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# Wide Dynamic Range Vegetation Index for Remote Quantification of Biophysical Characteristics of Vegetation

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## Summary

The Normalized Difference Vegetation Index (NDVI) is widely used for monitoring, analyzing, and mapping temporal and spatial distributions of physiological and biophysical characteristics of vegetation. It is well documented that the NDVI approaches saturation asymptotically under conditions of moderate-to-high aboveground biomass. While reflectance in the red region ($\rho_{red}$) exhibits a nearly flat response once the leaf area index (LAI) exceeds 2, the near infrared (NIR) reflectance ($\rho_{NIR}$) continue to respond significantly to changes in moderate-to-high vegetation density (LAI from 2 to 6) in crops. However, this higher sensitivity of the $\rho_{NIR}$ has little effect on NDVI values once the $\rho_{NIR}$ exceeds 30 %. In this paper a simple modification of the NDVI was proposed. The Wide Dynamic Range Vegetation Index, WDRVI = $(a*\rho_{NIR}-\rho_{red})/(a*\rho_{NIR}+\rho_{red})$, where the weighting coefficient $a$ has a value of 0.1–0.2, increases correlation with vegetation fraction by linearizing the relationship for typical wheat, soybean, and maize canopies. The sensitivity of the WDRVI to moderate-to-high LAI (between 2 and 6) was at least three times greater than that of the NDVI. By enhancing the dynamic range while using the same bands as the NDVI, the WDRVI enables a more robust characterization of crop physiological and phenological characteristics. Although this index needs further evaluation, the linear relationship with vegetation fraction and much higher sensitivity to change in LAI will be especially valuable for precision agriculture and monitoring vegetation status under conditions of moderate-to-high density. It is anticipated that the new index will complement the NDVI and other vegetation indices that are based on the red and NIR spectral bands.

**Key words:** leaf area index – reflectance – remote estimation – vegetation fraction – vegetation index

**Abbreviations:** NDVI = Normalized Difference Vegetation Index. – NIR = near infrared. – WDRVI = Wide Dynamic Range Vegetation Index. – LAI = Leaf Area Index. – VF = Vegetation Fraction. – $\rho_{red}$ = reflectance in the red spectral range. – $\rho_{NIR}$ = reflectance in near infrared range

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## Introduction

Observing the dynamics of the vegetated land surface synoptically from space plays a key role in understanding the global water, carbon, and nitrogen cycles. Green vegetation exhibits strong absorption in the red range of the spectrum (around 670 nm); reflectance in this range, $\rho_{red}$, is below 3–5 %. In the near infrared (NIR) range, green vegetation strongly reflects incident irradiation; reflectance in this region, $\rho_{NIR}$, reaches 40–60 %. This distinctive contrast in spectral behavior of vegetation has formed the background of terrestrial remote sensing for the past three decades. Spectral vegetation indices were devised and used as indicators of temporal and spatial variations in vegetation structure and density (see, e.g., reviews by Verstrate et al. (1996) and Moran et al. (1997) and references therein). The Normalized Difference Vegetation Index (Rouse et al. 1974) combines information contained in two spectral bands, the red and NIR: NDVI = $(\rho_{NIR}-\rho_{red})/(\rho_{NIR}+\rho_{red})$. It enables assessment and monitoring of changes in canopy biophysical properties such as the vegetation fraction (VF), leaf area index (LAI), fraction of absorbed photosynthetically active radiation, and net primary production (e.g., Asrar et al. 1984, Holben 1986, Sellers 1985, Tucker et al. 1986).

Since 1979, the study of global vegetation phenology using meteorological satellite data became possible with the availability of the Advanced Very High Resolution Radiometer (AVHRR) onboard National Oceanic and Atmospheric Administration (NOAA) polar-orbiting weather satellites (e.g., Eidenshink 1992, Goward et al. 1985, Justice et al. 1985). These sensors provide daily images of the earth at a nominal spatial resolution of 1.1 km. Land surface applications using AVHRR data have traditionally been based on the NDVI.

Considerable effort has been expended in improving the NDVI and in developing new indices, to compensate both for the atmosphere (Atmospherically Resistant Vegetation Index (ARVI): Kaufman and Tanre 1992) and canopy background (Soil Adjusted Vegetation Indices (SAVI): e.g. Huete 1988, Baret et al. 1989). The vegetation indices like the Modified Simple Ratio $(\rho_{NIR}/\rho_{red}-1)/(\rho_{NIR}/\rho_{red}+1)^{1/2}$ (Chen and Cihlar 1996) and the Renormalized Difference Vegetation Index $(\rho_{NIR}-\rho_{red})/(\rho_{NIR}+\rho_{red})^{1/2}$ (Roujean and Breon 1995) are considered more linearly related to various characteristics of aboveground vegetation.

Despite its extensive use, the main disadvantage of NDVI-like indices is the inherent nonlinear relationship with such biophysical characteristics as VF, LAI and aboveground biomass (e.g., Myneni et al. 1995, 2002, Huete et al. 2002). Generally, NDVI approaches saturation asymptotically under moderate-to-high biomass conditions and for certain ranges of the LAI and the VF (e.g., Sellers 1985, Baret and Guyot 1991, Buschmann and Nagel 1993, Gitelson et al. 2002 a, b, 2003). The nonlinear relationship between the NDVI and LAI has a physical basis as described in Myneni et al. (1995). Saturation effects have important consequences for detecting change and monitoring the dynamics of vegetated land surfaces. Therefore, the most relevant feature of improved vegetation indices should be «extended linearity to the biophysical parameters over a wide range of vegetation conditions» (Huete et al. 2002). Improved linearity and reduction of saturation effects allow increasing accuracy in the estimation of biophysical parameters.

This paper reports on the development and testing of a significant enhancement to the NDVI that yields much greater sensitivity in conditions of moderate-to-high vegetation density, which improves retrieval of crop phenology, the VF, and the LAI.

## Methods

Reflectance spectra of irrigated wheat were collected during two growing seasons near the city of Beer-Sheva, Israel (31° 13′ N; 34° 48′ W). In the first year, experiments were conducted from middle of December 1997 until the middle of May 1998, and used four wheat varieties – «*Ariel*», «*Ayalon*», «*Beit-Hashita*», and «*Yaniv*». During the 1998–1999 growing season, only the «*Ayalon*» variety was used. The data were collected over the course of the growing season, from sowing until harvesting, at one- to two-week intervals. VF ranged from 0 to 100 %. Reflectance spectra were measured within each field at a few randomly selected locations above the canopy using a Licor LI-1800 spectroradiometer in the range 400–1100 nm with a spectral resolution of 2 nm. The methods were described in details elsewhere (Gitelson et al. 2002 a, b).

Reflectance spectra of maize were collected during 1998, 2001, and 2002; reflectance spectra of soybean were collected during 2002. The study area was the University of Nebraska Agricultural Research and Development Center, located near Mead, Nebraska, USA (96° 28′ W; 41° 09′ N). In 1998, the specific study site was a one-acre field of maize planted in a randomized design of 16 plots. The VF ranged from 0 to 88 %. Hyperspectral data were collected using a Spectron Engineering SE-590 portable spectroradiometer in the range from 365 to 1126 nm, mounted on an all-terrain sensor platform (Rundquist et al. 2001). A white Spectralon reflectance standard (Labsphere, Inc., North Sutton, NH) was used to calibrate the spectroradiometer. Upwelling radiance of the reference panel was measured twice in each plot before and after measurements of maize reflectance. Spectral data were collected at regular intervals (every three weeks) throughout the season at four stages of maize development (cf. Gitelson et al. 2002 a, b).

In 2001, one dryland and two irrigated maize production fields (each 65 ha) were studied; in 2002, data were collected over one irrigated maize field and two soybean fields (one irrigated and one dryland). Six plots were established per field for spectral measurements, each with six randomly selected sampling points. VF ranged from 0 to 94 % and LAI from 0 to 6.2.

Spectral measurements were made using a dual-fiber system with two inter-calibrated Ocean Optics USB2000 radiometers mounted on an all-terrain sensor platform (Rundquist et al. 2001). The data were collected in the range 400–900 nm with a spectral resolution of about 1.5 nm (cf. Gitelson et al. 2003). Eighteen campaigns were carried out in 2001 and 31 in 2002 from the beginning of June through the beginning of October.

In all experiments, radiometric data were collected close to solar noon (between 11:00 and 13:00); thus, changes in the solar zenith angle were minimized. Each measurement campaign took about one half-hour in each field. Over the course of the growing season, the solar elevation for the study site varied significantly. The correction of anisotropic reflectance from the calibration target was made in accord with Jackson et al. (1992).

On each sampling date, plants from a 1m length from either of two rows within each test site were collected and the total number of plants was recorded. Collection rows were alternated on successive dates to minimize edge effects on subsequent plant growth. In the lab, plants were separated into green leaves, dead leaves, stems, and reproductive organs. The green leaves were run through an area meter (Model LI-3100, Li-Cor, Inc., Lincoln NE) and the green leaf area per plant was determined (cf. Gitelson et al. 2003).

Green VF (the vertical projection of the green vegetation including leaves, stems, and branches to the ground surface expressed as percent of the reference area) was estimated using digital imagery from a Kodak DC-40 camera. Digital images were acquired at each plot at the same height as the radiometric scan. The area (size) and location of the spectroradiometers field of view (FOV) in each image was determined and a model was designed to exclude data outside the FOV. To distinguish green plants from the natural background of soils and plant residues and to estimate green vegetation fraction, the green and red brightness values were used (Woebbecke et al. 1995).

The NDVI was calculated as $(\rho_{NIR}-\rho_{red})/(\rho_{NIR}+\rho_{red})$ with $\rho_{NIR} = \rho_{725-1000}$ and $\rho_{red} = \rho_{580-680}$ corresponding to the spectral channels of the AVHRR (Ohring et al. 1989).

## Results

In the crops studied, the NDVI was sensitive to changes in VF and LAI only at the beginning of the growing season when VF ranges from 0 to 40–50 % and LAI from 0 to 1.2 (Fig. 1 and Gitelson et al. 2002 a, b, 2003). When the VF approached 60 %, the NDVI leveled off and was not sensitive to the VF ranging between 60 and 100 %. In maize and soybean, the NDVI reached maximal values around 0.8 and then remained virtually invariant while the LAI changed between 2 and 6.

The reason for saturation of the NDVI in wheat, maize and soybean was analyzed by establishing the relationships between the NDVI and its constituents, the red ($\rho_{red}$) and the NIR ($\rho_{NIR}$) reflectance (Fig. 1). As canopy density increased,

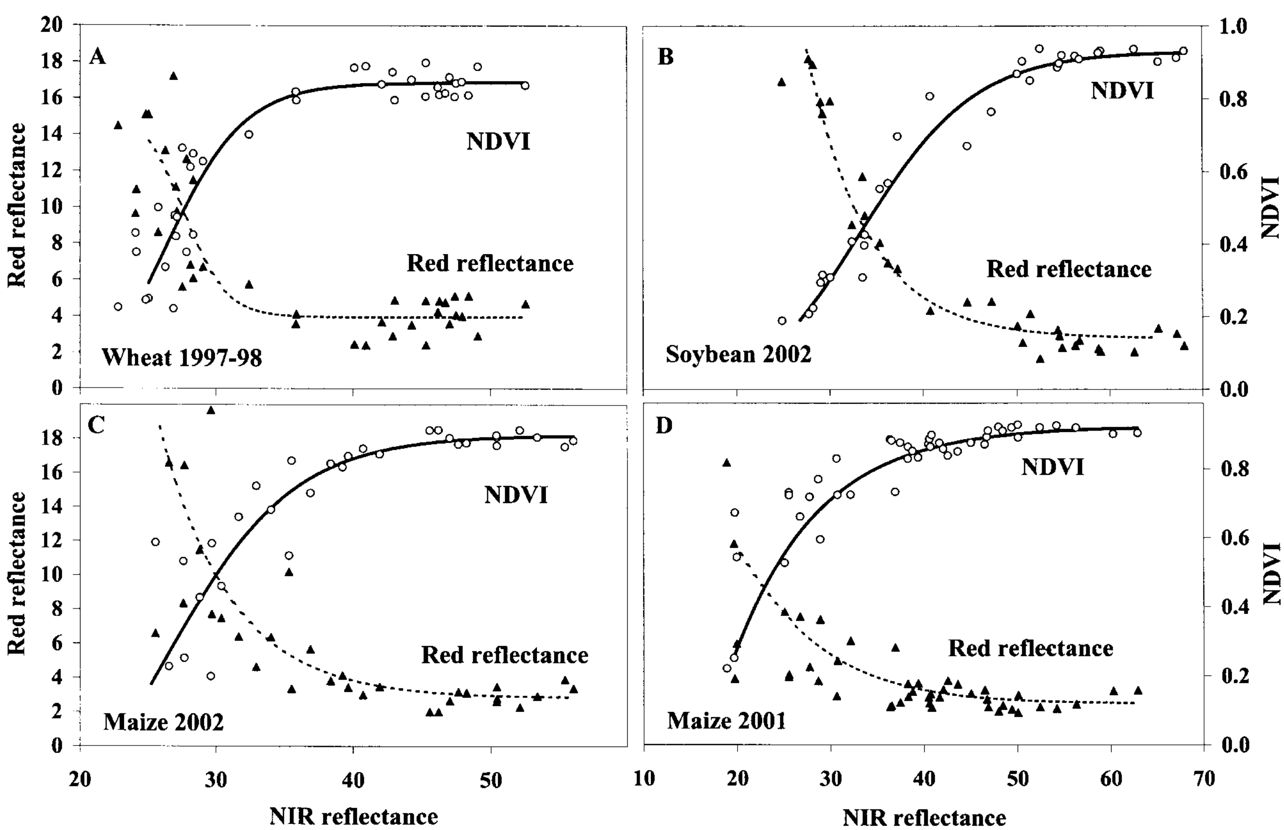


**Figure 1.** The NDVI and the red reflectance plotted versus the NIR reflectance for (A) wheat (Israel 1998/99), (B) soybean (Nebraska 2002), (C) maize (Nebraska 2002), and (D) maize (Nebraska 2001). The red reflectance saturated at moderate-to-high vegetation density, decreasing below 3 %, while the NIR reflectance continued to increase with an increase in the canopy density. However, this high variability of the $\rho_{NIR}$ had little effect on NDVI values when the $\rho_{NIR}$ exceeded 30 %. The NDVI approached a saturation level asymptotically for a NIR reflectance around 30 % that corresponded to LAI around 2 and VF around 60 %.

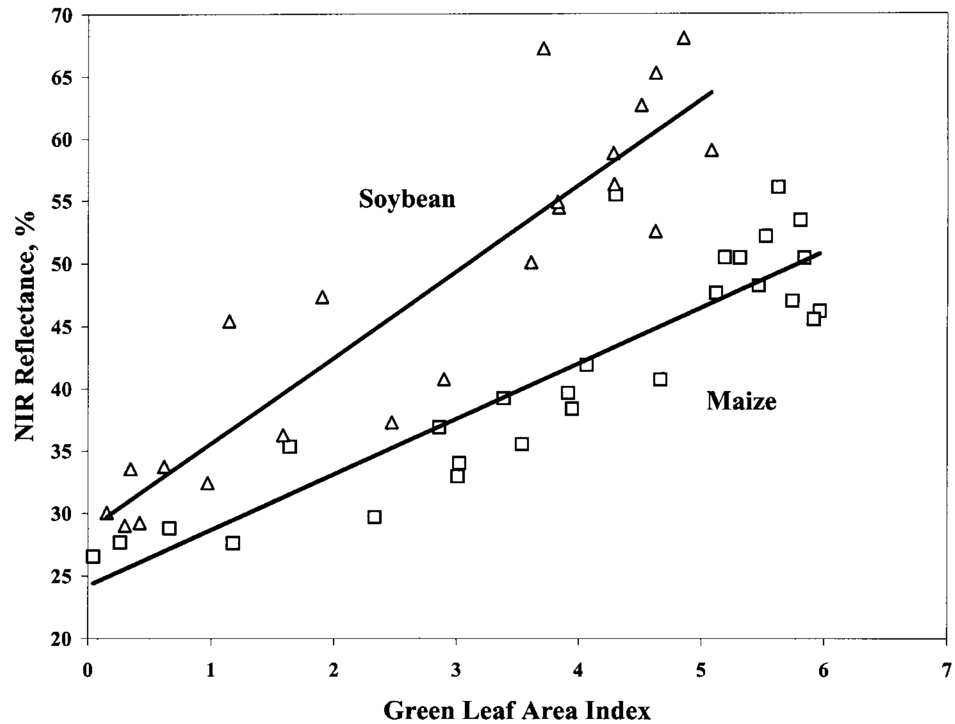


**Figure 2.** NIR reflectance plotted versus maize and soybean green leaf area index.

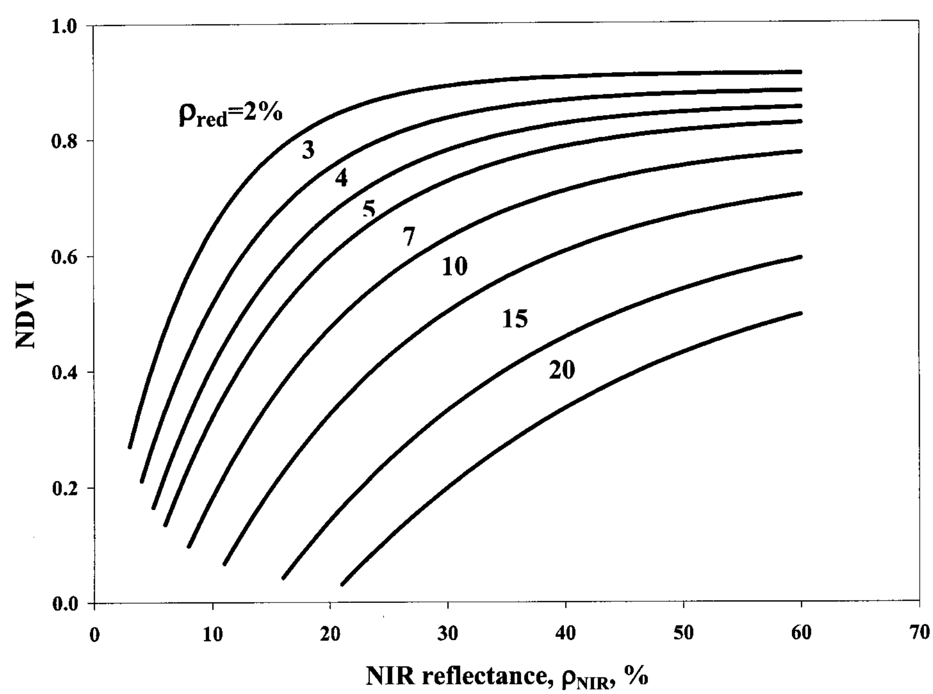


**Figure 3.** The NDVI plotted versus the NIR reflectance, $\rho_{NIR}$. The NDVI was calculated for the $\rho_{NIR}$ from 2 to 60 % and a $\rho_{red}$ ranging from 2 to 20 %. A $\rho_{red}$ between 10 and 20 % corresponds to sparse vegetation, while a $\rho_{red}$ between 2 to 7 % is typical for moderate-to-high vegetation density. For a $\rho_{red}$ between 10 and 20 %, the NDVI shows significant sensitivity to change in the $\rho_{NIR}$ with a slightly decreasing slope at high $\rho_{NIR}$ values. For $\rho_{red}$ < 7 %, the NDVI fails to respond to changes in the $\rho_{NIR}$ between 30 and 65 %.

the $\rho_{red}$ decreased; the $\rho_{red}$ of crops followed an inverse curvilinear relationship that reached an asymptote around 3 % when the $\rho_{NIR}$ exceeded 30 %. The NDVI approached a saturation level asymptotically at a $\rho_{NIR}$ around 30 % that corresponded to the VF around 60 % and LAI around 2. Thus, when LAI > 2 and VF > 60 %, both the $\rho_{red}$ and the NDVI approached asymptotic values and exhibited virtually no additional change. In contrast, the $\rho_{NIR}$ continued to increase with an increase in LAI (Fig. 2). However, an increase in the $\rho_{NIR}$ from 30 % to 55–65 % produced virtually no change in the NDVI.

Figure 3 illustrates the relationship between the NDVI and $\rho_{NIR}$ as the $\rho_{red}$ ranges from 2 to 20 %. A high $\rho_{red}$ corresponds to sparse vegetation, while a $\rho_{red}$ between 2 to 5 % is typical of moderate-to-high crop density. For a $\rho_{red}$ between 10 and 20 %, the NDVI changed significantly with the $\rho_{NIR}$; the slope of the relationship decreased slightly at high $\rho_{NIR}$ values. For a $\rho_{red}$ smaller than 7 %, the NDVI was sensitive to change in a $\rho_{NIR}$ below 25–30 % but showed little sensitivity to change in the $\rho_{NIR}$ above 30 %. Sensitivity of the NDVI to $\rho_{NIR}$ was dependent upon the $\rho_{NIR}/\rho_{red}$ ratio, decreasing with an increase in the ratio. For a $\rho_{NIR}$ exceeding 30 % and for a $\rho_{red}$ between 2 and 7, the sensitivity of the NDVI to increasing $\rho_{NIR}$ diminished drastically.

Thus, while the red reflectance response to LAI > 2 was nearly flat (Fig. 1), significant NIR response from wheat, soybean, and maize canopies was found (Fig. 2) to provide valuable information on the LAI and VF. Nevertheless, this sensitivity of the $\rho_{NIR}$ to crop biophysical characteristics did not affect the NDVI when $\rho_{NIR}$ exceeded 30 %. The reason for the small sensitivity of the NDVI to a moderate-to-high vegetation density results from the very mathematical formulation of the index: the ratio of the difference to sum, $(\rho_{NIR} - \rho_{red})/(\rho_{NIR} + \rho_{red})$. The normalization procedure makes the NDVI insensitive to variation in $\rho_{NIR}$ when $\rho_{NIR} \gg \rho_{red}$ (Fig. 3). For $\rho_{NIR}/\rho_{red} \gg 1$, both the numerator and denominator approach equivalence and the sensitivity of the index to the $\rho_{NIR}$ becomes negligible.

The only way to make the dynamic range of the NDVI wider is to rely on the non-saturated NIR band under moderate-to-high biomass conditions (Fig. 2). The sensitivity of the NDVI to $\rho_{NIR} > 30$ % can be enhanced by introducing a weighting coefficient $a < 1$ to decrease the disparity between the contributions of the $\rho_{NIR}$ and the $\rho_{red}$ to the NDVI. We call this index the Wide Dynamic Range Vegetation Index (WDRVI) and suggest the following form:

$$\mathrm{WDRVI} = (a*\rho_{NIR} - \rho_{red})/(a*\rho_{NIR} + \rho_{red})$$

The performance of the NDVI and that of the WDRVI with $a$ ranging from 0.05 to 0.2 for an estimation of VF in wheat, soybean, and maize is shown in Figure 4. The NDVI increased

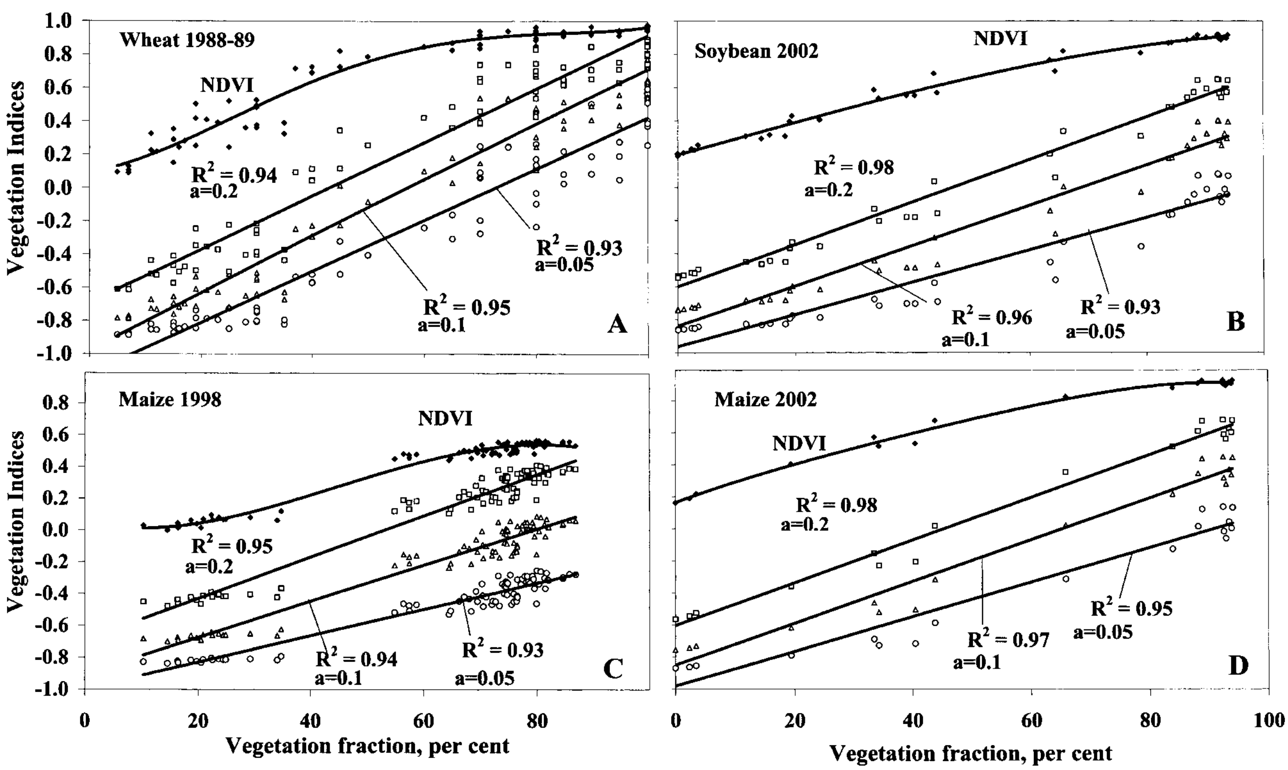


**Figure 4.** The NDVI and the WDRVI plotted versus the vegetation fraction of (A) wheat (Israel 1998/99), (B) soybean (Nebraska 2002), (C) maize (Nebraska 1998), and (D) maize (Nebraska 2002). For all crops studied, the NDVI leveled off and remained insensitive to a VF > 60 %. The WDRVI with coefficient $a$ between 0.05 and 0.2 maintained fairly linear relationships with the vegetation fraction.

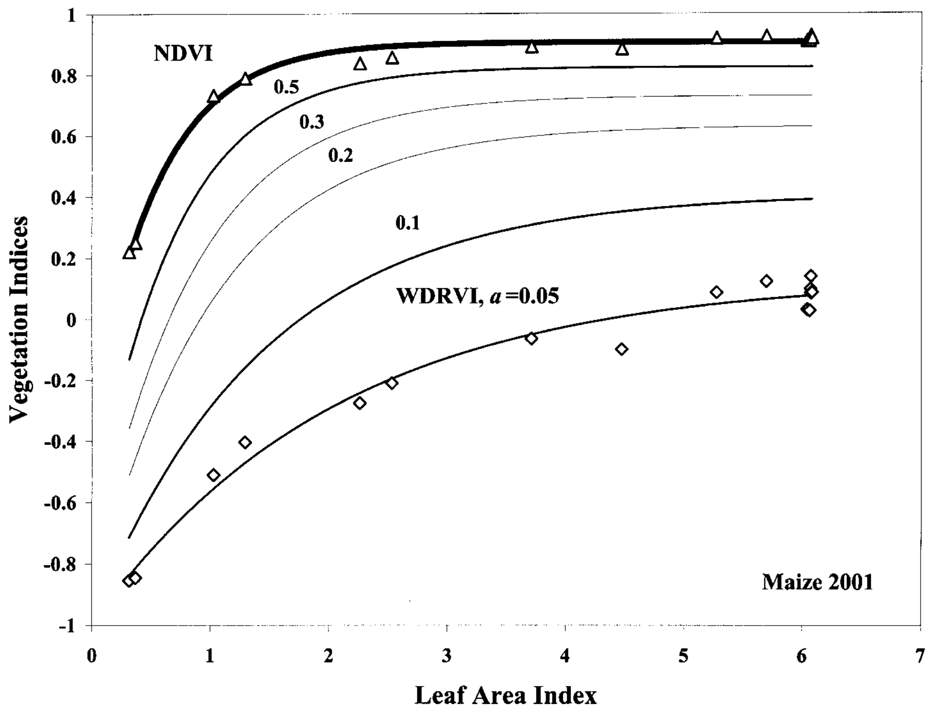


**Figure 5.** The vegetation indices plotted versus green LAI in maize (Nebraska 2001). The lines are best-fit functions. The NDVI increased with an increase in the LAI until the LAI = 2, then it leveled off and remained insensitive to an increasing LAI between 2 and 6. With a decrease in coefficient *a* in the WDRVI, the relationship WDRVI versus LAI became more linear and sensitivity of the index to the LAI increased significantly.

with an increasing vegetation fraction up to 50–60 % and then leveled off and remained insensitive to VF>60 %. In contrast, the WDRVI was sensitive to the VF across the entire range of its variation. For all crops studied, linear relationships between VF and the WDRVI (*a* between 0.05 and 0.2) were obtained with coefficients of determination greater than 0.93.

The performance of the NDVI and the WDRVI to estimate LAI is compared in Figure 5. With an increase in LAI, the NDVI increased until LAI reached 2. Then it leveled off and remained insensitive to LAI ranging between 2 and 6. In contrast, with a decrease in weighting coefficient *a*, the relationship WDRVI vs. LAI became more linear and more sensitive to an increasing LAI. This enhancement is especially pronounced in the range of the LAI ranged from 2 to 6 with the coefficient *a* in the WDRVI between 0.05 and 0.2; the sensitivity of the WDRVI to the LAI increased at least three-fold compared to that of the NDVI. The weighting coefficient *a*, when in the range of 0.05 and 0.2, made the magnitudes of $a * \rho_{NIR}$ and $\rho_{red}$ comparable and thereby enabled each to affect the index.

Comparison of the NDVI with the WDRVI demonstrates that for *a* ranging between 0.05 and 0.2, the dynamic range of the WDRVI was consistently greater than that of the NDVI (Fig. 6 A). The WDRVI was especially sensitive to moderate-to-high vegetation density when the NDVI exceeded 0.6.

Sensitivities of the WDRVI and the NDVI to LAI were compared quantitatively using the following expression:

$$S_r = [d(WDRVI)/d(NDVI)] * [\Delta WDRVI/\Delta NDVI]^{-1}$$

where d(WDRVI) and d(NDVI) are the first derivatives of the indices with respect to LAI, and $\Delta WDRVI = WDRVI_{max} - WDRVI_{min}$ and $\Delta NDVI = NDVI_{max} - NDVI_{min}$ are the ranges of the WDVI and the NDVI, i.e., the difference between the maximal and minimal WDRVI and NDVI values observed during growing season.

The function $S_r$ tracks the relative sensitivity of WDRVI and NDVI to changes in crop LAI. Values of $S_r < 1$ indicate that NDVI is more sensitive than that of WDRVI. When $S_r = 1$, the sensitivities of the indices are equal. Values of $S_r > 1$ indicate that WDRVI is more sensitive than the NDVI. Figure 6 B shows that for $a = 0.05–0.3$, when NDVI ranges between 0 and 0.63, the $S_r < 1$. This range of the NDVI corresponds to LAI in soybean and maize around one (cf. Fig. 5). Thus, when the LAI ranges between 0 and 1, the NDVI is more sensitive than the WDRVI. Once the NDVI >0.63, $S_r > 1$; it means that the WDRVI is more sensitive to the LAI >1 than NDVI (cf. Fig. 5).

It is important to emphasize that the threshold of equal sensitivity for the NDVI and the WDRVI, viz. around 0.65, should be understood as relevant to proximal sensing, when the top-of-canopy (TOC) reflectance is involved in index calculations. The threshold will likely be close to this value for close-range

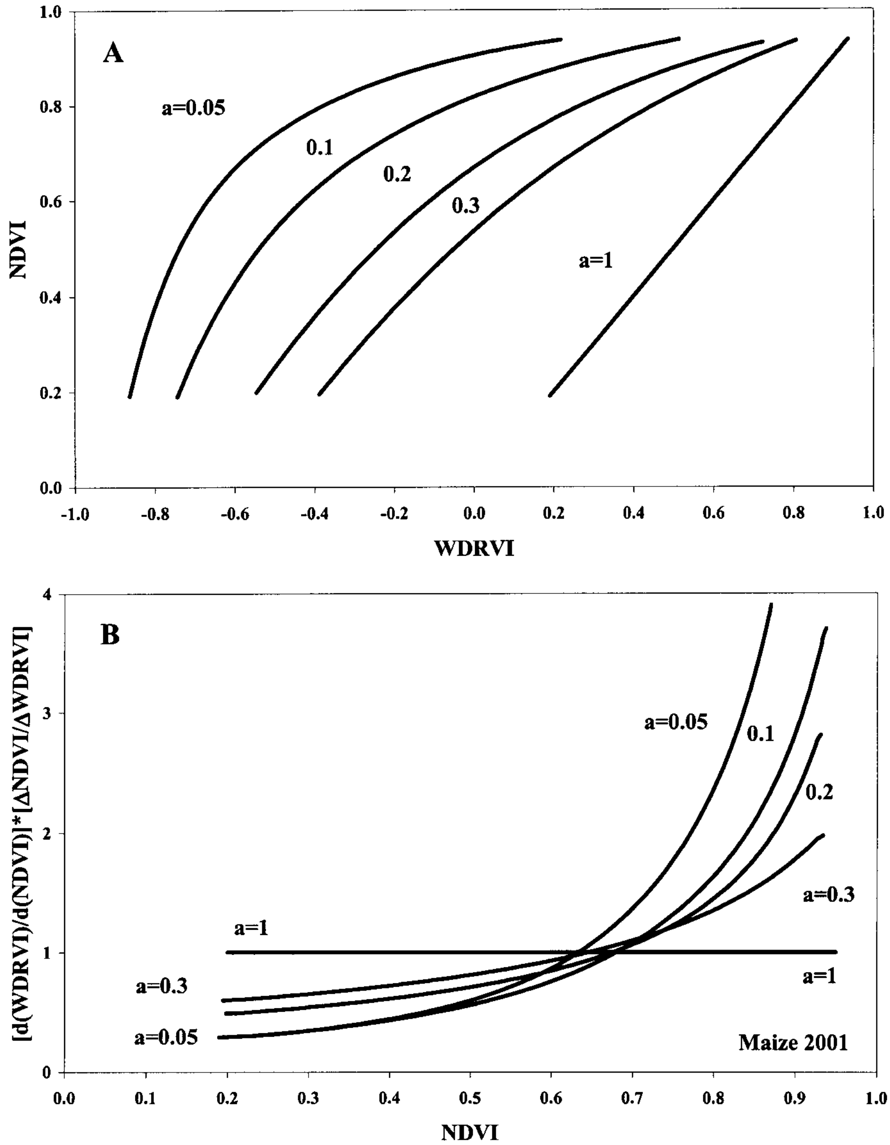


**Figure 6. (A)** Relationship between the WDRVI and the AVHRR NDVI for maize and soybean (Nebraska 2002). For *a* ranging between 0.05 and 0.3, the dynamic range of the WDRVI was consistently greater than that of the NDVI. Once NDVI > 0.6 (it corresponds to LAI > 1) the slope of the relationship NDVI versus WDRVI dropped significantly, showing higher sensitivity of the WDRVI to LAI that that of the NDVI. **(B)** Relative sensitivity of the WDRVI to that of NDVI to change in maize LAI, expressed as the function $S_r = [d(WDRVI)/d(NDVI)] * [\Delta WDRVI/\Delta NDVI]^{-1}$, plotted versus NDVI in maize for various coefficient *a*. Values of $S_r < 1$ indicate that NDVI is more sensitive than that of WDRVI. When $S_r = 1$, the sensitivities of the indices are equal. Values of $S_r > 1$ indicate that WDRVI is more sensitive than the NDVI. For $a = 0.05–0.3$, when NDVI ranges between 0 and 0.63, the $S_r < 1$. This range of the NDVI corresponds to LAI in soybean and maize around one (cf. Fig. 5). Thus, for LAI ranging between 0 and 1, the NDVI is more sensitive to LAI than the WDRVI. Once the NDVI > 0.63, $S_r > 1$; it means that once the LAI > 1, the WDRVI is more sensitive than NDVI (cf. Fig. 5).

sensing of other vegetation types. However, the threshold will occur at significantly lower NDVI values when for top-of-atmosphere (TOA) reflectances measured by spaceborne sensors are used in index calculations. The differences between TOC and TOA NDVI for vegetated surfaces have been observed to range from 0.20 to 0.37 (Kaufman 1989, p. 391 and 409); thus, the threshold value for TOA NDVI is expected to range between 0.3 and 0.4.

## Discussion and Conclusion

This study provided evidence that in crops studied the $\rho_{NIR}$ responds significantly to changes in moderate-to-high crop density (Fig. 2). This $\rho_{NIR}$ response was used to enhance empirically the dynamic range of the NDVI, especially under conditions of moderate-to-high vegetation density. Comparable values of the $\rho_{red}$ and $a * \rho_{NIR}$ enable the improved performance of the WDRVI as compared to the NDVI. This modification of the NDVI has been shown to improve the correlation between the WDRVI and VF, making the relationship between them linear. It also increased – by at least 3-fold – the sensitivity of the WDRVI to LAI ranging between 2 and 6.

The present analysis provides a methodological approach to identifying specific values of the coefficient *a* in the WDRVI. The next step is to apply the approach to a much larger database of canopy spectra and eventually using data from MODIS, AVHRR, Thematic Mapper, and other prominent spaceborne sensors.

The differential sensitivity of the NDVI and the WDRVI to vegetation density could be combined for improved vegetation dynamics. A smooth weighting function that selects the NDVI for lower vegetation density and the WDRVI for higher vegetation density could optimize monitoring of vegetation cover and density using a single, blended index. This application also requires a large representative data set of canopy spectra to derive the right optimization.

The WDRVI, by increasing its dynamic range while using the same bands as the NDVI, enables a better characterization of vegetation biophysical properties and land surface condition under high biomass situations. The promise of the new index is to resolve vegetation structure in areas currently subject to saturation of NDVI-like indices (ARVI and SAVI among others) due to moderate-to-high biomass density. We expect that WDRVI will be able to refine timing of phenological stages and stress identification in crops. Although this needs further evaluation, linear relationship with VF and much higher sensitivity to change in LAI will be especially valuable for monitoring of vegetation status with moderate-to-high vegetation density.

The WDRVI approach also can be used to enhance the dynamic range of the Green Atmospherically Resistant Index (Gitelson et al. 1996), which uses the green and NIR bands. To make the WDRVI atmospherically resistant and soil-adjusted, the concept of the Atmospherically Resistant Vegetation Index (Kaufman and Tanre 1992) and concept of soil-adjusted indices (e.g., Huete et al. 1988, 1997, Baret et al. 1989) can be applied to the WDRVI in the same way as has been applied to the NDVI.

To optimize the vegetation signal with improved sensitivity to high biomass regions, many alternative vegetation indices have been proposed over the past decade and they have shown more linear relationships between remotely sensed data and percent canopy cover, leaf area index, and green leaf biomass (e.g., Kim et al. 1994, Huete et al. 1997, Daughtry et al. 2000, Gitelson et al. 2002 a, b, 2003). However, these approaches use spectral channels that are not available in the vast archive of AVHRR imagery, making them unsuitable to correct the extensive and invaluable historical record as well as data recorded by numerous proximal and aircraft remote sensing studies.

The application of the WDRVI approach to AVHRR imagery makes it possible to increase sensitivity to moderate-to-high vegetation biomass, thus providing the opportunity for a fresh look at archived image time series to enhance the understanding of global land surface dynamics.

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