Derivative Analysis of AVIRIS Data for Crop Stress Detection

Spectral derivatives and band ratios based on AVIRIS image data were used to identify nitrogen deficiency and drought stress in a Nebraska corn field.

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Abstract

Low-altitude Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) hyperspectral imagery of a cornfield in Nebraska was used to determine whether derivative analysis methods provided enhanced plant stress detection compared with narrow-band ratios. The field was divided into 20 plots representing 4 replicates each of 5 nitrogen (N) fertilization treatments that ranged from 0 to 200 kg N/ha in 50 kg/ha increments. The imagery yielded a 3 m ground pixel size for 224 spectral bands.

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Derivative analysis provided no advantage in stress detection compared with the performance of narrow-band ratio indices derived from the literature. This result was attributed to a high leaf area index at the time of overflight (LAI $\approx$ 5 to 6) and the high signal-to-noise character of the narrow AVIRIS bands.

Introduction

Historically, spectroscopists have used signal derivative and ratio computations to remove background signals or noise that interferes with signals of interest (Butler and Hopkins, 1970). Similar techniques are now being used in remote sensing. For example, soil reflectance and its variability over a planted field can represent a noise source and can interfere with attempts to estimate crop parameters in agricultural remote sensing (Li et al., 1993). Demetriades-Shah et al. (1990) demonstrated that derivative analysis minimized the influence of soil background in plant canopy spectra. This result was enabled by the approximately linear dependence of soil reflectance on wavelength. In contrast, vegetation spectra can be described by a cubic or higher-order polynomial. Thus, within an image pixel, the contribution of soil background is minimized in a second derivative of the spectral reflectance curve, whereas the spectral contribution from vegetation remains (Demetriades-Shah et al., 1990). Consequently, derivative analysis was superior to broadband ratio algorithms in plant stress detection. Similarly, second derivatives in the red-edge spectrum have been used to remove background noise from imagery of rangeland forage areas (Li et al., 1993). By applying derivative analysis, the difference between the backgrounds of burned and unburned areas was significantly reduced.

Penuelas et al. (1993) used derivatives to study spectral changes resulting from plant stress. Leaf water status and reflectance in the 950 to 970 nm region was assessed using derivative analysis and conventional band ratio reflectances. A Water Band Index (WBI) and the first derivative minimum over the 900 to 970 nm spectral regions tracked the relative water content of gerbera, pepper, and bean leaves. Penuelas et al. (1994) developed indices based on derivative analysis and narrow band ratios that proved successful in tracking diurnal changes in photosynthetic rate and seasonal changes in chlorophyll and nitrogen in sunflower leaves. Adams et al. (1999) used derivative analysis to derive a Yellowness Index (YI) for plant chlorosis detection. The YI is a three-point approximation of the second spectral derivative using a finite divided difference method and reflectances at 580, 624, and 668 nm.

The computation of a derivative spectrum is not difficult. Dividing the difference in reflectance between successive wavebands by the corresponding wavelength interval yields the approximate derivative spectrum. By repetition of this procedure, higher order derivative spectra can be computed. However, derivative spectra are highly sensitive to noise. Thus, smoothing must generally be done prior to derivative computation. Tsai and Philpot (1998) used the methods of Savitzky-Golay (1964) and Kawata-Minami (1984), along with a mean filter to smooth spectra prior to derivative analysis. Tsai and Philpot suggested that when the spectral features of interest are relatively broad and noise occurs at relatively high frequencies, there is little difference in results from the three methods.

Adams et al. (1999) proposed that there is no reason why higher order derivatives cannot be taken using points farther away from the central wavelength to provide an integrated measure of spectral slope change. Using the finite divided difference in this manner affects a smoothing that diminishes high frequency noise between the points used to compute the derivative (Tsai and Philpot, 1998).

The objective of the present study was to use Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) hyperspectral imagery to determine whether high-resolution derivative analysis methods provided enhanced capability of detecting nitrogen deficiency in corn compared with simpler, narrow-band ratio approaches.

Methods

The Variable Rate (VRAT) Nitrogen (N) Application site established by the U.S. Department of Agriculture, Agricultural Research Service (USDA ARS) at Shelton, Nebraska, represented a well-studied quarter section that supported a corn crop. Four replicate blocks, each containing five treatment plots, were established along a central alleyway that ran from east to west (Figure 1b). N treatments, applied using anhydrous ammonia and assigned randomly within each block, ranged from 0 to 200 kg N/ha in 50 kg N/ha increments. All N treatment plots were watered by a central pivot irrigation system on a three-day period to avoid drought stress. Bare soil patches east and west of the plots provided references for the soil spectrum and for calibration of AVIRIS data to percent reflectance. At the time of overflight, some weeds had become established in the eastern soil patch. Additionally, an arcuate water-stressed region at the north-central margin of the field was established. This region was created by withholding irrigation as the central pivot unit passed for 3 to 4 weeks prior to sensor overflight, enabling a comparison between water and nutrient stress effects on selected reflectance indices. The 200 kg N/ha plots served as experimental controls for comparison with the less fertilized plots. Visually, plots that received little (50 kg/ha) or no fertilizer could be discerned from the control plots. However, the unaided eye could not distinguish among the 100, 150, and 200 kg N/ha plots.

AVIRIS data were acquired over the VRAT field on July 22, 1999. The AVIRIS image cube consisted of 3 m ground sample distance pixels at 224 spectral bands per pixel. Data from several flight lines were collected and returned to the Jet Propulsion Laboratory in Pasadena, California, for georeferencing and radiometric calibration. These data were then corrected for atmospheric effects using the ATmosphere REMoval, or ATREM routine (Gao et al., 1992). The relative reflectance imagery produced by ATREM was then scaled to correspond more closely to measured in-field crop reflectance through the use of an empirical line function procedure. Ground spectral data were acquired by portable spectroradiometers (model ASD-FS, Analytical Spectral Devices, Boulder, Colorado, USA). Canopy spectra of each plot were recorded from a cherry picker elevated to approximately 5 m above the ground. Average spectra were obtained from repeated spectral measurements of each plot (Figure 1a).

For present purposes, the AVIRIS data were truncated to cover the 400 to 1035 nm range. These image data were then used to compute various derivative and ratio-based indices that were tested for their capability as indicators of N deficiency in corn. First and second derivatives were computed at 12 band locations within the 495 to 1025 nm range suggested by Thenkabail et al. (2000) for use in the detection of pigment and moisture variation in crop canopies (Table 1). At least three points were needed to compute the second derivative, so bands 5 and 6 as well as bands 6 and 7 were combined for the analysis. Additionally, the derivative indices of Penuelas et al. (1994) and the Yellowness Index of Adams et al. (1999) were computed as defined by the authors (Table 2). For comparison with the derivative indices, narrow-band ratio indices including the Normalized Difference Vegetation Index (NDVI), Normalized Pigments Chlorophyll Ratio Index (NPCI) (Penuelas et al., 1994), Physiological Reflectance Index (PRI) (Gamon et al., 1992), and Water Band Index (Penuelas et al., 1993) were computed.

Derivatives and derivative-based indices were compared among treatments to determine statistically significant effects at $p \leq 0.01$. Using image-processing software, Regions of Interest (ROIs) were defined for each plot. Extracted ROI data were entered into a spreadsheet and a Kolmogorov-Smirnov normality test was applied. In general, extracted ROI data were not normally distributed. Therefore, a non-parametric Kruskal-Wallis Analysis of Variance (ANOVA) (Haber and Runyon, 1977) and the Dunn Multiple Comparison test (Siegel, 1956) were employed to determine statistical differences. The Dunn test output a two-by-two pairing that quantified whether paired plots are distinguishable from one another and the controls for a given p-value.

Results and Discussion

First derivatives of AVIRIS reflectances computed at 495, 568, 682 and 696, 982, and 1025 nm (Thenkabail et al., 2000) provided separation among all N treatments (Table 1). Although d1 at 568 nm provided separation among all N treatments, it remained insensitive to water stress. Also, 568 nm was the only band at which d2 identified all N treatments and water stress (Table 1). This result was somewhat unexpected since d2 serves to minimize the influence of soil reflectance (Demetriades-Shah et al., 1990). Nevertheless, leaf area index was high and approaching a maximum value when the AVIRIS data were acquired in late July. Thus, it is unlikely that soil reflectance influenced canopy reflectance significantly. It is also noteworthy that while providing separation among N treatments, d1 and d2 at 568 nm exhibited opposite sensitivities to water stress. First and second derivatives at the remaining Thenkabail et al. (2000) bands were far less effective in distinguishing among the N treatments (Table 1).

The d1 minimum in the green spectrum (dg) and d1 maximum near the reflectance red edge (dRE) provided treatment separation (Table 2) similar to the derivatives at the first five bands listed in Table 1. This suggests that in tandem, derivatives in the green-peak and red-edge spectral regions might provide a method to distinguish between water and nutrient stress in corn.

These observations corroborate earlier findings that the green-peak and red-edge spectral regions are generally critical for the detection of plant stress (e.g., Schepers et al., 1996; Carter and Knapp, 2001). The d2 maximum near the red edge (ddRE) identified only the 0, 50, and 100 kg N/ha treatments separately from the controls (Table 2), as did several d2 listed in Table 1. A similar separation of test plot treatments was true also for the d1 maximum in the green spectrum (dG), which additionally was sensitive to water stress (Figure 1c). Derivative-based, normalized difference indices represented by the EGFN (normalized difference between dRE and dG) and the GGFN (normalized difference between dG and dg) did not separate N treatments as well as derivatives per se (Table 2). Penuelas et al. (1994) found the GGFN to correlate closely with photosynthetic efficiency, but it performed poorly in the present study because dg and dG were similar in value. Likewise, the EGFN and YI yielded low ranges in value among pixels. Thus, these indices separated only the untreated and 50 kg/ha treatments from the controls.

A narrow-band NDVI derived from the 680 and 850 nm AVIRIS bands performed as well as any derivative index in the detection of N deficiency (Table 2). Conversely, the NPCI based on the 430 nm and 680 nm bands, which compare the relative amount of chlorophyll to the total amount of chlorophyll plus carotenoids (Penuelas et al., 1994), provided no separation of treatments. Both chlorophyll and the carotenoids absorb strongly in the 300 to 500 nm range, but carotenoids do not absorb strongly in the red spectrum (Margalef, 1974). Thus, although nutrient stress may yield greater leaf concentrations of carotenoids relative to chlorophyll (Young and Britton, 1990), chlorophyll concentration can be estimated by comparing leaf reflectance between these spectral regions (Penuelas et al., 1994). In an earlier analysis of the present data that did not involve reflectance-based indices, AVIRIS reflectance was most sensitive to N treatment at 711 nm (Carter and Estep, 2002). Consequently, a modified NPCI (NPCImod) derived from reflectances at 500 nm and 711 nm provided separation among all N treatments with no sensitivity to water stress (Table 2). This heightened sensitivity to N deficiency translated to an increased visual contrast among treatments in the NPCImod image (Figure 1d). The brighter areas in the image depict N deficiency, while the water stressed area is not seen.

The ratio of reflectances at 970 nm and 900 nm (WBI) separated the 0, 50, and 100 kgN/ha treatments from the controls and indicated water stress (Table 2). However, d1 at the 982 nm and 1025 nm bands recommended by Thenkabail et al. (2000) distinguished among all N treatments in addition to the water stressed area (Table 1). Penuelas et al. (1993) found that the first derivative minimum in the 900 to 970 nm region tracked the relative water content of leaves, as did the WBI. Although leaf water content seemed to be the primary influence on reflectance in this near-infrared region, leaf internal structure appeared to have some effect on reflectance, as noted also by others (e.g., Maas and Dunlap, 1989; Aldakheel and Danson, 1997). This influence of leaf internal structure on reflectance might be explained by a stress-induced increase in intercellular air space. If nutrient or water stress effectively increased the amount of intercellular air space in the corn leaves, the observed increase in near-infrared reflectance would be explained (Gates et al., 1965). Even so, near-infrared reflectance has received little attention as a potential indicator of nutrient deficiencies.

Conclusions

Derivative and band ratio indices derived from AVIRIS imagery acquired at 3 m spatial resolution over the USDA ARS VRAT site at Shelton, Nebraska, were tested for their capability to discriminate N deficiency and water stress in corn. Focusing upon recommended band sets (Thenkabail et al., 2000) and derivative-based indices (Adams et al., 1999; Penuelas et al., 1994), it was determined that the green, red edge, and near-infrared spectra were especially important in discriminating among N fertilization treatments and between nutrient and water stress. Relatively simple narrow-band indices, such as an NDVI based on the 680 nm and 850 nm bands or a modified NPCI incorporating the 500 nm and 711 nm bands, performed as well as any derivative index in discriminating among all N treatments and in separating nutrient stress from water stress (Table 2).

A prime motivation behind the use of derivative indices is their effectiveness in minimizing the influence of soil background reflectance (Demetriades-Shah et al., 1990). In the present study, this capability was muted by high leaf area indices within the experimental plots. Nevertheless, derivative indices might also be useful in tracking spectral shifts that occur in the far red spectrum when one moves from leaf to canopy reflectances (Zhumar, 1993; Carter and Estep, 2002). These displacements in spectral absorption features arise because of multiple radiation transfer among canopy leaves, which serve to enhance absorption and move the red edge position toward longer wavelengths in the far-red portion of the spectrum.

Acknowledgments

This research was funded by NASA's Earth Observations Commercial Applications Hyperspectral Program under the Earth Science Applications Directorate. It resulted from collaborative efforts among the USDA Agricultural Research Service – Beltsville, Maryland; the Boeing Company; Battelle Pacific Northwest Research Laboratory; the University of California, Santa Barbara; and Marconi. Participation by Lockheed Martin Space Operations – Stennis Programs was supported by the NASA Earth Science Applications Directorate under contract number NAS 13-650 at the John C. Stennis Space Center, Mississippi. The authors thank Marcia Wise for editing the manuscript.

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Table and Figure Captions

Table 1

Separability of N treatments resulting from statistical analysis of AVIRIS image data[a].

Table 2

Separation of N fertilization treatments in corn by selected reflectance-derivative and narrow-band ratio indices derived from AVIRIS imagery[a].

Figure 1

(a) Soil spectrum vice spectra of untreated and control plots, (b) USDA ARS VRAT field with test plots and water stress area, (c) dG image, and (d) modified NPCI result.

Table 1

Band Center (nm)	Bandwidth (nm)	N Treatment Separation by d1	N Treatment Separation by d2
568	10	0, 50, 100, 150	0, 50, 100, 150, W
495	30	0, 50, 100, 150, W	0, 50, 100
682 and 696	4 and 4	0, 50, 100, 150, W	0, 50, 100
982	30	0, 50, 100, 150, W	0, 50, 100, W
1025	10	0, 50, 100, 150, W	0, W
550	20	0, 50, 100	0, 50, 100
525	20	0, 50, 100, W	0, 50, 100
668 and 682	4 and 4	0, 50, 100, W	0, 50, 100
720	10	0, 50, 100, W	0, 50, 150, W
920	20	0, 50, 100, W	none
845	70	0, 50, 150, W	W

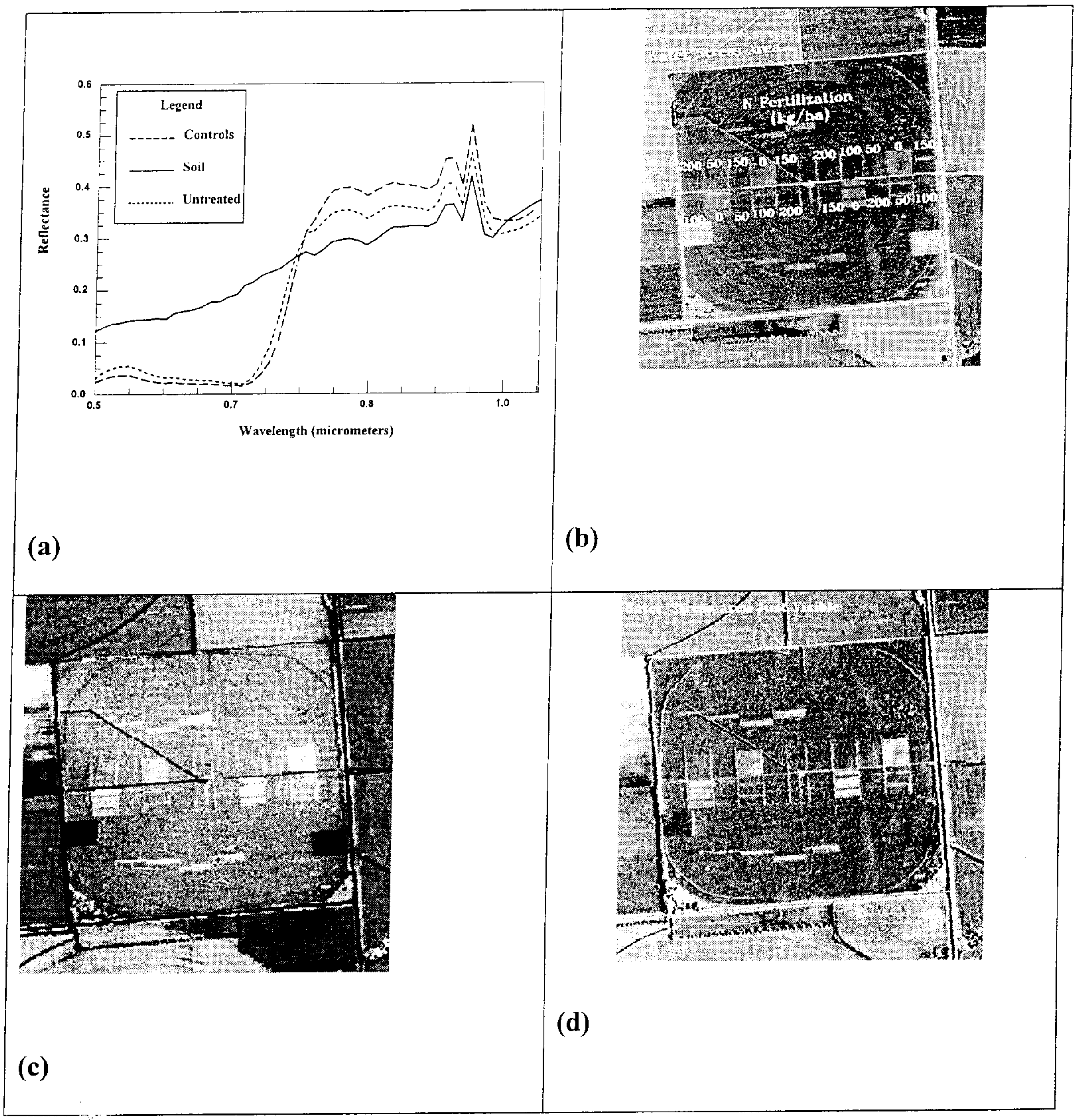
[a] Capabilities of spectral reflectance curve derivatives to separate N treatments at $p < 0.0001$ (detection of water stress indicated by W). Cases where nutrient stress was detected but water stress was not suggest that the tested algorithm is capable of discerning between nutrient and water stress in corn.

Table 2

Index	Definition	N Treatments Separated
Derivative		
dg	d1 minimum, green	0, 50, 100, 150
dRE	d1 maximum, red edge	0, 50, 100, 150, W
ddRE	d2 maximum, red edge	0, 50, 100
dG	d1maximum, green	0, 50, 100, W
EGFN	(dRE-dG)/(dRE+dG)	0, 50
YI	d2	0, 50
GGFN	(dG-dg)/(dG+dg)	none
Reflectance Ratio		
NDVI	(R850-R680)/(R850+R680)	0, 50, 100, 150
NPCImod	(R711-R500)/(R711+R500)	0, 50, 100, 150
WBI	R970/R900	0, 50, 100, W
PRI	(R550-R530)/(R550+R530)	0, 50, 150
NPCI	(R680-R430)/(R680+R430)	none

[a] Capabilities of spectral reflectance curve derivatives or ratios to separate N treatments at $p < 0.0001$ (detection of water stress indicated by W). Cases where nutrient stress was detected but water stress was not suggest that the tested algorithm is capable of discerning between nutrient and water stress in corn.

Figure 1



Legend
Controls
Soil
Untreated
Reflectance
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.5
0.7
0.8
1.0
Wavelength (micrometers)
(a)
N Fertilization
(kg/ha)
200 50 150 0 150 200 100 50 0 150
100 0 50 100 200 150 0 200 50 100
(b)
(c)
(d)