely suited to these image processing tasks and can handle complex feature space and integrate different data types (Atkinson and Tatnall, 1997). As a nonparametric approach they offer significant

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performance advantages compared to standard statistical classification techniques (Qiu and Jensen, 2004) especially in the classification of plant reflectance spectra, which typically are not normally distributed (Noble and Crowe, 2005).

ANN model development can often be complex in terms of establishing an optimal or near-optimal network architecture and training set. This difficulty has been somewhat mitigated through development of software packages specifically designed for ANN model development and classification (NeuralWare, 2003). That approach was used here and is consistent with available tools and methods that may be suitable for a semi-operational to operational context, however, the focus of this paper is on new applications involving hyperspectral, very high resolution ground data instead of an extensive algorithm comparison or sensitivity analysis.

ANNs first appeared in the remote sensing literature in the late 1980's (Key *et al.*, 1989; Benediktsson *et al.*, 1990), with application to weed-crop discrimination appearing in the late 1990's (Yang *et al.*, 1998, 2000; Moshou *et al.*, 2001). Past ANN research has focused primarily on multispectral image classification. ANNs have successfully classified corn (*Zea mays* L.) and weed species using leaf texture (color co-occurrence) measures with up to 97 percent overall accuracy (Burks *et al.*, 2000a, 2000b, and 2005). ANN classification results using leaf shape features have also been encouraging with radish (*Raphanus sativus* L.) and weed species classified with 100 percent overall accuracy (Cho *et al.*, 2002). Shape features were also used to distinguish carrot (*Daucus carota* L.) from two weed species (ryegrass (*Lolium perenne* L.) and fat hen (*Chenopodium album* L.)) with 62 to 82 percent of plant images correctly classified (Aitkenhead *et al.*, 2003). Yang *et al.* (2000) evaluated network architecture effects on classification accuracy in discriminating corn from seven weed species with class accuracies of 60 to 100 percent for corn and 40 to 80 percent for weed classes. This study was later expanded (Yang *et al.*, 2003) to detect four weed species in corn, and the resulting networks produced accuracies of 54 to 90 percent for corn and 32 to 100 percent for single weed species.

Few studies, however, have addressed crop/weed discrimination with ANNs using ground-based hyperspectral data. Plant spectral reflectance characteristics in bands outside the visible region of the electromagnetic spectrum provide more information than three-band RGB color imaging sensors and may increase the feasibility of crop and weed discrimination (Okamoto *et al.*, 2007). Though imaging sensors are limited, Moshou *et al.* (2001) used point based spectral measurements and self-organizing map network models to classify corn and sugar beet (*Beta vulgaris* L.) from weed species with very high accuracies (corn 96 percent, weed 90 percent, sugar beet 98 percent, and weed 97 percent).

The objective of this study was to evaluate single date and multi-temporal classification of several crop and weed species from very high resolution hyperspectral image data acquired at ground level. Classification accuracy of the new hybrid segmentation-Artificial Neural Network (HS-ANN) classification technique was compared to Maximum Likelihood Classification (MLC) for potential application to future real-time SSHM practices.

Materials and Methods

Sensor System

The hyperspectral imaging system and image acquisition software were developed by DeltaTee Enterprises Ltd. (Calgary, Alberta, Canada). The line scanning system uses a magnetic carriage to step a linear variable filter across a Charge-Coupled Device (CCD) sensor for hyperspectral (61 wavebands from 400 to 1,000 nm at 10 nm increments) image acquisition of a static target. The imaging sensor was manufactured by Point Grey Research (Vancouver, British Columbia, Canada), and used a 0.5 inch progressive scan CCD sensor (Sony, ICX414AL). This sensor outputs a 640 pixel × 480 pixel 16-bit image with a signal-to-noise ratio of greater than 60 dB. The system focuses incoming radiation with an 8 mm C-mount VIS-NIR lens (Schneider Kreuznach, Germany) fixed to create 44° vertical and 33° horizontal fields-of-view with the focus and aperture (f/1.4 to f/11) adjusted manually.

Prior to analysis, image radiometric pre-processing included dark current correction, frequency resampling, uniformity correction, and conversion to reflectance. The latter was achieved by imaging a Spectralon® (Labsphere, Inc., North Sutton, New Hampshire, USA) calibration panel immediately prior to image acquisition and computing the ratio of irradiance to radiance with reference to wavelength-specific panel calibration coefficients.

The hyperspectral camera system was situated on a boom arm, mounted on a flat-bed truck and centered at 1 m target distance (Figure 1). Imagery acquired from each target was 1.25 mm × 1.25 mm spatial resolution over the 400 to 1000 nm spectral range at 10 nm intervals. Image data were acquired under clear sky conditions at nadir view angle ± 2 hours from solar noon (13:38 local time) to reduce the illumination intensity variation associated with changes in solar zenith angle and intermittent cloud cover. Data acquisition was limited to days of negligible wind to minimize leaf movement during plot imaging.

Image Data Collection

Three crop species (field pea (PEA), *Pisum sativum* L.; canola (CAN), *Brassica napus* L.; and spring wheat (WHT), *Triticum aestivum* L.), and two weed species (redroot pigweed (RRP), *Amaranthus retroflexus* L.; and wild oat (WO), *Avena fatua* L.) were seeded to field plots located at the Agriculture and Agri-Food Canada Research Centre (AAFC-LRC) in Lethbridge, Alberta, Canada (49.7°N, 112.833°W). Building on our earlier work at AAFC-LRC (e.g., Smith and Blackshaw 2003; Blackshaw *et al.*, 2005 and 2006; Peddle and Smith, 2005; Kokko and Hill, 2005),

Figure 1. Flat-bed truck with sensor mounted on boom arm for image acquisition. A color version of this figure is available at the ASPRS website: **www.asprs.org**.

weed seeds were surface broadcast on plots (5 m × 2.5 m) prior to seeding the various crops. Seeder movement over plots allowed broadcast seeds to be embedded in the soil, facilitating germination.

Field plots of the eleven treatments (5 monocultures and 6 crop/weed combinations) were seeded on four dates to increase the window of opportunity for collecting timely (weather/crop stage dependant) image data. Treatments seeded on 06 July 2005 provided temporal sampling as image data were acquired at approximately one, two, three, and four weeks (14 July, 19 July, 26 July, and 03 August, respectively) after seeding. The 19 July and 26 July acquisition dates encompassed the timeframe of optimal plant growth stage for herbicide application and thus were used for investigation of threshold techniques and evaluation of ANNs and MLC.

Segmentation

An efficient, rapid threshold method was developed for defining vegetation pixels based on image data acquired over field-based crop and weed treatments. The Modified Chlorophyll Absorption in Reflectance Index (MCARI) (Equation 1), designed to be responsive to both chlorophyll variation and resistant to non-photosynthetic material effects (Daughtry *et al.*, 2000; Haboudane *et al.*, 2002) was used to separate vegetation from background. MCARI was calculated as:

$$MCARI = [(R_{700} - R_{670}) - 0.2*(R_{700} - R_{550})]*(R_{700}/R_{670}) \quad (1)$$

where R_{550}, R_{670}, and R_{700} are reflectance at 550, 670, and 700 nm, respectively. The spectral reflectances in these wavelength regions (550, 670, and 700 nm) were different between vegetation (foreground) and soil or litter (background) providing separation in spectral space which lends itself well to segmentation by threshold techniques.

Defining the minimum MCARI value for vegetation was achieved through manual identification of vegetation pixels in the image data. The lowest value MCARI value of sunlit and shadowed vegetation pixels in the images was observed to be 0.1. Leaf edge pixels affected by background mixing showed a MCARI value lower than 0.1 and was defined as the minimum value for the threshold. A vegetation mask was created by assigning pixel values ≥0.1 as green plant matter and values <0.1 excluded as non-vegetated and, therefore, not of interest (Figure 2). MCARI thresholding was applied to all field-based image data acquisitions prior to classification.

Classification

The supervised classification methods (MLC and ANN) required input training data for each species. Particular attention was given not only to representation of species spectrally but also spatially across each image scene. Accordingly, each image was divided into nine equal sections. Training samples were defined from regions of interest (ROI) from leaves using the ENVI image analysis system (ENVI, 2007). These were selected from one to four regions per section (based on leaf size) with each section sampled uniformly across plots (e.g., CAN leaves were sampled from both CAN/WO and CAN/RRP treatments). This ensured that any sensor variation across the image

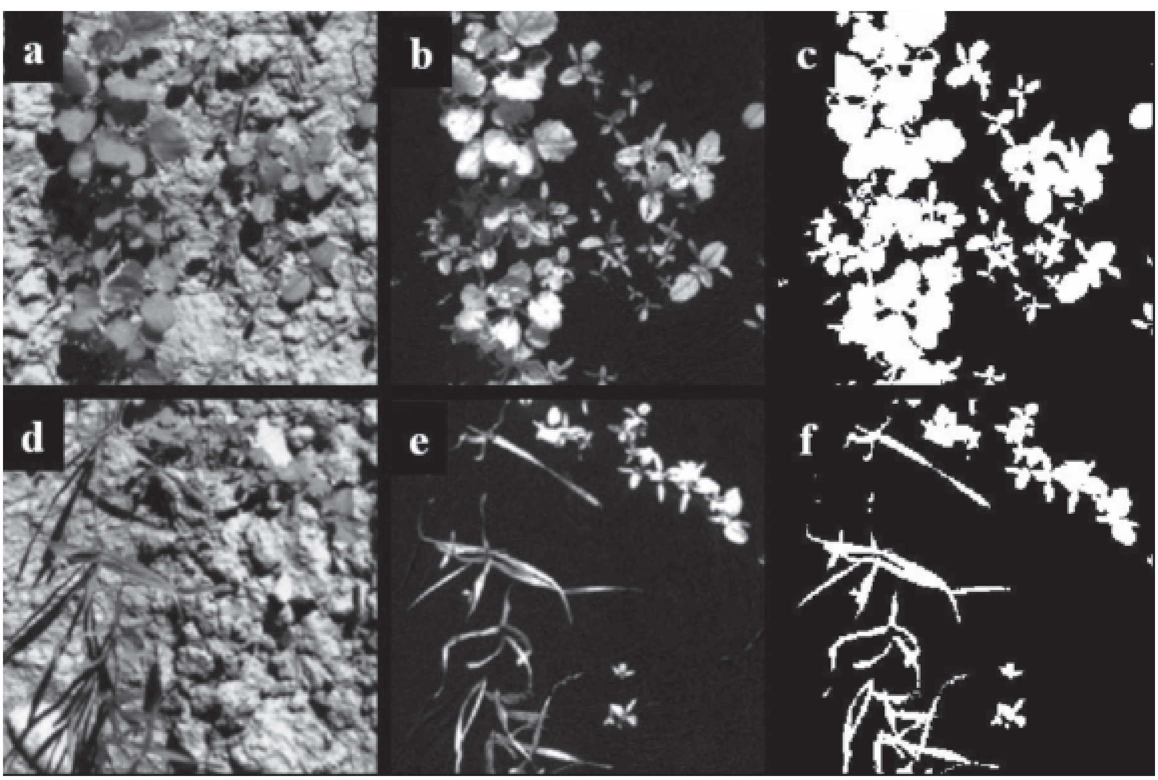


Figure 2. Results from MCARI threshold technique for segmenting vegetation ((a) CAN/RRP and (d) WHT/RRP) from background. MCARI vegetation index is calculated (b and e) and a value of 1 was applied to all pixels with a value of ≥0.1 to create a mask of only vegetation pixels (c and f). A color version of this figure is available at the ASPRS website: **www.asprs.org**.

Table 1. Pixels Used for Validation of Field Plot Classification Output

Crop/Weed	# Crop Pixels	# Weed Pixels
	19 July Acquisition	
CAN/RRP	10268	2839
WHT/WO	1869	62
PEA/WO	2804	268
WHT/RRP	1301	2739
CAN/WO	8222	27
PEA/RRP	3763	3384
	26 July Acquisition	
CAN/RRP	35008	5101
WHT/WO	975	339
PEA/WO	4101	358
WHT/RRP	1887	4684
CAN/WO	17379	292
PEA/RRP	4451	5076

scene would be represented in the classification training dataset. After the selection of leaf regions, a one of *n* sampling procedure reduced the training set to approximately 500 pixels for each species (Hill *et al.*, 2002).

Training pixels used for classification of the 19 July and 26 July image data were also combined into a multi-temporal training set to assess the temporal variability observed between these two dates. This resulted in approximately 2,000 pixels (1000 crop and 1000 weed) used as input to train the multi-temporal series classifications.

Classification accuracy assessment was based on independent, mutually exclusive data separate from the training set and obtained from remaining leaves not used in training (Table 1). As classifications were run on a per plot basis, the validation sites could not be defined across treatments as was the case in training. Class validations were tabulated as contingency tables using the post classification assessment modules in ENVI/IDL (ENVI, 2007). Standard methods of accuracy assessment (overall accuracy, Kappa co-efficient, user and producer accuracies, and assessment of spatial patterns of error) were implemented and used to evaluate and compare results from the classification methods tested.

Building Artificial Neural Network Models

Feed-forward ANN modeling was conducted using Predict® software, version 3.11 (NeuralWare Inc., Pittsburgh, Pennsylvania) and following protocols developed by Hill *et al.* (2002). Multi-layer perceptron model development involved: (a) selecting internal validation, training, and internal test data subsets, (b) analyzing and transforming data, (c) selecting variables, (d) network construction and training, and (e) model verification. The ANN software was set to partition training data into subsets with 30 percent removed to form an intermediate internal test set, and the remaining 70 percent used to develop ANN models. This internal test set was separate from the independent, mutually exclusive validation data set described above that was used for accuracy assessment and reporting. Networks were trained using an adaptive gradient learning rule (a form of back-propagation). The Predict® software used a constructive method for determining a suitable neural network architecture. This cascade learning procedure iteratively added processing elements to the hidden layer until performance on the internal test set showed no further improvement in prediction (NeuralWare, 2003). This method of network development produced a different architecture (varied inputs and number of hidden nodes) for each prediction model.

The procedure was run over 20 iterations, which produced 20 prediction models for each crop/weed combination. The best model was chosen from the set of 20 on the basis of a suitable NN architecture (i.e., minimum number of input neurons connected to a hidden layer that had fewer neurons than the input layer) combined with a high internal and external validation accuracy. This best model was then used to classify field plot treatments.

Results and Discussion

Single Date Classification

All classifications used the entire 61 band dataset as input to the classification algorithms. This provided a test of classification accuracy for the two methods (MLC and HS-ANN) with a single image acquisition. Due to insufficient emergence of WO, the 19 July classification of CAN/WO and WHT/WO combinations could not be considered.

Results from both the MLC and HS-ANN classification validations are presented in Table 2 and Table 3. Overall

Table 2. MLC Classification Accuracy Assessment with 61 Wavebands Input to Classification for (a) 19 July and (b) 26 July Image Acquisitions

a	Crop Class Accuracy		Weed Class Accuracy		Overall MLC	
	User (%)	Producer (%)	User (%)	Producer (%)	Accuracy (%)	Kappa
CAN/RRP	96.9	80.8	58.2	90.7	82.9	0.59
PEA/WO	97.6	94.1	52.3	67.9	91.8	0.56
WHT/RRP	85.8	95.4	87.8	64.9	85.5	0.65
PEA/RRP	87.7	96.3	95.3	84.9	90.9	0.82

b	Crop Class Accuracy		Weed Class Accuracy		Overall MLC	
	User (%)	Producer (%)	User (%)	Producer (%)	Accuracy (%)	Kappa
CAN/RRP	98.6	81.2	44.0	92.3	82.6	0.49
WHT/WO	93.4	67.2	48.3	86.4	72.1	0.43
PEA/WO	95.2	51.0	11.1	70.4	52.6	0.06
WHT/RRP	74.0	61.5	86.0	91.2	82.7	0.56
CAN/WO	99.8	90.7	14.0	89.0	90.6	0.22
PEA/RRP	78.5	85.2	86.5	79.5	82.2	0.64

Table 3. HS-ANN Classification Accuracy Assessment with 61 Bands Input to Classification for (a) 19 July, and (b) 26 July Image Acquisitions

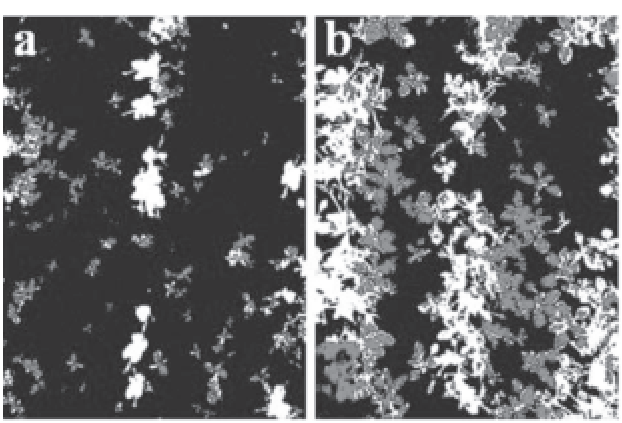
a	Crop Class Accuracy		Weed Class Accuracy		Overall HS-ANN	
	User (%)	Producer (%)	User (%)	Producer (%)	Accuracy (%)	Kappa
CAN/RRP	98.4	94.5	82.7	94.5	94.5	0.85
PEA/WO	99.3	95.6	66.8	93.3	95.4	0.75
WHT/RRP	94.2	89.0	79.2	88.5	88.8	0.75
PEA/RRP	94.6	94.0	93.3	94.1	94.0	0.88

b	Crop Class Accuracy		Weed Class Accuracy		Overall HS-ANN	
	User (%)	Producer (%)	User (%)	Producer (%)	Accuracy (%)	Kappa
CAN/RRP	98.4	93.9	68.3	89.5	93.4	0.74
WHT/WO	88.8	74.6	51.2	70.9	73.7	0.41
PEA/WO	98.6	77.5	25.3	86.9	78.2	0.30
WHT/RRP	74.9	91.8	96.4	87.6	88.8	0.74
CAN/WO	99.8	90.1	13.0	87.4	90.1	0.20
PEA/RRP	81.8	84.9	86.3	83.4	84.1	0.68

accuracies of over 80 percent were obtained with the MLC except in two cases (WHT/WO and PEA/WO on 26 July). However, the more robust Kappa co-efficient statistic revealed several discrepancies. The highest MLC Kappa co-efficient occurred for the 19 July PEA/RRP classification (0.82), however, Kappa values for other crop/weed combinations ranged from 0.06 to 0.65. These values indicated confusion between classes, which were assessed further using individual class user and producer accuracies. The 19 July classifications provided high accuracies (86 to 97 percent and 81 to 97 percent user and producer) in terms of crop classes, but the weed class accuracies ranged from 52 to 95 percent. The 26 July validation did not show the same trend, as both crop and weed classes had low user and producer accuracies, especially in the crop/WO combinations. When considering overall MLC accuracy using the Kappa statistic, the best results were observed in classification of the PEA/RRP combination (for both acquisition dates), with the later date showing slightly lower class accuracy (Figure 3).

HS-ANN classification accuracies were markedly improved over the MLC based on overall percent accuracies and Kappa coefficients (Table 3a and 3b). The weed class user accuracies for 19 July were low (PEA/WO: 67 percent, CAN/RRP: 83 percent) but not as low as those observed in the MLC (up to 52 percent). The 26 July classifications produced less encouraging results than those obtained on 19 July. The highest weed class errors occurred in commission of PEA (75 percent) and CAN (87 percent) pixels to the WO class on 26 July.

In terms of the location and spatial pattern of classification error in field plots, RRP was classified better by MLC (Figure 4e and Figure 5e), but darker and shadowed CAN and WHT pixels were classified incorrectly (Figure 4b and Figure 5b). Crop species were classified with higher accuracy using the HS-ANN technique, with error restricted to leaf edges



(a) (b)

Figure 3. Single date MLC classification of PEA (white) and RRP (grey) on (a) 19 July and (b) 26 July image data. A color version of this figure is available at the ASPRS website: **www.asprs.org**.

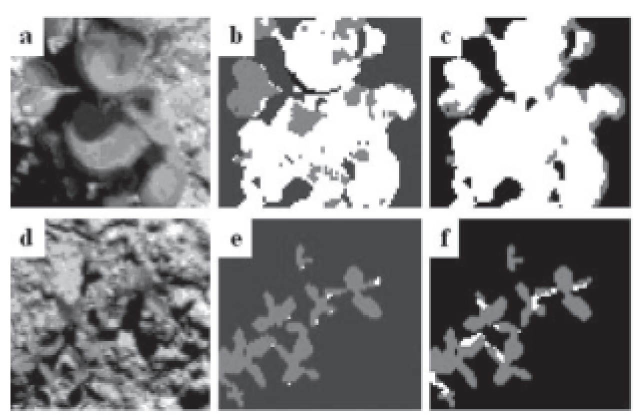


Figure 4. MLC (b and e) and HS-ANN (c and f) classification of 19 July CAN (a, b, and c)/RRP (d, e, and f) treatment. A color version of this figure is available at the ASPRS website: **www.asprs.org**.

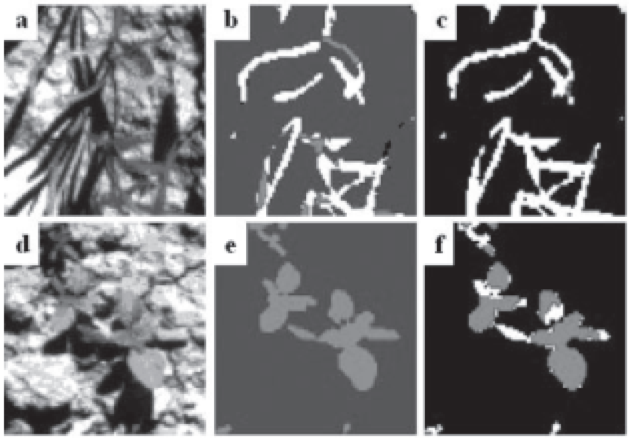


Figure 5. MLC (b and e) and HS-ANN (c and f) classification of 19 July WHT (a, b, c)/RRP (d, e, and f) treatment. A color version of this figure is available at the ASPRS website: **www.asprs.org**.

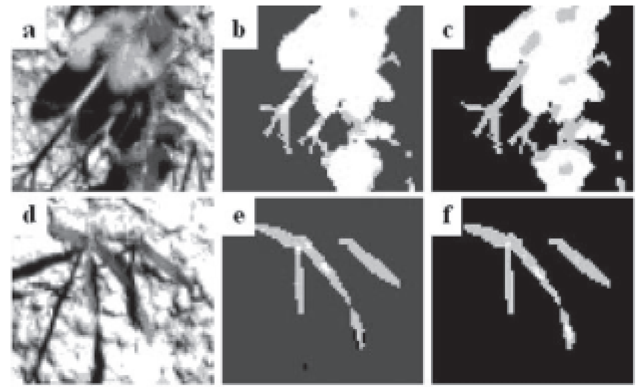


Figure 6. MLC (b and e) and HS-ANN (c and f) classification of 19 July PEA (a, b, and c)/WO (d, e, and f) treatment. A color version of this figure is available at the ASPRS website: **www.asprs.org**.

(Figure 4c) and darker pixels in RRP incorrectly classified (Figure 4f and Figure 5f).

Spatially, mis-classification was similar in the Crop/WO classifications for both MLC and HS-ANN techniques. WO was classified well (Figure 6e and 6f, and Figure 7e and 7f) with mis-classification occurring mainly in PEA tendrils (Figure 6b and 6c) and CAN petioles and leaf veins (Figure 7b and 7c).

Overall, the crop/RRP classifications were less prone to error than the crop/WO in both the MLC and HS-ANN output. Higher classification accuracy was also obtained on the earlier plant stage (19 July), and represented a trend observed with both classification methods.

Multi-temporal Classification

The two dates of image acquisition enabled comparison of the classification algorithms regarding not only spatial variation but also variability of spectral reflectance in the temporal domain. This series of classifications used both 19 July and 26 July data for training the MLC and ANNs. Once the models were built, crop/weed combinations from each date were classified.

In examining the MLC class validation (Table 4a and 4b), with the exception of the PEA/RRP combination, generally poor results were obtained with low user accuracies on both July 19 (33 to 84 percent) and July 26 (7 to 78 percent) and producer accuracies on 19 July (67 to 84 percent) for the weed classes. Crop producer accuracy was also low (34 to 80 percent) for all combinations on the later acquisition date. The best results occurred with the 19 July PEA/RRP combination (91 percent, Kappa = 0.82) followed by WHT/RRP (85 percent, Kappa = 0.64) (Figure 8a and 8b). Similar to the single date MLC classifications, the earlier date showed higher class accuracies than 26 July.

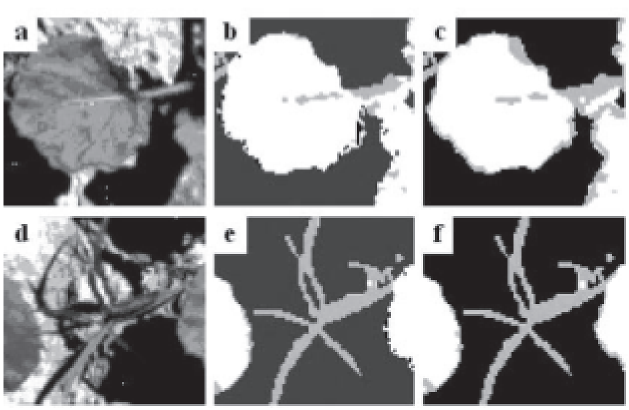


Figure 7. MLC (b and e) and HS-ANN (c and f) classification of 26 July CAN (a, b, and c)/WO (d, e, and f) treatment. A color version of this figure is available at the ASPRS website: **www.asprs.org**.

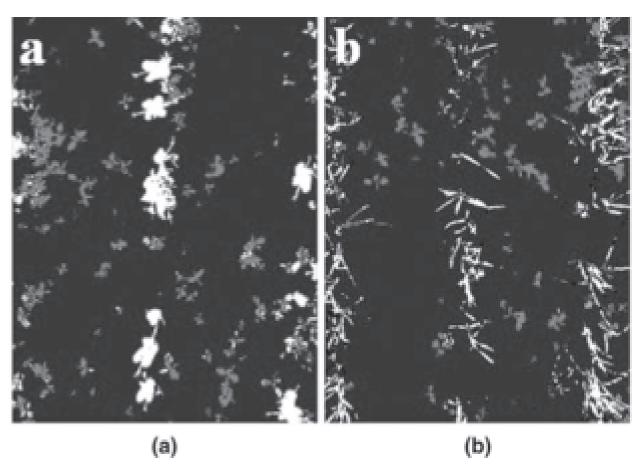


Figure 8. Multi-temporal MLC classification output of crop (white) (PEA (a), WHT (b)) and weed (grey) (RRP (a and b)) combinations acquired on 19 July. A color version of this figure is available at the ASPRS website: **www.asprs.org**.

Table 4. Classification Accuracy Assessment for Multi-temporal Classifications of MLC for (a) 19 July and (b) 26 July

a	Crop Class Accuracy		Weed Class Accuracy		Overall MLC	
	User (%)	Producer (%)	User (%)	Producer (%)	Accuracy (%)	Kappa
CAN/RRP	94.6	76.0	51.5	84.3	77.8	0.48
PEA/WO	97.3	86.8	32.7	66.8	85.1	0.38
WHT/RRP	86.9	93.4	83.7	67.1	84.9	0.64
PEA/RRP	89.1	94.4	93.3	87.2	91.0	0.82
b	**Crop Class Accuracy**		**Weed Class Accuracy**		**Overall MLC**	
	User (%)	Producer (%)	User (%)	Producer (%)	Accuracy (%)	Kappa
CAN/RRP	99.9	56.1	24.9	97.4	61.4	0.24
WHT/WO	97.1	38.0	35.2	96.8	53.2	0.22
PEA/WO	95.7	51.0	11.6	74.0	52.8	0.07
WHT/RRP	77.9	34.0	78.5	96.1	78.3	0.37
CAN/WO	100	78.5	7.2	98.6	78.8	0.11
PEA/RRP	83.9	80.3	83.9	86.4	83.6	0.67

Similar to the trend observed in the single date classifications, the multi-temporal HS-ANN overall accuracies were also better (3 to 31 percent) than the MLC, with 19 July (Figure 9, and Table 5a) out performing 26 July (Table 5b). Low user accuracies (14 to 74 percent) were observed for both dates in the weed class with the exception of the WHT/RRP and PEA/RRP combinations. The crop class accuracies were high for all combinations between both dates, except for WHT/RRP, which exhibited 79 percent and 71 percent user accuracy on 19 July and 26 July, respectively. The WHT/WO classifications which proved difficult in the single date analyses, improved with the use of the HS-ANN method and multi-temporal data (85 percent, Kappa = 0.61). As was observed with the multi-temporal MLC classifications, the best results were achieved with the PEA/RRP on both dates, with crop/RRP classifications generally better than the crop/WO combinations.

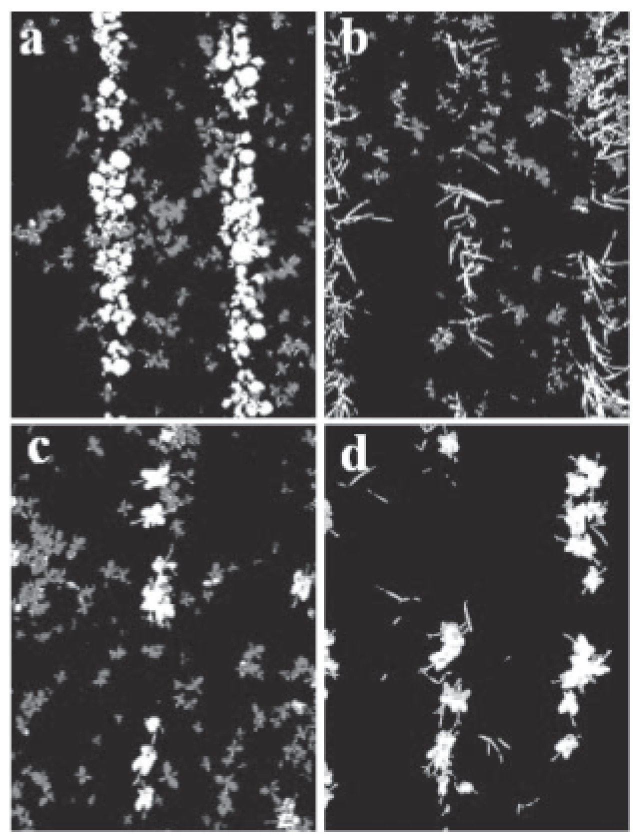


Figure 9. Multi-temporal HS-ANN classification output of crop (white) (CAN (a), WHT (b), PEA (d) and weed (grey) (RRP (a,b,and c), WO (d)) combinations acquired on 19 July. A color version of this figure is available at the ASPRS website: **www.asprs.org**.

Conclusions

Segmentation of ground-based image data prior to classification is an efficient way of simplifying the classification of crop and weed species. Through the prior elimination of background pixels, only foreground classes need be discriminated, thus reducing the number of classes required for image generalization. The MCARI-based thresholding method provided a simple yet efficient method to derive consistent results in defining leaf matter under full sun or shaded scenarios and thus was functional in defining pixels of vegetation from high spatial resolution image data. This allowed for more focused and therefore efficient classification which is a critical factor towards developing real-time systems.

Typically, ANN model development could be considered more difficult and time consuming than MLC when taking into account network architecture, training parameters and analyst experience required to build accurate models. This difficulty can be somewhat mitigated by using specialized software that simplifies network development and which may be reasonably comparable to that of MLC training procedures in terms of user requirements. Regardless of

Table 5. Classification Accuracy Assessment for HS-ANN Multi-temporal Classifications for (a) 19 July, and (b) 26 July

a	Crop Class Accuracy		Weed Class Accuracy		Overall HS-ANN	
	User (%)	Producer (%)	User (%)	Producer (%)	Accuracy (%)	Kappa
CAN/RRP	97.2	91.4	74.5	90.3	91.2	0.76
PEA/WO	99.6	89.8	47.2	95.9	90.3	0.58
WHT/RRP	78.8	86.0	93.0	89.0	88.0	0.73
PEA/RRP	90.6	91.7	90.7	89.4	90.6	0.81

b	Crop Class Accuracy		Weed Class Accuracy		Overall MLC	
	User (%)	Producer (%)	User (%)	Producer (%)	Accuracy (%)	Kappa
CAN/RRP	97.9	91.6	60.0	86.6	61.4	0.24
WHT/WO	91.3	88.4	72.4	73.5	53.2	0.22
PEA/WO	97.3	84.8	29.6	72.4	52.8	0.07
WHT/RRP	70.5	90.1	95.5	84.8	78.3	0.37
CAN/WO	99.5	92.4	14.3	75.1	78.8	0.11
PEA/RRP	88.3	84.6	87.0	90.1	83.6	0.67

training difficulty, however, once network models are developed, integration into a real-time SSHM processing chain would be relatively straightforward.

Single date and multi-temporal classifications were evaluated for discriminating between single crop/weed combinations. The single date series of classifications set a baseline evaluation of the capability of MLC and ANN algorithms to address species discrimination when only a single image is acquired, and from class validation this initial test provided promising results. The multi-temporal classifications enabled assessment of weed and crop discrimination, accounting for not only spatial variation but also variation in reflectance characteristics over time. This procedure would lend itself better to operational or end-use applications as training data for these methods, which account for spectral variation over the optimal herbicide application periods, could be built into the processing procedure.

The earlier plant stage (19 July) showed consistently better classification results than the latter 26 July acquisition, suggesting that optimal species discrimination can be obtained at early plant growth stages. Higher class accuracies were observed with multi-temporally trained HS-ANNs (84 to 92 percent), with improvements in accuracies up to 13 percent (19 July) and 31 percent (26 July) compared to MLC. MLC was hindered somewhat by the addition of the second date and was not well suited to this type of application.

From these validated classification results it is concluded that the HS-ANN classification models out performed MLC and showed that HS-ANN classification techniques are better suited to real-time SSHM in terms of species discrimination accuracy for the crop and weed types tested. This hybrid segmentation - artificial neural network approach has demonstrated an important and highly practical application of advanced AI techniques and has potential for development of operational, real-time SSHM for protection and enhancement of vital food crops.

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