Precision Agriculture, 5, 477–508, 2004

A Review on Remote Sensing of Weeds in Agriculture

K. R. THORP lei-tian@uiuc.edu
L. F. TIAN
Illinois Laboratory for Agricultural Remote Sensing, University of Illinois, Urbana-Champaign, 1304 West Pennsylvania Avenue, Urbana, IL, USA

Abstract. In the effort of developing precision agriculture tools, remote sensing has been commonly considered as an effective technique for weed patch delineation, where weed infestations are detected based on variations in the plant canopy spectral response. Because the canopy spectral response is important for weed detection, discussions on the irradiative interaction of light in plant canopies and the effect of variable soil background on the canopy spectral response are presented in this review. Also, a presentation of the current techniques for removal of soil effects, including vegetation indices and spectral mixture analysis, shows that these techniques have not been adequately developed for use in remote sensing-based weed detection applications. Given the nature of light interaction in a plant canopy, this review proposes that the spectral response of a plant canopy depends on both the species and the biomass density. Remote detection of weeds from ground-, aircraft-, and satellite-based platforms has been accomplished on a wide scale, yet the use of these weed detection methods to make variable-rate herbicide applications has not occurred as often. By judging success based on variable-rate herbicide applications rather than precise weed localization, some of the current problems in weed sensing may be skirted.

Keywords: remote sensing, weed distribution, weed detection, vegetation indices, vegetative reflectance

Introduction

Since weeds grow in definite patches, successful delineation of patch boundaries creates a potential for applications of herbicide on a site-specific, need-only basis. Remote sensing has been widely explored as a tool for detection and mapping of weeds in agricultural crops (Lamb and Brown, 2001; Moran *et al*., 1997; Zwiggelaar, 1998). Supporting this practice, numerous inquiries into the nature of weed spatial distribution have confirmed that weeds generally clustered together in patches within a field (Marshall, 1988; Rew *et al*., 1996; Wiles *et al*., 1992). In addition, substantial portions of an agricultural field may contain absolutely no weeds or the existence of weeds below threshold levels at which the crop is threatened (Chancellor and Goronea, 1994; Johnson *et al*., 1995; Thornton *et al*., 1990). By detecting the location of weeds within an agricultural field, remote sensing provides a means for the development of weed maps, such that herbicide applications can occur on a site-specific basis (Brown and Steckler, 1995; Stafford and Miller, 1993; Thompson *et al*., 1991). Reductions in herbicide use as a result of this practice reduce management costs for growers (Medlin and Shaw, 2000) and promote environmental friendliness (Timmermann *et al*., 2001).

Up till now, the success of remote sensing-based agricultural weed detection has been limited. Carefully controlled experiments have shown that homogeneous plots

of crops and weeds are distinguishable in remote sensing images (Menges *et al*., 1985; Richardson *et al*., 1985). However, remote detection of weeds growing naturally in a post-emergence crop setting has proven to be a more difficult task. Most researchers have used classification algorithms to delineate weed patches based on statistical variability in the spectral response of soil, crop, and weed/crop canopies. Classification algorithms work well for pre-emergence sensing of weeds because the response of bare soil is, in general, spectrally separable from a weed spectral response (Lamb and Weedon, 1998). However, for post-emergence weed sensing, the ability of a classification to accurately detect weeds is lessened because weeds and crops exhibit similar spectral characteristics (Lamb and Brown, 2001). Soil background effects are another problem that complicates weed detection in post-emergence row crops. Due to the wavelength-dependent nature of radiation transmission in vegetation canopies, a nonlinear, nonadditive relationship exists in the interaction of radiation between a plant canopy and its underlying soil. This nonlinear interaction most greatly influences the canopy spectral response at levels of intermediate canopy coverage when equal amounts of vegetation and soil are visible above the scene (Huete *et al*., 1985). Unfortunately, this is also the stage at which remote sensing must be used to generate weed maps for post-emergence herbicide applications. To remove soil background effects from reflectance data, spectral unmixing models have been employed as a sub-pixel classifier to separate soil and vegetation in images containing mixed spectra (Huete, 1986; Ray and Murray, 1996; Zhang *et al*., 1998). However, use of these techniques for applications in agricultural remote sensing have not appeared often in literature. More commonly, researchers have assessed the contribution of vegetation in reflectance data using vegetation indices (Bouman, 1992; Huete, 1988; Hurcom and Harrison, 1998; Jackson, 1983; Kauth and Thomas, 1976; Wiegand *et al*., 1991). The incorporation of both spectral reflectance properties and a spatial description of crop row positions may also facilitate weed detection in agricultural row crops (Zwiggelaar, 1998).

Data for remote sensing-based weed research has been collected using sensors mounted on balloons, remote control crafts, airplanes, satellites, and virtually every other mechanism capable of flight. Remote sensing-based spectral information has also been collected for weed detection at ground level. Improvements in sensor technology over the past two decades have raised the potential for successful weed delineation. In the 1980s, weed detection research was accomplished using color photography and analog video equipment (Menges *et al*., 1985; Richardson *et al*., 1985). Now, remote sensing data is commonly collected using digital technology (Lamb and Weedon, 1998; Medlin *et al*., 2000). Also, with the introduction of hyperspectral data acquisition systems, spectral information can now be collected in very narrow wavebands, which has begun to stimulate more thorough investigations into nature of wavelength dependent light interaction in plants and plant canopies (Thenkabail *et al*., 2000).

Measuring weed distribution

Remote sensing has been used as a tool for agricultural weed detection, because weed growth is not uniform in agricultural fields. This phenomenon was first

studied for the development of statistical models that required weed spatial distribution inputs. Models such as these were important for estimating yield loss (Brian and Cousens, 1990), establishing economic thresholds for weed control (Thornton *et al.*, 1990), and simulating variable-rate herbicide applications (Johnson *et al.*, 1995). Inputs for early models were obtained by collecting random samples of weed growth or weed seed bank information under the assumption that weeds were equally likely to appear at any location within a sample area (King *et al.*, 1986; Lybecker *et al.*, 1991; Mortensen and Coble, 1991). Random sampling strategies for weed distribution studies are appropriate if the samples are independent of each other and the sample variance throughout the field is uniform (Cochran, 1977). However, for aggregated weed populations, assumptions of equal sample variance do not hold, because the sampling locations are spatially related (Cardina *et al.*, 1995). Later field investigations used a grid-based sampling approach to describe the spatial distribution of weed growth (Marshall, 1988; Mortensen *et al.*, 1993; Wiles *et al.*, 1992). Results showed that weed distributions could generally be characterized with the negative binomial function. In addition, low values for the k-parameter of this function indicated that the natural spatial distribution of weeds could be characterized as nonuniform and patchy. This meant that weeds grew in definite clumps and that the presence of a weed at a certain location increased the probability that another weed existed a short distance away. This was true for both broadleaf weeds (Wiles *et al.*, 1992) and grasses (Marshall, 1988). Incorporation of the inherent patchiness of weed infestations into statistical models requiring weed distribution inputs then became a priority for much research in weed science (Brian and Cousens, 1990; Maxwell and Ghersa, 1992; Navas, 1991; Thornton *et al.*, 1990; VanGroenendael, 1988).

The use of numerical statistics such as the negative binomial accurately described the degree of aggregation of weeds, but it could not be used to describe the arrangement, location, or any spatial aspect of the weed patches within the field (Cardina *et al.*, 1997; Mortensen *et al.*, 1993). For this reason, researchers began analyzing weed density data using geostatistics, a technique for descriptive analysis of spatial variation. The first step in a geostatistical analysis involves the construction of a semivariogram, a plot that relates the variance of point values to the distance between them. Using information from the semivariogram, an interpolation method such as kriging is then used to generate data values for unsampled locations (Lopez-Backovic, 1988). Geostatistical methods have recently been used to generate weed density maps for fields based on sampled point values (Cardina *et al.*, 1995; Cardina *et al.*, 1996; Cardina *et al.*, 1997; Donald, 1994; Johnson *et al.*, 1995; Mortensen *et al.*, 1993). Donald (1994) used geostatistical analysis and kriging to describe and map the distribution of shoot density and root growth for Canada thistle (*Cirsium arvense* (L.) Scop.). Semivariogram functions generated in this research showed that shoot growth, percent shoot emergence, root bud density, and fresh root weight for Canada thistle had a high spatial dependence. Cardina *et al.* (1995) recognized that the assumptions of spatial statistics would be violated in the incidence of a large-scale dependence between the population mean and variance. To insure the independence of mean and variance and the absence of trend, a

median polishing procedure was used to detrend their data before the construction of semivariograms. Further geostatistical analysis in this research determined that the density of common lambsquarters (*Chenopodium album* L.) was spatially correlated at distances up to 16 m. In a related study, Cardina *et al.* (1996) used geostatistics with kriging to relate seedbank and seedling populations for both common lambsquarters and annual grasses. Better Spearman rank correlations and a greater visual correspondence of kriged maps were achieved between the seedbank and seedling populations for common lambsquarters than that for grass species. Cardina *et al.* (1997) concluded that semivariograms and kriged maps helped to describe the scale to which weed populations were aggregated, but further research should focus on understanding the processes that cause changes in weed spatial distribution over time.

Experiments based on statistical and geostatistical analysis have shown that a substantial portion of a grower's field may contain absolutely no weeds or the existence of weeds below a set threshold. In a study of 14 soybean (*Glycine max* (L.) Merr.) fields in North Carolina, Wiles *et al.* (1992) found that up to 29% of each field's experimental quadrants, measuring 9.1 m by the width of the row spacing, contained no weeds. Using 35 mm aerial photography, Thornton *et al.* (1990) concluded that only 18% of a wheat (*Triticum aestivum* L.) field was infested with wild oats (*Avena fatua* L.). Ironically, observers at ground level claimed that the field was ''riddled'' with weeds. In a survey of 12 soybean fields in eastern Nebraska, Johnson *et al.* (1995) determined that on average 71% of the sample area contained no broadleaf weeds and 94% contained no grasses when pre-emergence herbicide was used. In the case that no herbicide was used before planting, 30% of the sampled area was free of broadleaf weeds and 70% was free of grass species. Given a hypothetical threshold of 10 weeds per square meter, Cardina *et al.* (1996) found that 40% of a soybean field would require herbicide treatment 1 year while 90% of the same field would require treatment in a different year when weeds covered a larger area. Similarly, Johnson *et al.* (1995) determined that herbicide savings from variable-rate applications would be greatest for weed infestations with a high degree of patchiness. Rew *et al.* (1996) used a semi-automated weed mapping system to analyze the spatial distribution of quackgrass (*Elymus repens* L.) in five cereal fields. Visual assessments of the weed growth in these fields indicated that the weed exemplified a patchy distribution, but mapping results showed that the size and morphology of these patches varied both within and between fields. As a result, they concluded that potential reductions in herbicide use as a result of patch spraying would vary with patch morphology and infestation level. Chancellor and Goronea (1994) determined that, by setting threshold values to intermediate levels and removing a partial quantity of weeds in a field, 70% of the weed threat could be removed using only 50% of the herbicide required for a blanket application. Additional research is required to determine if the threshold level for weeds within patches differs from the threshold level for the whole field (Audsley, 1993).

Mechanism for vegetative reflectance

The science of remote sensing involves the use of ground-, aircraft-, or satellite-based sensors to monitor the reflection of electromagnetic radiation from the

traget. As a result, the function of these sensors is very similar to that of the human eye, which detects a form of electromagnetic radiation called visible light. Other familiar forms of electromagnetic radiation include radio waves, heat, microwaves, ultraviolet light, X-rays, and γ-rays, and all forms are collectively grouped, according to wavelength, in the electromagnetic spectrum (Lillesand and Kiefer, 2000; Tipler, 1991). Though the human eye can see a wide range of colors, the visible spectrum, which ranges from 400 to 700 nm in wavelength, represents only a small percentage of the complete electromagnetic spectrum. In fact, the range of spectral information useful in agricultural remote sensing is much wider than that of the visible spectrum. Particularly, near-infrared (NIR) light, which ranges from 700 to 850 nm, is a good indicator of the relative health of vegetated areas. Generally, an area having very vibrant vegetation will reflect much more NIR radiation than a more sparsely vegetated area (Qi *et al.*, 1994). However, since human eyes cannot see NIR light, this important physical property of vegetation is unnoticeable to a human bystander. With the aid of optical remote sensors, the reflectance of electromagnetic radiation from vegetation, including that in the NIR region, can be detected and quantified. Then, with further processing, this information can be used to formulate a strategy for site-specific crop management.

Agricultural remote sensing began in the mid-twentieth century, although the science was not used for weed detection until the 1980s. Early work in agricultural remote sensing focused on the characteristics and mechanism of reflectance, absorption, and transmission of radiation in plant leaves (Gates *et al.*, 1965; Knipling, 1970; Woolley, 1971). Reflectance curves for leaves of a particular species may differ slightly depending on surface characteristics, thickness, internal leaf structure, and pigment content. A typical reflectance curve of a healthy tobacco (*Nicotiana tabacum* L.) plant leaf, as shown in Knipling (1970), is given in Figure 1. This graph shows the percent reflectance of incident light as a function of its wavelength from 400 to 2800 nm. Vegetative reflectance of visible light, 400 to 700 nm, is generally lower than 10% with a peak at 550 nm. As radiation of the visible wavelengths enter a healthy leaf, the layer of chloroplasts, which contain chlorophyll, absorbs radiation in wavebands centered at 450 and 670 nm (Lillesand and Kiefer, 2000). These wavelengths correspond to blue and red light, respectively. Light with a 550 nm wavelength, which corresponds to green light, is not absorbed as strongly. Therefore, healthy plants appear green to the human eye, because the leaves reflect more green light than blue or red light. In the near-infrared region, 700 to 1300 nm, reflectance of incident energy from plant leaves increases to approximately 50%. The high reflectance at the NIR wavelengths is due to the internal cellular structure of the leaf (Mestre, 1935). As radiation of NIR wavelengths enters the leaf's mesophyll layer, multiple reflections and refractions occur inside the hydrated plant cells and the air pockets that separate them. Very little of this NIR energy is absorbed by plant material. As a result, half of the energy is effectively transmitted downward through the leaf and the other half is reflected upward through the plane of incidence. Reflectance of energy in the infrared region beyond 1300 nm is fully dependent on the water content of the leaf (Allen and Richardson, 1968). Leaves that are properly hydrated will show distinct humps in the reflectance

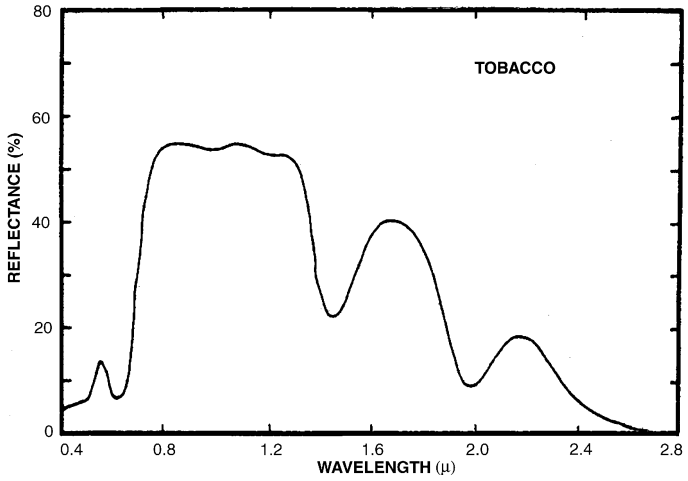

Figure 1. A typical reflectance curve for vegetation given in Knipling (1970), this is the plot of light reflectance from a tobacco leaf over the range of 400–2800A nm.

curve from 1300 through 2500 nm that are comparable to the reflectance of a sheet of water at an equivalent thickness to the water content in the leaf. A dehydrated leaf will not show these distinct humps.

The spectral reflectance of a vegetation canopy will differ from the reflectance of individual plant leaves due to variations in leaf area and orientation, illumination angle, shadows, background surfaces such as soil, and the presence of multiple leaf layers (Colwell, 1974; Knipling, 1970). Lillesaeter (1982) developed a mathematical model to estimate the spectral response of multiple leaf layers based on laboratory reflectance measurements of a single leaf. Also, in the research of Wanjura and Hatfield (1986), the reflectance and transmittance of visible light by a plant canopy decreased as the leaf area index (LAI) increased; meaning a greater portion of visible light was absorbed by the plant canopy. For NIR radiation, increases in LAI increased the canopy reflectance, but relative changes in absorption and transmittance were inconsistent between crop species. Note that LAI is the ratio of the total area of leaves over the area of ground covered by them. Changing atmospheric conditions, such as sun angle and cloud cover will also introduce significant amounts of variability in crop canopy spectral reflectance. The effect of a changing source incident angle and view angle has been studied for crop canopies (Lord *et al.*, 1985) and for individual leaves in a laboratory setting (Woolley, 1971; Walter-Shea *et al.*, 1989). Plant canopy reflectance is also affected by background materials such as soil and crop residue, and this is discussed later.

Vegetation indices

Perhaps the most widely accepted method for describing vegetative growth using reflectance spectra is through the calculation of band ratios or vegetation indices.

Vegetation indices are spectrally-based values generated through the mathematical manipulation of reflectance measurements from two or more spectral wavelengths. Theoretically, the calculation of vegetation indices should provide values that are more highly correlated to LAI, biomass, or vegetative cover than the raw reflectance measurements (Wanjura and Hatfield, 1987). A plethora of these indices have been developed for use in remote sensing research over the past 30 years (Ashley and Rea, 1975; Baret *et al.*, 1989; Huete, 1988; Jackson, 1983; Jordan, 1969; Kauth and Thomas, 1976; Major *et al.*, 1990; Qi *et al.*, 1994; Richardson and Wiegand, 1977; Rondeaux *et al.*, 1996; Tucker, 1979), but the normalized difference vegetation index (NDVI) (Ashley and Rea, 1975) has become the most popular. The NDVI is expressed as

$$\mathrm{NDVI} = \frac{\lambda_{\mathrm{NIR}} - \lambda_{\mathrm{red}}}{\lambda_{\mathrm{NIR}} + \lambda_{\mathrm{red}}} \tag{1}$$

where λ_{NIR} is the broad-band NIR reflectance and λ_{red} is the broad-band red reflectance. In addition to the NDVI, the other two most basic vegetation indices include the ratio vegetation index ($\mathrm{RVI} = \lambda_{\mathrm{NIR}} - \lambda_{\mathrm{red}}$) (Jordan, 1969) and the difference vegetation index ($\mathrm{DVI} = \lambda_{\mathrm{NIR}} - \lambda_{\mathrm{red}}$) (Tucker, 1979). A comprehensive list of broad-band vegetation indices can be found in Bannari *et al.* (1995). By contrasting a plant's characteristically low red reflectance with its high NIR reflectance, vegetation indices, such as the NDVI, can accurately distinguish pure vegetation spectra from that of other pure spectra such as soil, water, and rock. However, robustness issues, which are discussed later, exist in the case of mixed spectra. Discrepancies on what vegetation indices actually measure also exist in literature. In a simulation study, Bouman (1992) concluded that the NDVI could estimate LAI with relatively small errors. Hurcum and Harrison (1998) determined that the NDVI was a better measure of vegetative cover than LAI and biomass in semi-arid vegetation. Thenkabail *et al.* (2000) found that LAI and biomass were more highly correlated with vegetation indices than crop height and canopy cover. Lawrence and Ripple (1998) achieved satisfactory results in correlating vegetation indices to canopy cover of forest vegetation at Mount Saint Helens, Washington. Wiegand *et al.* (1991) developed a set of equations relating vegetation indices and cumulative seasonal vegetation indices to measures of fractional photosynthetically active radiation (FPAR), cumulative daily photosynthetically active radiation (CDPAR), aboveground dry photomass, economic yield, LAI, and plant cover. In their study of cotton (*Gossypium hirsutum* L.), vegetation indices calculated from Satellite Pour l'Observation de la Terre (SPOT) imagery, collected from a French earth observation satellite, were most highly related to cotton boll counts ($r^2 = 0.76$) and plant cover ($r^2 = 0.67$). In their study of corn (*Zea mays* L.), vegetation indices were more related to FPAR ($r^2 = 0.97$) than yield ($r^2 = 0.33$). Lack of consistency in vegetation index performance can be attributed to the fact that the measured spectral response of a given environment depends uniquely on the atmosphere, sensor calibration, ambient lighting conditions, soil background, and the homogeneity of the scene (Bannari *et al.*, 1995).

Most vegetation indices were developed many years ago for use with broad-band, multispectral data (Ashley and Rea, 1975). At that time, sensors collected

only a few bands of reflectance data at very wide bandwidths, so only a limited number of bands were available for the development of vegetation indices. In recent years, improvements in sensor technology have provided a new generation of remote sensing systems that can collect hundreds of spectral bands at very narrow wavelengths. Since the development of these "hyperspectral" systems, many of the data processing techniques once used for multispectral analysis have needed reevaluation, because the narrow-band datasets contain much more highly descriptive spectral information than the older datasets. Therefore, a recent goal in agricultural remote sensing has been to determine which hyperspectral bands are most useful for crop assessments and to find the optimum width for these bands (Thenkabail *et al*., 2000). Thenkabail *et al*. (2000) measured the spectral reflectance of cotton, soybeans, corn, potato (*Solanum erianthum* L.), and sunflower (*Helianthus* L.) over 490 discrete narrow bands and calculated an NDVI-based index of all possible two-band combinations (119,805 useful combinations). Using a simple linear regression analysis, each of the 119,805 indices was correlated to measures of wet crop biomass and LAI. A contour plot was then drawn to show which band combinations provided the highest correlations with these crop characteristics. As another approach to finding optimum hyperspectral bands, Thenkabail *et al*. (2000) also employed a multiple linear regression analysis, a better modeling technique than the standard NDVI according to the research of Lawrence and Ripple (1998). Thenkabail *et al*. (2000) determined that the optimal multiple linear regression model included a combination of four bands. With narrow-band NDVIs and multiple linear regression emerging as the top analysis tools, Thenkabail *et al*. (2000) concluded that the most significant narrow bands for assessment of crop biophysical variables were located in the longer wavelength portion of the red region (650 to 700 nm), in the shorter wavelength portion of the green region (500 to 550 nm), in a section of the NIR (900 to 940 nm), and in a moisture sensitive area of the NIR (982 nm). Furthermore, in all cases, values generated using these analysis techniques were more highly correlated to crop characteristics than that from the older broad-band indices.

Utilizing the continuous nature of hyperspectral datasets, other researchers have developed derivative-based vegetation indices that involve the calculation of first- and second-order derivatives of reflectance data. As a result, the slope and curvature of reflectance data can be analyzed, because the derivative of a function tends to emphasize changes between wavebands while suppressing the actual reflectance level (Schowengerdt, 1997). Derivatives of signals have been used extensively in analytical chemistry to remove background noise and unwanted signals in absorption spectroscopy applications. However, until recently, derivatives have not been commonly used for analysis of remote sensing data. Philpot (1991) provided the following computations for approximating the first three continuous derivatives at wavelength, λ, using hyperspectral data collected in discrete wavebands:

$$\frac{df}{d\lambda} = \frac{f(\lambda) - f(\lambda^+)}{\Delta\lambda} \tag{2}$$

$$\frac{d^2f}{d\lambda^2} = \frac{f(\lambda^-) - 2f(\lambda) + f(\lambda^+)}{(\Delta\lambda)^2} \tag{3}$$

$$\frac{d^3f}{d\lambda^3} = \frac{f(\lambda^-) - 3f(\lambda) + 3f(\lambda^+) - f(\lambda^{++})}{(\Delta\lambda)^3} \tag{4}$$

where λ^- is the nearest smaller wavelength, λ^+ the nearest larger wavelength, and λ^{++} is the nearest larger wavelength to λ^+. Though derivatives are effective at removing low frequency background signals from reflectance data, high frequency noise will be magnified in the process of differentiation if cautionary steps are not taken to remove the noise beforehand (Demetriades-Shah *et al*., 1990). Several filtering methods have been tested for smoothing of reflectance data before the application of derivatives, including the Savitzky–Golay least-square-fitting procedure, the Kawata–Minami smoothing algorithm, and a simple mean–filter (Tsai and Philpot, 1998). Each of these methods involves the convolution of a filter window across all wavelengths available in the reflectance data; however, the Savitzky–Golay and Kawata–Minami procedures convolve a shaped filter instead of a standard averaging filter. These specialized filters were developed for more accurate discrimination of signal and noise in comparison to standard filters (Kawata and Minami, 1984; Savitzky and Golay, 1964). In addition, the Savitzky–Golay method provides an option for differential smoothing, where the filter window performs both the smoothing and the differentiation operations in one pass. Since the other filtering methods do not provide this option, a separate differentiation procedure, Eq.(2) for instance, must be completed after smoothing. In their derivative analysis of rice (*Oryza sativa* L.) spectra using these smoothing methods, Tsai and Philpot (1998) determined that the mean-filter achieved the strongest smoothing but also suppressed the most spectral detail. Also, the Kawata-Minami smoothing procedure did not remove much noise. Finally, Tsai and Philpot (1998) concluded that the size of the filter window was the most influential factor on performance.

Derivative analysis is particularly useful for detection of vegetation in reflectance data due to the presence of the ''red edge'' located between 680 and 750 nm in the spectral response of vegetation (Horler *et al*., 1983). The steep increase in reflectance across this short waveband corresponds to the transition between absorption of visible red and reflection of NIR in plant leaves (Gates *et al*., 1965). The precise location of the red edge, the point of maximum slope in the red to NIR transition, depends on the concentration of chlorophyll and other pigments such as amaranthin within the plant leaves (Curran *et al*., 1991). Blackburn (1998) developed a set of derivative reflectance indices for estimating the concentrations of chlorophyll a, chlorophyll b, and carotenoids in plant leaves and plant canopies. Results showed that first and second derivatives of pseudo absorbance, the logarithm of inverse reflectance, were strongly correlated with pigment characteristics in the leaves. Because derivatives can mask the effect of unwanted signals, Hall *et al*. (1990) and Demetriades-Shah *et al*. (1990) proposed that derivative techniques should be used for elimination of the soil signal in reflectance measurements taken over partial canopies. Supporting this idea, Elvidge *et al*. (1993) determined that a red edge could

be detected in the mixed response of vegetation and soil where the total percent of green vegetation cover was as low as 4.8%. Chen *et al.* (1993) developed an index, the derivative green vegetation index (DGVI), by integrating the area under the derivative peaks at the red edge location. Preliminary results indicated that derivative indices, particularly the second derivative, had potential for reducing soil background effects in partial canopy reflectance measurements.

Mechanism for soil and vegetation irradiative interaction

Removal of weeds from agricultural crops generally occurs before the crop canopy closes. As a result, the presence of exposed bare soil and crop residue complicates the analysis of remote sensing imagery for weed detection, because these materials exhibit their own unique spectral properties. Surface moisture content has the greatest influence on the reflectance of soils. Remote sensing research has consistently shown that wet soils reflect less radiation than dry soils (Cipra *et al.*, 1971; Nitsch *et al.*, 1991). In the visible and NIR wavelengths, this phenomenon is due to reflections that remain totally internal within the water layer covering the soil (Bach and Mauser, 1994). Also, water naturally absorbs radiation in other regions of the spectrum, which causes a reduced reflectance at these wavelengths. Condit (1971) showed a reduction in wet versus dry soil reflectance over all wavelengths from 320 to 1000 nm for 285 soils across the United States. Bowers and Hanks (1965) concluded that in addition to surface moisture content, organic matter and particle size also influence a soil's ability to reflect and absorb radiation. In addition, Stoner and Baumgardner (1981) found that soil organic matter content and iron oxide composition caused spectral reflectance variations in 485 uniformly moist soils of the United States and Brazil. Since the brightness of a soil is related to its moisture content (Planet, 1970) and other properties, similarly colored soils may have analogous reflectance properties in the visible range; however, spectral differences between 600 nm and 800 nm are more evident (Stoner *et al.*, 1980). Crop residue cover also causes variations in a soil spectral response. Stoner *et al.* (1980) showed that a cover of corn residue reduced the reflectance of a dry and wet soil of the same type by an equal magnitude. Also, littered sugarcane (*Saccharum officinarum* L.) residue had a lower reflectance than bare soil and standing sugarcane residue had a higher reflectance than bare soil over a range of 500—2500 nm (Gausman *et al.*, 1975). Results from Nitsch *et al.* (1991) suggested that the statistical separability of bare soil and crop residue reflectivity depends mainly on the type of soil and the type of residue.

To use remote sensing in a crop field, one has to address the condition of the low canopy coverage in the early stage of crop development. Extensive research has been done to examine the effect of soil background on the reflectance of partial canopies. Wanjura and Hatfield (1986) found an increased concentration of NIR radiation over the soil surface between crop rows. They concluded that reflections of NIR radiation from the sides of the plants caused the increased flux of energy toward the soil between rows. Huete *et al.* (1985) inserted trays containing various types of soil between the rows of a cotton canopy and measured the response of the canopy

interaction with different soil backgrounds throughout the growing season. Various vegetation indices were shown to inconsistently predict "greenness" for partial canopy covers between 20% and 75%. They concluded that, in this range of coverage, standard vegetation indices improperly model the effect of soil brightness on partial canopy reflectance. Furthermore, soil brightness influences were found to increase with increasing canopy cover up to 60%, suggesting that soil and plant spectra collectively interact in a nonadditive, nonlinear fashion to produce a composite spectral response. In a related experiment, Huete (1987) developed a plant-soil radiant flux model to separate composite spectra into soil reflected and vegetation reflected components. Depending on the percentage of canopy cover, the soil reflected component of the model exhibited similar properties to that of the surrounding vegetation, namely a low red reflectance and high NIR reflectance. Huete (1987) concluded that, in the case of significant canopy coverage, only a small portion of red radiation reaches the underlying soil surface due to intense absorption by chlorophyll. On the other hand, the plant leaves readily scatter and transmit NIR radiation deep into the canopy. Since vegetation can differentially alter the intensity of radiant flux through the canopy, the spectral response of underlying soil will exhibit properties of both soil and vegetative reflectivity. Also, since soil brightness determines the magnitude of this unique soil response, it follows that errors in "greenness" measurements by vegetation indices depend on both the quantity of vegetation available for radiant flux differentiation and the brightness of underlying soil. At low canopy coverage, vegetative irradiance is not strong enough to significantly affect the soil reflectance. At high coverage, the fullness of the canopy attenuates much of the soil reflectance altogether. At intermediate coverage though, soil backgrounds magnify the overall vegetative response of the canopy by reflecting vegetation-transmitted radiation. In Huete's (1987) research, this magnification at intermediate canopy coverage generated inconsistencies strongly related to soil brightness in all of the most common vegetation indices. Heilman and Kress (1987) reported results similar to Huete (1987) in their study of the reflectance properties above and below a cotton canopy at various growth stages. In addition, Elvidge and Lyon (1985) obtained results similar to Huete *et al*. (1985) in their use of vegetation indices to assess green biomass in arid and semi-arid regions of Nevada.

Huete and Jackson (1988) used an atmospheric radiant flux model to compare ground-based irradiance measurements of partial canopies with a simulated spectral response at the top of clear and turbid atmospheres. Results showed that the degree of wavelength dependent and independent scattering and absorption of ground-reflected radiation by the atmosphere depends on the brightness of the soil background. Vegetation indices calculated from the simulated upper atmospheric spectral responses were also shown to vary with the degree of atmospheric turbidity. Therefore, they concluded that the spectral response of ground-reflected radiation over partial canopies measured with sensors in the upper atmosphere vary as a function of both soil brightness and atmospheric turbidity. Implications of this study were that aerial and satellite remote sensing data taken over partial canopy covers will suffer the same soil background effects as seen in the ground-based studies of Huete *et al*. (1985) and Heilman and Kress (1987). In addition to soil effects though, aerial and satellite remote sensing data also contain atmo-

spheric effects that vary based on atmospheric conditions (Huete and Jackson, 1988), the path length to the sensor, and the magnitude and wavelength of the spectral signal (Lillesand and Kiefer, 2000). However, whereas soil background effects are difficult to quantify and remove from spectral data (Huete and Jackson, 1988), atmospheric effects are easily removed through image calibration (Smith and Milton, 1999).

Techniques for removal of soil effects

Standard vegetation indices have not robustly estimated quantities of vegetation in partial canopies due to the differential flux of red and NIR radiation through the canopy and the complex interaction of radiation between soil and vegetation (Huete, 1987; Huete and Jackson, 1988; Huete *et al*., 1985; Jackson *et al*., 1979). In particular, the perpendicular vegetation index (PVI) (Richardson and Wiegand, 1977), which assumes that combinations of soil and vegetative reflectance are additive, provides undercompensated index values at high vegetation coverage with increasing undercompensation as soil brightness increases (Huete *et al*., 1985). Thus, the index works well for very low canopy coverage when soil and plant interactions are minimal. On the other hand, ratio indices, such as the NDVI, overcompensate index values at low canopy coverage with increased overcompensation as soil brightness decreases (Huete *et al*., 1985). Thus, these indices work well over areas of very high coverage. Since standard indices consistently failed to estimate quantities of vegetation over partial canopy covers, Huete (1988) developed a soil-adjusted vegetation index (SAVI) that incorporated a soil-adjustment factor, L, into the NDVI equation. The SAVI can be expressed as

$$\text{SAVI} = \frac{(\lambda_{\text{NIR}} - \lambda_{\text{red}})}{(\lambda_{\text{NIR}} + \lambda_{\text{red}} + L)}(1 + L) \tag{5}$$

where λ_{NIR} and λ_{red} are the broad-band spectral responses in the NIR and red wavebands respectively. For optimal removal of soil influences, Huete (1988) proposed that the L term should vary inversely with the amount of vegetation present. However, a constant L of 0.5 was used to effectively reduce soil-induced variations in the vegetation indices for the Huete *et al*. (1985) data. To further minimize soil influences, Qi *et al*. (1994) developed a modified soil-adjusted vegetation index (MSAVI) that replaced L in the SAVI model with an inductive L function of

$$1 - \text{MSAVI} \tag{6}$$

since the L term is inversely related with vegetation cover. Then, through mathematical induction, the MSAVI becomes

$$\text{MSAVI} = \frac{1}{2}\left(2\lambda_{\text{NIR}} + 1 - \sqrt{(2\lambda_{\text{NIR}} + 1)^2 - 8(\lambda_{\text{NIR}} - \lambda_{\text{red}})}\right) \tag{7}$$

where, again, λ_{NIR} and λ_{red} are the broad-band spectral responses. By optimizing the SAVI model with an iterative process, soil background influences were further

minimized in the calculation of vegetation indices. Other researchers have developed soil-adjusted indices similar to the original SAVI model. Baret *et al.* (1989) developed the transformed soil-adjusted vegetation index (TSAVI), a modification of the SAVI that included parameters for adjustment of the bare soil line. Also, the $SAVI_2$, developed by Major *et al.* (1990), incorporated adjustment parameters for solar angles, leaf area distribution (LAD), and LAI into a ratio index. Though these models have performed as well as the SAVI and MSAVI, they require inputs other than the reflectance parameters of the scene of interest. A robust soil-adjusted vegetation index would not possess this unattractive property. Rondeaux *et al.* (1996) reexamined the "SAVI family of indices" and proposed the optimized soil-adjusted vegetation index (OSAVI) as the best index for agricultural applications. With variables similar to the SAVI and MSAVI, the OSAVI can be expressed as

$$\text{OSAVI} = \frac{(\lambda_{\text{NIR}} - \lambda_{\text{red}})}{(\lambda_{\text{NIR}} + \lambda_{\text{red}} + 0.16)} \tag{8}$$

So far, research in the area of soil-adjusted vegetation indices has been developmental in nature with results that seem to vary between researchers. In some cases, soil-adjusted indices have performed worse than the standard vegetation indices. For example, in a study of forest vegetation at Mount Saint Helens, Washington, the NDVI performed better than all the soil-adjusted indices (Lawrence and Ripple, 1998). Also, Thenkabail *et al.* (2000) cites no significant improvement in using soil-adjusted indices to reduce soil effects in narrow-band data. Further development and support is necessary before a particular soil-adjusted vegetation index can be standardized.

Hall *et al.* (1990) and Demetriades-Shah *et al.* (1990) proposed derivative-based vegetation indices as a unique method for the removal of soil background effects from reflectance data. Chen *et al.* (1993) implemented this idea for their study of a partially vegetated pine (*Pinus* L.) plantation. Calculation of the index values used in this research involved three steps, including noise removal and reflectance curve smoothing, differentiation of the reflectance curve, and integration of the area under the derivative peak that emerged at the red edge. (The reason for integrating a previously differentiated signal is unclear.) Derivatives were calculated to the first and second order. Integration under the first derivative curve was performed using the zero-line and a local baseline. Integration with a local baseline improved the results by accounting for background information that was not removed in the first derivative calculation. However, integration under the second derivative curve provided the best overall results. In a similar pine canopy study, derivative-based indices measuring the amplitude of the chlorophyll red edge were shown to reduce the effects of soil background further than any other vegetation index available at that time, including the NDVI, SAVI, and TSAVI (Elvidge and Chen, 1995). Using derivative techniques in a laboratory analysis of mixed plant/soil spectra, Datt and Paterson (2000) concluded that the second derivative transform reduced much of the soil background effects in the red and NIR wavelengths. Also in their research, the derivative indices were more strongly correlated to vegetation cover and LAI than the NDVI. On the other hand, Thenkabail *et al.* (2000) cites no success in correlating derivative-based indices to crop biophysical variables such as LAI and biomass.

Similar to the soil-adjusted vegetation indices, further work is required to generate further understanding of derivative-based indices and their applications in agricultural remote sensing.

Similar to Huete (1987), other researchers have developed mathematical models to explain the complex irradiative interaction between plant canopies and underlying soil. Used for "unmixing" of combined spectral responses, these models generally require as inputs the pure response of each component in the spectral mixture. Though the simplest unmixing models are linear, where the spectral responses of each pure component are assumed to be averaged in the combined response, most researchers believe that the spectral interaction of soil and vegetation is nonlinear in nature (Borel and Gerstl, 1994; Datt and Paterson, 2000; Huete *et al*., 1985). The production of acceptable nonlinear models for unmixing soil and vegetative spectral combinations is a current goal in remote sensing research (Roberts *et al*., 1993; Zhang *et al*., 1998); however, some studies still employ linear unmixing techniques like those originally used by Huete (1986) (Hurcom and Harrison, 1998). Huete (1986) used a factor analytic approach to decompose spectral mixtures of cotton and soil into dry soil, wet soil, and vegetation components. According to Huete (1986), the quality of the resulting separation was highly dependent on the input variables, and acceptable results were obtained only when the input variables were carefully designed and controlled. More recently, Yao *et al*. (2002) used unmixing to analyze the combined spectral response of corn, soil, and shadow. At an elevated position, an RGB (red, green, blue) digital camera and a field spectrometer were aligned such that data from both instruments could be simultaneously collected over the same area. Near to the ground, pure spectra of each component in the mixture were also collected. Estimates of the percent cover for each component were generated in a color segmentation of the RGB digital images. Pure spectra and percent cover values were then used in a linear unmixing procedure to successfully extract the component spectral response curves for corn and soil. Though spectral unmixing techniques have great potential as a sub-pixel classifier, literature shows relatively few instances of its use in agricultural remote sensing applications. A larger body of research is present for spectral unmixing of vegetation and soil in arid and desert regions (Hurcom and Harrison, 1998; Ray and Murray, 1996; Roberts *et al*., 1993; Roberts *et al*., 1998). Applications of this research involve unmixing of imagery with a relatively low spatial resolution, such as that from the airborne visible-infrared imaging spectrometer (AVIRIS) (Roberts *et al*., 1993; Roberts *et al*., 1998), to map vegetation over relatively large areas of arid and desert lands. Both linear and nonlinear unmixing methods have been applied for delineation of green vegetation, nonphotosynthetic vegetation, soil, and vegetative shade in these areas (Ray and Murray, 1996; Roberts *et al*., 1993). A nonlinear unmixing model has also been developed for mixture analysis of soil, rock, and vegetation spectra collected with the Airborne Imaging Spectrometer over the PoYang Lake area in China (Zhang *et al*., 1998). Further development of spectral unmixing methods and the extension of these methods into agricultural may be greatly beneficial in the forward progress of remote sensing for weed detection and for precision farming as a whole.

Methods for weed detection

Post-emergence applications of herbicide for weed control generally occur during intermediate crop growth stages before canopy closure. As a result, the complex irradiative interaction between soil and vegetation will have a definite effect on remote sensing imagery collected for post-emergence weed detection. To further complicate the image analysis, agricultural fields can potentially contain a variety of soil types, soil moisture conditions, and crop residues, and each exhibits its own unique spectral response (Nitsch *et al*., 1991). Several other items also affect the reflectance of a crop/weed canopy, including solar angle and cloud cover (Lord *et al*., 1985), the type of weed or crop species present (LaMastus *et al*., 2000), and the density of plants (Medlin *et al*., 2000). Needless to say, the use of remote sensing for weed detection in agriculture has been somewhat of a daunting task.

Aerial and satellite weed sensing

Aerial remote sensing platforms were first used for weed detection in the early 1980s. Menges *et al*. (1985) utilized conventional color (CC) and color infrared (CIR) photography as a means to distinguish weeds from agricultural crops in experimental plots. They found that the 850 nm, NIR reflectance between weed and weed/crop canopies was more variable than the visible reflectance at 550 nm, supporting the use of CIR over CC photography. In addition, they were successful in distinguishing climbing milkweed (*Aarcostemma cyanchoides* L.) in orange (*Citrus ortensis* (L.) Osbeck.) groves, ragweed parthenium (*Parthenium hysterophorus* L.) in carrot (*Daucus carota* (L.) var. *sativa*), johnsongrass (*Sorghum halepense* (L.) Pers.) in cotton and in sorghum (*Sorghum bicolor* (L.) Moench.), London rocket (*Sisymbrium irio* L.) in cabbage (*Brassica oleracea* L.), and Palmer amaranth (*Amaranthus palmeri* S. Wats.) in cotton. Richardson *et al*. (1985) sensed weeds using video cameras with narrow-band spectral filters over the lenses to separate images into blue, green, red, and NIR components. With these cameras, they were able to distinguish homogenous plots of johnsongrass and pigweed (*Amaranthus palmeri* S. Wats.) from weed-free sorghum, cotton, and cantaloupe (*Cucumis melo* L.) plots. In comparing the advantages of video remote sensing and CIR photography, Everitt *et al*. (1993b) favored the former for its quick turnaround time, lower cost, and higher compatibility with computer image processing systems, and they favored the latter for its superior image resolution.

Due to the potential interaction of weed spectral responses with crop, soil, and residue, image analyses for weed detection in past research have mainly involved thematic classifications (Brown *et al*., 1994; Everitt *et al*., 1987; Medlin *et al*., 2000; Menges *et al*., 1985; Richardson *et al*., 1985). Therefore, weed infestation areas were delineated based on the statistical variability of the spectral dataset as a whole (Schowengerdt, 1997). Since the exact weed/crop/soil/residue interaction is difficult to model, thematic classifications simply categorize the spectral information into groups having similar spectral properties. For example, a remote sensing image could be divided into soil/residue, crop, and crop/weed classes assuming these three

classes were spectrally different. Early research utilized homogeneous plots of weeds and crops in an attempt to experimentally control the weed, crop, and soil/residue interaction; however, thematic classifications were still used in the analysis due to similarities in weed and crop reflectance (Menges *et al*., 1985; Richardson *et al*., 1985). In these experiments, classification accuracies as high as 98.6% were reported in their use of remote sensing to distinguish between the homogeneous plots of weeds and crops. Computer-based detection of weeds within a crop stand "seemed feasible" at that time (Richardson *et al*., 1985). Given its limitations, remote sensing for weed detection in agriculture progressed slowly since the first experiments by Menges *et al*. (1985) and Richardson *et al*. (1985). Hatfield and Pinter (1993) suggested that a better understanding of the relationships between infestations, weed species, and crop growth stage was necessary before remote sensing could be successful in sensing weeds within crop canopies.

Though remote sensing-based weed detection has been difficult for agricultural applications, the science has been used extensively to identify weed infestations on rangelands. In general, thematic classifications were used to delineate rangeland weeds from soil and other vegetation based on some unique spectral characteristic of the particular weed. Everitt *et al*. (1987) used CIR photography to quantify infestations of broom snakeweed (*Guitierezia sarothrae* (Pursh.) Britt. and Rusby) and spiny aster (*Aster spinosus* Benth.) on rangeland areas of Texas and New Mexico. Due to a more erectophile canopy structure, the NIR reflectance of these weeds was lower than that of other rangeland species. In related work, Everitt *et al*. (1992a) used both CC photography and CC video imagery to detect common goldenweed (*Isocoma coronopifolia* (Gray) Greene) and Drummond goldenweed (*I. drummondii* (T.&G.) Greene) during their flowering stages. Spectral reflectance measurements of these plant canopies during flowering showed that the visible reflectance from 630 to 690 nm was greater than that of surrounding plant species and bare soil. By the early 1990s, CIR and CC video cameras were being used more frequently than aerial photography in remote sensing for rangeland weed detection. Everitt *et al*. (1992b) used a multispectral video system that acquired CIR composite imagery to quantify infestations of false broomweed (*Ericameria austrotexana* M.C. Johnst.) and spiny aster. They also used CC video imagery to successfully detect Chinese tamarisk (*Tamarix chinensis* Lour.). Satellite imagery was also popular for rangeland weed detection at that time. Everitt *et al*. (1993a) used photographic, videographic, and SPOT satellite images to quantify areas of shin oak (*Quercus havardii* Rydb.) populations on the Rolling and High Plains of Texas. In comparison to other plant species in this area, plant canopy reflectance measurements of shin oak were lower in both the visible reflectance from 630 to 690 nm and the NIR reflectance from 760 to 900 nm during its mature phenological stage. Also, Anderson *et al*. (1993) classified three-band, multispectral satellite imagery to map infestations of false broomweed on south Texas rangelands. Researchers also began to incorporate global positioning systems (GPS) and geographic information systems (GIS) into their remote sensing experiments for ground-referencing and mapping purposes. Everitt *et al*. (1993b) used CC aerial video imagery to detect blackbrush acacia (*Acacia rigidula* Benth.) and huisache (*A. farnesiana* (L.) Willd.). GPS information was encoded on the videotape in real-time, and the geographic coordinates of blackbrush acacia and

huisache infestations were entered into a GIS at a later time. In related research, Everitt *et al*. (1994) were able to sense Big Bend loco (*Astragalus mollissimus* var. *earlei* (Rybd.) Tidestr.) and Wooton loco (*A. wootonii* Sheld.) using both CIR photography and CIR video imagery due to the weeds' high NIR reflectance from 760 to 900 nm. GPS data were integrated with both camera systems to provide geographic references for each image, and this data was later used in a GIS to map Big Bend loco populations. Everitt *et al*. (1995) integrated GPS, GIS, and CIR and CC photography and videography to detect and map leafy spurge (*Euphorbia esula* L.). This weed, found on the Great Plains of the United States, produces yellow bracts in June, which causes its visible reflectance from 630 to 690 nm to be higher than other species common to the area. By the late 1990s, rangeland remote sensing was beginning to utilize digital technology for image acquisition. Lass *et al*. (1996) obtained digital imagery using four charge-coupled devices (CCDs) with spectral filters attached. They were able to classify infestations of yellow starthistle (*Centaurea solstitialis* L.) and common St. Johnswort (*Hypercium perforatum* L.) from other rangeland vegetation with omission and commission errors of less than 20%. In related work, Lass and Callihan (1997) used digital multispectral imagery to delineate yellow hawkweed (*Heiracium pratense* Tausch) and oxeye daisy (*Chrysanthemum leucanthemum* L.) within pastures and forest meadows in Idaho. These weeds were most accurately detected during their flowering stages. Remote sensing research on rangeland areas of the western and central United States shows the progress of remote sensing technology for weed detection in the past 15 years.

Initial work in remote sensing for weed detection within crop canopies was accomplished using CIR video systems similar to those used over the southern rangelands. Brown *et al*. (1994) used filters to separate still-video images into blue, green, red, and NIR narrow-band components for detection of weeds in no-till corn. A maximum likelihood classification was used to fit the raw data into weed, corn, and soil/residue classes. The classified image was visually comparable to a full-color photograph of the same area. Supporting the need for newer technology, they cite difficulty in converting between video and digital formats. With advances in digital technology in the 1990s, Lamb and Weedon (1998) used a four-camera, airborne, digital imaging system to record blue, green, red, and NIR wavebands over a fallow field of weeds (*Pancium effusum* R. Br.) in oilseed rape (*Brassica napus* L.) stubble. Image analysis included an unsupervised classification of an NDVI and supervised classifications of multi-band images. Ground referencing was accomplished by visually mapping weedy areas with a GPS unit on an all-terrain vehicle (ATV). Overall classification accuracy assessments for this pre-emergence weed detection application ranged from 85 to 87%. Dissimilar spatial resolution characteristics between ground-referencing equipment and aerial imaging systems and observer inconsistencies in recognizing the 25% weed coverage threshold were cited as sources of error. In similar research, Lamb *et al*. (1999) collected multispectral imagery of wild oats (*Avena* spp.) in seedling triticale (X *Triticoecale* Wittmack) at spatial resolutions varying from 0.5 to 2 m. Using this imagery, they correlated the standard NDVI and the SAVI developed by Huete (1988) to ground-based measurements of weed density with correlation coefficients up to 0.71. Higher correlations were achieved with images of greater spatial resolution.

Overall, the SAVI was more highly correlated to weed density measurements than the NDVI. Christensen *et al.* (1994) correlated the RVI to weed density with a 0.25 coefficient of determination. Medlin *et al.* (2000) used a digital multispectral camera system to detect weed infestations in two soybean fields approximately eight weeks after planting. Weed density measurements were made by hand-counting weeds inside a one square-meter area at nearly 1400 sample locations in each field. Using discriminant analysis techniques to analyze the remote sensing data, infestations of sicklepod (*Senna obtusifolia* (L.) Irwin and Barnaby), pitted morningglory (*Ipomoea lacunose* L.), and horsenettle (*Solanum carolinense* L.) were detected with at least 75% accuracy. In addition, populations of sickelpod and pitted morningglory with a density greater than 10 per square-meter were classified with at least 85% accuracy. They cite problems in accurate classification of areas with no weeds due to the influence of highly variable soil conditions. Vioix *et al.* (2001) used a remote control aircraft to obtain color photographs at spatial resolutions of less than one centimeter. After digitizing to RGB bitmaps, vegetation was separated from soil using color properties, and weeds were separated from crop rows with an algorithm that included a Gabor filter. The method worked well for crops of corn, sugar beet (*Beta vulgaris* L.), and onion (*Allium cepa* L.), though it failed to detect weeds within the crop rows as a result of the chosen processing procedure. In recent years, the analysis of multispectral remote sensing imagery for agricultural weed detection has been accomplished using a variety of processing techniques including thematic classifications, vegetation indices, and color segmentation.

Recent developments in hyperspectral and multispectral technology have caused a revival of remote sensing-based weed species detection experiments similar to the ones originally completed by Menges *et al.* (1985) and Richardson *et al.* (1985). In the newer experiments however, digital hyperspectral and multispectral remote sensing data have replaced the CIR photographs and video remote sensing data used in the 1980s. LaMastus *et al.* (2000) used a four-band multispectral camera system to detect weed species growing homogeneously at densities ranging from 1 to 8 plants per square meter. In discriminant analyses over various dates from two growing seasons, plots of pitted morning glory were correctly classified from other weed species with accuracies ranging from 69 to 88%. Lower classification accuracies were seen for plots of sicklepod, entireleaf morning glory (*Ipomoea hederacea* var. *integriscula* Gray), and common cocklebur (*Xanthium strumarium* L.). They suggested that hyperspectral data might be more successful for weed species delineation than multispectral data. Varner *et al.* (2000) grew common cocklebur between rows of soybeans. Using a supervised classification of hyperspectral remote sensing imagery, they were able to correctly classify cocklebur in soybeans from weed-free soybeans on two separate dates with accuracies of 78% and 86%. Copenhaver *et al.* (2001) used hyperspectral remote sensing imagery and ground-based spectrometer data to analyze the separability of narrow-band reflectance between weedy and weed-free soybean plots. Statistical separability existed across a broad range of the NIR region when contrasting weed-free soybean plots to soybeans mixed separately with common lambsquarters, giant foxtail (*Setaria faberi* Herrm.), shattercane (*Sorghum drummondii* (Steud.) Millsp. and Chase), and common waterhemp (*Amaranthus rudis*

Sauer), but reflectance separability in the visible wavebands varied more widely between treatments. When contrasting between the plots containing the four weed species, separability in spectral data was found at a variety of wavelengths, but results were inconsistent between data sources and collection dates. The research was not able to discern whether spectral separability arose from spectral differences in plant species or simply from variations in stand density. Indeed, the answer to this question will determine if remote sensing is able to delineate individual weed species. Due to the novelty of hyperspectral remote sensing, literature on the use of the technology for weed species delineation exists in small quantities, and available results are mostly preliminary. However, with continued exploration, techniques for weed species delineation may be possible using hyperspectral remote sensing imagery (Bechdol *et al*., 2000).

Photo-detectors for weed sensing

Detection of weeds in agricultural crops using aerial and satellite remote sensing data has been a tough problem due to the complex interaction of crop, weed, soil, and residue spectra. For this reason, other research has focused on the use of ground-based sensing for weed detection. Early on, ground-based discrimination between vegetation and soil was accomplished using photo-detectors. These sensors electronically measured visible and NIR reflectance and subsequently calculated an index for estimation of vegetative presence over an area. The spatial resolution of photo-detector systems is the "foot print" (field of view) of the sensor, about 0.3–1 m on the ground. Within the field of view, a photo-detector can sense an average "greenness" of the area, so that an estimation of vegetation coverage in the area can be made from the sensor readings.

Hooper *et al*. (1976) developed a photoelectric sensor that utilized a tungsten–halogen light source to scan the ground. Light reflected from the ground was then split into visible and NIR components for electronic calculation of a band ratio, and a hand-held sprayer was triggered when vegetation was detected. The performance of this sensor was affected by variations in both sunlight intensity and soil reflectance properties. Yet, in field tests, the volume of chemical used was highly correlated to total area of weed patches, and approximately 90% of the grass species within the area were killed as a result of patch spraying. Haggar *et al*. (1983) developed a similar weed sensor that calculated a vegetation index using red and NIR reflectance to distinguish between soil and vegetation. Shearer and Jones (1991) used photoelectric sensing to detect inter-row weed growth, and a control circuit was designed for activation of a spray nozzle on a vehicle-based spray system. Testing in soybeans showed a 15% reduction in herbicide usage with no apparent decline in the level of weed control. Hanks and Beck (1998) analyzed two commercially available systems, the Detectspray Model S-50 and the WeedSeeker Model PhD 1620, that use photoelectric sensor readings to trigger spray nozzles. Since photoelectric sensors are not able to distinguish between crop and weeds, plastic spray hoods were used to prevent vegetation within the crop rows from triggering the spray. The WeedSeeker proved to be a more

versatile design, because the system incorporated an internal light source, which made its performance less susceptible to variations in ambient lighting conditions. Field-testing of the two systems showed that a 63–85% reduction in herbicide use could be realized with no significant loss in weed control. The Detectspray system was also tested in research by Blackshaw *et al.* (1998a) and Blackshaw *et al.* (1998b). In this research, the performance of the system was limited by dense or tall crop residue, and very small weeds were often difficult to detect. Weed species were detected with varying consistency depending on the number of leaves, growth stage, and density. Also, since the sprayer relied on ambient lighting conditions, the lack of solar irradiance at night and at times 70–80 min after sunrise and before sunset limited the sprayer performance. In spite of these limitations, Detectspray application results were comparable to conventional applications on 80% of the test dates, and herbicide usage was reduced from 19–80% depending on the type of application. Due to the simplicity in processing of photoelectric data, photoelectric sensors have been easily incorporated into variable-rate herbicide application systems; however, these systems are generally limited to the detection of significant weed cover between crop rows with appropriate lighting. Normally, a base rate is needed to control the very young weeds in the field because photo-detector would not be sensitive to early stage of weed infestations.

Machine vision for weed sensing

Since photo-detectors cannot distinguish between weeds and crop material, other researchers have approached ground-based weed sensing using machine vision technology. In this case, images are collected with ground-based camera systems and subsequent image processing routines are used to segment vegetation from soil background and delineate weeds from crop. Segmentation of vegetation from soil background using machine vision has typically involved the use of color indices that are sensitive to green reflectance. Woebbecke *et al.* (1995a) developed several color indices using chromatic coordinates to distinguish living plant material from background. They found that a modified hue index, the *2g–r–b* index, and the green chromatic coordinate performed better than other indices that were developed. Andreasen *et al.* (1997) segmented vegetation in digital images by establishing a threshold for the median-filtered histogram of the green chromaticity coordinate. An algorithm was developed to determine the threshold level at which optimum pixel classification occurred and total error probability was minimized. El-Faki *et al.* (2000) used color indices in an application to distinguish between crops with green stems and weeds with red stems. In this research, indices were useful for locating green plant material such that the red stems of the weeds in question were more exposed. Instead of using color machine vision, Guyer *et al.* (1986) collected one-band grayscale images of plant/soil mixtures using a camera that was sensitive over the broad range of 400–1000 nm. Under incandescent lighting, segmentation of vegetation from soil was successful when the pixel value threshold was set at 1.5 standard deviations above

the mean. Thomas *et al.* (1988) developed an image processing procedure for measuring plant canopy cover in overhead slide photographs. They cite measurement inaccuracies in the instances of poor lighting conditions and poor contrast between plant and soil. Indeed, segmentation of vegetation from soil has been most successful under controlled lighting conditions in the past, but for practical applications in precision agriculture image segmentation must perform adequately under variable lighting conditions. For this reason, Tian and Slaughter (1998) developed an environmentally adaptive segmentation algorithm (EASA) for robust segmentation of vegetation under the naturally variable conditions of outdoor lighting. The algorithm used a partially supervised process based on a set of manually selected cluster seeds to divide training images into a set number of classes. After the clustering process, a look-up table (LUT) was derived based on the Bayes' decision boundaries for the classes that represented the object of interest, as defined through human inspection. In this fashion, a new LUT could be quickly generated for various lighting conditions, crop hybrids, weed species, and soil types by retraining the classifier. The EASA was implemented with shape-based pattern recognition in a machine vision system for detection of weeds in tomato (*Lycopersicon esculentum* L.) seedlings. Using this system, 65–78% of the targeted tomato plants were correctly identified, and weeds were incorrectly identified as crop less than 5% of the time (Tian *et al.*, 1997). Segmentation of vegetation in variable lighting conditions has also been accomplished using a binary-encoded genetic algorithm in the hue, saturation, and intensity (HSI) color space (Tang *et al.*, 2000).

Once vegetation is separated from soil background in an agricultural machine vision application, weeds are then distinguished from crop using spectral, spatial, and/or textural information within the images. Franz *et al.* (1991b) used discriminant analysis to identify weed seedlings in digital images based on the spectral properties of their leaves. Skewness in the red waveband and the mean and variance in the NIR and blue band were used as features for discrimination between weed species. Leaf orientation with respect to illumination source was cited as the major source of error; however, for 48 observations in which this was not a factor, only 6.25% of the observations were misclassified. Zhang and Chaisattapagon (1995) calculated gray level ratios of images collected using a variety of color filters. Red and green filters were useful in identifying weeds having reddish stems, such as redroot pigweed (*A. retroflexus* L.), kochia (*Bassia scoparia* (L.) Schrad.), and Russian thistle (*Salsola iberica* Sennen and Pau). Jia and Krutz (1992) developed an algorithm to locate corn plants by detecting, through a spectral analysis, the main veins of the plant leaves. Using a technique such as this, weeds could be identified indirectly by assigning to the weed category all plants that do not have a unique crop feature, such as a corn plant's thick main vein. Instead of spectral properties, other researchers have used leaf shape properties to distinguish between plant species. Guyer *et al.* (1986) defined four shape-based parameters for leaves including complexity, elongatedness, central moment, and principle axis moment. Each of these parameters was measured for eight plant species at various growth stages through the processing of grayscale images. They concluded that weed leaves showed discernible differ-

ences in shape-based properties. In further research, Guyer *et al.* (1993) developed 13 high-level shape features from 17 leaf measurements with the intent to quantitatively determine the more subjective properties of leaf shape. In some cases, the machine vision system and human evaluators chose the same subjective shape property for a leaf 65% of the time. Woebbecke *et al.* (1995b) performed an analysis using eleven shape features in images of corn, soybeans, and ten weeds found in the mid-western United States. Dicots and monocots were most successfully discriminated between 14 and 23 days after emergence using aspect and the first invariant central moment as features for classifying leaf shape. Similarly, Zhang and Chaisattapagon (1995) found that five shape-based features could effectively distinguish the leaves of redroot pigweed, kochia, and wild buckwheat (*Polygonum convolvulus* L.) from wheat leaves. However, the shape parameters were not able to differentiate between the broadleaf weed species. Problems in using shape features for identification of *in situ* plant species include the presence of occluded or overlapped leaves (Franz *et al.*, 1991a), variations in plant leaf size and shape as a function of growth stage (Woebbecke *et al.*, 1995b), and the variable three-dimensional orientation of leaves in relation to the machine vision sensor (Franz *et al.*, 1991b). The third method for discrimination of plant species in ground-based weed detection applications involves the measurement of the textural appearance of a plant or plant canopy as a whole. Shearer and Holmes (1990) used 33 color texture features, calculated from co-occurrence matrices of image hue, saturation, and intensity, to identify nursery plants with discriminant analysis. A classification accuracy of 91% was obtained in an analysis using 350 observations of seven plants. Shearer and Holmes (1990) concluded that the use of both hue and intensity information together in the analysis provided a much better result than intensity alone. Burks *et al.* (2000) used color co-occurrence matrices to calculate textural features and achieved a 93% overall accuracy in classifying between five weed species and soil using hue and saturation only. Meyer *et al.* (1998) also determined textural features from color co-occurrence matrices, and classification accuracies were 93% and 85% for classifying between grasses and broadleaf weeds, respectively. Lower classification accuracies, between 30% and 70%, were seen in the attempts to classify between individual species. Zhang and Chaisattapagon (1995) calculated the Fourier spectrum of leaf images and found that the multidirectional pattern of broadleaf weeds such as wild buckwheat, Palmer amaranth, and kochia could be used to distinguish the weeds from wheat, which showed a unidirectional textural pattern in Fourier space. They also used Fourier analysis to analyze the fineness of plant canopy textures.

Comparing with other methods, machine vision weed sensing in the field is a ''information rich'' system. The spatial resolution of the machine vision system is generally much higher—between 0.0003 and 0.005 m per pixel depending on the system setup. The image processing results are more accurate because the resolution and better color definition of image pixels. Although the system cost is relatively higher, the potential of machine vision system in weed sensing for real-time selective herbicide application has been shown by several researchers (Lee, 1999; Tian, 2002).

Future research needs

A large portion of this review focuses on the mechanism of light reflectance in plant leaves and the nonlinear interaction of radiation between plant canopies and the soil background. These are fundamental issues in the development of a proper remote sensing-based weed detection strategy. As shown by Huete (1987), the nonlinearity of the spectral response over partial plant canopies is most problematic at intermediate levels of canopy coverage. This is precisely the time that remote sensing imagery must be collected for weed detection in post-emergence crops. In addition, Thorp (2002) speculated that, at the time weed detection must occur, soil background may actually have a greater influence on the spectral response of a field than vegetation. In this research, remote sensing-based weed maps were developed for post-emergence variable-rate herbicide applications in separate fields over two growing seasons. As a precursor to weed map development, Thorp (2002) performed a simple principle component (PC) transformation on each image and correlated the PC transformed bands to ground reference measures of vegetation cover. In all cases, the *second* PC band was more highly correlated to vegetation cover than the first PC band. Also, the first PC band was most visually comparable to a bare soil image of the field, suggesting that soil background contributed more to the overall variance in the scene than vegetation. Perhaps the strength of the soil influence has been underestimated in the past, because research has focused so intently on weed delineation. However, it can be ignored no longer. Future work should focus on the improvement of techniques for reduction of the soil influence and the incorporation of these techniques into weed map development strategies. Pinpointing the precise level of canopy coverage at which soil influences are no longer a problem would also be beneficial.

Vegetation indices have been used quite regularly to assess the vigor of vegetation over an area, and some have been developed specifically for minimizing soil background effects in the spectral response of partial canopies (Huete, 1988). Literally hundreds of vegetation indices exist, yet none has emerged as the panacea for use in any situation. In fact, the performance of these indices seems to be quite circumstantial, as researchers continually report conflicting statements as to which indices give the best results. According to Bannari *et al.* (1995), inconsistancy in index performance can be attributed to the atmosphere, sensor calibration, sensor viewing conditions, solar angle, and soil background. The matter is further complicated when vegetation indices are used to analyze the spectra of heterogeneous environments, such as that of post-emergence row crops at intermediate growth stages. Current vegetation indices are therefore not adequate for reducing the soil signal in remote sensing imagery collected for detection of weeds in post-emergence crops. As a solution to this problem, several areas for further exploration were discussed in this review, namely hyperspectral indices and spectral unmixing. Spectral unmixing provides a unique opportunity, because, if done properly, a composite spectral response can be broken into its component responses. Given the complexity of reflectance signals collected for agricultural weed detection, perhaps an accurate dissection of the composite

signal into soil and vegetative components should be the first step in the development of an effective data processing strategy. We must imagine how the images would look if crops and weeds grew in soil with the reflectance properties of a blackbody. In this case, the spectral response of the field would depend most strongly on the presence of vegetation. This phenomenon could actually be studied quite easily by inserting a material with a very low reflectivity, such as black velvet (Tipler, 1991), between the rows of a crop canopy. By understanding the soil background influence more thoroughly, procedures could then be developed for purification of images through the removal of the soil signal.

After the soil background issue is addressed, researchers must find a solution to the weed species delineation argument. Some believe that reflectance data can be used to distinguish between weed species (LaMastus *et al*., 2000), while others argue that the reflectance signal can only be used to quantify an area's biomass density. Most definitely, the solution to this problem has been clouded by the difficulties in achieving a "pure" reflectance signal for a given species. With this in mind, we should begin by studying species that are capable of producing a very lush canopy density, so that soil background influences and species competition are minimized. By collecting spectral readings of several lush stands of species at various growth stages and simultaneously harvesting plant material for biomass analysis at each stage, the dependence of spectral readings on biomass could be determined for these species. Significantly different reflectance values *at equal biomass* for two species would then support the cause for believers in weed species delineation. Some studies have compared the spectral responses of species without considering the total biomass present at the time of spectral data collection (Copenhaver *et al*., 2001). Yet, given the nature of light interaction in a plant canopy, it seems more probable that the spectral response of a lushly vegetated area would depend on *both* the species and the quantity of biomass rather than weed species or biomass alone. Often there is no black or white solution to a given problem, and perhaps this is true for the argument concerning weed species delineation.

Once remote sensing data can be correctly interpreted for detection of weeds, the next step involves the implementation of a proper data acquisition system. Essentially, there are two types of passive sensors: imaging sensors and nonimaging sensors. These can be further divided into multispectral and hyperspectral sensors, and they can all be incorporated onto ground-, aircraft-, or satellite-based platforms. This review has presented multiple examples in which weeds have been detected using a variety of sensors on a variety of platforms, but which method will work best for agricultural weed detection? Currently, each type of system has its own unique advantages and limitations (Moran *et al*., 1997), and it is unclear which data acquisition strategy embodies the correct direction for the future of agricultural weed sensing. In order for progress to be made in this arena, perhaps future work should focus more emphatically on the use of weed maps to make variable-rate herbicide applications. To date, research has focused very intently on the development of techniques for weed detection, but a relatively small body of work exists in the actual implementation of these techniques in variable-rate herbicide applications. By taking the current weed detection technology to the next level, perhaps the most crucial

attributes of a weed sensing strategy could be identified, and maybe some of the more difficult weed sensing problems could be circumvented.

Rigorous completion of variable-rate herbicide applications would also address another problem in this area. Namely, the successful delineation of weeds does not necessarily guarantee the success of variable-rate herbicide applications, because there are currently no methods for assigning rates of herbicide based on the results of a weed sensing procedure. Maps for variable-rate herbicide applications have been generated using spectral response properties, percent cover measurements, and weed density measurements. However, there exists no equation that relates any of these properties to a rate of herbicide. In fact, label recommendations for many foliar herbicides suggest that herbicide rates are more dependent on weed size, height, and species rather than spectral properties, percent cover, or weed density. Other factors, which influence herbicide rate selections to a lesser degree, include the age of the weeds, the level of plant activity at the time of spraying, the weed history, and the desired level of weed control. Therefore, to correctly apply herbicide to agricultural crops in a site-specific manner, a weed sensing procedure must be coupled with other pertinent information such that herbicide rates can be correctly assigned for adequate control of a particular field's weed infestation condition.

Conclusions

The purpose of agricultural weed detection is to map the spatial variability of weed growth, such that herbicide can be applied on a site-specific, need-only basis. In support of this practice, the inherent patchiness of weed growth has been verified. These studies have also shown much variability in the size, morphology, and distribution of weed patches both within and between agricultural fields. Remote sensing has been used for weed detection, because weedy areas of an agricultural field should theoretically have a stronger vegetative spectral response than areas without weed pressure. However, the presence of variable soil backgrounds and residue covers complicates this spectral response and hinders the analysis of vegetative presence. These soil background effects have been ignored in most remote sensing-based weed detection applications. Very rarely have techniques been used to quantify and reduce the soil background effects in imagery before completing the analysis for weed cover. This step must be incorporated into future data processing strategies. Vegetation indices and spectral mixture analysis have been employed as tools for removal of the soil signal in the reflectance of partial canopies. Further development of these techniques may be beneficial for studying the relative contribution of crop, weeds, and soil in image pixels and for reducing the effects of unwanted signals. Since it is difficult to obtain a "pure" spectral response of a given species, it is unclear whether remote sensing can be used to distinguish between weed species or if it simply detects differences in biomass density. To address this problem, future work should focus on comparing the spectral response of various species while also considering the level of biomass at the time of reflectance data collection. Hyperspectral data, with its greater spectral resolution, may be the best choice for investigations such as these. Finally, in studying the relevant literature for this review, it was

interesting to notice how often studies failed to extend their proposed weed detection techniques into the arena of variable-rate herbicide applications. Since this is the ultimate goal for any weed detection method, the current focus should be modified such that proposed weed detection techniques are more often used to make variable-rate herbicide applications.

Acknowledgements

This material is based upon work supported by the Illinois Council for Food and Agricultural Research under Award No. C-FAR 1-5-9528, United Soybean Board Project No. 1248, and USDA Hatch Project No. 4003. Any options, findings and conclusions or recommendations in this publication are those of the author(s) and do not necessarily reflect the views of sponsors or the University of Illinois.

References

Allen, W. A. and Richardson, A. J. 1968. Interaction of light with a plant canopy. Journal of the Optical Society of America **58**(8), 1023–1028.

Anderson, G. L., Everitt, J. H., Richardson, A. J. and Escobar, D. E. 1993. Using satellite data to map false broomweed *(Ericameria austrotexana)* infestations on south Texas rangelands. Weed Technology **7**(4), 865–871.

Andreasen, C., Rudemo, M. and Sevestre, S. 1997. Assessment of weed density at an early stage by use of image processing. Weed Research **37**, 5–18.

Ashley, M. D. and Rea, J. 1975. Seasonal vegetation differences from ERTS imagery. Photogrammetric Engineering and Remote Sensing **41**, 713–719.

Audsley, E. 1993. Operational research analysis for patch spraying. Crop Protection **12**, 111–119.

Bach, H. and Mauser, W. 1994. Modelling and model verification of the spectral reflectance of soils under varying moisture conditions. In: *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium*, IGARSS '94 (IEEE, Piscataway, NJ, USA) Vol. 4, pp. 2354–2356.

Bannari, A., Morin, D., Bonn, F. and Huete, A. R. 1995. A review of vegetation indices. Remote Sensing Reviews **13**, 95–120.

Baret, F., Guyot, G. and Major, D. J. 1989. TSAVI: A vegetation index which minimizes soil brightness effects on LAI and APAR estimation. In: *Proceedings of the 12th Canadian Symposium on Remote Sensing*, IGARSS'89, July 10–14 1989 (IEEE,Vancouver, Canada) Vol. 3, pp. 1355–1358.

Bechdol, M. A., Gualtieri, J. A., Hunt, J. T., Chettri, S. and Garegnani, J. 2000. Hyperspectral imaging: a potential tool for improving weed and herbicide management. In: *Proceedings of the 5th International Conference on Precision Agriculture* (ASA-CSSA-SSSA, Madison, WI, USA).

Blackburn, G. A. 1998. Quantifying the chlorophylls and carotenoids at leaf and canopy scales: an evaluation of some hyperspectral approaches. Remote Sensing of Environment **66**, 273–285.

Blackshaw, R. E., Molnar, L. J., Chevalier, D. F. and Lindwall, C. W. 1998a. Factors affecting the operation of the weed-sensing Detectspray system. Weed Science **46**, 127–131.

Blackshaw, R. E., Molnar, L. J. and Lindwall, C. W. 1998b. Merits of a weed-sensing sprayer to control weeds in conservation fallow and cropping systems. Weed Science **46**, 120–126.

Borel, C. C. and Gerstl, S. A. W. 1994. Nonlinear spectral mixing models for vegetative and soil surfaces. Remote Sensing of Environment **47**, 403–416.

Bouman, B. A. M. 1992. Accuracy of estimating the leaf area index from vegetation indices derived from crop reflectance characteristics, a simulation study. International Journal of Remote Sensing **13**(16), 3069–3084.

Bowers, S. A. and Hanks, R. J. 1965. Reflection of radiant energy from soils. Soil Science **100**(2), 130–138.

Brian, P. and Cousens, R. 1990. The effect of weed distribution on predictions of yield loss. Journal of Applied Ecology **27**(2), 735–742.

Brown, R. B. and Steckler, J. -P. G. A. 1995. Prescription maps for spatially variable herbicide application in no-till corn. Transactions of the ASAE **38**(6), 1659–1666.

Brown, R. B., Steckler, J. -P. G. A. and Anderson, G. W. 1994. Remote sensing for identification of weeds in no-till corn. Transactions of the ASAE **37**(1), 297–302.

Burks, T. F., Shearer, S. A. and Payne, F. A. 2000. Classification of weed species using color texture features and discriminant analysis. Transactions of the ASAE **43**(2), 441–448.

Cardina, J., Johnson, G. A. and Sparrow, D. H. 1997. The nature and consequence of weed spatial distribution. Weed Science **45**, 364–373.

Cardina, J., Sparrow, D. H. and McCoy, E. L. 1995. Analysis of spatial distribution of common lambsquarters (*Chenopodium album*) in no-till soybeans (*Glycine max*). Weed Science **43**(2), 258–268.

Cardina, J., Sparrow, D. H. and McCoy, E. L. 1996. Spatial relationships between seedbank and seedling populations of common lambsquarters (*Chenopodium album*) and annual grasses. Weed Science **44**(2), 298–308.

Chancellor, W. J. and Goronea, M. A. 1994. Effects of spatial variability of nitrogen, moisture, and weeds on the advantages of site-specific applications for wheat. Transactions of the ASAE **37**(3), 717–724.

Chen, Z., Elvidge, C. D. and Jansen, W. T. 1993. Description of derivative-based high spectral-resolution (AVIRIS) green vegetation index. In: *Proceedings of SPIE: Imaging Spectroscopy of the Terrestrial Environment*, April 14–15 1993, edited by G. Vane (Orlando, Florida, USA) Vol. 1937, pp. 43–54.

Christensen, S., Nordbo, E. and Kristensen, K. 1994. Weed cover mapping with spectral reflectance measurements. Aspects of Applied Biology – Sampling to Make Decisions **37**, 171–179.

Cipra, J. E., Baumgardner, M. F., Stoner, E. R. and MacDonald, R. B. 1971. Measuring radiance characteristics of soil with a field spectroradiometer. Soil Science Society of America Proceedings **35**, 1014–1017.

Cochran, W. 1977. *Sampling Techniques* (John Wiley & Sons Inc., New York, NY, USA).

Colwell, J. E. 1974. Vegetation canopy reflectance. Remote Sensing of Environment **3**, 175–183.

Condit, H. R. 1971. The spectral reflectance of American soils. Photogrammetric Engineering **36**, 955–966.

Copenhaver, K., Gress, T., White, S. and Varner, B. 2001. Weed detection and delineation in soybeans. Final report of ITD/Spectral Visions to NASA Earth Science Application Directorate (ESAD) 2001. www.ag2020.org.

Curran, P. J., Dungan, J. L., Macler, B. A. and Plummer, S. E. 1991. The effect of a red leaf pigment on the relationship between red edge and chlorophyll concentration. Remote Sensing of Environment **35**, 69–76.

Datt, B. and Paterson, M. 2000. Vegetation-soil spectral mixture analysis. In: *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium*, IGARSS '00 (IEEE, Piscataway, NJ, USA) Vol. 5, pp. 1936–1938.

Demetriades-Shah, T. H., Steven, M. D. and Clark, J. A. 1990. High resolution derivative spectra in remote sensing. Remote Sensing of Environment **33**, 55–64.

Donald, W. W. 1994. Geostatistics for mapping weeds, with a Canada thistle (*Cirsium arvense*) patch as a case study. Weed Science **42**(4), 648–657.

El-Faki, M. S., Zhang, N. and Peterson, D. E. 2000. Weed detection using color machine vision. Transactions of the ASAE **43**(6), 1969–1978.

Elvidge, C. D. and Chen, Z. 1995. Comparison of broad-band and narrow-band red and near-infrared vegetation indices. Remote Sensing of Environment **54**, 38–48.

Elvidge, C. D., Chen, Z. and Groeneveld, D. P. 1993. Detection of trace quantities of green vegetation in 1990 AVIRIS data. Remote Sensing of Environment **44**, 271–279.

Elvidge, C. D. and Lyon, R. J. P. 1985. Influence of rock-soil spectral variation on the assessment of green biomass. Remote Sensing of Environment **17**, 265–279.

Everitt, J. H., Alaniz, M. A., Escobar, D. E. and Davis, M. R. 1992a. Using remote sensing to distinguish common *(Isocoma coronopifolia)* and Drummond goldenweed *(Isocoma drummondii)*. Weed Science **40**(4), 621–628.

Everitt, J. H., Anderson, G. L., Escobar, D. E., Davis, M. R., Spencer, N. R. and Andrascik, R. J. 1995. Use of remote sensing for detecting and mapping leafy spurge (*Euphorbia esula*). Weed Technology **9**(3), 599–609.

Everitt, J. H., Escobar, D. E., Alaniz, M. A., Villarreal, R. and Davis, M. R. 1992b. Distinguishing brush and weeds on rangelands using video remote sensing. Weed Technology **6**(4), 913–921.

Everitt, J. H., Escobar, D. E., Villarreal, R., Alaniz, M. A. and Davis, M. R. 1993a. Canopy light reflectance and remote sensing of shin oak *(Quercus havardii)* and associated vegetation. Weed Science **41**(2), 291–297.

Everitt, J. H., Escobar, D. E., Villarreal, R., Alaniz, M. A. and Davis, M. R. 1993b. Integration of airborne video, global positioning system, and geographic information system technologies for detecting and mapping two woody legumes on rangelands. Weed Technology **7**(4), 981–987.

Everitt, J. H., Pettit, R. D. and Alaniz, M. A. 1987. Remote sensing of broom snakeweed *(Gutierrezia sarothrae)* and spiny aster *(Aster spinosus)*. Weed Science **35**(2), 295–302.

Everitt, J. H., Richerson, J. V., Alaniz, M. A., Escobar, D. E., Villarreal, R. and Davis, M. R. 1994. Light reflectance characteristics and remote sensing of Big Bend loco (*Astragalus mollissimus* var. *earlei*) and Wooton loco (*Astragalus wootonii*). Weed Science **42**(1), 115–122.

Franz, E., Gebhardt, M. R. and Unklesbay, K. B. 1991a. Shape description of completely visible and partially occluded leaves for identifying plants in digital images. Transactions of the ASAE **34**(2), 673–681.

Franz, E., Gebhardt, M. R. and Unklesbay, K. B. 1991b. The use of local spectral properties of leaves as an aid for identifying weed seedlings in digital images. Transactions of the ASAE **34**(2), 682–687.

Gates, D. M., Keegan, H. J., Schleter, J. C. and Weidner, V. R. 1965. Spectral properties of plants. Applied Optics **4**(1), 11–20.

Gausman, H. W., Gerbermann, A. H., Wiegand, C. L., Leamer, R. W., Rodriguez, R. R. and Noriega, J. R. 1975. Reflectance differences between crop residues and soils. Soil Science Society of America Proceedings **39**, 752–755.

Guyer, D. E., Miles, G. E., Gaultney, L. D. and Schreiber, M. M. 1993. Application of machine vision to shape analysis in leaf and plant identification. Transactions of the ASAE **36**(1), 163–171.

Guyer, D. E., Miles, G. E., Schreiber, M. M, Mitchell, O. R. and Vanderbilt, V. C. 1986. Machine vision and image processing for plant identification. Transactions of the ASAE **29**(6), 1500–1507.

Haggar, R. J., Stent, C. J. and Isaac, S. 1983. A prototype hand-held patch sprayer for killing weeds, activated by spectral differences in crop/weed canopies. Journal of Agricultural Engineering Research **28**, 349–358.

Hall, F. G., Huemmrich, K. F., Goward, S. N. 1990. Use of narrow-band spectra to estimate the fraction of absorbed photosynthetically active radiation. Remote Sensing of Environment **32**, 47–54.

Hanks, J. E. and Beck, J. L. 1998. Sensor-controlled hooded sprayer for row crops. Weed Technology **12**, 308–314.

Hatfield, J. L. and Pinter Jr., P. J. 1993. Remote sensing for crop protection. Crop Protection **12**(6), 403–413.

Heilman, J. L. and Kress, M. R. 1987. Effects of vegetation on spectral irradiance at the soil surface. Agronomy Journal **79**, 765–768.

Hooper, A. W., Harries, G. O. and Ambler, B. 1976. A photoelectric sensor for distinguishing between plant material and soil. Journal of Agricultural Engineering Research **21**, 145–155.

Horler, D. N. H., Dockray, M. and Barber, J. 1983. The red edge of plant leaf reflectance. International Journal of Remote Sensing **4**(2), 273–288.

Huete, A. R. 1986. Separation of soil-plant mixtures by factor analysis. Remote Sensing of Environment **19**, 237–251.

Huete, A. R. 1987. Soil-dependent spectral response in a developing plant canopy. Agronomy Journal 79, 61–68.

Huete, A. R. 1988. A soil-adjusted vegetation index (SAVI). Remote Sensing of Environment **25**, 295–309.

Huete, A. R. and Jackson, R. D. 1988. Soil and atmosphere influences on the spectra of partial canopies. Remote Sensing of Environment **25**, 89–105.

Huete, A. R., Jackson, R. D. and Post, D. F. 1985. Spectral response of a plant canopy with different soil backgrounds. Remote Sensing of Environment **17**, 37–53.

Hurcom, S. J. and Harrison, A. R. 1998. The NDVI and spectral decomposition for semi-arid vegetation abundance estimation. International Journal of Remote Sensing. **19**(16), 3109–3125.

Jackson, R. D. 1983. Spectral indices in *n*-space. Remote Sensing of Environment **13**, 409–421.

Jackson, R. D., Reginato, R. J., Pinter, Jr. P. J. and Idso, S. B. 1979. Plant canopy information extraction from composite scene reflectance of row crops. Applied Optics **18**(22), 3775–3782.

Jia, J. and Krutz, G. W. 1992. Location of the maize plant with machine vision. Journal of Agricultural Engineering Research **52**, 169–181.

Johnson, G. A., Mortensen, D. A. and Martin, A. R. 1995. A simulation of herbicide use based on weed spatial distribution. Weed Research **35**, 197–205.

Jordan, C. F. 1969. Derivation of leaf-area index from quality of light on the forest floor. Ecology **50**(4), 663–666.

Kauth, R. J. and Thomas, G. S. 1976. The tasseled cap – a graphic description of the spectral-temporal development of agricultural crops as seen by Landsat. In: *Proceedings of the Symposium on Machine Processing of Remotely Sensed Data*, June 29–July 1 1976 (Purdue University, West Lafayette, IN, USA) pp. 41–51.

Kawata, S. and Minami, S. 1984. Adaptive smoothing of spectroscopic data by a linear mean-square estimation. Applied Spectroscopy **38**(1), 49–58.

King, R. P., Lybecker, D. W., Schweizer, E. E. and Zimdahl, R. L. 1986. Bioeconomic modeling to simulate weed control strategies for continuous corn *(Zea mays)*. Weed Science **34**(6), 972–979.

Knipling, E. B. 1970. Physical and physiological basis for the reflectance of visible and near-infrared radiation from vegetation. Remote Sensing of Environment **1**, 155–159.

LaMastus, F. E., Smith, C. M., Shaw, D. R. and King, R. L. 2000. Potential for weed species differentiation using remote sensing. In: *Proceedings of the 5th International Conference on Precision Agriculture* (ASA-CSSA-SSSA, Madison, WI, USA) (CD-ROM).

Lamb, D. W. and Brown, R. B. 2001. Remote-sensing and mapping of weeds in crops. Journal of Agricultural Engineering Research. **78**(2), 117–125.

Lamb, D. W. and Weedon, M. 1998. Evaluating the accuracy of mapping weeds in fallow fields using airborne digital imagery: *Panicum effusum* in oilseed rape stubble. Weed Research **38**, 443–451.

Lamb, D. W., Weedon, M. M. and Rew, L. J. 1999. Evaluating the accuracy of mapping weeds in seedling crops using airborne digital imaging: *Avena* spp. in seedling triticale. Weed Research **39**, 481–492.

Lass, L. W. and Callihan, R. H. 1997. The effect of phenological stage on the detectability of yellow hawkweed (*Heiracium pratense*) and oxeye daisy (*Chrysanthemum leucanthemum*) with remote multispectral digital imagery. Weed Technology **11**(2), 248–256.

Lass, L. W., Carson, H. W. and Callihan, R. H. 1996. Detection of yellow starthistle (*Centaurea solstitialis*) and common St. Johnswort (*Hypericum perforatum*) with multispectral digital imagery. Weed Technology **10**(3), 466–474.

Lawrence, R. L. and Ripple, W. J. 1998. Comparisons among vegetation indices and bandwise regression in a highly disturbed, heterogeneous landscape: Mount St. Helens, Washington. Remote Sensing of Environment **64**, 91–102.

Lee, W. S., Slaughter, D. C. and Giles, D. K. 1999. Robotic weed control system for tomatoes. Precision Agric. **1**(1): 95–113.

Lillesaeter, O. 1982. Spectral reflectance of partly transmitting leaves: laboratory measurements and mathematical modeling. Remote Sensing of Environment **12**, 247–254.

Lillesand, T. M. and Kiefer, R. W. 2000. *Remote Sensing and Image Interpretation. 4th edn* (John Wiley & Sons Inc., New York, NY, USA).

Lopez-Backovic, I. 1988. Using geostatistics to consider variability of soil and crop properties. ASAE Paper No. 88-1605. (ASAE, St. Joseph, MI, USA).

Lord, D., Desjardins, R. L., Dube, P. A. and Brach, E. J. 1985. Variations of crop canopy spectral reflectance measurements under changing sky conditions. Photogrammetric Engineering and Remote Sensing **51**(6), 689–695.

Lybecker, D. W., Schweizer, E. E. and King, R. P. 1991. Weed management decisions in corn based on bioeconomic modeling. Weed Science **39**(1), 124–129.

Major, D. J., Baret, F. and Guyot, G. 1990. A ratio vegetation index adjusted for soil brightness. International Journal of Remote Sensing **11**(5), 727–740.

Marshall, E. J. P. 1988. Field-scale estimates of grass weed populations in arable land. Weed Research **28**, 191–198.

Maxwell, B. D. and Ghersa, C. 1992. The influence of weed seed dispersion versus the effect of competition on crop yield. Weed Technology **6**(1), 196–204.

Medlin, C. R. and Shaw, D. R. 2000. Economic comparison of broadcast and site-specific herbicide applications in nontransgenic and glyphosate-tolerant *Glycine max*. Weed Science **48**, 653–661.

Medlin, C. R., Shaw, D. R., Gerard, P. D. and LaMastus, F. E. 2000. Using remote sensing to detect weed infestations in *Glycine max*. Weed Science **48**, 393–398.

Menges, R. M., Nixon, P. R. and Richardson, A. J. 1985. Light reflectance and remote sensing of weeds in agronomic and horticultural crops. Weed Science **33**(4), 569–581.

Mestre, H. 1935. The absorption of radiation by leaves and algae. Cold Spring Harbor Symposium on Quantitative Biology **3**, 191–209.

Meyer, G. E., Mehta, T., Kocher, M. F., Mortensen, D. A. and Samal, A. 1998. Textural imaging and discriminant analysis for distinguishing weeds for spot spraying. Transactions of the ASAE **41**(4), 1189–1197.

Moran, M. S., Inoue, Y. and Barnes, E. M. 1997. Opportunities and limitations for image-based remote sensing in precision crop management. Remote Sensing of Environment **61**, 319–346.

Mortensen, D. A. and Coble, H. D. 1991. Two approaches to weed control decision-aid software. Weed Technology **5**(2), 445–452.

Mortensen, D. A., Johnson, G. A. and Young, L. J. 1993. Weed distribution in agricultural fields. In: *Soil Specific Crop Management*, edited by P. C. Roberts, R. H. Rust, and W. E. Larson (ASA-CSSA-SSSA, Madison, WI, USA), ch. 9, pp. 113–124.

Navas, M. L. 1991. Using plant population biology in weed research: A strategy to improve weed management. Weed Research **31**, 171–179.

Nitsch, B. B., VonBargen, K., Meyer, G. E. and Mortensen, D. A. 1991. Visible and near infrared plant, soil, and crop residue reflectivity for weed sensor design. ASAE Paper No. 91-3006. (ASAE, St. Joseph, MI, USA).

Philpot, W. D. 1991. The derivative ratio algorithm: Avoiding atmospheric effects in remote sensing. IEEE Transactions on Geoscience and Remote Sensing **29**(3), 350–357.

Planet, W. G. 1970. Some comments on reflectance measurements of wet soils. Remote Sensing of Environment **1**, 127–129.

Qi, J., Chehbouni, A., Huete, A. R., Kerr, Y. H. and Sorooshian, S. 1994. A modified soil adjusted vegetation index. Remote Sensing of Environment **24**, 119–126.

Ray, T. W. and Murray, B. C. 1996. Nonlinear spectral mixing in desert vegetation. Remote Sensing of Environment **55**, 59–64.

Rew, L. J., Cussans, G. W., Mugglestone, M. A. and Miller, P. C. H. 1996. A technique for mapping the spatial distribution of *Elymus repens*, with estimates of the potential reduction in herbicide usage from patch spraying. Weed Research **36**, 283–292.

Richardson, A. J., Menges, R. M. and Nixon, P. R. 1985. Distinguishing weed from crop plants using video remote sensing. Photogrammetric Engineering and Remote Sensing **51**(11), 1785–1790.

Richardson, A. J. and Wiegand, C. L. 1977. Distinguishing vegetation from soil background information. Photogrammetric Engineering and Remote Sensing **43**(12), 1541–1552.

Roberts, D. A., Gardner, M., Church, R., Ustin, S., Scheer, G. and Green, R. O. 1998. Mapping chaparral in the Santa Monica mountains using multiple endmember spectral mixture models. Remote Sensing of Environment **65**, 267–279.

Roberts, D. A., Smith, M. O. and Adams, J. B. 1993. Green vegetation, nonphotosynthetic vegetation, and soils in AVIRIS data. Remote Sensing of Environment **44**, 255–269.

Rondeaux, G., Steven, M. and Baret, F. 1996. Optimization of soil-adjusted vegetation indices. Remote Sensing of Environment **55**, 95–107.

Savitzky, A. and Golay, M. J. E. 1964. Smoothing and differentiation of data by simplified least squares procedures. Analytical Chemistry **36**(8), 1627–1639.

Schowengerdt, R. A. 1997. *Remote Sensing: Models and Methods for Image Processing. 2nd edn.* (Academic Press, San Deigo, CA, USA).

Shearer, S. A. and Holmes, R. G. 1990. Plant identification using color co-occurrence matrices. Transactions of the ASAE **33**(6), 2037–2044.

Shearer, S. A. and Jones, P. T. 1991. Selective application of post-emergence herbicides using photoelectrics. Transactions of the ASAE **34**(4), 1661–1666.

Smith, G. M. and Milton, E. J. 1999. The use of the empirical line method to calibrate remotely sensed data to reflectance. International Journal of Remote Sensing **20**(13), 2653–2662.

Stafford, J. V. and Miller, P. C. H. 1993. Spatially selective application of herbicide to cereal crops. Computers and Electronics in Agriculture **9**, 217–229.

Stoner, E. R. and Baumgardner, M. F. 1981. Characteristic variations in reflectance of surface soils. Soil Science Society of America Journal **45**, 1161–1165.

Stoner, E. R., Baumgardner, M. F., Weismiller, R. A., Biehl, L. L. and Robinson, B. F. 1980. Extension of laboratory-measured soil spectra to field conditions. Soil Science Society of America Journal **44**, 572–574.

Tang, L., Tian, L. and Steward, B. L. 2000. Color image segmentation with genetic algorithm for in-field weed sensing. Transactions of the ASAE **43**(4), 1019–1027.

Thenkabail, P. S., Smith, R. B. and DePauw, E. 2000. Hyperspectral vegetation indices and their relationships with agricultural crop characteristics. Remote Sensing of Environment **71**, 158–182.

Thomas, D. L., daSilva, F. J. K. and Cromer, W. A. 1988. Image processing technique for plant canopy cover evaluation. Transactions of the ASAE **31**(2), 428–434.

Thompson, J. F., Stafford, J. V. and Miller, P. C. H. 1991. Potential for automatic weed detection and selective herbicide application. Crop Protection **10**, 254–259.

Thornton, P. K., Fawcett, R. H., Dent, J. B. and Perkins, T. J. 1990. Spatial weed distribution and economic thresholds for weed control. Crop Protection **9**, 337–342.

Thorp, K. R. 2002. Variable-rate Applications of Herbicide Using Weed Maps Generated from Remote Sensing Imagery. M.S. thesis, University of Illinois at Urbana-Champaign, Urbana, IL, USA.

Tian, L. F. and Slaughter, D. C. 1998. Environmentally adaptive segmentation algorithm for outdoor image segmentation. Computers and Electronics in Agriculture **21**(3), 153–168.

Tian, L., Slaughter, D. C. and Norris, R. F. 1997. Outdoor field machine vision of tomato seedlings for automated weed control. Transactions of the ASAE **40**(6), 1761–1768.

Tian, L. 2002. Sensor-based precision chemical application system. Journal of Computers and Electronics in Agriculture **36**(23), 133–149.

Timmermann, C., Gerhards, R., Krohmann, P., Sokefeld, M. and Kuhbauch, W. 2001. The economical and ecological impact of the site-specific weed control. In: *Proceedings of the 3rd European Conference on Precision Agriculture*, edited by G. Grenier and S. Blackmore (agro Montpellier, Montpellier, France) Vol. 2, pp. 563–568.

Tipler, P.A. 1991. *Physics for Scientists and Engineers: Extended Version*. (Worth Publishers, Inc., New York, NY, USA).

Tsai, F. and Philpot, W. 1998. Derivative analysis of hyperspectral data. Remote Sensing of Environment **66**, 41–51.

Tucker, C. J. 1979. Red and photographic infrared linear combinations for monitoring vegetation. Remote Sensing of Environment **8**, 127–150.

VanGroenendael, J. M. 1988. Patchy distribution of weeds and some implications for modeling population dynamics: a short literature review. Weed Research **28**, 437–441.

Varner, B. L., Gress, T. A., Copenhaver, K., Wax, L. M., Sprague, C. L. and Tranel, P. J. 2000. Detection of cockleburs (*Xanthium strumarium* L.) in soybeans using hyperspectral imagery. In: *Proceedings of the 5th International Conference on Precision Agriculture* (ASA-CSSA-SSSA, Madison, WI, USA).

Vioix, J-B., Douzals, J-P., Assemat, L., LeCorre, V., Dessaint, F. and Guillemin, J-P. 2001. Development of a combined spatial and spectral method for weed detection and localisation. In: *Proceedings of the 3rd European Conference on Precision Agriculture*, edited by G. Grenier and S. Blackmore (agro Montpellier, Montpellier, France) Vol. 2, pp. 605–610.

Walter-Shea, E. A., Norman, J. M. and Blad, B. L. 1989. Leaf bidirectional reflectance and transmittance in corn and soybeans. Remote Sensing of Environment **29**, 161–174.

Wanjura, D. F. and Hatfield, J. L. 1986. PAR and IR reflectance, transmittance, and absorptance of four crop canopies. Transactions of the ASAE **29**(1), 143–150.

Wanjura, D. F. and Hatfield, J. L. 1987. Sensitivity of spectral vegetative indices to crop biomass. Transactions of the ASAE **30**(3), 810–816.

Wiegand, C. L., Richardson, A. J., Escobar, D. E. and Gerbermann, A. H. 1991. Vegetation indices in crop assessments. Remote Sensing of Environment **35**, 105–119.

Wiles, L. J., Oliver, G. W., York, A. C., Gold, H. J. and Wilkerson, G. G. 1992. Spatial distribution of broadleaf weeds in North Carolina soybean (*Glycine max*) fields. Weed Science **40**(4), 554–557.

Woebbecke, D. M., Meyer, G. E., VonBargen, K. and Mortensen, D. A. 1995a. Color indices for weed identification under various soil, residue, and lighting conditions. Transactions of the ASAE **38**(1), 259–269.

Woebbecke, D. M., Meyer, G. E., VonBargen, K. and Mortensen, D. A. 1995b. Shape features for identifying young weeds using image analysis. Transactions of the ASAE **38**(1), 271–281.

Woolley, J. T. 1971. Reflectance and transmittance of light by leaves. Plant Physiology **47**, 656–662.

Yao, H., Tian, L., Tang, L. and Thorp, K. 2002. Corn canopy reflectance study with a real-time high-density spectral-image mapping system. ASAE Paper No. 02-3144. (ASAE, St. Joseph, MI, USA).

Zhang, N. and Chaisattapagon, C. 1995. Effective criteria for weed identification in wheat fields using machine vision. Transactions of the ASAE **38**(3), 965–974.

Zhang, L., Li, D., Tong, Q. and Zheng, L. 1998. Study of the spectral mixture model of soil and vegetation in PoYang Lake area, China. International Journal of Remote Sensing **19**(11), 2077–2084.

Zwiggelaar, R. 1998. A review of spectral properties of plants and their potential use for crop/weed discrimination in row crops. Crop Protection **17**(3), 189–206.