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Potential Use of Plant Spectral Characteristics in Weed Detection

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Summary: Plant and soil reflectance spectra were measured using a spectrometer. Significant wavelengths and feature values for weeds (leaf/stem), wheat (leaf/stem) and soil were determined using the mean difference and category contrast methods. Calibration models were developed on these wavelengths using partial least squares and discriminant analysis. All models classified soil with a classification rate of 100%. Weed stems can be, in most cases, correctly identified from other classes. However, to correctly identify stems of specific weed species and to differentiate between green objects - wheat leaf, wheat stem, and weed leaf - were more difficult. This study demonstrated the potential of using spectra properties of plants and soil in weed detection.

Keywords: Wheat, Weed, Sensor, Spectra characteristics, Wavelength, Partial Least Square, Near-Infrared Reflectance

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INTRODUCTION

The story of agriculture is the story of weed interference. Weeds cost billions of dollars annually in lost production and cost of control. For the past decades, herbicide application in crop fields has been increasing substantially. It was estimated that about \$3.1 billion was spent annually to control weeds in the United States (McWhorther, 1984). British crop growers spend in excess of 200 million pounds a year on weed prevention. Although herbicides have assisted the economic viability of farmers and helped reduce the risk of soil erosion, there are many situations where weed control with sprays is more expensive than cultivation, and the use of herbicides may be seen as a potential ecological hazard (Felton and McCloy, 1992). Reduced dependence on herbicides is desirable in cutting down the costs of crop production and retarding the development of herbicide resistance.

Traditional approaches to herbicide application are based on the assumption that weeds are uniformly distributed in the fields. However, the vast majority of agricultural fields has, in some degree, spatial variations in weeds infestation. The distribution of weeds, particularly grass weeds in cereal crops, is often "patchy", rather than even or random. Ben and Hamm (1985) pointed out that portions of cereal crop fields are free of weeds and various weed species often can be found in a certain field. If weeds are automatically identified and classified, they can be precisely targeted with specific herbicides (Scarr, 1997). It is obvious that a precision weed detection system combined with selective spray has considerable potential in crop production.

It is a complex problem to discriminate between crops and different weeds species. With the advancement of computer technology, machine vision systems are found to be a possible solution for weed identification (Thompson *et al.*, 1990). A machine vision system classifies plants based on their color, shape, or texture information. Casady *et al.* (1990) reported that color provides an excellent, but frequently overlooked, source of information in machine vision applications. Guyer *et al.* (1986) stated that weed detection based on leaf shape would be quite complicated as the plant grows mature. Shape-based discrimination is suitable for crops having leaves with distinct forms, e.g. sugarbeet. For crops with spindly leaves, however, shape recognition would become complicated as the leaves are often difficult to be separated from other objects. Scarr *et al.* (1997) reported that analyzing a small, homogeneously textured sub-region within a plant image is a more robust approach for identifying a particular species. When a set of variables or image features (including texture and shape measures) that characterize a particular image is obtained, it can be used to generate a classification rule for crop/weed discrimination.

In recent years, the Near-Infrared Reflectance (NIR) method has been adopted as a quantitative tool for pattern recognition in many areas. Dowell (1992) studied the potential of using tristimulus values and spectral reflectance for identification of normal and damaged peanut kernels using a monochromatic machine vision system, a contact colorimeter, a non-contact colorimeter, and a spectrophotometer. Casady *et al.* (1990) measured the optical properties of soybean seeds using a spectroradiometer. They found that the reflectance between 436 and 724 nm provided the most useful information for separating normal from damaged seeds. Majumdar *et al.* (1996) examined the potential of using tristimulus values, color solid scale values, and reflectance characteristics of grains as discriminating features among various seed types, including bulk samples of cereals, pulses, oilseeds, and specialty crops. They concluded that the tristimulus values, the color scale values, and the percent reflectance ratios at different wavelengths in the visible range of the electromagnetic spectrum could be used to effectively identify most of the grains tested in their study. Fleton and McClay (1992) developed a sensor to reliably discriminate green plants (weeds) against a background of soil and dead plant materials based on the spectral characteristics of green vegetation. The red and near-infrared wavebands provided the optimal discrimination. They claimed that their sensor detected more than 95% of weeds on most of the farms. Vrindts and Baerdemaeker (1996) studied the possibility of classifying soil, crops, and weeds using their spectral responses at certain wavelengths. Spectrum data of leaves of four crops (potato, sugarbeet, corn, and chicory), soil, and weeds were collected. They concluded that plant leaves and soil could be correctly classified on a limited number of wavelengths selected through a discriminant analysis.

The NIR analysis has gained popularity as a direct result of improvement in spectrum measurement techniques and the development of powerful mathematical tools, such as multivariate statistical analysis in pattern recognition. Multiterm Linear Regression (MLR), Partial Least Square regression (PLS), and Principal Component Regression (PCR) have been used to extract necessary information from a huge amount of spectral data (Wang, 1997). Zhang *et al.* (1998) demonstrated their research on noninvasive monitoring of deep-tissue pH using NIR spectroscopic measurement combined with the multivariate calibration technique - PLS analysis. The results showed that the calibration models from PLS provided adequate accuracy and sensitivity for *in vivo* clinical monitoring of deep-tissue. Wang (1997) measured the reflectance spectra of single wheat kernels from 400 to 2000 nm to classify wheat for grading purpose. Principal Component Analysis (PCA) was used to find the scores of each spectrum vector as inputs to a neural network for final classification. The classification accuracy reached 98%.

Spectral reflectance combined with multivariate analysis may provide a new solution to weed detection. If a limited number of significant wavelengths can be selected to identify weeds and classify weeds species, new types of weed sensors can be designed for practical field applications. Efficiency of herbicide use can be, as a result, greatly improved.

The objectives of this research were

1. to investigate the feasibility of weed detection based on spectral characteristics of crops, weeds, and soil,
2. to determine significant wavelengths for discriminating weeds against crops and soil, and
3. to develop classification models and methods for weed detection using plant spectral properties.

MATERIALS AND METHODS

Materials

Spectral characteristics of 35 plants species, including five crops (corn, common sunflower, soybean, sorghum, and wheat), 30 weed species, and soil, were studied for weed classification. For each plant species, spectra of leaves and stems were collected separately at two growth stages - three and six weeks from the date of planting. To provide replicate samples, crops and weeds were planted in three groups, with the dates of planting apart from each other by two weeks.

Three species of weeds (Kochia, Redroot Pigweed, and Russian Thiestle) and wheat were studied for this paper. Spectra of stems and leaves of these plant species were taken as eight classes, while soil was defined as the ninth class. The spectra of each class were randomly divided into two sets, the training set for setting up calibration model and the validation set for validating the calibration model.

Equipment

Leaves and stems of plants were individually placed on a spectralon background and illuminated with white light from a diode-array spectrometer (DA7000, Perten Instruments, Inc., Springfield, IL). Plants were illuminated via an 8-mm diameter fiber bundle positioned 13-mm from the spectralon surface and oriented 45° from vertical. A 2-mm diameter reflectance probe was oriented vertically, 18 mm from the spectralon surface. The reflectance probe carried the reflected energy to the spectrometer which measures visible (400-750 nm) and NIR (750-1700 nm) reflectance at a rate of 30 spectra per second. Procedures included collecting a baseline, collecting eight spectra from each sample, and averaging these eight spectra. Collecting and averaging the eight spectra took less than one second. The baseline was a spectrum of the spectralon background.

Data Analysis

Raw absorbance Log (1/Reflectance) data in the spectra region of 400-1700 nm were collected using the optical radiation measurement system. The spectra were transferred from ASCII file to binary file so as to be readable by GRAMS/32 (Galactic, 1996), a spectroscopic software package combining data importing, processing, viewing, organizing, and accessing capabilities. The add-on application PLSplus/IQ of the software included powerful multivariate analysis tools, such as PCA, PLS-1, and PLS-2, which can be used to build quantitative calibration models as well as qualitative discriminant models. These software packages were used as the main data analysis tools for this research. Figure 1 shows the procedure for developing the weed-classification calibration model.

Data Preprocessing

1. Spectrum Normalization:

Raw spectra from the spectrometer were truncated to the range between 406 nm and 1680 nm. The discarded regions, 400-406 nm and 1680-1700 nm, showed large fluctuations which were caused by measurement errors.

Many uncontrollable factors had strong effects on raw spectra. The samples that were measured using diffuse reflectance often exhibit significant differences in the spectra. Light scattering could often be considered as the most important contributor to the variation in the spectra data. Standard Normal Variate (SNV) is a method for removing the major effects of light scattering on spectra. It removes the mean value from a spectrum and normalizes the spectrum using the standard deviation of the responses across the entire spectral range. Equations (1) and (2) show the SNV algorithm.

$$\bar{a}_i = \left(\sum_{j=1}^{p} A_{i,j} \right) \Big/ p \tag{1}$$

$$A_{i(SNV)} = \frac{\left(A_i - \bar{a}_i \right)}{\sqrt{\dfrac{\sum_{j=1}^{p} \left(A_{i,j} - \bar{a}_i \right)^2}{(p-1)}}} \tag{2}$$

where

A is an n by p matrix of the training set of spectra across the entire spectral range,
A_i is a 1 by p vector of the ith spectrum in the training set,

$\bar{a}_i$ is the mean response of the ith spectrum in the training set,
n is the number of spectra in the training set,
p is the number of wavelengths in the spectra, and
$A_{i(SNV)}$ is the SNV-correlated $1 \times p$ vector of the ith spectrum in the training set.

Another preprocessing procedure, mean centering, was required by the PLS algorithm. Mean spectrum calculated from all the spectra in the calibration set was subtracted from single spectra. This process enhanced the subtle differences between the spectra.

2. Significant Wavelengths Selection

Practical real-time in-field weed detection requires a minimum number of significant wavelengths to be used to classify weeds, crop, and soil background. Spectral regions containing no useful information for discrimination do not need to be included in calibration. Reducing the number of wavelengths also reduces the use of computer memory and processing time. Efforts were made to select significant wavelengths within the visible and NIR wavebands using the following methods.

a. Mean difference:

This method averages the normalized training set of spectra within each class. The mean spectra of different classes were then subtracted from each other to produce the mean differences between classes. Figure 2 shows mean differences between wheat stem and Redroot Pigweed stem, between soil and Redroot Pigweed stem, and between wheat leaf and Redroot Pigweed stem, respectively. The peaks and valleys selected from mean differences between different classes were compared. If a peaks or a valley was found in more than one mean differences, it was chosen as the significant wavelength. The significant wavelengths selected for three weed species, Kochia, Redroot Pigweed, and Russian Thistle, against wheat and soil were 464, 542, 635, 676, 705, 1074, 1449, and 1515 nm.

b. Category Contrast

Observations on normalized mean spectra of different classes revealed that, at certain wavelengths, the contrasts between major categories of object features were maximized. Such wavelengths found for the contrast between the leaf (wheat and weeds) category and stem (wheat and weeds) category were 675 and 1453 nm. In general, the peak values at 1453 nm (NIR region) of plant stems were higher than those at 675 nm (red region). To the contrary, the peak values at 1453 nm for plant leaves were generally lower than those at 675 nm. The contrast was signified at the wavelengths of 545 and 614 nm between green leaves and reddish stems. In addition, spectra reflection of soil was different from plants (wheat and weeds) in the general trends across the entire visible and NIR wavebands. Two wavelengths 751 and 1453 nm can be used to categorically differentiate soil from living plants. Figure 3 shows the optical characteristics of Redroot Pigweed stem, wheat leaf, wheat stem and soil. Based on category contrast, five wavelengths (545, 614, 675, 751, 1453 nm) were selected for calibration.

In addition to these methods, "divergence", as introduced by Tou and Gonzalez (1974), was also studied for significant wavelengths selection. Divergence is a measure of "distance" or dissimilarity between two classes. Different from the mean-difference and category contrast methods, the divergence method considered the statistical distributions of the spectra responses when calculating the "distance" and to evaluate the effectiveness of class discrimination.

Divergence (J_{ij}) is defined as the total average information for discriminating class i from class j for pattern x (spectrum, in this study).

$$J_{ij} = \int_x \left[p_i(x) - p_j(x)\right] \ln \frac{p_i(x)}{p_j(x)} dx \tag{3}$$

where

$p_i(x)$ is the probability of occurrence of x, given that it belongs to class i, and
$p_j(x)$ is the probability of occurrence of x, given that it belongs to class j.

If two pattern classes are characterized by two n-variate normal populations, the divergence for these two classes becomes

$$J_{ij} = \frac{1}{2} tr\left[(C_i - C_j)(C_j^{-1} - C_i^{-1})\right] + \frac{1}{2} tr\left[(C_i^{-1} + C_j^{-1})(m_i - m_j)(m_i - m_j)'\right] \tag{4}$$

where

m_i and m_j are the mean vectors of class i and j, respectively, and
C_i and C_j are $n \times n$ covariance matrices of classes i and j, respectively.

At each wavelength, since $n = 1$ and $C_i = C_j$, Equation (4) can be expressed as

$$J_{ij} = \frac{1}{2}\left[(\sigma_i^2 - \sigma_j^2)\left(\frac{1}{\sigma_j^2} - \frac{1}{\sigma_i^2}\right)\right] + \frac{1}{2}\left[\left(\frac{1}{\sigma_i^2} + \frac{1}{\sigma_j^2}\right)(\mu_i - \mu_j)^2\right] \tag{5}$$

where

μ_i and μ_j are the mean responses of class i and j at this wavelength
σ_i and σ_j are the standard deviations of the responses of classes i and j at this wavelength.

Divergence for classes i and j can then be plotted over the entire spectral range. Peaks on this plot can be selected as the significant wavelengths. Divergences for soil vs. Redroot Pigweed stem, wheat stem vs. Redroot Pigweed stem, and wheat leaf vs. Redroot Pigweed stem are shown in Fig.4. From Fig. 2 and Fig. 4, the similarities between mean difference and divergence were obvious. For example, both mean difference and divergence curves of "Soil vs. Redroot Pigweed" showed peaks within the ranges of 700 - 100 nm and 1400 - 1680 nm. Peaks also found between 500 and 600 nm on the divergence and mean difference curves for "wheat stem vs. Redroot Pigweed". The similarity between the divergence and mean difference curves demonstrated in Fig. 2 and 4 suggested that the mean difference method is a reasonably effective method for significant wavelengths selection.

3. Assignment of Feature Values

Feature values are data given to each class, each group of classes, or each feature of class to set up calibration model. They represent the characteristics of classes or groups of classes. In this study, the feature values were assigned in two ways:

- Randomly assign values to each group, or
- Assign values to features representing the contrasts between category of objects.

Two calibration models were developed in this study. Model I used eight significant wavelengths selected by the mean difference method. Random feature values were assigned to each class or group of classes. It was found that different combinations of feature values had different effects on calibration results. Results based on various feature value combinations were compared.

Model II was based on the five significant wavelengths selected using the category contrast method. Four features of samples were selected, each corresponding to a category contrast. A feature value was the differences between two mean difference responses:

$$C_1 = \bar{a}_{614} - \bar{a}_{675} \tag{6}$$

$$C_2 = \bar{a}_{675} - \bar{a}_{545} \tag{7}$$

$$C_3 = \bar{a}_{675} - \bar{a}_{1453} \tag{8}$$

$$C_4 = \bar{a}_{751} - \bar{a}_{675} \tag{9}$$

where

$\bar{a}_{545}$, $\bar{a}_{614}$, $\bar{a}_{675}$, $\bar{a}_{751}$, $\bar{a}_{1453}$ are mean responses of a class at wavelengths 545, 614, 675, 751, and 1453 nm, respectively, and
C_1, C_2, C_3, and C_4 are feature values of the class.

PLS Calibration

Partial Least Squares (PLS) is a mathematical tool that can be used to decompose the spectra into a set of "variation spectra", called **eigenvectors, or factors,** that represent the changes in the absorbances within the wavelength range of the spectra.

PLS performs the decomposition on both spectral and feature data simultaneously so that the calibration models established are directly related to the features of interest.

$$\underset{(n\times p)}{A} = \underset{(n\times f)}{S} \times \underset{(f\times n)}{F_a}$$
$$\underset{(n\times m)}{C} = \underset{(n\times f)}{U} \times \underset{(f\times m)}{F_c} \qquad (10)$$

where

A = spectra data,
C = feature values,
S, U = spectral and feature value scores assigned to F_a and F_c, respectively,
F_a, F_c = spectral and feature value factors (eigenvectors), respectively,
n = number of spectra in the training set,
p = number of data points (wavelengths) in a spectrum,
m = number of features, and
f = number of factors.

The training set consisting of spectra of nine classes was used as the input to PLS/IQ software to set up the calibration model. Before PLS analysis was performed to the training set, the data were preprocessed (SNV and mean centering). PLS analysis gave the number of factors used in the calibration model and the predicted feature values.

Once the calibration model was established, the validation set of spectra was tested using the model. The qualitative discriminant Analysis (DA) available in the GRAMS/32 (Galactic, 1996) allowed an "unknown" spectrum to be compared against multiple models, each of which was established using spectra of one specific class. This algorithm gives an indication of the likelihood of unknown spectrum matching a particular model and identifies it as the corresponding class. For nine classes, this method requires the establishment of nine separate PLS calibration models.

In this study, classification was accomplished using a slightly different method. Instead of nine separate calibration models, only one PLS model was established for all nine classes. Once the model is set up, the feature values predicted by the model, together with their corresponding classes were used as inputs for a multivariate DA model. The DISCRIM procedure in the Statistics Analysis System (SAS, 1993) was then used to generate multiple discriminant functions. For the validation set of spectra, the PLS model in GRAMS was used first to predict the feature values. The DA model then examined the predicted feature values and classified the spectra into different classes.

Procedure

The procedures for data analysis and processing using Model I and Model II are summarized as follows:

Model I used four groups of classes, i.e. weed leaf (WL), weed stem (WS), wheat (WH), and soil (SOI). The procedure included the following steps:

- Data normalization using SNV
- Mean centering
- Significant wavelengths selection based on the mean difference method
- Random or orderly selection of the feature value for each group of spectra
- PLS analysis
- DA Analysis

Model II used nine classes directly. The procedure included the following steps:

- Data normalization using SNV
- Mean centering
- Wavelengths selection based on category contrast
- Assignment of feature values based on category contrast
- PLS analysis
- DA analysis

RESULTS AND DISCUSSION

Model I

To classify four groups of samples, one feature was used and various combinations of the feature values were randomly assigned to each group. The results showed that value assignment had a strong effect on classification.

When the feature values were assigned orderly based on some spectral characteristics, the classification results were improved. One spectral characteristic feature was general color perception. Visual perceptions have suggested that the leading color for wheat and weed leaves was green and the leading color of weed stems and soil was brown. Two feature value assignment schemes (Table 1) were compared. The first scheme supported the visual perception, whereas the second scheme opposed it. The results are shown in Table 2 and Table 3. Feature values assigned in accord with visual perception resulted in a higher classification accuracy for wheat and weed stem. The classification accuracy of weed stems reached 100%.

Table 4 gives the results of discriminant analysis using the model based on eight wavelengths and a feature values assignment scheme of WL = 1. WS = 3, WH = 2, and SOI = 5. Assigning a larger value to the soil class improved the classification accuracy for the wheat class (from 25.30% to 51.81%) with the cost of decreased classification rate for the weed stems class (from 100% to 88.89%). It seemed that Model I successfully classified most of the weed stems with a few misclassifications between soil and reddish weed stem. The model however had great difficulties in dealing with wheat leaves, which, as a whole, were largely misclassified into weed stems and leaves.

CONCLUSIONS

1. Study of spectra differences between weeds, crops, and soil provided useful information for selection of significant wavelengths, which may be used to design a practical weed sensor.

2. Two calibration models were developed for weed detection. The first model used eight wavelengths selected by mean differences between spectral responses of different classes and one feature with feature values randomly assigned to different classes. The second model used five wavelengths selected using category contrast and four features with feature values assigned using category contrast. Both models used partial least squares and discriminant analysis for classification. The second model outperformed the first model, especially in differentiating weed species.

3. Among nine classes tested (leaf and stem of wheat, leaves and stems of three weed species, and soil), soil was classified from other classes with a classification rate of 100%. Weed stems can be, in most cases, correctly identified from other classes. However, to correctly identify stems of specific weed species and to differentiate between green objects - wheat leaf, wheat stem, and weed leaf - were more difficult.

4. Further study should be conducted to improve the classification accuracy by collecting a larger amount of samples of plants and soil. With large sample sizes, divergence feature function can be applied to select the effective wavelengths statistically, which may further improve the calibration models.

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Table 1 Feature-value Assignment Scheme

Scheme	WL (Weed Leaf)	WS (Weed Stem)	WH (Wheat Leaf + Stem)	SOI (Soil)
Scheme 1	1	2	3	4
Scheme 2	1	3	2	4

Table 2 Classification results for Model I using six wavelengths and feature values of WL = 1, WS = 3, WH = 2, and Soil = 4

	To					
	VARIETY	WL	WS	WH	SOI	Total
From	WL	21 61.76%	1 2.94%	12 35.29%	0 0%	34 100%
	WS	0 0%	18 100%	0 0%	0 0%	18 100%
	WH	51 61.45%	11 13.25%	21 25.30%	0 0%	83 100%
	SOI	0 0%	0 0%	0 0%	7 100%	7 100%

Table 3 Classification results for Model I using six wavelengths and feature values of WL = 1, WS = 2, WH = 3, and Soil = 4

	To					
	VARIETY	WL	WS	WH	SOI	Total
From	WL	25 73.53%	8 23.53%	1 2.94%	0 0%	34 100%
	WS	2 11.11%	14 77.78%	2 11.11%	0 0%	18 100%
	WH	39 46.99%	34 40.96%	10 12.05%	0 0%	83 100%
	SOI	0 0%	0 0%	0 0%	7 100%	7 100%

Table 4 Classification results of Model I using 8 wavelengths and feature values of WL1= 1, WS = 3, WH = 2, and Soil = 5

		To				
	VARIETY	WL	WS	WH	SOI	Total
From	WL	20 58.82%	0 0%	14 41.18%	0 0%	34 100%
	WS	0 0%	16 88.89%	2 11.11%	0 0%	18 100%
	WH	38 45.78%	2 24.10%	43 51.81%	0 0%	83 122%
	SOI	0 0%	0 0%	0 0%	[illegible] 100%	5 100%

Table 5 Classification results of Model II using 5 wavelengths and feature values based on category contrast

		To				
	VARIETY	WL	WS	WH	SOI	Total
From	WL	25 73.53%	0 0	9 26.47%	0 0	34 100%
	WS	0 0	15 83.33%	3 16.67%	0 0	18 100%
	WH	41 49.40%	1 1.20%	41 49.40%	0 0	83 100%
	SOI	0 0	0 0	0 0	5 100%	5 100%

Table 6 Classification results of Model II for 9 classes using 5 wavelengths and feature values based on category contrast

VARIETY	KCL	KCS	RRL	RRS	RTL	RTS	WHL	WHS	SOI	Total
KCL	6 85.71%	0 0%	0 0%	0 0%	1 14.29%	0 0%	0 0%	0 0%	0 0%	7 100%
KCS	0 0%	2 50%	0 0%	1 25%	0 0%	1 25%	0 0%	0 0%	0 0%	4 100%
RRL	0 0%	0 0%	12 52.17%	0 0%	2 8.70%	0 0%	9 39.13%	0 0%	0 0%	23 100%
RRS	0 0%	0 0%	0 0%	12 100%	0 0%	0 0%	0 0%	0 0%	0 0%	12 100%
RTL	0 0%	0 0%	0 0%	0 0%	4 100%	0 0%	0 0%	0 0%	0 0%	4 100%
RTS	0 0%	0 0%	0 0%	0 0%	0 0%	[illegible] 100%	0 0%	0 0%	0 0%	2 100%
WHL	5 10%	0 0%	22 44%	0 0%	0 0%	0 0%	23 46%	0 0%	0 0%	50 100%
WHS	0 0%	0 0%	0 0%	1 3.03%	2 6.06%	4 12.12%	0 0%	26 78.79%	0 0%	33 100%
SOI	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	5 100%	5 100%

Table 7 Classification results of Model I for 9 classes using 8 wavelengths and feature values of WL1= 1, WS = 3, WH = 2, and Soil = 5

VARIETY	KCL	KCS	RRL	RRS	RTL	RTS	WHL	WHS	SOI	Total
KCL	4 57.14%	0 0%	1 14.29%	0 0%	0 0%	0 0%	2 28.57%	0 0%	0 0%	7 100%
KCS	0 0%	2 50%	0 0%	2 50%	0 0%	0 0%	0 0%	0 0%	0 0%	4 100%
RRL	13 56.52%	0 0%	0 0%	0 0%	7 30%	0 0%	2 8.70%	1 4.35%	0 0%	23 100%
RRS	0 0%	0 0%	0 0%	10 83.33%	0 0%	0 0%	0 0%	0 0%	2 16.67%	12 100%
RTL	0 0%	0 0%	0 0%	0 0%	4 100%	0 0%	0 0%	0 0%	0 0%	4 100%
RTS	0 0%	0 0%	0 0%	0 0%	0 0%	2 100%	0 0%	0 0%	0 0%	2 100%
WHL	22 44%	0 0%	4 8%	0 0%	14 28%	0 0%	10 20%	0 0%	0 0%	50 100%
WHS	0 0%	0 0%	0 0%	1 3.03%	9 27.27%	10 30.30%	0 0%	13 39.39%	0 0%	33 100%
SOI	0 0%	3 60%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	2 40%	5 100%

Table 8 Validation results of Model II for 9 classes using 5 wavelengths and feature values based on category contrast

From	KCL	KCS	RRL	RRS	RTL	RTS	WHL	WHS	SOI	Total
KCL	6 85.71%	0 0%	0 0%	0 0%	0 0%	0 0%	1 14.29%	0 0%	0 0%	7 100%
KCS	0 0%	1 25%	0 0%	2 50%	0 0%	0 0%	0 0%	1 25%	0 0%	4 100%
RRL	0 0%	0 0%	10 50%	0 0%	1 5%	0 0	9 45%	0 0%	0 0%	20 100%
RRS	0 0%	3 37.50%	0 0%	4 50%	0 0%	1 12.50%	0 0%	0 0%	0 0%	8 100%
RTL	0 0%	0 0%	0 0%	0 0%	2 66.67%	0 0%	0 0%	1 33.33%	0 0%	3 100%
RTS	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	2 100%	0 0%	2 100%
WHL	0 0%	0 0%	2 4.17%	0 0%	2 4.17%	0 0%	44 91.67%	0 0%	0 0%	48 100%
WHS	0 0%	2 6.45%	0 0%	0 0%	1 3.23%	6 19.35%	0 0%	22 70.97%	0 0%	31 100%
SOI	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	5 100%	5 100%

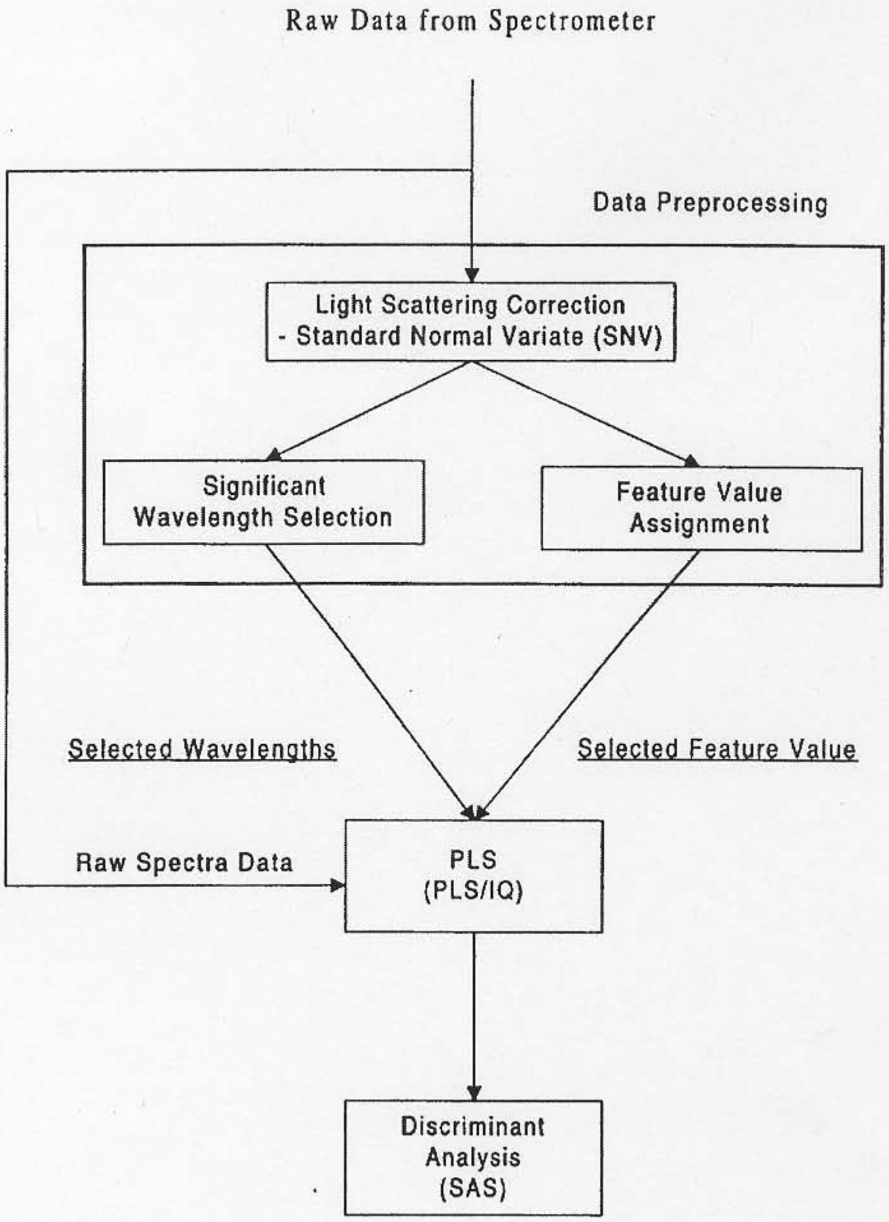
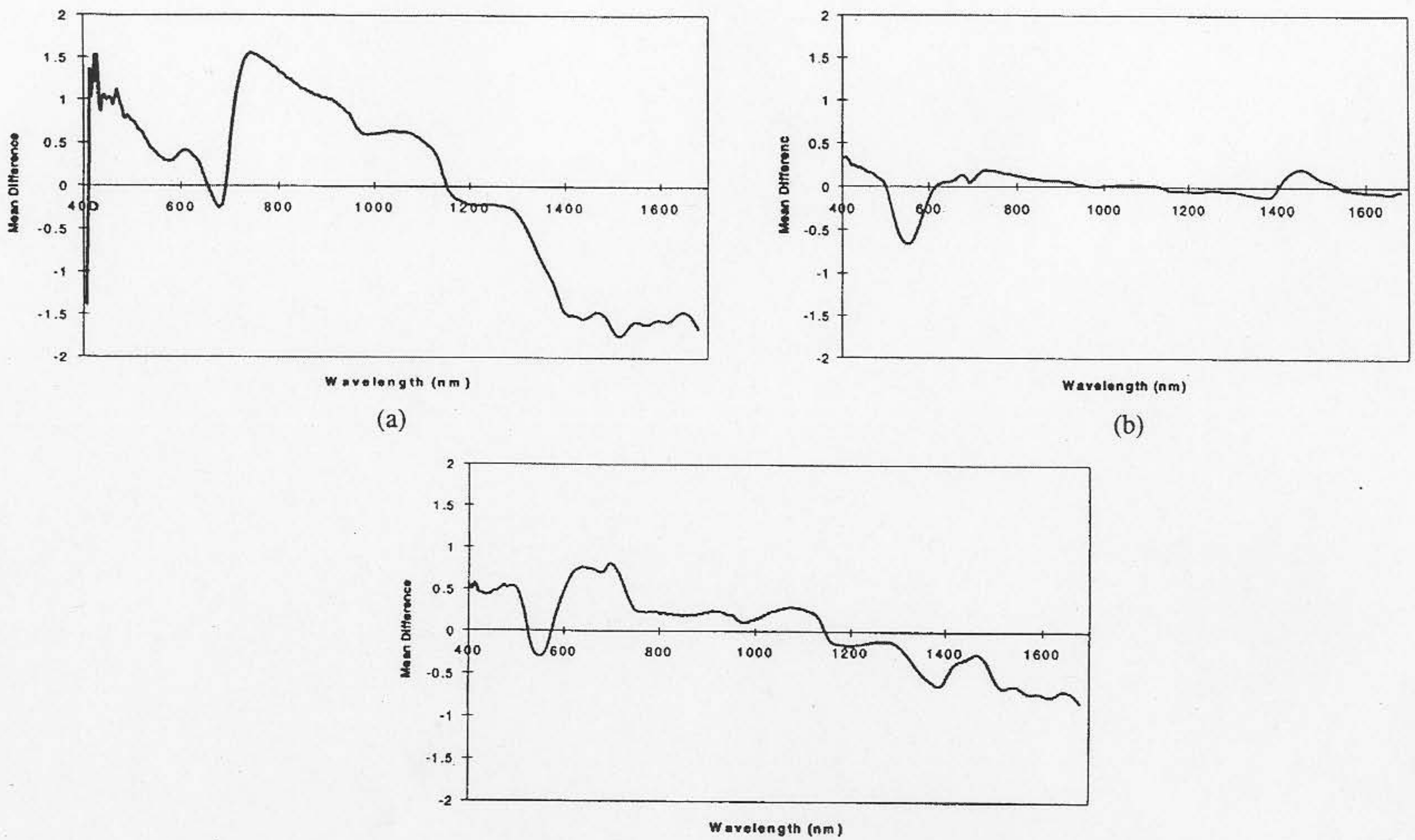


Fig. 1 Procedures for Calibration Establishment



(c)

Fig. 2 Mean Difference Between Classes

(a) Soil vs. Redroot Pigweed Stem (b) Wheat Stem vs. Redroof Pigweed Stem
(c) Wheat Leaf vs. Redroot Pigweed Stem

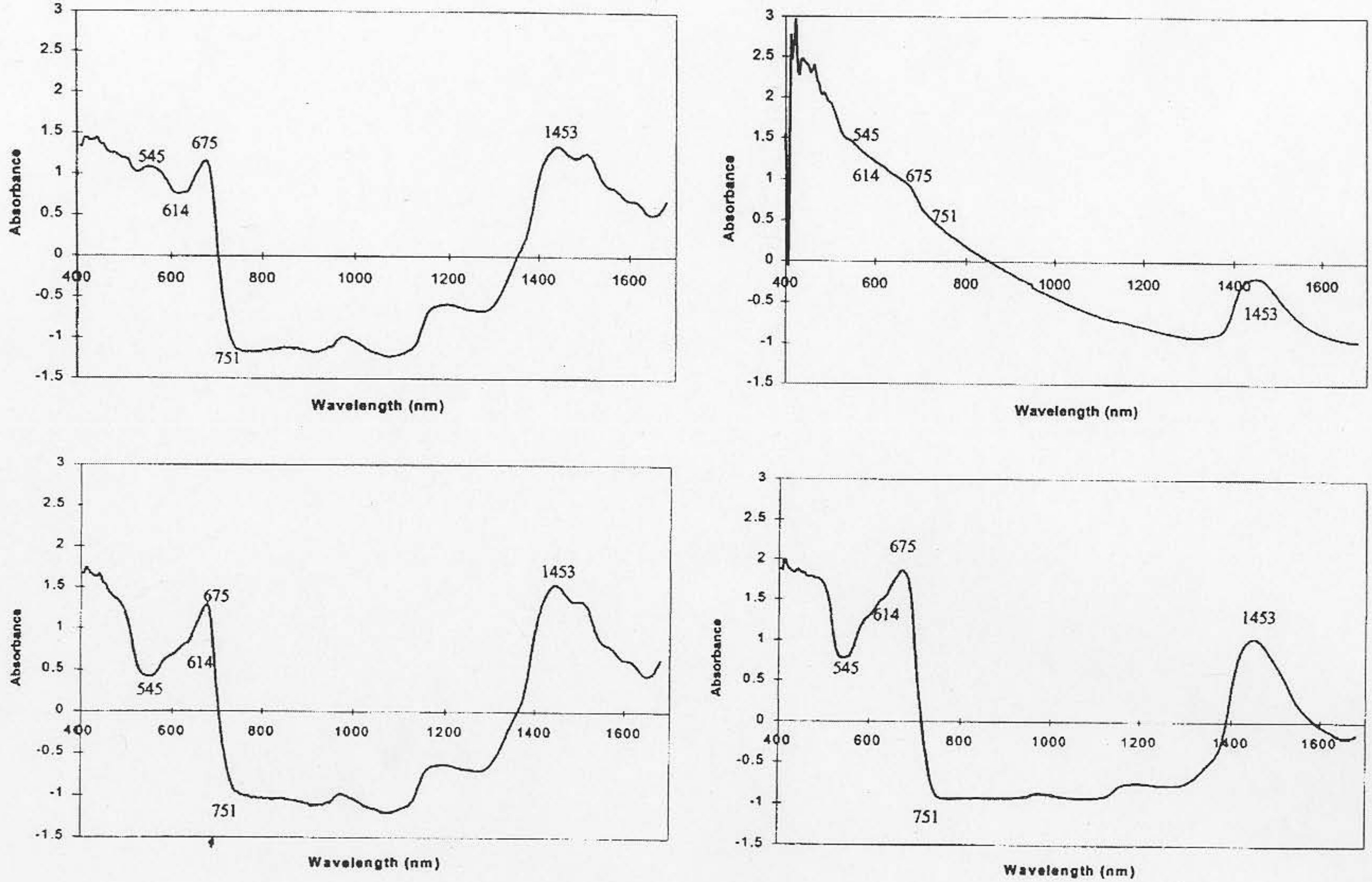


Fig.3 Spectral Characteristics of Classes

(a) Red Root Pigweed Stem (b) Soil (c) Wheat Stem (d) Wheat Leaf

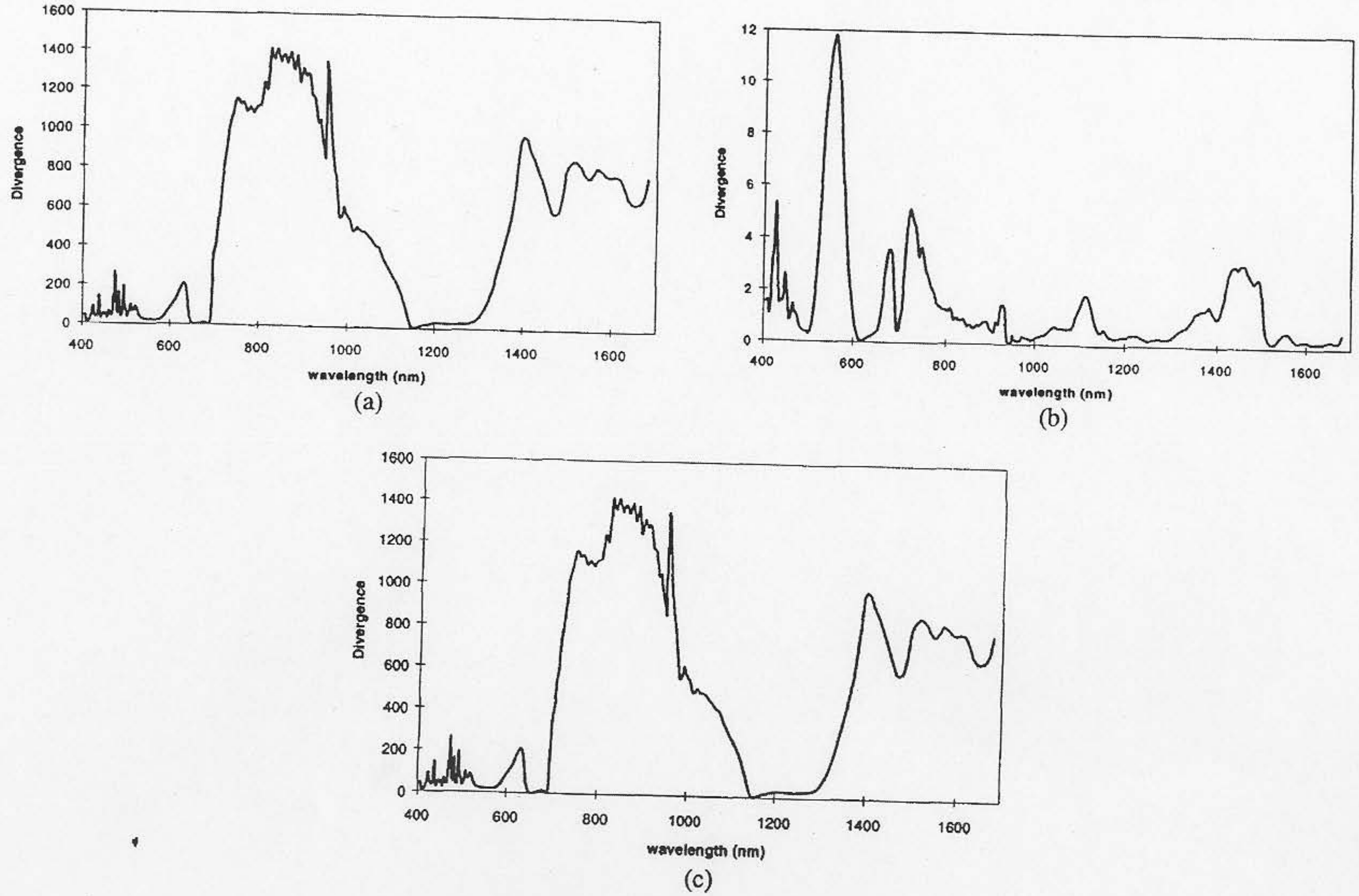


Fig. 4 Divergence Between Classes

(a) Soil vs. Redroot Pigweed Stem (b) Wheat Stem vs. Redroof Pigweed Stem

(c) Wheat Leaf vs. Redroot Pigweed Stem