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# Remote Sensing for Crop Management

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## Abstract

*Scientists with the Agricultural Research Service (ARS) and various government agencies and private institutions have provided a great deal of fundamental information relating spectral reflectance and thermal emittance properties of soils and crops to their agronomic and biophysical characteristics. This knowledge has facilitated the development and use of various remote sensing methods for non-destructive monitoring of plant growth and development and for the detection of many environmental stresses which limit plant productivity. Coupled with rapid advances in computing and position-locating technologies, remote sensing from ground-, air-, and space-based platforms is now capable of providing detailed spatial and temporal information on plant response to their local environment that is needed for site specific agricultural management approaches. This manuscript, which emphasizes contributions by ARS researchers, reviews the biophysical basis of remote sensing; examines approaches that have been developed, refined, and tested for management of water, nutrients, and pests in agricultural crops; and assesses the role of remote sensing in yield prediction. It concludes with a discussion of challenges facing remote sensing in the future.*

## Introduction

Agricultural production strategies have changed dramatically over the past decade. Many of these changes have been driven by economic decisions to reduce inputs and maximize profits and by environmental guidelines mandating more efficient and safer use of agricultural chemicals. However, growers now have a heightened sensitivity to concerns over the quality, nutritional value, and safety of agricultural products. They are selecting cultivars and adjusting planting dates to accommodate anticipated patterns in weather, e.g., *El Niño* or *La Niña* events (Jones *et al.*, 2000). They are also relying on biotechnological innovations for suppressing pests, e.g., insect protected (Bt) and Roundup® ready crops (Monsanto Company, 2003). The possibility for selling carbon credits to industry is breathing new life into on-farm conservation tillage practices that enhance carbon sequestration (Robert, 2001).

Perhaps the most significant change in agriculture during the past ten years is the shift towards precision, or site-specific, crop management (National Research Council, 1997). Growers have long recognized within-field variability in potential productivity. Now, at the beginning of the 21st Century, they are seeking new ways to exploit that variability. In the process, they are discovering they need more information on soil and plant conditions than was required a decade ago. Not only does this information need to be accurate and consistent across their farm and from year to year, it must also be available at temporal and spatial scales that match rapidly evolving capabilities to vary cultural procedures, irrigations, and agrochemical inputs.

A very large body of research spanning almost four decades has demonstrated that much of this required information is available remotely, via aircraft- and satellite-based sensor systems. When combined with remarkable advances in Global Positioning System (GPS) receivers, microcomputers, geographic information systems (GIS), yield monitors, and enhanced crop simulation models, remote sensing technology has the potential to transform the ways that growers manage their lands and implement precision farming techniques.

The objective of this paper is to review progress that has been made in remote sensing applications for crop management and, in particular, highlight the role that the USDA and its primary research agency, the Agricultural Research Service (ARS), has had in the movement. Of course, these advances have not been a singular effort by ARS (Pinter *et al.*, 2003; p. 615 this issue). They have resulted from long-standing cooperation among a number of different agencies and institutions, all in pursuit of expanding remote sensing's role in providing information for crop management. We will begin with some fundamental relationships between the electromagnetic spectrum and basic agronomic conditions and biophysical plant processes, and then present specific examples of remote sensing

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applications in irrigation scheduling, nutrient management, pest control, and yield prediction. We will conclude with a discussion of gaps in our knowledge and an assessment of challenges that remain for the future.

## Biophysical Basis for Agricultural Remote Sensing

Modern applications of remote sensing to agriculture have their foundation in pioneering work by ARS scientists William Allen, Harold Gausman, and Joseph Woolley who provided much of the basic theory relating morphological characteristics of crop plants to their optical properties (Allen *et al.*, 1969; Gausman *et al.*, 1969; Woolley, 1971; Allen *et al.*, 1973; Gausman, 1973; Gausman, 1974; Gausman *et al.*, 1974; Gausman, 1977). These scientists and their teams also published many high resolution spectral signatures for natural and cultivated species, identifying spectral features associated with normal plant growth conditions and those caused by nutrient deficiency, pests, and abiotic stresses (Gausman and Allen, 1973; Gausman *et al.*, 1975a; Gausman *et al.*, 1976; Gausman *et al.*, 1978; Gausman *et al.*, 1981; Peynado *et al.*, 1980).

### Spectral Reflectance Properties of Leaves

Green plant leaves typically display very low reflectance and transmittance in visible regions of the spectrum (i.e., 400 to 700 nm) due to strong absorptance by photosynthetic and accessory plant pigments (Chappelle *et al.*, 1992). By contrast, reflectance and transmittance are both usually high in the near-infrared regions (NIR, 700 to 1300 nm) because there is very little absorptance by subcellular particles or pigments and also because there is considerable scattering at mesophyll cell wall interfaces (Gausman, 1974; Gausman, 1977; Slaton *et al.*, 2001). This sharp dissimilarity in reflectance properties between visible and NIR wavelengths underpins a majority of remote approaches for monitoring and managing crop and natural vegetation communities (Knipling, 1970; Bauer, 1975).

Plant stress and/or normal end-of-season senescence typically result in lower chlorophyll concentrations that allow expression of accessory leaf pigments such as carotenes and xanthophylls. This has the effect of broadening the green reflectance peak (normally located near 550 nm) towards longer wavelengths, increasing visible reflectance (Adams *et al.*, 1999), and causing the tissues to appear chlorotic. At the same time, NIR reflectance decreases, albeit proportionately less than the visible increases. With increasing stress, the abrupt transition or "red edge" that is normally seen between visible and NIR in green vegetation begins to shift towards shorter wavelengths and, in the case of senescent vegetation, may disappear entirely.

Optical properties of leaves in a third region of the solar spectrum, the middle- or shortwave-infrared (SWIR, 1300 to 2500 nm), are strongly mediated by water in tissues. Reflectance in this region is relatively high for vigorously growing vegetation but decreases as tissues dehydrate. However, research suggests such drought-induced decreases in SWIR reflectance are not sufficiently large over biologically significant changes in plant water content for the practical use of this wavelength interval in the diagnosis of water stress in the field (Bowman, 1989; Carter, 1991).

### Spectral Reflectance Properties of Soils

Compared with plants, the spectral signatures of most agricultural soils are relatively simple. They usually exhibit monotonic increases in reflectance throughout visible and NIR regions (Condit, 1970; Stoner and Baumgardner, 1981; Price, 1990). High soil water and high organic matter contents generally cause lower reflectances while dry, smooth surfaced soils tend to be brighter (Daughtry, 2001). Occurrence of specific minerals in soil have been associated with unique spectral features (e.g., higher red reflectance in the presence of iron oxides). In the SWIR, soil spectra display more features than those observed in shorter wavelengths but are still dominated by water content, litter, and minerals (Gausman *et al.*, 1975b; Henderson *et al.*, 1992; Daughtry, 2001). The presence of crop residue causes significant changes in reflectance properties compared to bare soil, as well as from partial plant canopies. Therefore, it is important to account for residue when observations are being made across a range of soils and crop production practices (Aase and Tanaka, 1991; Daughtry *et al.*, 1996; Nagler *et al.*, 2000). The application of various remote sensing approaches to soil management, especially as it pertains to definition of zones for crop management, is reviewed in detail by Barnes *et al.* (2003; p. 619 this issue).

### Crop Canopies and Vegetation Indices

Not surprisingly, the spectral signatures of crop canopies in the field are more complex and often quite dissimilar from those of single green leaves measured under carefully controlled illumination conditions (Plate 1). Even when leaf spectral properties remain relatively constant throughout the season, canopy spectra change dynamically as the proportions of soil and vegetation change and the architectural arrangement of plant components vary. Vegetation indices (VIs) provide a very simple yet elegant method for extracting the green plant quantity signal from complex canopy spectra. Often computed as differences, ratios, or linear combinations of reflected light in visible and NIR wavebands (Deering *et al.*, 1975; Richardson and Wiegand, 1977; Tucker, 1979; Jackson, 1983), VIs exploit the basic differences between soil and plant spectra discussed earlier. Indices such as the ratio vegetation index ($RVI = NIR/Red$) and normalized difference vegetation index [$NDVI = (NIR - Red)/(NIR + Red)$], perform exceptionally well when management goals require a quantitative means for tracking green biomass or leaf area index through the season or for detecting uneven patterns of growth within a field (Jackson and Huete, 1991; Wiegand *et al.*, 1991). Soil-adjusted VIs such as SAVI and modified SAVI have been developed to minimize effects of varying background soil reflectance properties on VI performance (Huete, 1988; Qi *et al.*, 1994).

Vegetation indices have served as the basis for many applications of remote sensing to crop management because they are well correlated with green biomass and leaf area index of crop canopies (Figure 1a). Of particular interest from energy balance, modeling, and crop management perspectives, VIs have also been shown to provide robust estimates of the fractional amount of net radiation going into soil heat flux (Figure 1b; Clothier *et al.,* 1986; Daughtry *et al.*, 1990; Kustas *et al.*, 1993), as well as the fraction of absorbed photosynthetically active radiation (fAPAR) captured by the canopy for potential use in photosynthesis (Figure 1c; also see Hatfield *et al.* (1984a), Wiegand and Richardson (1984), Wanjura and Hatfield (1986), Daughtry *et al.* (1992), and Pinter *et al.* (1994)). Vegetation indices are also finding application as surrogates for basal crop coefficients ($K_{cb}$) used in evapotranspiration and irrigation scheduling algorithms (Figure 1d).

Vegetation indices are frequently used synonymously with plant health or vigor. This can be misleading, because broad waveband VIs typically lack diagnostic capability for identifying a particular type of stress or for determining why biomass is at a certain level. Narrower band indices such as the Photochemical Reflectance Index (PRI), Water Band Index (WBI), and Normalized Pigment Chlorophyll Ratio Index (NPCI) are examples of reflectance indices that are correlated with certain physiological plant responses

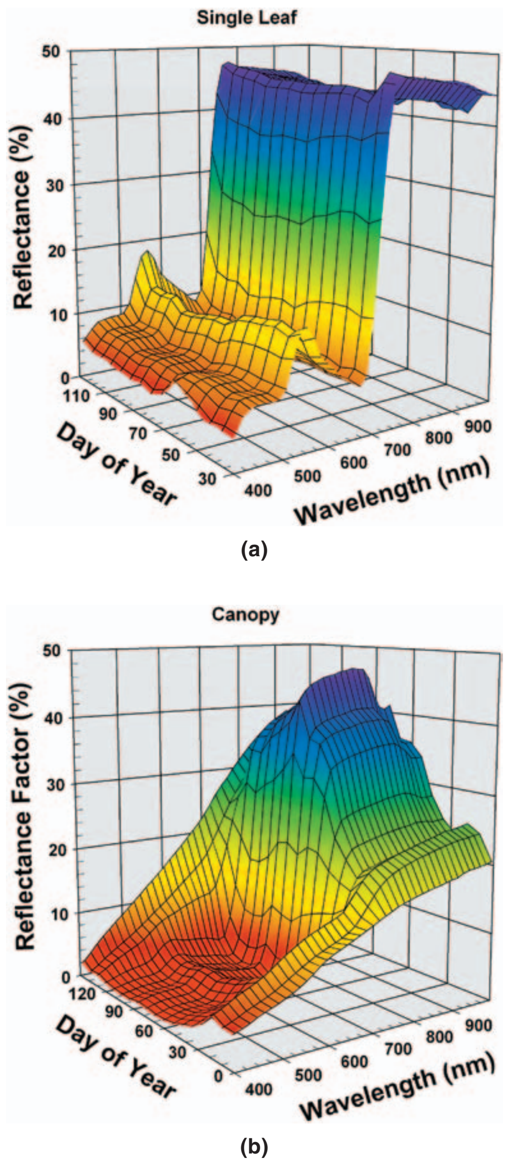


Plate 1. Seasonal trends in hyperspectral reflectance properties of spring wheat (*Triticum aestivum* L.) in an Arizona field experiment. Spectra were obtained from (a) uppermost fully expanded leaves using a portable spectroradiometer and an external integrating sphere and (b) canopies under natural solar illumination (solar zenith = 57°) using the same radiometer equipped with a 15° field-of-view optics. Spectra are displayed as a function of day of year and wavelength. Data are averages of measurements from four replicates of well-watered, amply fertilized treatments. (Pinter, unpublished data).

and have promise for diagnosing water and nutrient stress (Peñuelas *et al.*, 1994; Gamon *et al.*, 1997). A canopy chlorophyll content index (CCCI; Clarke *et al.*, 2001) relies on a VI plus the reflectance in a narrow red edge band (~720 nm) to distinguish nutrient stress from other causes of reduced green biomass in cotton.

Hyperspectral (i.e., reflectance for many contiguous narrow wavelength bands) approaches have been proposed and tested with varying degrees of success to detect water-, nutrient-, and pest-induced stress in plants while minimizing unwanted signals from varying soil conditions or biomass amounts. These methods commonly use derivative analysis, peak fitting procedures, and ratio analysis to associate spectral features with a particular stress (Horler *et al.*, 1983; Demetriades-Shah *et al.*, 1990; Chappelle *et al.*, 1992; Masoni *et al.*, 1996; Osborne *et al.*, 2002b). When functional relationships between hyperspectra and plant properties cannot be envisioned using simple or multiple regressions, more sophisticated statistical approaches such as principal component, neural net, fuzzy, and partial least-squares regression analysis have been employed (Plate 2; Warner and Shank, 1997; Kimes *et al.*, 1998). Spectral mixing techniques (McGwire *et al.*, 2000) draw on a library of "pure" hyperspectral signatures of scene components (endmembers) to decompose images into their separate constituents (e.g., sunlit and shaded soil, healthy and stressed plant areas).

#### Emitted Thermal Radiation

All objects on the Earth's surface emit radiation in the thermal-infrared (TIR) region of the spectrum (~8 to 14 $\mu$m). This emitted energy, which is proportional to the absolute surface temperature of an object, has proven very useful in assessing crop water stress because the temperatures of most plant leaves are mediated strongly by soil water availability and its effect on crop evapotranspiration (Jackson, 1982). Following Tanner's (1963) observation that plant temperatures often differ substantially from air temperature, ARS researchers examined environmental determinants of crop temperature and began to speculate on ways to use the latter for monitoring water stress (Wiegand and Namken 1966; Ehrler, 1973). When infrared thermometers became affordable and more widely available in the mid-70s, ARS scien-

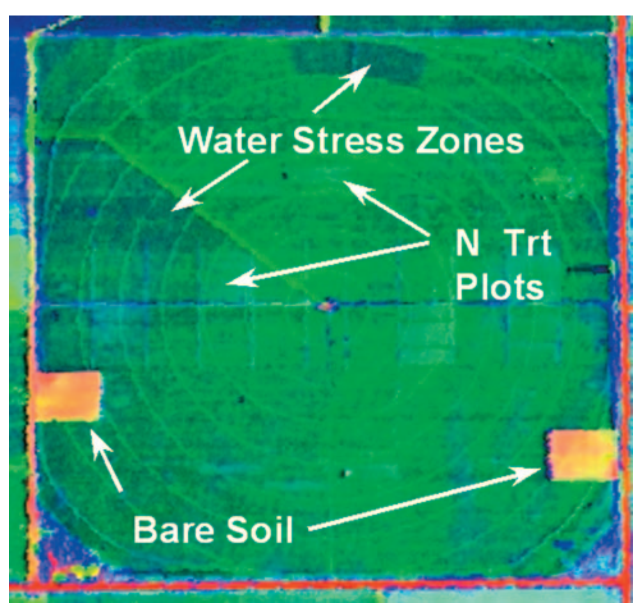


Plate 2. A false-color image derived from principle components analysis of AVIRIS hyperspectral data (224 bands from 370 to 2510 nm) acquired over a 60-ha, center-pivot irrigated corn field near Shelton, Nebraska on 22 July 1999. Ground resolution is about 3 m. Image shows bare soil areas, subplots within the field where nitrogen fertilizer was applied in varying amounts, and zones where irrigations were delayed to create some water stress in the plants. (Schepers, unpublished data).

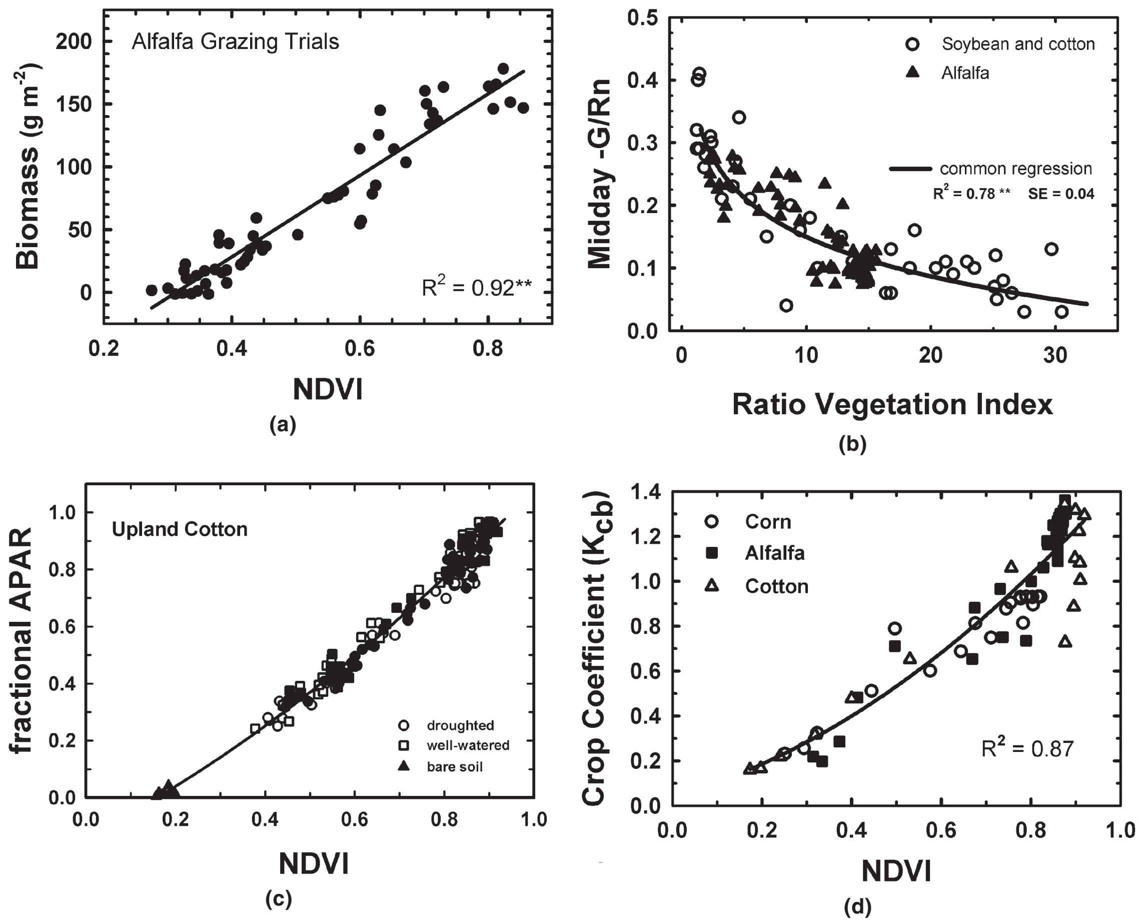


Figure 1. Vegetation indices show a strong correlation with many agronomic and biophysical plant parameters. (a) The normalized difference vegetation index (NDVI) was significantly correlated with changes in alfalfa biomass during a lamb grazing study by Mitchell *et al.* (1990). (b) The ratio of red to near-infrared reflectance was useful for estimating the fractional portion of net radiation (Rn) going into soil heat flux (G) in energy balance studies of Clothier *et al.* (1986) and Kustas *et al.* (1993). (c) NDVI can be used as a surrogate for estimating the fractional amount of photosynthetically active radiation absorbed by a cotton canopy for potential use in photosynthesis (Pinter *et al.*, 1994). (d) NDVI also provides a means for estimating basal crop coefficients ($K_{cb}$) used in irrigation scheduling approaches for corn (after Bausch and Neale, 1987) and alfalfa and cotton (Hunsaker and Pinter, unpublished data).

tists who had been using thermocouples to measure plant temperatures, quickly adopted the new technology, and developed a number of non-contact methods for assessing water status and predicting crop yields over wider regions.

Descriptive terms were coined to describe the thermal indices used in these methods. "Stress-Degree-Day" (SDD; Idso *et al.*, 1977b), "Crop Water Stress Index" (CWSI; Idso *et al.*, 1981; Jackson *et al.*, 1981), "Non-water-stressed baselines" (Idso, 1982), "Thermal Kinetic Window" (TKW; Mahan and Upchurch, 1988), and "Water Deficit Index" (WDI; Moran *et al.*, 1994) began to appear in the agronomic literature as routine measures of plant stress induced by water stress. Studies have shown that many physical and biological (e.g., disease) stresses that interfere with transpiration result in elevated plant temperatures and are correlated with plant water status and reductions to potential yield (Idso *et al.*, 1977a; Ehrler *et al.*, 1978; Pinter *et al.*, 1979; Howell *et al.*, 1984b; Burke *et al.*, 1990; Hatfield, 1990). As an important component of the surface energy balance, the TIR has also been used extensively in remote techniques for assessing evapotranspiration (Hatfield *et al.*, 1983; Jackson *et al.*, 1987; Moran *et al.*, 1989b; Carlson *et al.*, 1995; Kustas and Norman, 1996).

### Exogenous Factors Affecting Remote Observations

It is important to recognize that remote assessment of crop growth and plant response to environmental stress is by no means as simple or as straightforward as identifying chemicals *in vitro* via their spectral absorption features. Optical and thermal properties of plant canopies change with stage of growth due to age of individual tissues and architectural arrangement of organs (Plate 1; also see Gausman *et al.* (1971) and Hatfield *et al.* (1984b)). They are also strongly affected by illumination and viewing angles, row orientation, topography, meteorological phenomena, and other factors not directly related to agronomic or biophysical plant properties (Richardson *et al.*, 1975; Jackson *et al.*, 1979; Pinter *et al.*, 1983a; Pinter *et al.*, 1985; Pinter, 1986; Pinter *et al.*, 1987; Qi *et al.*, 1995; Walthall, 1997). A significant challenge for agricultural remote sensing applications is to be able to separate spectral signals originating with a plant response to a specific stress from signals associated with normal plant biomass or the background "noise" that is introduced by exogenous non-plant factors. Results from multiple crops across a number of different locations indicate that general relationships between spectral properties and plant response are achievable (Wiegand *et al.*, 1990; Wiegand *et al.*, 1992b; Richardson *et al.*, 1992).

## Water Management

Poor irrigation timing and insufficient applications of water are ubiquitous factors limiting production in many arid and semi-arid agricultural regions. As a consequence, considerable ARS research has focused on remote sensing strategies for determining when and how much to irrigate by monitoring plant water status, by measuring rates of evapotranspiration, and by estimating crop coefficients.

### Plant Water Status

ARS scientists have proposed, refined, and tested a number of non-invasive, thermal indices for determining whether plants are meeting transpirational demands of the atmosphere and inferring plant water status from that measurement. These indices, which include the SDD, CWSI, and WDI mentioned above, have been used in research on more than 40 different crop species (Gardner *et al.*, 1992a; Gardner *et al.*, 1992b). Although they vary in complexity as well as the amount of ancillary meteorological and crop specific parameters that are required, each index is based on plant temperatures that can be obtained remotely using infrared radiation thermometers or thermal imaging devices (Millard *et al.*, 1978; Gardner *et al.*, 1992b).

The underlying concepts are simple. As plants deplete soil water reserves, transpirational cooling is reduced, and plant temperatures rise relative to ambient air temperature or those of a well-watered reference crop. The total range over which plant temperatures vary due to soil water availability is dependent upon evaporative demand of the atmosphere and crop specific transpiration characteristics. Upper and lower boundary temperatures or "baselines" can be obtained empirically from prior field observations of stressed and well-watered canopies as proposed by Idso *et al.* (1981) and Idso (1982) or estimated from theoretical energy balance considerations per Jackson *et al.* (1981; 1988). They can also be derived from a combination of empirical and/or theoretical approaches (Clawson *et al.*, 1989; Wanjura and Upchurch, 2000). Most studies have shown that the thermal infrared is more sensitive to acute water stress than is reflectance in visible, NIR, or SWIR wavelengths. However, the reflective portion of the spectrum and VIs also respond to plant water status when it produces a change in canopy architecture, e.g., wilting or leaf rolling (Jackson and Ezra, 1985; Moran *et al.*, 1989a), and whenever there is chronic water stress that slows growth, reduces green leaf area index (GLAI), or alters senescence rates (Idso *et al.*, 1980; Pinter *et al.*, 1981).

Thermal plant water stress indices typically provide adequate lead time for scheduling irrigations in regions where supplemental water is needed to grow a crop. However, successful application of the technique depends on sufficient evaporative demand by the atmosphere, adequate water holding capacity of the soil, and irrigation depth. The TIR is less practical for scheduling irrigations in mesic areas, where lower evaporative demand reduces temperature differences between well-watered and stressed plants. Under these conditions, measurement errors and variation in plant temperatures due to fluctuations in wind speed can obscure the water stress signal (Keener and Kirchner, 1983; Stockle and Dugas, 1992; Wanjura and Upchurch, 1997). But even in humid regions, thermal techniques can provide useful information when crops are exposed to a prolonged dry spell or when spatial variation in soils causes stress in portions of the field (Feldhake and Edwards, 1992; Feldhake *et al.*, 1997; Sadler *et al.*, 1998, Sadler *et al.*, 2000). Benasher *et al.*, (1992) found thermal indices less useful for managing micro-irrigation drip systems where the amount of soil water replenished at each irrigation was relatively small compared with the daily requirements of the crop.

Thermal indices can overestimate water stress when canopy cover is incomplete and sensors view a combination of cool plant and warm soil temperatures. For ground-based measurements, this problem can be minimized by restricting observations to the transpiring foliage elements or by using an oblique viewing angle. However, mixed pixels are often unavoidable in nadir data from overhead sensors. An elegant solution to this problem combines a VI (to account for the amount of plant cover) with the TIR in a concept called the Water Deficit Index (Moran *et al.*, 1994; Clarke, 1997; Clarke *et al.*, 2001). The approach improves early season detection of water stress for irrigation scheduling purposes and enhances the utility of TIR from aircraft and satellite platforms.

The agricultural remote sensing literature abounds with examples of the application of thermal indices to schedule irrigations in various crops, e.g., alfalfa (Hutmacher *et al.*, 1991; Moran *et al.*, 1994), bermuda grass (Jalalifarahani *et al.*, 1993; Jalalifarahani *et al.*, 1994), clover (Oliva *et al.*, 1994a; Oliva *et al.*, 1994b), corn (Nielsen and Gardner, 1987; Fiscus *et al.*, 1991; Yazar *et al.*, 1999; Wanjura and Upchurch, 2000; Wanjura and Upchurch, 2002), cotton (Pinter and Reginato, 1982; Reginato and Howe, 1985; Shanahan and Nielsen, 1987; Wanjura and Upchurch, 2000; Wanjura and Upchurch, 2002), sorghum (Hatfield, 1983a), soybeans (Nielsen, 1990), sunflowers (Nielsen, 1994), and wheat (Idso *et al.*, 1981; Howell *et al.*, 1986; Nielsen and Halvorson, 1991; Alderfasi and Nielsen, 2001).

Most of the thermal irrigation scheduling algorithms have been developed and tested at field plot scales using ground-based infrared radiometers. At present, thermal data from satellite platforms are limited to sensor systems with spatial resolutions that are too coarse for practical use in irrigated agriculture (e.g., ETM+ on Landsat 7 has a 10.4- to 12.5-$\mu$m sensor with a 60-m spatial resolution). Aircraft TIR has not been widely available despite early demonstrations of its potential usefulness (Bartholic *et al.*, 1972; Millard *et al.*, 1978). This is unfortunate because the thermal infrared contains unique information on plant water status that is not available in the reflective portion of the spectrum. A cost/benefit study by Moran (1994) shows that irrigation scheduling with thermal infrared sensors on aircraft is both practical and affordable if growers within an irrigation district band together to purchase imagery.

Methods for using TIR to assess spatial variation in soil water availability also have utility in precision agriculture applications. As an example, Hatfield *et al.* (1982) showed that patterns of surface temperature across fields in the Central Valley of California varied with management practices, and that these patterns were related to the uniformity of water application. Hatfield *et al.* (1984c) found that spatial variation of surface temperature within wheat and grain sorghum fields changed with the degree of water availability. They found that, as soil water content decreased below 50 percent of available, the surface temperature variability increased and suggested that this could be used as a potential management tool. Opportunities for utilizing spatial variation as a management tool for water have not been fully exploited. One alternative may be to mount infrared sensors on irrigation booms to provide the capability to adjust irrigation amounts based on crop needs as the unit travels across the field.

#### Evapotranspiration (ET) and Crop Coefficients

Approaches for assessing the spatial and temporal dynamics of ET have been developed and tested by ARS scientists at field, farm, and regional scales (Jackson, 1985; Reginato *et al.*, 1985; Jackson *et al.*, 1987; Moran and Jackson, 1991; Kimball *et al.*, 1999). These techniques typically combine ground-based meteorological observations with remote measures of reflected and emitted radiation and then estimate latent energy (LE) exchange as a residual in the energy balance equation. For cloud-free days, the near instantaneous, remote estimates of LE obtained near midday with data from satellites or aircraft can be converted to daily values with reasonably good accuracy (Jackson *et al.*, 1983; Hatfield *et al.*, 1983; Kustas *et al.*, 1990). These techniques hold considerable promise for estimating water use over broad areas, but applications have been hampered by lack of thermal sensors with suitable temporal and spatial resolution on satellite or aircraft platforms.

Another methodology for keeping track of plant water needs makes use of routine meteorological estimates of potential evapotranspiration along with multispectral proxies for crop coefficients ($K_{cb}$). State-of-the-art irrigation scheduling routines such as the FAO-56 approach (Allen *et al.*, 1998) require $K_{cb}$ which are defined as the ratio between actual crop evapotranspiration and potential evapotranspiration of a grass or alfalfa reference crop growing under optimum agronomic conditions. Because $K_{cb}$ are usually obtained from published curves or tables, they lack flexibility to account for temporal and spatial variation in crop water needs caused by unusual weather patterns, differences in plant population, non-uniform water application, nutrient stress, or pest pressures. ARS scientists recognized the similarity between $K_{cb}$ behavior and the seasonal trajectory of multispectral VIs and first proposed, then later demonstrated, their use for irrigation scheduling (Jackson *et al.*, 1980; Bausch and Neale, 1987; Bausch and Neale, 1989; Bausch, 1993; Choudhury *et al.*, 1994; Bausch, 1995). When VI surrogates for $K_{cb}$ (Figure 1d) are included in scheduling programs, the resulting feedback from plants enables growers to better adjust irrigation timing and amounts to avoid critical soil water deficits and offers the possibility for fine-tuning precision irrigation systems.

#### Salinity Stress

Salts in soils and irrigation water are important factors limiting productivity in many croplands (Rhoades *et al.*, 1989). Remedial solutions require mapping of affected areas in space and time. This can be accomplished using remote sensing measurements which identify contaminated soils by their unusually high surface reflectance factors or by detecting reduced biomass or changes in spectral properties of plants growing in affected areas (Wiegand *et al.*, 1992a; Wiegand *et al.*, 1994; Wiegand *et al.*, 1996; Wang *et al.*, 2001; Wang *et al.*, 2002a; Barnes *et al.*, 2003 (p. 619, this issue)). Significant correlations exist between mid-season VIs and final yields of cotton and sorghum crops which are affected by salinity stress at sub-field spatial scales (Wiegand *et al.*, 1994; Yang *et al.*, 2000). Studies have also shown an increase in canopy temperature of plants exposed to excessive salts in irrigation water (Howell *et al.*, 1984a; Wang *et al.*, 2002b), suggesting the possibility of previsual detection of stress which could be remedied by increasing the leaching fraction or switching to a higher quality of water.

#### Thermal Kinetic Window

ARS scientists noted that transpirational cooling has an important role in maintaining tissue temperatures of irrigated crops well below damaging levels (i.e., less than 40°C) even in desert regions where plants are regularly exposed to high radiant and sensible heat loads (Burke *et al.*, 1985; Hatfield *et al.*, 1987; Mahan and Upchurch, 1988; Upchurch and Mahan, 1988). Using the apparent Michaelis constant ($K_m$) and variable fluorescence, they defined a range of temperatures that they called the "Thermal Kinetic Window" (TKW) within which biochemical processes of tissues were functioning at optimal rates and they proposed that infrared thermometers could be used to reveal whether plants were within that range (Burke and Hatfield, 1987; Burke *et al.*, 1990). The TKW was found to be species dependent, corresponding to what might be expected based on a crop's geographical distribution and seasonal growth patterns, e.g., the TKW for wheat was about 20°C, while that for cotton was about 28°C (Hatfield and Burke, 1991; Burke, 1994). The ARS team also discovered that biomass production and final yields were well correlated with the amount of time a crop spent within its TKW (Burke *et al.*, 1988), and went on to develop and patent a sensor system called BIOTIC (Wanjura and Mahan, 1994, Mahan *et al.*, 2000; Wanjura and Upchurch, 2000), which uses the concept to control micro-irrigations and overcomes some of the problems noted by Benasher *et al.* (1992).

## Nutrient Management

Efficient management of nutrients is one of the main challenges facing production agriculture. Here, remote sensing is providing field-scale diagnostic methods that will enable detection of nutrient deficiencies early enough to avoid yield or quality losses. When interfaced with variable rate sprayer equipment, real-time canopy sensors could supply site-specific application requirements that lessen contamination of surface- or groundwater supplies and improve overall nutrient use efficiency (Schepers and Francis, 1998).

#### Nitrogen

Ample supplies of nitrogen (N) are essential for modern crop production. However, N is often over-applied without regard to crop requirements or potential environmental risk just to insure that adequate levels are present for the crop. A case in point involves corn grown in the upper Midwestern United States where synchronizing N applications to coincide with maximum crop uptake is desirable but tissue testing of leaves is not widely employed for determining crop needs and thus fields are often over fertilized. Relative techniques were developed for using a SPAD chlorophyll meter[1], color photography, or canopy reflectance factors to assess spatial variation in N concentrations across growers' corn fields (Schepers *et al.*, 1992; Blackmer *et al.*, 1993; Blackmer *et al.*, 1994; Blackmer *et al.*, 1996a; Blackmer *et al.*, 1996b; Blackmer and Schepers, 1996; Schepers *et al.*, 1996). Because these techniques were based on comparisons with readings obtained from an adequately fertilized strip in the same field, they obviated strict requirements for beforehand knowledge of the relationship between nutrient concentration and crop reflectance, or precise sensor calibration, or the need to convert data to surface reflectance factors.

In the Great Plains, where more than half of the N required for corn is typically applied prior to planting, a strategy that delivers small amounts of fertilizer only "as needed" during the season can reduce N leaching by rainfall or excessive irrigation. Bausch and Duke (1996) devel-

[1] The SPAD meter (Minolta Camera Co. Ltd, Japan) is a handheld device that estimates *in vivo* pigment concentrations using differential transmittance of light through the leaf by light emitting diodes (LED) at 650 nm and 940 nm (Wood *et al.* 1993; Adamsen *et al.*, 1999).

oped an N reflectance index (NRI) from green and NIR reflectance of an irrigated corn crop. The NRI was highly correlated with an N sufficiency index calculated from SPAD chlorophyll meter data and provided a rapid assessment of corn plant N status for mapping purposes. A more recent study using the NRI to monitor in-season plant N resulted in reducing applied N using fertigation by 39 kg N $ha^{-1}$ without reducing grain yield (Bausch and Diker, 2001). Because this index was based on the plant canopy as opposed to the individual leaf measurements obtained with SPAD readings, it has potential for larger scale applications and direct input into variable rate fertilizer application technology.

Taking an indirect approach, Raun *et al.* (2001) reasoned that a mid-season, remote estimate of potential yield would help growers adjust topdress N applications based on preplant soil N tests, within season rates of mineralization, and projected N removal. They estimated potential grain yields of winter wheat (*Triticum aestivum* L.) from several post-dormancy NDVI measurements which were normalized by the number of growing degree days that had accumulated between the observation dates. This normalization adjusted for differences in local weather and also compensated for spatial variations in N requirements caused by differences in soil properties and management options that affected stand establishment and early season growth. Conceivably such approaches could be implemented wherever remote means for predicting yield are feasible.

#### Other Nutrients

Monitoring symptoms caused by other nutrient deficiencies can be problematic because they rarely occur uniformly across a field and often need to be distinguished against background variation in canopy density. Osborne *et al.* (2002a; 2002b) have conducted research which shows usefulness of hyperspectral data in distinguishing differences in N and P at the leaf and canopy level, but the relationships were not constant over all plant growth stages. Adams *et al.* (1993; 2000) have detected Fe, Mn, Zn, and Cu deficiencies in soybean leaves using both leaf fluorescence and hyperspectral reflectance techniques that evaluate leaf chlorosis based on the shape of the reflectance spectrum between 570 and 670 nm (Yellowness Index; Adams *et al.*, 1999). The increased availability of hyperspectral imaging sensors and advanced analysis tools like partial least-squares regression and spectral mixing techniques mentioned earlier will facilitate studies to extend this concept to the canopy level.

It should be mentioned that ARS scientists have worked for a number of years with the Environmental Protection Agency (EPA), the U.S. Geological Survey (USGS), and NASA in developing and refining new remote sensing technologies for detecting changes in plant biochemistry, physiology, and metabolism [e.g., early research using plant fluorescence to detect water stress in citrus (McFarlane *et al.*, 1980)]. These newer approaches using laser induced fluorescence (LIF) have considerable potential for previsual identification of nutrient and water stress and for detecting optimal levels of plant growth and yield under different fertilization rates in the field (Chappelle *et al.*, 1984a; Chappelle *et al.*, 1984b; McMurtrey *et al.*, 1994; McMurtrey *et al.*, 1996; Corp *et al.*, 1997; Daughtry *et al.*, 1997; Daughtry *et al.*, 2000).

## Pest Management

Remote sensing lends itself exceptionally well to the detection of anomalous locations within a field or orchard that have been differentially affected by weeds, diseases, or arthropod pests (Hatfield and Pinter, 1993). In fact, more than 35 years ago, ARS scientists were using aerial color-infrared photography for this purpose and relating their findings to laboratory spectra of pest damaged leaves (Hart and Myers, 1968).

#### Weeds

Weeds represent a large management cost to growers because they compete with crops for water, nutrients, and light, often reducing crop yield and quality. Inappropriate or poorly timed herbicide applications can also have unintended side effects on crop performance and the environment. Thus, in recent years there has been a shift away from uniform, early season weed control options towards approaches that rely on using herbicide-ready crops and applying post-emergence herbicides only as needed. This strategy has generated increased interest in using remote sensing to define the extent of weed patches within fields so they can be targeted with variable rate ground and aerial spray rigs. Such approaches avoid applications to weed-free areas, reducing herbicide usage and potential contamination of ground water without compromising weed control.

Obviously, weed identity is important when tailoring herbicide choices and treatment rates. Early laboratory studies by Gausman *et al.* (1981) revealed species differences in optical properties of weeds. Later, Richardson *et al.* (1985) demonstrated that multispectral aerial video images could be used to distinguish uniform plots of Johnsongrass and pigweed from sorghum, cotton, and cantaloupe plots. They speculated that, as technology improves and provides narrower band data, similar techniques might provide real-time information on weed infestations that were mixed in with the crop canopies. This approach is proving very useful in managing weed species such as salt cedar and leafy spurge in wildlands and range managed for grazing (see review by Hunt *et al.* (2003; p. xxx this issue)). Dickson *et al.* (1994) and Dickson and Bausch (1997) developed a method for crops that used digital images in visible wavelengths, neural networks, and the spatial characteristics of weed patches for identifying velvetleaf and wild proso millet weeds in corn fields. Their method achieved an overall accuracy of 94 percent when tested on an independent data set.

Hanks and Beck (1998) utilized spectral contrasts between green plants and bare soil to trigger real-time spraying of herbicide only on the plants that were present between soybean rows, controlling weeds as effectively as with conventional continuous-spray methods, but reducing herbicide usage and production costs. Machine vision techniques have also been used for identifying weed seedlings based on leaf shapes (Franz *et al.*, 1991; Franz *et al.*, 1995) and for guiding an automatic precision herbicide sprayer (Tian *et al.*, 1999).

The ability to detect accidental herbicide damage to a crop has considerable value to a grower for insurance or litigation purposes. Comparing visual assessment of herbicide injury in cotton with color-infrared photography, NIR videography, and wideband handheld radiometer approaches, Hickman *et al.* (1991) concluded that remote detection and mapping of moderate herbicide damage was not only possible, but that the application amounts could be estimated. Donald (1998a; 1998b) used video photography to quantify stunting of corn and soybean plants exposed to herbicide damage. Using a laboratory-based multispectral fluorescence imaging system (MFIS), Kim *et al.* (2001) were able to detect changes in soybean leaf fluorescence after they were treated with a herbicide. To improve application efficiency of herbicides, Sudduth and Hummel (1993) developed a portable NIR spectrophotometer for use in estimating soil organic matter as part of the estimation procedure for the amount of herbicide to be applied. Thus, remote sensing can not only offer field-scale assessment of herbicide injury problems but also can help define the optimum rate of herbicide application.

### Arthropod and Nematode Pests

Demonstrated remote sensing methodologies for identifying and managing insect, mite, and nematode populations include detecting actual changes in plant pigments caused by pest presence, monitoring plants for damage done by the pests, and identifying areas susceptible to infestation. In what are now considered classic studies, ARS scientists Hart and Meyers (1968) used color-infrared (CIR) photography and supporting hyperspectral reflectance data to identify trees in citrus orchards that were infested with brown soft scale insects (*Coccus hesperidum*). They were able to monitor changes in infestation levels because the honeydew excreted by the scale insects was an excellent growth medium for a sooty mold fungus that had very low reflectance in both the visible and NIR wavelength regions and tended to accumulate as the season progressed (Gausman and Hart, 1974). Similar strategies using CIR film and multispectral videography have been used to detect citrus blackfly (*Aleurocanthus woglumi* Ashby) and brown soft scale problems in citrus as well as whitefly (*Bemesia spp.*) infestations in cotton (Figure 2; also Hart *et al.*, 1973; Everitt *et al.*, 1991; Everitt *et al.*, 1994; Everitt *et al.*, 1996).

In a greenhouse study designed to characterize the effects that sucking insects have on leaf reflectance, Riedell and Blackmer (1999) infested wheat seedlings with aphids (*Diuraphis noxia* Mordvilko) or greenbugs (*Schizaphis graminum* Rondani). After 3 weeks they measured reflectance properties of individual leaves in an external integrating sphere. Compared with healthy plants, the leaves from infested plants had lower chlorophyll concentrations and displayed significant changes in reflectance spectra at certain wavelengths (notably 500 to 525, 625 to 635, and 680 to 695 nm), suggesting the potential usefulness of canopy spectra for identifying outbreaks in actual field situations.

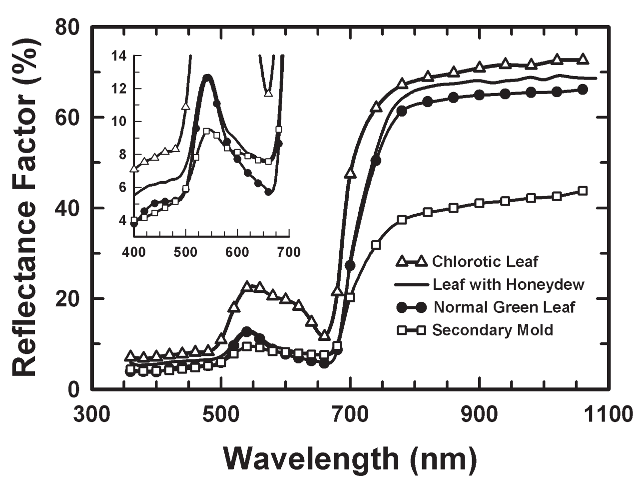


Figure 2. Comparisons between hyperspectral reflectance factors of a normal green cotton leaf and a cotton leaf covered with honeydew produced by whiteflies (*Bemesia tabaci*), a leaf covered with a secondary mold *Aspergillus sp.* growing on the whitefly honeydew, and a chlorotic leaf without honeydew. Data were acquired with a Spectron SE-590 spectroradiometer. Solar incidence angle was 45 degrees to the leaf surface and viewing angle was normal to leaf surface (Pinter, unpublished data).

Using hyperspectral imagery obtained during NASA's Airborne Visible Infrared Imaging Spectrometer (AVIRIS) flights over cotton fields in California, Fitzgerald *et al.* (in press) were able to determine the extent and severity of strawberry spider mite (*Tetranychus turkestani* U.N.) damage in different fields. They first built a reference library of "pure" spectral signatures (endmembers) from mite-infested leaves, which take on a reddish pigmentation, as well as from healthy leaves and sunlit and shaded soil. Then using spectral mixing analysis, they decomposed ("unmixed") the hyperspectral AVIRIS images of the fields into components associated with the endmembers, including the healthy and mite-stressed signatures. With this type of georeferenced imagery over broad regions, mite-afflicted zones within fields could be precisely located for traditional pest scouting and variable rate pesticide applications. Targeted approaches to pest management reduce the total amount of pesticides used and have the added benefit of providing *refugia* for beneficial insects which are then able to quickly recolonize the treated areas and minimize the chances of secondary pest outbreaks.

A simple approach for detecting pests relies on changes in green plant biomass or GLAI caused by herbivory, leaf skeletonizing, or root pruning. These pest problems appear as anomalous regions in the midst of otherwise vigorously appearing vegetation in aerial photographs or in images generated from multispectral VIs. Typically, this approach works much better in monocultural field crops than in mixed crop- or natural ecosystems. Early examples from ARS research include use of CIR film to evaluate effect of crop rotation and soil fumigation on a nematode (*Rotylenchulus reniformis*) occurring in Texas cotton fields (Heald *et al.*, 1972). Cook *et al.* (1999) used multitemporal NIR videography to monitor the seasonal progression of the southern root knot nematode (*Meloidogyne incognita* Chitwood) and its associated soil-borne fungi complex in kenaf (*Hibiscus cannabinus* L.). Of course, areas of reduced plant vigor could conceivably be caused by a number of factors unrelated to pests, so it is likely that additional spectral, spatial, and temporal clues, provided within the context of a decision support system, will be required to uniquely identify the problem.

Given the current remote sensing technologies, it is unlikely that methods capable of detecting very low numbers of important arthropod or nematode pests will be developed soon. However, knowing when and where to look for them can be advantageous for directing field scouts and taking pre-emptive control measures. Active radar systems have been used to monitor the dispersal and migratory flight behavior of economically important insects, including honeybees, noctuid moths, and grasshoppers (Loper *et al.*, 1987; Hobbs and Wolf, 1989; Beerwinkle *et al.*, 1993; Wolf *et al.*, 1995). This is information that could be obtained routinely using the existing network of weather radars (Westbrook and Isard, 1999) and used to alert growers that local crops are at heightened risk.

It is also feasible to use large scale aerial photography to identify landscape features and relate them to the abundance of pests and their predators as was done by Elliott *et al.* (1999) for the cereal aphid in South Dakota. Hypothesizing that certain insects, like the tarnished plant bug (*Lygus lineolaris*), were more likely to feed in the most rapidly growing sections of cotton fields, Willers *et al.* (1999) used NDVI images of commercial cotton fields first to estimate crop vigor (Plate 3) and then to guide field scouts to those areas for directed sampling. The imagery and scouting reports were used in a GIS to construct plausible maps of insect abundance. The maps were loaded into the controller of a GPS-equipped ground sprayer which then applied pesticide to high risk areas. In commercial field trials, these approaches reduced pesticide use by nearly 40 percent and lessened the overall impact of toxic chemicals on the environment (Dupont *et al.*, 2000).

#### Disease

Examples in which ARS employed remote sensing technology for detecting crop disease and assessing its impact on productivity include using CIR photography to identify circular areas affected by cotton root rot, *Phymatotrichum omnivorum* (Heald *et al.*, 1972; Henneberry *et al.*, 1979) and to estimate yield losses caused by blackroot disease in sugar beets (Schneider and Safir, 1975). Cook *et al.* (1999) also demonstrated the potential for aerial video imagery to detect *P. omnivorum* in kenaf, a crop whose tall growth habit makes it almost impossible to survey from the ground.

The TIR can provide early, sometimes previsual, detection of diseases that interfere with the flow of water from the soil through the plant to the atmosphere. As an example, Pinter *et al.* (1979) found that cotton plants whose roots were infected with the soil-borne fungus *P. omnivorum* and sugar beets infected with *Pythium apanidermatum* both displayed sunlit leaf temperatures that were 3 to 5°C warmer than adjacent healthy plants. The TIR was also useful for detecting root disease in red clover under irrigated conditions (Oliva *et al.*, 1994a). Much more research is required when using remote sensing for identifying specific diseases or when separating them from other causes of plant stress. Hyperspectral techniques are likely to provide some assistance, but coupling existing techniques with weather driven computer models of disease development will probably provide the best approach.

### Yield Prediction

Yield is a very important end-of-season observation that integrates the cumulative effect of weather and management practices over the entire season. Remote sensing approaches can provide growers with final yield assessments and show variations across fields. In this respect, they are similar to combine-mounted yield monitors that are a key component of precision agriculture. But remote measurements differ in that they also can be taken frequently during the season, providing temporal information on growth rates and plant response to dynamic weather conditions and management practices. There are two general approaches to using remote sensing for yield assessment. The first is a direct method, in which predictions are derived totally from the remote measures. The second is indirect, whereby remotely sensed parameters are incorporated into computer simulations of crop growth and development, either as within-season calibration checks of model output (e.g., biomass or GLAI) or in a feedback loop used to adjust model starting conditions or processes (Maas, 1988; Mass, 1993).

#### Temporal Remote Sensing Models

Two general classes of empirical models have been developed for predicting crop yield: reflectance-based (green leaf area or biomass) and thermal-based (stress) models. The former were based to a large extent on early studies by ARS scientists who related leaf and canopy reflectance to yields of cotton (Thomas *et al.*, 1967) and vegetable crops (Thomas and Gerberman, 1977) and NASA and university researchers looking at grasses, corn, soybeans, wheat and alfalfa (e.g., Pearson *et al.*, 1976; Tucker *et al.*, 1979; Tucker *et al.*, 1980a; Tucker *et al.*, 1980b; Tucker *et al.*, 1981). Approaches by Idso *et al.* (1977c), Pinter *et al.* (1981), and Aase and Siddoway (1981) integrated either canopy albedo data or VIs through the season, reasoning that this was similar to leaf area duration methods agronomists often used to predict final yields. It is likely that these empirical approaches are variety specific as suggested by Hatfield (1981), who was unable to find a consistent relationship between the spectral indices and yield in his survey of 82 different varieties of wheat. Aase and Siddoway (1981) had cautioned that the relationships of spectral indices to yield were dependent upon normal grain-filling conditions for the crop, and deviations from normal soil, weather, or agronomic practices may not always be reflected in a simple VI time trajectory. An interesting observation by Idso *et al.* (1980) revealed that the yields of spring wheat and barley cultivars were related to the rate of crop senescence as measured by end of season decline in the NDVI. The higher yielding cultivars showed the most rapid rate of senescence.

A number of early studies related temporal trajectories of TIR water stress indices to yields of wheat (Idso *et al.*, 1977a; Idso *et al.*, 1977b), alfalfa (Reginato *et al.*, 1978), and cotton (Pinter *et al.*, 1983a). Crops exposed to higher levels of water stress during the season had the highest cumulative thermal stress indices and usually yielded the least. Hatfield (1983b) took the next step and coupled frequent spectral reflectance and thermal observations in a more physiological method to predict yields in wheat and grain sorghum (*Sorghum vulgare* L. Moench.). This method was found to be a good estimator of crop yield with a magnitude of errors (less than 10 percent) that was comparable to those observed in repeated small samples across large fields. While accurate, this method required daily measures of TIR during the grain-filling period to estimate crop stress from soil water and agronomic practices, e.g., nutrients. Of course, current satellite sensor systems have neither the temporal nor spatial resolution to meet this requirement for data, yet this study showed that combining information in different regions of the spectrum can be a powerful approach for predicting yield.

#### Advantages of Remote Sensing over Yield Monitors

For many crops, combine-mounted yield monitors have become the *de facto* standard for assessing within-field variability and determining zones for precision crop management. Yet there is a growing pool of information indicating that combine-derived yield maps may fail to accurately depict the spatial structure of plant yields within a field and seldom show the true extremes in variability (Arslan and Colvin, 2002). Likewise, the capability to diagnose or manage a specific yield-reducing stress is limited with the end-of-season maps that yield monitors produce. The increased availability of aircraft-based sensor systems with improved spatial and spectral resolution and the potential to obtain data several times during the season have prompted scientists to use remotely sensed imagery as a proxy for a yield map generated by a combine (Plate 4; Yang and Anderson, 1999; Yang *et al.*, 2000). Pre-harvest estimates of plant productivity enable growers to delineate management zones (Yang and Anderson, 1996) and to make earlier and better-informed marketing decisions. Pre-harvest imagery also facilitates directed field scouting for precise diagnosis of stress and, where possible, enables growers to take timely remedial actions.

In general, reliability of imagery to estimate yields decreases as the time before harvest increases because there is more opportunity for factors like drought, nutrient deficiency, insect infestation, and disease to impact yield. As an example, Shanahan *et al.* (2001) showed that the time of corn pollination was not a good growth stage to estimate

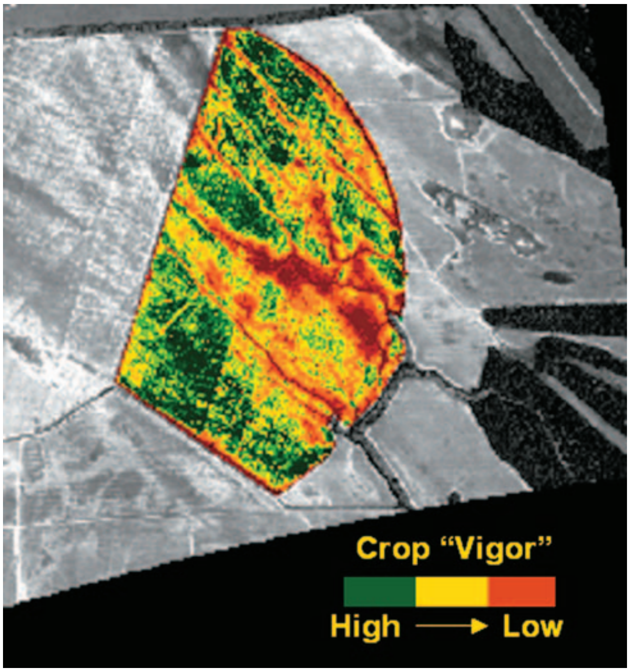


Plate 3. Multispectral imagery of an 81-ha Mississippi cotton field in which spatial variation in plant growth is represented by different colors. Areas with more vigorous plant growth (green) are more likely to attract and support high populations of tarnished plant bugs (*Lygus lineolaris*). (Image courtesy of ITD Spectral Visions, Stennis Space Center, Mississippi and ARS, Genetics and Precision Agriculture Research Unit, Mississippi State University.)

yield because any number of crop stresses could cause tassel emergence dates to vary. Imagery acquired midway through the grain fill period provided the best relationship ($r^2 > 0.80$) between several VIs and grain yield in their study. Yang *et al.* (2000) found similar results ($r^2 = 0.79$) for sorghum. Yields of rain-fed crops can be more difficult to estimate using remote sensing because water stress at certain critical growth stages can cause irreversible loss in yield potential. As was found during the Large Area Crop Inventory Experiment (MacDonald and Hall, 1980), it is likely that imagery collected several times throughout the season will improve yield predicting capabilities.

Producers can expect imagery and yield maps to display similar patterns, but statistical relationships between yield values extracted from a combine-generated yield map and imagery values are often weak. This may be because grain flow dynamics within the yield monitor, coupled with the direction of combine travel, make it difficult to compare the two techniques directly. Even when pixel averaging techniques are used and combine travel is properly accounted for, $r^2$ values less than 0.25 are common unless the field has an extreme range in yield values. Side-by-side yield comparisons between large yield monitors and small plot combines (Arslan and Colvin, 2002) or random hand-harvested plots within management zones (J. Schepers, unpublished) clearly illustrate that inaccuracies in yield monitors can reflect poorly, albeit unjustly, on the value of remote sensing as a valuable management tool. One idea being tested for commercialization is to combine pre-harvest imagery and yield monitor data to generate a map that more accurately depicts the spatial characteristics of within-field yield variation (similar to what is shown in Plate 4).

#### Integrating Remote Sensing with Crop Simulation Models

Although capabilities to simulate crop growth and development have increased considerably over the past decades, predicting the effects of management factors, unusual or extreme weather events, and pest pressures on crop water and nutrient requirements and final harvestable yields is still far from being an exact science. Remotely sensed imagery is a practical method for providing crop simulation models with canopy state variables which change dynamically in time and space (Wiegand *et al.*, 1979). At the same time, crop models can increase the information that can be derived from remotely sensed images by extrapolating for periods when inclement weather precludes data collection and by providing the ability to predict crop and yield response to changes in management strategies. Various approaches to integrating remotely sensed data into crop models have been the subject of a review on the topic by Moulin *et al.* (1998). While the objective of these integrated approaches often has been to monitor crop condition and yield at regional scales (e.g., Doraiswamy and Cook, 1995) and at the state and county levels (Doraiswamy *et al.*, 2003; p. 665 this issue), recent efforts have also focused on predicting within-field variability in crop status (Sadler *et al.*, 2002). Coupling the remotely sensed imagery with the models can be done directly through biomass, GLAI, and phenological stages, or indirectly by inferring fAPAR, plant water status, nutrient status, disease, insect, or weed pressure. Examples include

- Iterative adjustment of the model's initial conditions and cultivar specific parameters so that the model's predictions agree with periodic remotely sensed estimates of ET and LAI (Maas, 1993);
- Forcing model predictions to match remotely sensed estimates of actual field conditions at a given point in the season (Sadler *et al.*, 2002); and
- Using radiative transfer models so satellite reflectance data can be directly compared to a crop model's predictions (Nouvellon *et al.*, 2001).

Crop models provide the ability to simulate different management options under different weather conditions, while the remotely sensed data allow the models to account for spatial variability and provide occasional "reality checks." As these methods mature, it will become increasingly important to incorporate model output with multi-objective decision support systems that also consider factors such as economic, labor, and time constraints (Jones and Barnes, 2000). Decision support systems will also be needed to manage the large amounts of remotely sensed and other data contained in a GIS (Doraiswamy *et al.*, 2000).

## Other Aspects of Crop Management

#### Plant Population

Plant density is an important variable affecting productivity in many systems. Populations vary with planter performance, soil parameters, weather, field slope and aspect, seedling disease, etc. For some crops like corn or non-tillering varieties of grain sorghum, yield potential is reduced when population numbers are outside of fairly narrow optimum ranges. Tillering, or branching characteristics of other crops (e.g., wheat, cotton, soybeans) render final yields less sensitive to population density, although uniform stand emergence and early canopy closure are effective in achieving good weed control and in influencing early maturity. Conversely, too dense a stand can result in barren plants without marketable fruit or a canopy more susceptible to disease or attractive to arthropod pests. Variable-rate planters now make it possible to adjust seeding rate to compensate for emergence variations or achieve densities that are better matched to site-specific soil characteristics within the field.

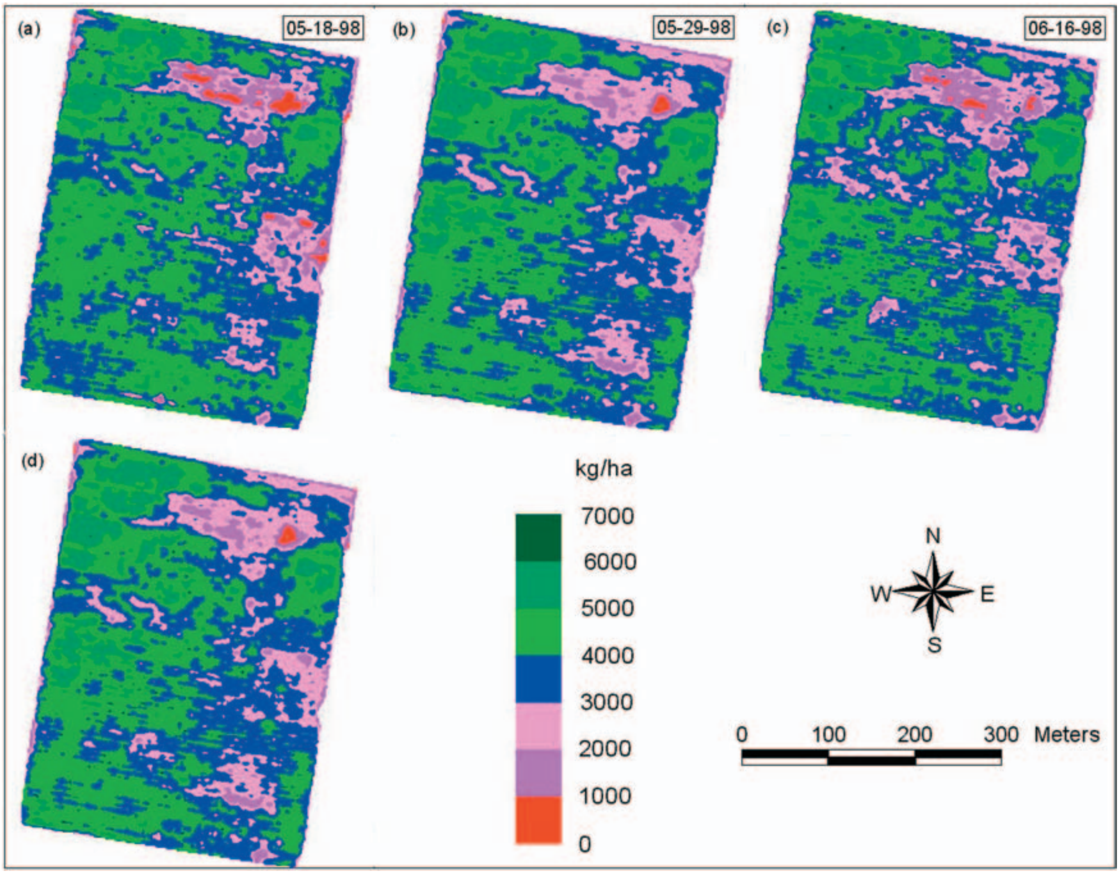


Plate 4. Within-season yield maps generated from digital color-infrared images from a grain sorghum field on three dates during the growing season (a, b, and c) and data obtained with a yield monitor at the end of the season (d) (from Yang *et al.*, 2000).

One goal of commercial remote sensing providers is to offer reliable, early season estimates of plant density which would enable growers to identify seedling diseases or insect infestations, to decide on the need for replanting, to plan herbicide and fertilizer needs, and to interpret end-of-season yield maps. Plattner and Hummel (1996) devised a non-contact, combine-mounted sensor that used a photoelectric emitter and detector pair to provide information on corn plant population, spacing, skips, and doubles. The sensor estimated plant spacing at the early growth stage with an error of 3 percent and at harvest with a 6 percent error. In field tests, filtering algorithms were able to remove the effects of narrow beam interruptions due to small weeds, but large corn leaves were a source of error.

Ideally, multispectral imagery taken shortly after emergence could be used to determine plant populations for management purposes. In practice, however, the seedling plants are usually too small and their signal is overwhelmed by that of the soil. Acquiring imagery very early in the day (i.e., large solar zeniths) or with off-nadir viewing angles offers a potential solution to plant detection at low leaf area levels (Pinter *et al.*, 1983b; Bausch and Diker, 2001). As more sensitive sensors are deployed and techniques for calibration and removing effects of changes in soil background improve (Moran *et al.*, 2003; p. 705 this issue), capabilities for accurate assessment of early season plant density should improve.

### Growth Regulators and Defoliants

Growers are increasingly using chemical plant growth regulators such as mepiquat chloride (Pix®) as a means for manipulating plant growth to facilitate mechanical harvesting and encourage early maturity. In the late 1970s, aerial CIR photography was used by ARS scientists to monitor the effectiveness of defoliants used to reduce late-season fruiting and decrease the number of overwintering pink bollworms (*Pectinophora gossypiella* Saunders; Henneberry *et al.*, 1979). Subsequently, Richardson and Gausman (1982) examined the effect of Pix® on the reflectance properties of cotton leaves and canopies, demonstrating the potential for remote sensing to survey acreages of treated cotton. Shanahan and Nielsen (1987) used the CWSI to evaluate performance of plant growth regulators in conserving early season water use by corn in semiarid regions. More recently researchers used high spatial resolution, multispectral imagery to apply Pix® only where it was needed to control rank growth in 400+ ha of cotton in Mississippi (Dupont *et al.*, 2000).

## Overall Challenges and Opportunities

Twenty years ago, in a seminal essay on the potential use of remote sensing for making day-to-day farm management decisions, Ray Jackson (1984) stressed the overall importance to the grower of (1) timeliness, (2) frequency, and (3) spatial resolution of data (in that order). Most of his observations remain relevant today. There have been substantial improvements in instantaneous field of view but very few farmers presently have access to regular images of their farms and even when they do, slow turnaround of the processed product continues to be a problem.

Despite these shortcomings, there is no question that remote sensing technologies will permeate many aspects of farming in the future. Grower acceptance will increase as products with higher spatial and temporal resolution become more affordable. That, in turn, will reduce costs, encouraging better coverage and faster image delivery. Building grower confidence will also require that remote sensing providers pay greater attention to calibration issues, convert imagery to reflectance, and standardize on optimum wavelengths and data collection techniques (see Moran *et al.*, 2003; p. 705 this issue). This will result in a more consistent product that tells the same story from year to year and brings value-added information to overall farming operations.

From a research perspective, however, there are several overarching and inter-related challenges that must be dealt with in order to advance remote sensing beyond today's largely qualitative applications for crop management. The first deals with understanding and being able to model bidirectional reflectance properties of agricultural targets. Even the most basic relationship between green leaf area index and NDVI changes significantly with solar illumination angles, sensor viewing direction, or plant row orientation. So a proper accounting for bidirectional effects will render observed spectral characteristics less dependent on the time of day or season when data are acquired, or on non-agronomic properties like row direction or spacing.

A second major research challenge is to develop stress detection algorithms that perform reliably across space and time. Techniques should be independent of location, soils, and management factors. They should also function well throughout the season, from planting through maturity. Here, there is a need to identify unique signatures for specific stresses amidst the constantly changing background associated with normal crop growth and development, i.e., spectral complexities introduced by incomplete plant cover. Newer techniques, such as spectral mixing analysis, can be used to discern water-, nutrient-, and pest-induced stress signals from "noise" introduced by soil and non-plant factors. Advanced approaches will integrate remotely sensed parameters with expert and decision support systems that compare spatial and temporal patterns in crop spectra and emittance with historical data and do so within the context of current weather and management procedures. Combining remote observations with existing crop simulation models will impart a spatial dimension to the models that will improve their predictive capabilities and usefulness to farm managers.

The sheer quantity of spectral, temporal, and spatial information contained in a sequence of remotely sensed images offers unique opportunities for monitoring and managing agricultural resources at both the local and global scales. At the field and farm level, historic imagery could be combined with crop calendars, heat units, precipitation records, and yield monitor data to develop maps showing areas that are prone to water stress, nutrient deficiency, or pest problems under a particular environmental scenario. Current imagery could then be used in decision support systems to provide early warning of yield reducing stress. With variable rate technology becoming more widespread, such information would be invaluable to producers within their decision-making framework. Archived satellite imagery also provides scientists and policy makers with an opportunity to monitor the impact of global change on world agriculture. Growers seeking an equitable, scientifically based method for assessing their environmental stewardship or credits for carbon sequestration could likewise use imagery to document their achievement.

## Conclusions

Modern management of agricultural resources is a complex endeavor that is now benefiting from a convergence of technical advances in information sciences, geographic positioning capabilities, and remote sensing systems. Much of the fundamental research relating spectral properties of soils and crops to agronomic and biophysical parameters has been accomplished by ARS researchers working collaboratively with NASA and university scientists in a variety of programs over the past four decades. Many aspects of crop management have already begun to benefit from applications of remote sensing technology. As growers gain more confidence in its use, additional opportunities will present themselves. The future brings tremendous prospects for integrating the spatially and temporally rich information provided through remotely sensed multi- and hyperspectral imagery with the capabilities of management-oriented crop simulation models.

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