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RELATING SPECTRAL OBSERVATIONS OF THE AGRICULTURAL LANDSCAPE TO CROP YIELD

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Abstract

Remote sensing and microscopy share several common concerns including wavelength and sensor selection, signal processing, and image analysis. For crop yield assessments, multispectral observations are acquired photographically, videographically, or with optical-mechanical scanners from aircraft and spacecraft. Sensors are chosen at wavelengths of high atmospheric transmission and maximum contrast between the soil background and the vegetation growing out of it. Vegetation indices have been developed that maximize the information about the photosynthetic size of the vegetation in the landscape and, hence, about crop stresses and yield. Three such indices that reduce the multispectral observations to a single numerical index are described and software for one general procedure that permits characterization of each major spectral component of multiband scenes is appended. Microscopists may encounter analogous situations for which the techniques developed in agricultural remote sensing can be useful.

Key Words: Vegetation indices, sensor selection, image analysis, crop yield, photography, videography, multispectral scanners, remote sensing, sample background.

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Introduction

From limited exposure to the microscopy literature (e.g., Hawkes *et al.* 1988), it is apparent that remote sensing and microscopy share several common concerns including wavelength and sensor selection, signal processing, and image analysis. Therefore, this paper describes and illustrates some of the spectral characteristics of the components of the agricultural landscape and some of the analysis techniques that have proven useful in agricultural applications of remote sensing. Hopefully, analogous situations will permit microscopists to exploit our experience.

The term remote sensing, coined in 1960 or 1961 and popularized through the International Remote Sensing Symposia, sponsored by the University of Michigan and NASA, refers literally to making observations without making physical contact with the object(s) being observed. In agriculture, we typically view the agricultural landscape from the air, and record the field of view photographically or on magnetic tape as video and optical-mechanical multispectral scanner outputs.

In this paper we describe how spectral observations of crops provide information about their response to growing conditions and to estimate yield. At the farm manager level, such information can be the basis for near-real-time decisions for alleviating or ameliorating growth-and yield-limiting conditions detected, so that productivity is maintained or production inputs are reduced. Yield estimates for sample fields are also aggregated to county, state and national levels; in this form the information influences prices of economically important crops on the world market by indicating the supply of the commodity relative to the usual annual consumption. Thus information on crop conditions and yield has both local and global implications.

Manifestations of Crops in the Agricultural Landscape

The three main components of the earth surface where crops are grown are soil, green vegetation, and water bodies. Green vegetation, that containing chlorophyll, is specified because live, green vegetation is photosynthesizing, hence productive, and because standing dead vegetation, senesced leaves, and plant litter are spectrally indistinguishable from soil once decomposition is in progress. This suggests an important point: there must be spectral contrast among the features of interest, the background, and those features not of interest in the field of view for the wavelengths used in any proposed measurement system to be appropriate for the application. For the cropland case under consideration, soil is the background against which the crops are viewed and out of which they grow, while water bodies, fallow soil areas, and areas devoted to other land uses, comprise the areas of non-interest.

Fortunately, for those of us interested in crop conditions and yield, there are contrasts in the reflectance from green plants, soil, and water in the wavelength interval 400 to 2500 nm. As shown in Figure 1, the reflectance of soil typically increases gradually with increasing wavelength in this interval if the soil is dry. However, liquid water absorbs strongly in the infra-red interval 1350-2500 nm so that wet and dry soils differ markedly in reflectance. Reflectance from plants is influenced some by leaf structure in this interval but it is also dominated by the optical properties of water in the plant tissue. Chlorophyll and other pigments in living plants strongly absorb impinging light (electromagnetic radiation) in the visible wavelength range (400 to 700 nm).

In the near-infrared (750 to 1350 nm) region a typical crop plant leaf reflects about 45% and transmits about 45% of the electromagnetic radiation. In plant canopies, some of the energy transmitted by the uppermost leaves is reflected and transmitted by leaves below them. Consequently, the healthier the crop and the more leaf layers in its canopy, the higher the observed reflectance. The maximum reflectance, about 65%, known as infinite reflectance, occurs when the impinging energy is totally attenuated within the canopy, that is, before any of it reaches the ground. In the near-infrared region, leaf cellular structure is mainly responsible for observed reflectance, transmittance, and absorbance, not pigmentation or water content.

Most of the response of crop plants is due to the leaves since they dominate the interactions with electromagnetic radiation. Although laboratory spectrophotometer data on individual or stacked leaves indicate that a reflectance response may be observable under field conditions, they do not guarantee it (Myers *et al.*, 1966). The amount of sunlit soil and shadows in the instantaneous field-of-view, planting configuration, soil wetness, condition of the atmosphere, sun and observer angles, and plant architecture (leaf angle, size, arrangement on plant, and internal structure) affect field spectra (Colwell, 1974; Jackson *et al.*, 1979). Therefore, Park *et al.* (1977) suggested that a change in reflectance of about 10% may be significant under field conditions.

In remote sensing, simulation models have become popular for describing the interaction of visible and near-infrared electromagnetic radiation with the crop-soil background scene. Models that describe radiative transfer in turbid media (Goel, 1988) are the most useful class of models and, of those, the one most frequently applied is the scattering by arbitrarily inclined leaves (SAIL) model of Verhoef (1984). The SAIL model requires information about five canopy parameters: leaf area index (LAI), which is the ratio of green leaf area to ground area; leaf angle distribution; single leaf reflectance; single leaf transmittance; and, soil reflectance. External variables needed include solar zenith and azimuth angles, instrument view and azimuth angles, and proportion of specular to diffuse radiation. It has been found for corn, at least, that constant values of leaf angle distribution and of single leaf reflectance and transmittance can be used for the whole growing season (Major *et al.*, 1992). Uncertainty in values of soil reflectance on particular dates as it varies with rainfall, tillage, irrigation, and irregular soil drying under partial canopies is a major source of error in inversions of such models to estimate important plant parameters such as leaf area index. Such simulation models may have application in microscopy if the samples are translucent.

There may also be lessons for microscopists in the above information if the background discolors with age, if preservatives or other constituents with distinctive spectral signatures are unevenly mixed, or if sample components of interest can be dyed to increase contrast between them and those not of interest. For foods, there should be fewer variables to contend with than for canopies of plants examined under outdoor lighting and weather conditions.

Useful Wavelengths and Sensors

Laboratory and field studies have shown that bands centered on 570, 650, 680, 850, 1650, 2000 and 2100 or 2200 nm are candidates for vegetation discrimination and stress detection (Wiegand *et al.*, 1972). Figure 2 presents the linear correlation coefficients between percent vegetative cover [of the soil] by Milan and Penjamo wheat cultivars and reflectance at seven wavelengths (550, 650, 750, 900, 1100, 1650 and 2200 nm) measured with a field spectroradiometer on various days during the growing season (Leamer *et al*,. 1978). The wheat emerged 1 December and by 31 December ground cover averaged 25%. Vegetation cover and leaf area index increased into February as the plants began to senesce. The magnitude and sign of the correlation coefficients depend, respectively, on the reflectance contrast between the plants and soils and whether the plants or soil are the more reflective. In the green (550 nm) and near-infrared wavelengths (900 and 1100 nm), reflectance was greater the more completely the plants obscured the soil, and the correlations were positive. In contrast, in the red and far red (650 and 750 nm) where chlorophyll and other plant pigments are efficient absorbers and in the middle infrared bands (1650 and 2200 nm) where water in the plant tissue is strongly absorptive, reflectance was lower the more green foliage present and the correlations are negative. The correlation coefficients in the near-infrared and visible red bands are the strongest but opposite in sign and nearly mirror images of each other in Figure 2. Later we will describe how response differences in these two bands enable us to develop useful spectral vegetation indices.

Historically, black-and-white and conventional color aerial photography have been used to map soil, identify ecological plant communities, and assess disasters since the 1920's. In World War II camouflage detection film was a big military success because the camouflage cloth failed to mimic the reflectance of living vegetation in the near-infrared wavelengths where the film was sensitive. Military experience with NIR film led Colwell (1956) and others to apply film with similar responses in agriculture. Modern infrared aerial film, exemplified by Kodak Aerochrome Infrared Film 2443, is still much used in agriculture, and its wavelength sensitivities and color composite renditions are often closely simulated in CRT displays of videography and multispectral scanner data.

Aerial photography is now losing ground in competition with videography, optical mechanical scanners, and fixed array devices because (a) the data are already digital or can be readily digitized and, therefore, can be promptly statistically analyzed and be displayed and manipulated on image analysis systems, (b) photographic film and its processing are expensive relative to reusable magnetic tape, and (c) film processing delays data availability (Everitt *et al.*, 1991). Film still provides the highest resolution and remains the choice if that is a dominant requirement.

Table 1 summarizes the sensor systems and wavelength bands widely available for agricultural and other natural resource investigations. All the systems listed have a band in the interval 500-600 nm or "green" band, the interval 600-700 nm or "red" band, and the interval 760-1100 nm or "near-infrared" band. Usually, in displaying data on a CRT, the green wavelength response is input through the blue gun, the red wavelength response through the green gun, and the near-infrared response through the red gun of the CRT. The result is a

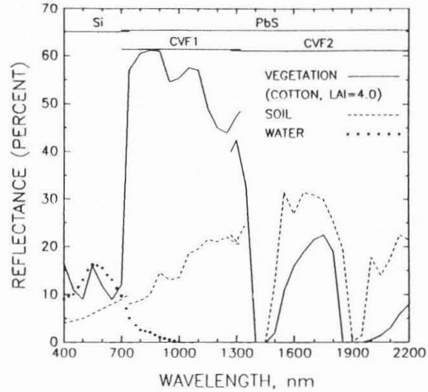

Figure 1. Reflectance of vegetation, soil, and water over the 400 to 2400 nm interval as measured with an Exotech model 2O-B spectroradiometer (after Leamer *et al.*, 1973). Data discontinuities are explained by use of two sensors (Si from 370 to 740 nm and PbS from 700 to 2520 nm) and two circular variable filters (700 to 1320 nm, 1270 to 2520 nm) within the PbS detector range.

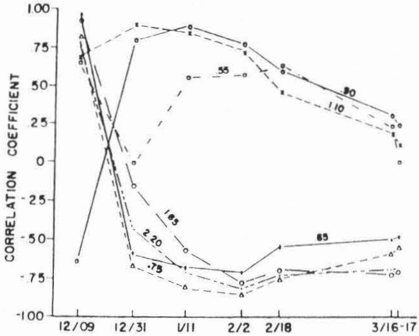

Figure 2. Correlation coefficients between percent vegetative cover of wheat and percent reflectance at seven wavelengths (in microns) on specific dates during the growing season after Leamer *et al.* (1978). The wavelengths (in μms) are indicated over the curves (in nanometers, they are 550, 650, 750, 900, 1100, 1650 and 2200).

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color rendition in the composite image that is similar to that in color infrared film. The wide dynamic range and high sensitivity of the video camera sensors permit a much narrower waveband than the optical mechanical

Table 1. Band number designations and wavelength intervals of sensor systems frequently used by agriculturalists.

Sensor System*									
Barnes MMR 12-1000, Landsat TM			**Exotech 100A Landsat MSS**		**SPOT-1 HRV**		**Video (Weslaco)**	
Band		**nm**	**Band**	**nm**	**Band**	**nm**	**Band**	**nm**
MMR	**TM**							
1	1	450-520	1	500-600	1	500-590	1	543-552
2	2	520-600	2	600-700	2	610-680	2	644-656
3	3	630-690	3	700-800	3	790-890	3	815-827
4	4	760-900	4	800-1100				
5	-	1150-1300						
6	5	1550-1750						
7	7	2050-2300						
8	6	10500-12500						

*Barnes Engineering modular multiband radiometer, Stamford, CT; Thematic mapper (TM) aboard LANDSAT earth observation satellites; Exotech Inc., Gaithersburg, MD; Multispectral scanner (MSS) aboard LANDSAT earth observation satellites; High resolution visible radiometer aboard French satellite, SPOT; Bands routinely used on video system developed by USDA-ARS, Weslaco, TX and duplicated at several other locations.

scanners on the polar orbiting satellites. Usable video data can, therefore, be obtained under poorer lighting conditions, e.g., under cloud cover as well as both earlier and later in the day, than with other systems. However, unless overridden, the built-in automatic gain control complicates the extraction of temporal trends in multidate observations (Wiegand *et al.*, 1992). Digital count data can be calibrated against reflectance standards on the ground at the time of the flights, but the higher the altitude of overflights, the larger the standards must be and they must be provided for each test site.

Bands 6 and 7 of the Barnes MMR and bands 5 and 7 of the LANDSAT thematic mapper (TM) are both at wavelengths affected by water absorption, and the 10500 to 12500 nm band is in the thermal emissive spectral region. The thermal band is excellent for drought and plant water stress studies (Wiegand *et al.*, 1983) because, as water becomes less available to plants, the proportion of the incident radiation that is dissipated as sensible heat increases. The 1550-1750 nm band has been recommended for discriminating among crop plant species based on spectrophotometer studies of individual leaves (Gausman *et al.*, 1973). Succulent species, those that have gelatinous water storage tissue in their leaves or stems, can be distinguished from non-succulent species, which include most crop plants (Everitt *et al.*, 1986). However, this band has not been consistently useful in field studies of non-succulent species, possibly because reflectance of the soil background becomes increasingly non-lambertian as wavelength increases from 900 to 2200 nm (Gerbermann *et al.*, 1987).

The Barnes and Exotech instruments in Table 1 are designed for ground measurements. The Exotech instrument can be hand-held and the Barnes instrument can be shoulder-mounted but both have 15° fields of view, and therefore, must be deployed on tractor- or truck-mounted booms in order to obtain spectral samples larger than 0.1 m^2 in size. Ground resolution of videography obtained with 15 mm focal length cameras flown at 1500 m and digitized to 512 x 512 pixels per frame is 1.7 m. The resolution of SPOT-1 HRV is 20 m and that of the thematic mapper on LANDSAT is 30 m, except for the thermal band which is 120 m.

Data Reduction to Extract Meaningful Information

Optical Density or Optical Counts

In the mid and late sixties, our most available source of data was aerial photography. We determined the optical density of multiemulsion color films with no filter (white light) and with red, green, and blue filters

Table 2. Simple correlations (r) between yield and digital counts of photographic and videographic images for corn. Means and standard deviations (Sd) of digital counts are also given, (after Wiegand *et al.*, 1988).

	r	DC	Sd
A. Photography			
No filter	-0.662*	126.3	1.9
Red filter	-0.320	138.0	1.1
Green filter	-0.044	114.2	0.8
Light table	-0.105	168.6	0.8
(NF-LT)/(RF-LT)	-0.736**	130.6	3.5
(NF-RF)/(NF-GF)	+0.717**	96.7	2.6
($n = 11$, $r_{0.05} = 0.576$, $r_{0.01} = 0.708$)			
B. Videography			
NIR	0.493	154.1	3.0
Red	-0.671*	28.7	3.1
YG	-0.545	67.9	3.0
NIR-Red	+0.748**	125.4	4.8
NIR-YG	+0.699**	86.2	4.4
YG-Red	+0.396	39.2	1.2
($n = 10$, $r_{0.05} = 0.602$, $r_{0.01} = 0.735$)			

* significance at the 0.05 level.
** significance at the 0.01 level.

in the light beam, while for black-and-white film optical densities were determined only to white light. However, by using three cameras each containing the same panchromatic film but equipped with different filters we also obtained multispectral data. A big advance in information extraction occurred when we realized that optical density differences between data pairs measured with different filters reduced the roll-to-roll variation in images due to film lots, chemical changes in the film during storage, illumination conditions at the time of exposure, and variations in processing. Wiegand *et al.* (1971) used optical density differences to discriminate crop and soil conditions in the Imperial Valley of California on simultaneously exposed multiemulsion and multibase space photography and concluded they were about equally useful for crop and soil discrimination.

The use of the optical density and optical count differences for interpretation has continued for both photography digitized by viewing positive transparencies with a video camera and digitized video imagery itself.

Table 2 summarizes the simple correlation coefficients between grain yield (kg/ha) and digital counts of photographic and videographic images of 12 cultivars of corn grown in plots replicated four times (Wiegand *et al.*, 1988). The color infrared photography (Kodak Aerochrome infrared film 2443) positive transparencies were digitized with no filter (NF), a red filter (RF), and a green filter (GF), between the TV camera used for digitizations and the backlighted photographic transparencies. In addition, the digital counts were determined for the light table (LT) with no transparency on it and no filter on the TV camera used for digitization. The video images with the yellow-green (YG), red (R), and near-infrared (NIR), spectral bands (see Table 1) were digitized directly from inflight tapes.

As shown in Table 2, the digital counts for the photographic transparencies using no filter (NF) were significantly ($p = 0.05$) correlated ($r = -0.662$) with yield and the difference ratios (NF - LT)/(RF - LT) and (NF - RF)/(NF - GF) were highly significantly ($p = 0.01$) related to yield at $r = -0.736$ and $r = +0.717$, respectively. For the video data the red band ($r = -0.671$), band difference (NIR - YG) ($r = 0.699$), and (NIR-Red) ($r = 0.748$) were significantly related to yield. The results from the photography and videography were very similar, suggesting that the two systems provide equivalent information.

Spectral Indices

A further advance was made by Kauth and Thomas (1976) who realized that digital count variations in LANDSAT MSS 4-band data space for soil were confined to a plane and that the reflectance variation for vegetation was nearly orthogonal to the soil plane. They used LANDSAT data for corn and soybean fields and the Gram-Schmidt mathematical procedure (Freiberger, 1960) to derive four orthogonal indices that characterized LANDSAT scenes. The indices were: brightness (BR) dominated by the soil; greenness (GN) dominated by the green vegetation; yellowness (YE) a minor component related to senesced vegetation and affected by red or ferruginous soils when present; and, the component nonsuch (NS) that was sensitive to atmospheric conditions particularly water content of the atmosphere. The original set of coefficients they published based on 7-bit digital counts for MSS bands 1, 2, and 3 and 6-bit digital counts for MSS4 were:

$$BR = 0.433(MSS1) + 0.632(MSS2) + 0.586(MSS3) + 0.264(MSS4) \quad (1a)$$

$$GN = -0.290(MSS1) - 0.562(MSS2) + 0.600(MSS3) + 0.491(MSS4) \quad (1b)$$

$$YE = -0.829(MSS1) - 0.522(MSS2) - 0.039(MSS3) + 0.194(MSS4) \quad (1c)$$

$$NS = 0.223(MSS1) + 0.012(MSS2) - 0.543(MSS3) - 0.810(MSS4) \quad (1d)$$

The coefficients are empirical in that a unique set of coefficients is obtained for each data set. Therefore, the data the coefficients are based on must be representative of the data to which they are applied. The coefficients are all positive for brightness; the coefficients for greenness are negative for the visible bands 1 and 2 and positive for the NIR bands 3 and 4; etc. The pattern of positive and negative signs is the same as for the above LANDSAT digital count data in both ground-measured reflectance factors and satellite observations expressed as exoatmospheric reflectances.

Richardson and Wiegand (1977a) observed that as green vegetation developed during the growing season there was displacement of the green vegetation points in near-infrared and visible band data space perpendicularly away from the soil background line. Their equation for the perpendicular vegetation index (PVI) reduces to:

$$\mathrm{PVI} = (\mathrm{NIR} - a\mathrm{RED} - b)/(\mathrm{SQRT}\ (1+a^2)) \qquad (2)$$

where the soil line is defined by:

$$\mathrm{NIR} = a(\mathrm{RED}) + b \qquad (3)$$

wherein a is the slope and b is the intercept of the soil line, and SQRT means square root.

The scatterplot of SPOT-1 NIR (790 to 890 nm) and Red (610-680 nm) band digital counts in Figure 3 further illustrate the PVI concept. The SPOT data were acquired 3 June 1989 over cropland in the eastern part of the Lower Rio Grande Valley of Texas. The lower edge of the scatterplot positions the soil line in the data. Those points equidistant from the soil line contain the same amount of photosynthetically active tissue. By definition, PVI of soil devoid of vegetation is zero. Those farthest from the soil line contain the most photosynthetically active tissue. Soil that is moist, recently tilled, or shaded by plants is less reflective than the same soil when dry. Among soils, the sandier and lower in organic matter they are, the more reflective.

Since both the GN of Kauth and Thomas (1976) and the PVI of Richardson and Wiegand (1977a) are dominated by the green vegetation, they have become known as vegetation indices (VI). The Kauth and Thomas "GN" has become the green vegetation index (GVI). To designate when it is based on 4 wavebands, "GVI4" is a further clarification. The value of the vegetation indices is that they capture most of the information about vegetation in the scene in a single numerical index. Brightness and greenness have repeatedly been shown through principal components analysis to explain 97 to 98% of the variation in cropland scenes.

Jackson (1983) reviewed the GVI4 and PVI derivations and clearly described the Gram-Schmidt procedure for any number of wavebands. The number of spectral indices (m) that can be calculated is equal to the number (n) of wavebands, or dimensions, available in the spectral data. The minimum number of observations is (m + 1). Appendix I is a program in FORTRAN for calculating the n-space coefficients (permission granted by R.D. Jackson). For the data set included in Jackson's paper (LANDSAT data expressed as percent reflectance) the equations are:

$$\mathrm{BR} = 0.328(\mathrm{MSS1}) + 0.373(\mathrm{MSS2}) + 0.578(\mathrm{MSS3}) + 0.647(\mathrm{MSS4}) \qquad (4a)$$

$$\mathrm{GN} = -0.448(\mathrm{MSS1}) - 0.690(\mathrm{MSS2}) + 0.067(\mathrm{MSS3}) + 0.565(\mathrm{MSS4}) \qquad (4b)$$

$$\mathrm{YE} = -0.613(\mathrm{MSS1}) + 0.612(\mathrm{MSS2}) - 0.393(\mathrm{MSS3}) + 0.309(\mathrm{MSS4}) \qquad (4c)$$

$$\mathrm{NS} = 0.562(\mathrm{MSS1}) - 0.100(\mathrm{MSS2}) - 0.713(\mathrm{MSS3}) + 0.408(\mathrm{MSS4}) \qquad (4d)$$

The coefficients in Eqs. (4a-d) can be compared with those obtained for LANDSAT digital counts by Kauth and Thomas (1976) in Eqs. (1a-d).

There is one noteworthy distinction between the two-band GN, or GVI2, calculated using the n-space procedure compared with use of Eqs. (2) and (3) to calculate PVI. As shown by Eq. (3), the intercept of the soil line is not necessarily zero, whereas the n-space procedure evidently assumes the soil line passes through the origin. Therefore, we routinely calculate the greenness of the soil when using the n-space procedure and subtract it algebraically from the greenness calculated for the vegetation. Then GVI2 equals PVI; otherwise, they differ slightly.

Another vegetation index that is widely used is the normalized difference vegetation index, NDVI (Rouse *et al.* 1974):

$$\mathrm{NDVI} = (\mathrm{NIR} - \mathrm{Red})/(\mathrm{NIR} + \mathrm{Red}).$$

This index has been widely used to interpret both satellite and ground spectral measurements. For commonly used NIR and Red bands and observations expressed as reflectance factors, it's value ranges from 0.20 ± 0.03 for fallow soil to 0.92 ± 0.03 for very dense green vegetation. NDVI tends to normalize out atmospheric variations, is highly correlated with GVI2 and PVI, and is easy to calculate.

Again, the main value of the vegetation indices (VI) is that they reduce spectral observations of vegetation from multiple bands to a single numerical index. Those VI referenced to the soil plane take differences in soil background reflectance, due to color, texture, chemical composition and moistness, into account.

Vegetation indices have been described in some detail and the n-space procedure software has been appended in anticipation that microscopists will find them useful for distinguishing sample constituents from the sample matrix, for analyzing data from several wavelengths, and for characterizing sources of variation in multispectral observations.

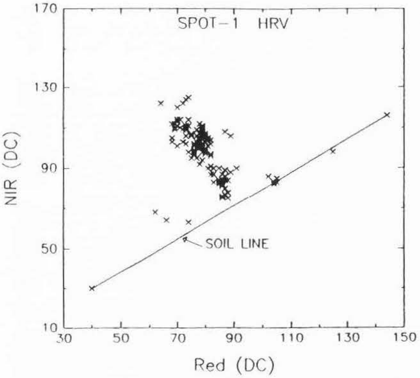

Figure 3. Scatterplot of NIR (790 to 890 nm) and RED (610 to 680 nm) SPOT-1 HRV band digital counts for cropland. The lower edge of the scatterplot illustrates the soil line concept and the distance from it of variably vegetated pixels are their respective perpendicular vegetation indices (Eq. 3).

Biological Consequences and Management Decisions

The uses of vegetation indices in agriculture are legion. They include determining the extent and severity of drought; survival and regrowth of crops from damage due to freezes and hail; mapping of rangelands for forage production as this impacts animal carrying capacity, readiness for grazing, and equitable fees for grazing rights; amount of vegetation present to protect soil from wind and water erosion; detection and quantification of plant stresses from pathogens, nematodes, and saline soils; and, estimates of crop yields.

One way of automating the processing of spectral data is to divide the data space, occupied by the sensor in use, into a number of decision regions and program a table look-up procedure. For example, Richardson and Wiegand (1977a, b) divided LANDSAT data space into 10 mappable categories: water; cloud shadow; low, medium and highly reflecting soil; cloud tops; low, medium, and dense plant cover; and, a threshold region into which no data should fall. The procedure rapidly sorts data into classification categories that can be interpreted for many of the applications in the above paragraph.

Vegetation indices have also been used in a set of equations collectively called spectral components analysis (e.g., Wiegand *et al.*, 1991) that interrelates vegetation indices, absorption of photosynthetically active radiation by crops, leaf area index, evapotranspiration, and crop yield. The equations are also useful for monitoring global vegetation resources (Wiegand and Shibayama, 1990).

Conclusions

The spectral manifestations of crops in the agricultural landscape are affected by the variables live green vegetation, standing dead vegetation, plant litter, shadows, amount and reflectance of the line-of-sight soil background, canopy architecture, and sun position. However, the live, green or photosynthetically active tissue contrasts sufficiently with the soil background in certain wavelengths to give a strong signal. Those wavelengths in the visible, near-infrared, and middle-infrared and the scanning, photographic, and videographic sensors useful for studying crops, have been identified. Data reduction procedures that use film optical density differences and ratios, and soil-adjusted spectral vegetation indices have extracted meaningful information about crop condition and production. Hopefully, those working in microscopy will find the data reduction and analysis procedures presented helpful.

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Discussion with Reviewers

D.W. Irving: In the abstract, what is meant by "photosynthetic size" of the vegetation?
Authors: Vegetation indices measure the amount of photosynthetically active tissue in plant canopies, hence their photosynthetic size.

D.W. Irving: In Figure 1, is this "dry" soil? I am wondering about the comparison between wet versus dry soil and how the spectra differ as a result of the water present. Since there is an abundance of water in some food systems, this information could be especially valuable. Please remember that NIR methods are currently being utilized in food analysis.
Authors: The soil in Figure 1 is dry. Moist or wet soil is both less reflective in the visible and more absorptive in the mid-infrared than dry soil. Typical reflectances for soil in the dry and moist conditions are given in the test data of Jackson in Appendix I. To aid in determining the soil line (Figure 3), we often take a sprinkler can and water with us to the field. We wet about a 1 m^2

area and wait until the soil no longer glistens. Then we take readings over both the wetted and adjacent dry soil.

B.L. Blad: In the section about crop manifestations, what does "a change in reflectance of about 10%" mean? Also, does the word "significant" mean statistically significant, detectable, or a real difference?
Authors: It is not clear what they meant, but we take their statement to mean a change in magnitude of 10%, i.e., from 10 to 11, or 50 to 55%, and that such differences are needed to be detectable considering the variation in field data.

B.L. Blad: In Figure 2, the caption says wavelengths are in nm while numbers on the curves are in μm!
Authors: The numbers on the curves are in micrometers (or μm), but Food Structure uses nanometers, so the conversion is given in the caption.

E. Brach: How easy will it be for microscopists to adapt or apply vegetation indices or a similar approach in their study of microstructures of molecules?
Authors: Most of the papers I heard at the Food Structure 1992 meeting (May 9-14) in Chicago dealt with the relative mix and inclusions of fat, protein, water, starch granules, and other constituents in foods. I see parallels between the field of view components sunlit soil, plants, shaded soil, and plant residues on a background of wet and dry soils and, for example, the constituents of sausage.

E. Brach: Do you foresee a time when the spectral components analysis equations will be programmed into the "onboard computer" of the Landsat or Spot satellites? In this way, the satellites will not only act as data acquisition platforms, but would also provide a signal processing function, thus transmitting in "real time" the agronomic conditions of crops flown over by them.
Authors: Vegetation indices convert the observations from "data" to "information" and the equations provide a way to interpret the information. The equations could be programmed into the onboard computers, but we may not be ready for that yet. The data should be preprocessed to take atmospheric, sun angle, and other effects into account, but models for real time use are not yet available to make those corrections.

APPENDIX I. PROGRAM, SCOEF.FOR, TO CALCULATE N-SPACE COEFFICIENTS ALONG WITH A TEST DATA SET

```
C   M IS THE NUMBER OF INDICES DESIRED;
C   N IS THE NUMBER OF BANDS FOR EACH SPECTRAL CATEGORY

C   THE NUMBER OF BANDS MUST BE EQUAL TO OR ONE LESS
C   THAN THE NUMBER OF SPECTRAL CATEGORIES USED.

      CHARACTER*14 NAMR
      CHARACTER*60 ICHR
      REAL*8 X(0:10,8),A(0:10,8),T(0:10,8),
     *D2(0:10,8),IY(0:10,8),D,S,S1
      DIMENSION DD(10),LABLE(6)
      IOUT=6
      WRITE(*,'('' ENTER INPUT FILE NAMR'')')
      READ(*,100) NAMR
  100 FORMAT(A14)
      OPEN(10,STATUS='OLD',FILE=NAMR)
      READ(10,101) ICHR
  101 FORMAT(A60)
      READ(10,*)M,N
      WRITE(IOUT,102) ICHR
  102 FORMAT(1X,A60)
      DO 1 K=0,M-1
      READ(10,'(6A2,10F7.0)')LABLE,(X(K,I),I=1,N)
1     WRITE(IOUT,'(1X,6A2,10F7.2)')LABLE,(X(K,I),I=1,N)
      WRITE(IOUT,'('' '')')
      DO 2 K=1,M
         IF(K.EQ.1)GOTO 20
         DO 3 J=1,K-1
            D1=0
```

```
              DO 4 I=1,N
4                D1=D1+(X(K,I)-X(0,I))*A(J,I)
              D2(K,J)=D1
3             WRITE(IOUT,'('' D2='',2I2,F10.5)')K,J,D2(K,J)
           S=0
20         DO 5 I=1,N
              D=0
              DO 6 J=1,K-1
6                D=D+D2(K,J)*A(J,I)
              T(K,I)=X(K,I)-X(0,I)-D
              WRITE(IOUT,'('' T='',2I2,F10.5)')K,I,T(K,I)
C  MAKE THE SOIL LINE DIRECTIONS POSITIVE
              IF(K.EQ.1)T(K,I)=ABS(T(K,I))
5             S=S+T(K,I)**2
           S=SQRT(S)
           WRITE(IOUT,'(''          COEFFICIENTS     NORMALIZING'')')
           WRITE(IOUT,'(''                           DENOMINATOR'')')
           DO 7 I=1,N
              A(K,I)=T(K,I)/S
7            WRITE(IOUT,'(1X,''A('',I2,'','',I2,'')='',2F15.5)')K,I,
     *A(K,I),S
2          WRITE(IOUT,'(''  '')')
C  CHECK FOR ORTHOGONALITY
           WRITE(IOUT,'('' ORTHOGONALITY  MATRIX'',//)')
        DO 8 K=1,M
           DO 8 J=1,M
              S1=0
              DO 10 I=1,N
10               S1=S1+A(K,I)*A(J,I)
C             IF(S1.GT..9999)S1=1
C             IF(S1.LT..000001)S1=0
8             IY(K,J)=S1
C  PRINT ORTHOGONALITY MATRIX
        DO 11 J=1,N
11            WRITE(IOUT,'(1X,10F10.7)')(IY(J,I),I=1,M)
        CLOSE(10)
        WRITE(IOUT,'(1X,//'' COMPUTE N-SPACE INDICES''//)')
        DO 22 I=0,M-1
        DO 21 J=1,M
        DD(J)=0.
        DO 21 K=1,N
     21 DD(J)=DD(J)+X(I,K)*A(J,K)
     22 WRITE(IOUT,'(1X,10F8.3)')(DD(J),J=1,M)
        STOP
        END
JACKSON (1983) TEST DATA
4 4
DRY SOIL       15.10  20.32  28.73  32.45
WET SOIL        7.59  11.79  15.52  17.65
GREEN VEG       3.45   2.80  28.51  43.82
SENESCED VEG   11.58  17.59  25.71  31.36
```

FOR THIS EXAMPLE WE SPECIFIED M = 4 AND N = 4. DRY SOIL, WET SOIL, GREEN VEGETATION, AND SENESCED VEGETATION ARE THE SPECTRAL CATEGORIES, WHILE THE FOUR COLUMNS OF DATA ARE SPECTRAL REFLECTANCES FOR LANDSAT BANDS 1, 2, 3, AND 4 AS DEFINED IN TABLE 1.