

A Modified Soil Adjusted Vegetation Index

J. Qi,* A. Chehbouni,† A. R. Huete,* Y. H. Kerr,† and S. Sorooshian‡

There is currently a great deal of interest in the quantitative characterization of temporal and spatial vegetation patterns with remotely sensed data for the study of earth system science and global change. Spectral models and indices are being developed to improve vegetation sensitivity by accounting for atmosphere and soil effects. The soil-adjusted vegetation index (SAVI) was developed to minimize soil influences on canopy spectra by incorporating a soil adjustment factor L into the denominator of the normalized difference vegetation index (NDVI) equation. For optimal adjustment of the soil effect, however, the L factor should vary inversely with the amount of vegetation present. A modified SAVI (MSAVI) that replaces the constant L in the SAVI equation with a variable L function is presented in this article. The L function may be derived by induction or by using the product of the NDVI and weighted difference vegetation index (WDVI). Results based on ground and aircraft-measured cotton canopies are presented. The MSAVI is shown to increase the dynamic range of the vegetation signal while further minimizing the soil background influences, resulting in greater vegetation sensitivity as defined by a "vegetation signal" to "soil noise" ratio.

indices are usually developed by combining two or more spectral bands. There are two general categories in combining two or more spectral bands: slope-based and distance-based vegetation indices (Jackson and Huete, 1991). Two of the most commonly used vegetation indices (VI) of these two categories are the normalized difference vegetation index (NDVI),

$$NDVI = \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + \rho_{red}}, \quad (1)$$

and perpendicular vegetation index (PVI),

$$PVI = a\rho_{NIR} - b\rho_{red}, \quad (2)$$

where ρ is reflectances in near-infrared (NIR) or red band. The a and b are soil line parameters. The concept of these two indices is depicted in Figures 1a and 1b, where the NDVI isolines are shown to converge at the origin while those of the PVI are parallel. These vegetation indices are primarily related to vegetation biophysical parameters (Asrar et al., 1984; Wiegand et al., 1991). Problems exist because of external factor effects, such as soil background variations (Huete et al., 1985; Huete, 1989). To reduce the soil background effect, Huete (1988) proposed using a soil-adjustment factor L to account for first-order soil background variations and obtained a soil-adjusted vegetation index (SAVI):

$$SAVI = \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + \rho_{red} + L} (1 + L), \quad (3)$$

where L is a soil adjustment factor (Fig. 1c). Although Huete (1988) found the optimal adjustment factor to vary with vegetation density, he used a constant $L = 0.5$, since this reduced soil noise considerably throughout a wide range of vegetation amounts. Furthermore, optimization of the L factor would require prior knowledge of vegetation amounts unless one developed an iterative function. Also, the use of a constant $L = 0.5$ results in a loss in the vegetation dynamic responses, since the L of 0.5 is usually larger than red reflectance values and, therefore, would buffer reflectance variations.

INTRODUCTION

There is currently an increasing interest in vegetation characterizations with remote sensing techniques. Since information contained in a single spectral band is usually insufficient to characterize vegetation status, vegetation

* Department of Soil and Water Science, University of Arizona, Tucson

† Laboratoire d'Etudes et de Recherches en Télédétection Spatiale (LERTS), Toulouse, France

‡ Hydrology and Water Resources Department, University of Arizona, Tucson

Address correspondence to Jianguo Qi, Southwest Watershed Research Ctr., USDA-ARS, 2000 E. Allen Rd., Tucson, AZ 85719.

Received 3 March 1993; revised 18 September 1993.

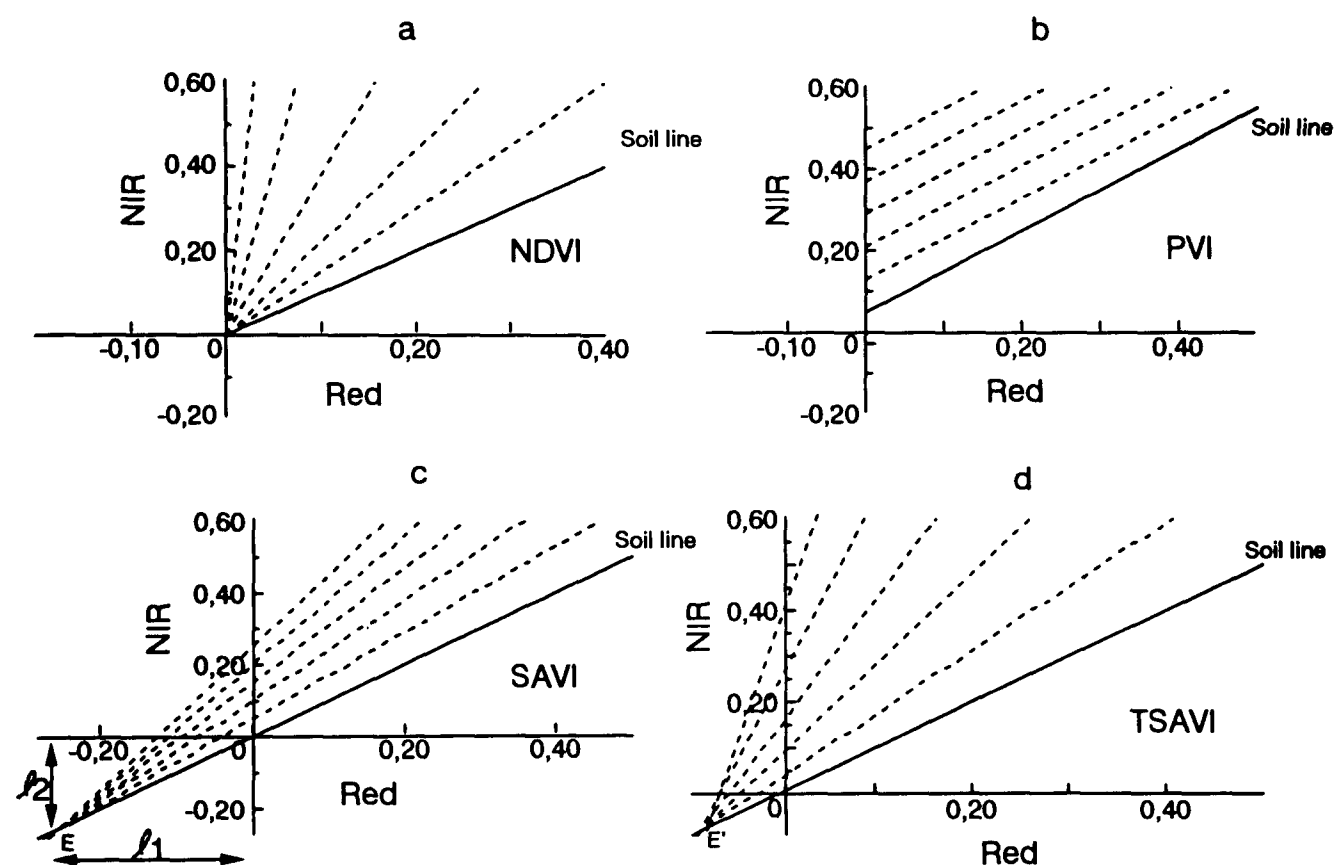


Figure 1. Concepts of vegetation isolines for various vegetation indices.

In this study, we develop a functional L factor, requiring no prior knowledge of vegetation amounts, to replace the constant $L = 0.5$, in the SAVI equation. The objective of this article is to find a self-adjustable L so as to increase the SAVI vegetation sensitivity by increasing the dynamic range and further reducing the soil background effects. The result would be an improved, modified SAVI (MSAVI) with a higher "vegetation signal" to "soil noise" ratio.

METHODS

In order to study the characteristics of the soil adjustment factor L , two data sets were obtained. The first data set consisted of ground-based spectral measurements of a cotton canopy (*Gossypium hirsutum* L. var. DPL-70) for a full season (0–100% green cover) under varying soil background conditions (Huete et al., 1985). At each cotton density, the soil background was varied by inserting different soils underneath the cotton canopy. The soil color ranged from very dark to very bright, and the soil moisture varied from wet to dry. The radiometric measurements were made over the cotton with a multi-modular radiometer (MMR) which had a spectral band in the red region (630–690 nm) and NIR region (760–900 nm). This data set enabled us to study the soil

background effects on vegetation indices. The second data set was collected over a cotton (*Gossypium hirsutum* L. var. DPL-70) field at Maricopa Agricultural Center (MAC), Maricopa, Arizona, USA. The reflectance factors were obtained with a radiometer equipped with SPOT filters and mounted on an aircraft. The SPOT spectral wavelength intervals were 610–690 nm for the red band and 790–890 nm for the near-infrared (NIR) band. The aircraft was flown at 150 m above ground along a transect in a 400 m × 1600 m rectangular cotton field during the growing season of 1989. The spatial transect made on 10 April 1989, contained a 5–10% cotton cover over spatially variable soil backgrounds which included 1) a dry sandy clay loam region (0–480 m), 2) a dry sandy loam (480–650 m), 3) a dry sandy clay loam (650–1000 m), and 4) a wet sandy clay loam (1000–1600 m). Throughout the rest of the year, the soil changed only in wetness due to irrigation and rainfall events. This data set allowed us to examine both dynamic responses of vegetation indices to cotton growth and the soil background effects.

THEORY

Background on Vegetation Indices

Different vegetation indices (VIs) have been developed to enhance vegetation signals from remote sensing mea-

surements. The NDVI [Eq. (1) and Fig. 1a] is a ratio-based VI while the PVI [Eq. (2) and Fig. 1b] is a representative of the linear combination category. The PVI is functionally equivalent to the weighted difference vegetation index (WDVI) (see Richardson and Wiegand, 1977; Clevers, 1988) since one is readily derived from the other:

$$WDVI = \rho_{NIR} - \gamma\rho_{red}, \quad (4)$$

where γ is the slope of the soil line. These three VIs were developed on the basis that all vegetation isolines (same vegetation density with different soil backgrounds) converge either at the origin (Fig. 1a) or at infinity (Fig. 1b).

The cotton ground data (Fig. 2a) show the isolines to have no common converging point. As a first approximation, Huete (1988) assumed that the converging point was a distance (OE) from the origin, and developed the SAVI [Eq. (3) and Fig. 1c]. By adding a constant soil adjustment factor $L = l_1 + l_2$, the SAVI models the first order of soil-vegetation interactions, and significantly reduces soil background effects across a wide range of vegetation conditions (Huete, 1988; Qi et al., 1993). In contrast to other VIs, the SAVI isolines neither converge at the origin as assumed by the NDVI nor are they parallel to the soil line as assumed by the PVI or WDVI. The $(1 + L)$ term in SAVI equation (3) is meant to restore the loss in "dynamic range" of the SAVI resulting from the addition of the L factor to the denominator as well as to bound the SAVI within the range of ± 1 .

Baret et al. (1989) and Baret and Guyot (1991) developed a transformed SAVI (TSAVI) by taking into account the soil line slope (γ) and intercept (i):

$$TSAVI = \frac{\gamma(\rho_{NIR} - \gamma\rho_{red} - i)}{\gamma\rho_{NIR} + \rho_{red} - \gamma i + X(1 + \gamma^2)}, \quad (5)$$

where X is a factor (0.08 in their case) adjusted so as to minimize the soil background effect. The concept of the TSAVI is graphically presented in Figure 1d, where the convergence point is closer to the origin than that of the SAVI. The improvement of the TSAVI over the SAVI was to take the soil line slope (γ) and intercept (i) into account, whereas the SAVI assumed them to be 1 and 0, respectively.

Major et al. (1990) modeled the vegetation isoline behavior by using the ratio b/a as the soil adjustment factor, with b as the intercept and a as slope of each isoline. They obtained a second version of the SAVI, $SAVI_2$:

$$SAVI_2 = \frac{\rho_{NIR}}{\rho_{red} + b/a}. \quad (6)$$

The $SAVI_2$ does not have an empirical adjustment factor for each isoline, but it contains the LAI parameter in the a and b modeling. Since the LAI is usually the target parameter being retrieved in remote sensing studies, the $SAVI_2$ will not be discussed later in this

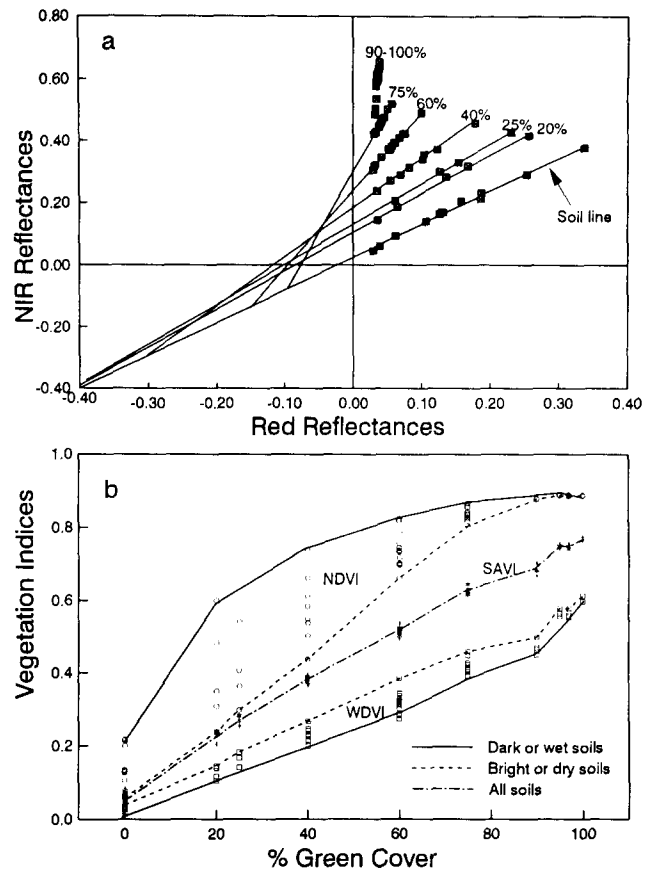


Figure 2. a) Scatter plot of ground-based data in the red-NIR space with regression (iso-) lines, and b) demonstration of dark or wet soil effect on NDVI, SAVI, and WDVI.

article. The TSAVI will not be discussed further here either since it is similar to the SAVI.

Improvement of the SAVI

Figure 2b depicts the relative dynamic ranges and soil noise influences for the SAVI in relation to those of the NDVI and WDVI using the data set presented in Figure 2a. For most of the range of % green vegetation covers, the NDVI appears more sensitive due to its higher, nonlinear, and convex response. This same response function also saturates the NDVI signal at beyond 80% green cover. The WDVI, on the other hand, has a nonlinear, slightly concave response to green vegetation cover, rendering it relatively insensitive to low amounts of vegetation. By contrast, the SAVI has a near-linear response, but overall lower signal than the NDVI throughout the range of green covers. The higher vegetation "signal" of the NDVI, however, must be compared with its corresponding sensitivity to soil-induced signal variations.

In Figure 3, the mean VI response is plotted along with the "soil noise," defined here as twice the standard deviation (σ) of VI variations due to differences in soil background, using the ground-based cotton data. The means and standard deviations of these VIs were calcu-

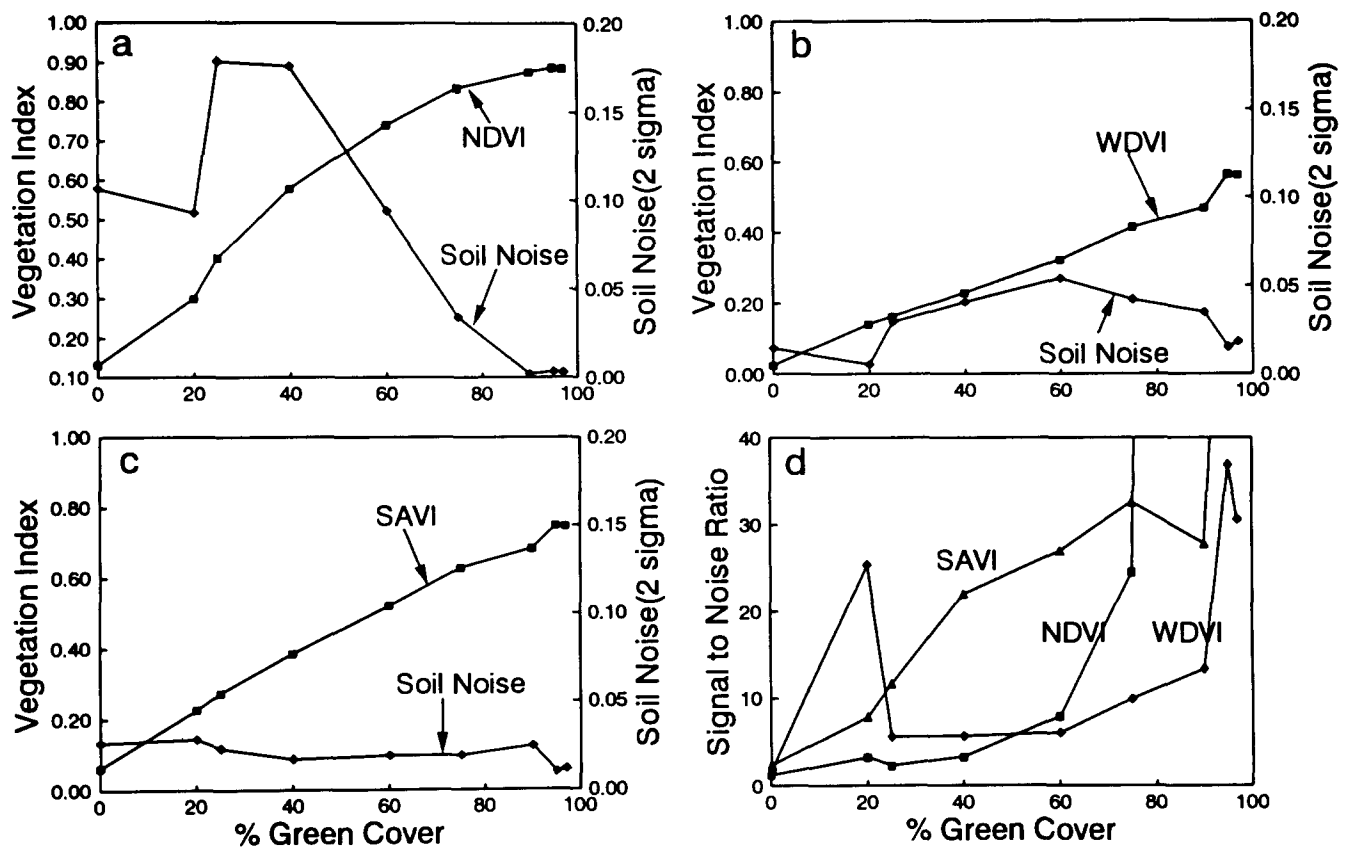


Figure 3. Dynamic ranges and soil noise levels of a) NDVI, b) WdVI, c) SAVI, and d) VI signal to noise ratios as a function of percentage green cotton cover.

lated for each cotton density of different soil backgrounds. The SAVI has a soil noise level of ~ 0.02 – 0.03 , while the WdVI has a noise level of 0.01 – 0.06 and the NDVI, 0.01 – 0.18 throughout range of vegetation covers. At 40% green cover, the noise level of the NDVI (0.18) is nearly 10 times that of the SAVI (< 0.02) and four times the WdVI (0.04) (Fig. 3). This corresponds to a vegetation estimate uncertainty of $\pm 23\%$ green cover for the NDVI, $\pm 7\%$ cover for the WdVI, and $\pm 2.5\%$ for the SAVI.

In Figure 3d, the vegetation signal to soil noise (S/N) ratio is computed for each index at each level of vegetation cover, according to the formula:

$$\frac{S}{N} = \frac{\overline{VI}}{2\sigma}$$

where the bar over VI indicates the mean and σ is the standard deviation of the VI values over different soil backgrounds. This ratio should be a better indicator of VI sensitivity than the simple dynamic range criteria. The SAVI has S/N values four or five times higher than the NDVI and WdVI values. The NDVI S/N becomes very high beyond 75% green cover due to the saturated VI signal, and has almost “zero” soil noise. The sensitivity of the SAVI, as measured by the S/N ratio, is consider-

ably greater than can be obtained with the NDVI signal under conditions of spatial and temporal (drying and wetting) variations in the soil background.

In Figure 4, the potential errors ($e\%$) of different vegetation indices, as defined below, in the estimation of vegetation amounts are compared:

$$e\% = \frac{VI - VI_0}{VI_0} * 100, \quad (8)$$

where VI_0 was calculated with optimal L values obtained by regression of each isoline of the ground cotton data used in Figure 2. The NDVI consistently overestimated ($NDVI > VI_0$) while WdVI consistently underestimated ($WdVI < VI_0$) the vegetation amount. In contrast, the SAVI only slightly overestimated the VI_0 at low vegetation cover and underestimated VI_0 at higher vegetation covers. Therefore, the SAVI is a more representative vegetation indicator than the other VIs.

Although the SAVI has higher S/N ratios than other indices, it still has some limitations. As shown in Figure 4, there exist potential errors on the vegetation estimations, especially at low and high vegetation covers. Also, the use of a constant L of 0.5 results in a loss in the vegetation dynamic responses, because the L of 0.5 is usually much larger than red reflectances and, conse-

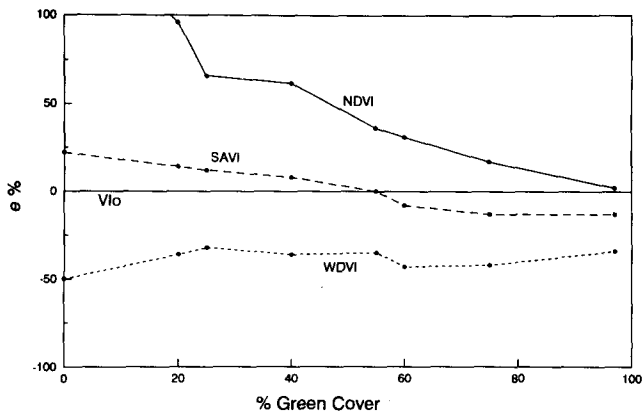


Figure 4. Potential errors on the “estimation” of green cotton cover with the use of different vegetation indices.

quently, buffers reflectances variations. Optimization of the L adjustment factor, therefore, could overcome these shortcomings while further increasing the value of the SAVI.

L Functions

The ground-based cotton, plotted in Figure 2a, showed the vegetation isolines converging at varying distances somewhere between the origin and infinity, not at a common point as indicated in Figures 1c and 1d. High vegetation isolines tend to converge close to the origin, while low vegetation isolines tend to intersect with the soil line further away from the origin (Fig. 2a). Thus, the optimal L for the soil adjustment varies with the amount of vegetation present. At low vegetation amounts, a large L value would best describe soil-vegetation interactions while, with increasing vegetation amounts, L should become smaller.

An Empirical L Function

There are many functions for L that would satisfy the above criteria of L decreasing with increasing vegetative cover. A simple approach would be to use $1 - \text{NDVI}$. However, because NDVI is influenced by soil backgrounds, especially by the soil brightness, the L would contain soil noise. In Figure 2b, we see that both the NDVI and WDWI vary with the soil brightness, but in an opposite manner, that is, darker (or wet) backgrounds result in higher NDVI values, but lower WDWI values than brighter (or dry) backgrounds for identical amounts of vegetation. To decrease the sensitivity to soil noise, one approach for an L function is to let the L function be the product of the NDVI and WDWI in order to cancel or minimize the soil brightness effect. Consequently, we propose the following self-adjustable L :

$$L = 1 - 2\gamma \text{NDVI} \times \text{WDVI}, \tag{9}$$

where γ is the primary soil line parameter (set to be 1.06 here), and the factor 2 is to increase the L dynamic

range. The resulting modified SAVI (MSAVI) would then be

$$\text{MSAVI}_1 = \frac{\rho_{\text{NIR}} - \rho_{\text{red}}}{\rho_{\text{NIR}} + \rho_{\text{red}} + L} (1 + L), \tag{10}$$

where L is given in Eq. (9), instead of a constant, and the suffix 1 is used to distinguish this version of the MSAVI from the inductive MSAVI that will be discussed later. The lower boundary of this empirical L function [Eq. (9)] goes to negative when the product of the NDVI and WDWI approaches 0.5, which requires a value of 0.7 for both NDVI and WDWI. For arid and semiarid regions, none of these two indices reaches 0.7 value and, therefore, the empirical L function usually ranges from 0 to 1. At high vegetation percentage cover, however, a small negative L value may be possible, though not seen graphically in Figure 2, because increasing vegetation density would result in an increase in the NIR while the red remains invariant. This could result in an isoline that is almost parallel to the NIR axis. As a result, the isoline will meet the soil line in the first quarter, resulting in a negative L value.

An Inductive L Function

The proposed empirical L function utilized the advantages of the opposite trends of NDVI and WDWI with the soil background variations. However, the soil noise was not completely canceled out because of the different degree of soil effects as seen in Figure 2b. Also, due to the negative low boundary, the resultant MSAVI may reach a value greater than 1, consequently limiting its use for high vegetation density surfaces. In this section, we will employ an induction method to derive L or MSAVI, which will be shown to be satisfactory.

Using any seed value, L_0 ($0 - +\infty$), would minimize the soil effects in MSAVI:

$$\text{MSAVI}_0 = \frac{\rho_{\text{NIR}} - \rho_{\text{red}}}{\rho_{\text{NIR}} + \rho_{\text{red}} + L_0} (1 + L_0). \tag{11}$$

Due to the use of L_0 , the MSAVI_0 would minimize the soil background effect and could be used in the search for an L function to further minimize the soil effect. Now, since we have obtained an MSAVI_0 that minimizes the soil effects, we could obtain another L function L_1 :

$$L_1 = 1 - \text{MSAVI}_0, \tag{12}$$

which would result in an MSAVI_1 that further minimizes the soil effect:

$$\text{MSAVI}_1 = \frac{\rho_{\text{NIR}} - \rho_{\text{red}}}{\rho_{\text{NIR}} + \rho_{\text{red}} + 1 - \text{MSAVI}_0} (2 - \text{MSAVI}_0). \tag{13}$$

Continuing this process n times, we obtain

$$L_n = 1 - \text{MSAVI}_{n-1}, \tag{14}$$

and

$$\text{MSAVI}_n = \frac{\rho_{\text{NIR}} - \rho_{\text{red}}}{\rho_{\text{NIR}} + \rho_{\text{red}} + 1 - \text{MSAVI}_{n-1}} (2 - \text{MSAVI}_{n-1}). \quad (15)$$

With this processing, there exists an iteration time N such that $\text{MSAVI}_N = \text{MSAVI}_{N-1}$, where soil effects cannot be minimized further. Then we have

$$\text{MSAVI}_N = \frac{\rho_{\text{NIR}} - \rho_{\text{red}}}{\rho_{\text{NIR}} + \rho_{\text{red}} + 1 - \text{MSAVI}_N} (2 - \text{MSAVI}_N). \quad (16)$$

One of the two solutions for Eq. (16) within the range of 0 and 1 is

$$\text{MSAVI}_N = \frac{-b - \sqrt{b^2 - 4c}}{2}, \quad (17)$$

where $b = -(2\rho_{\text{NIR}} + 1)$ and $c = 2(\rho_{\text{NIR}} - \rho_{\text{red}})$. Therefore, with an inductive L function of

$$L = 1 - \text{MSAVI}_2, \quad (18)$$

the resultant SAVI by induction, MSAVI_2 , becomes

$$\text{MSAVI}_2 = \frac{2\rho_{\text{NIR}} + 1 - \sqrt{(2\rho_{\text{NIR}} + 1)^2 - 8(\rho_{\text{NIR}} - \rho_{\text{red}})}}{2}. \quad (19)$$

RESULTS

In relation to the SAVI ($L = 0.5$), the dynamic range of the MSAVI_1 was increased (Fig. 5a) for the ground-based cotton data. Soil noise influences are also reduced and the VI response to percentage green cover becomes more linear. The vegetation estimate uncertainty is reduced from $\pm 2.5\%$ (SAVI) to $\pm 1.6\%$ (MSAVI_1). In Figure 5b, the vegetation signal to soil noise ratio is plotted for the SAVI and MSAVI s as a function of % green cover. The variable L function improved vegetation sensitivity, particularly at high vegetation densities. However, at 60% green cover and above, the S/N ratio (Fig. 5b) of the MSAVI_1 dropped below that of the SAVI.

The results of the MSAVI_2 by induction were compared with the previous MSAVI_1 and the original SAVI in Figure 5. The dynamic range was also increased (Fig. 5a) while the soil noise was kept minimal, resulting in a higher S/N ratio over the SAVI and slightly lower ratios over the MSAVI_1 at low vegetation cover and slightly higher S/N ratios at high vegetation density. Overall, the MSAVI_1 and MSAVI_2 were similar in many ways in sensitivity to vegetation and normalization of the soil noise. As a result, the MSAVI may be derived as in Eq. (10) or (19).

To further examine its vegetation dynamic responses and soil background variations, the MSAVI was applied to the aircraft cotton data set. In Figure 6, we can see the dramatic impact of wetting the soil surface in raising the NDVI values as well as the effect of the

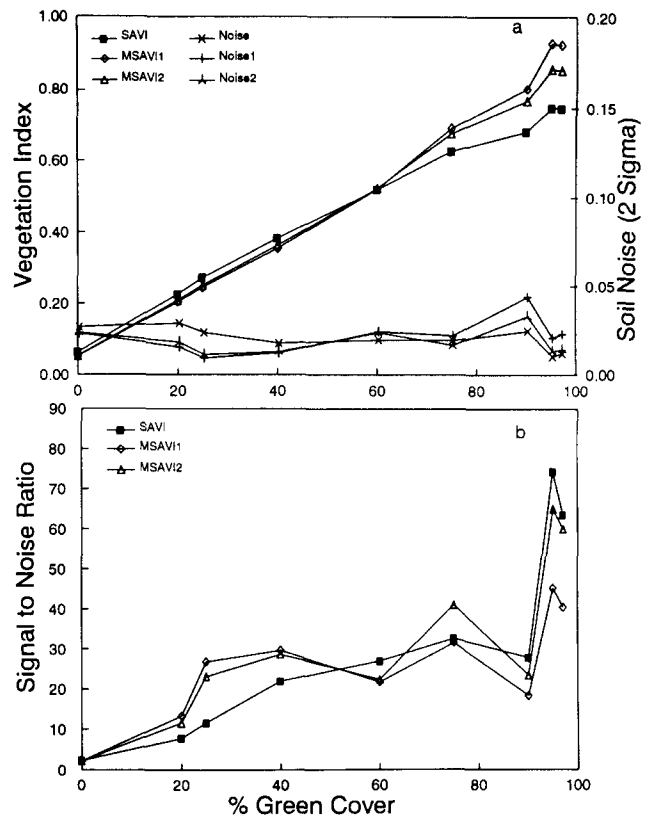


Figure 5. a) Dynamic ranges and soil noise levels and b) signal to noise ratios of the original SAVI and MSAVI .

brighter sandy loam substrate in decreasing the NDVI response. In contrast, the SAVI showed a very slight sensitivity to soil background influences while the MSAVI and WDVI nearly eliminated these influences completely. Over sparse or incomplete canopy covers, the NDVI produces higher VI values than the other indices. This is an artifact of the nonlinear “convex” response pattern of the NDVI to green cover. When ratioed by the amount of soil noise, this “apparent” sensitivity disappears as the S/N becomes the lowest of all the indices (Fig. 3d). The MSAVI is similar to the WDVI on soil noise reduction because the WDVI is actually MSAVI when the L approaches infinity. The L in MSAVI approaches the maximum value of 1 only; therefore, MSAVI resulted in higher VI values than WDVI .

The vegetation dynamic ranges of these indices to the cotton cover over the entire growing season are shown in Figure 7 and summarized in Table 1 along with the ground-based cotton experiment results. The MSAVI had the highest dynamic ranges of 0.87 and 0.94, respectively (Table 1) for the two data sets, and is almost linearly related to the cotton percentage cover, while the SAVI had dynamic ranges of 0.71 and 0.69, respectively. Therefore, the dynamic range of the MSAVI was increased by 15% and 30% compared with

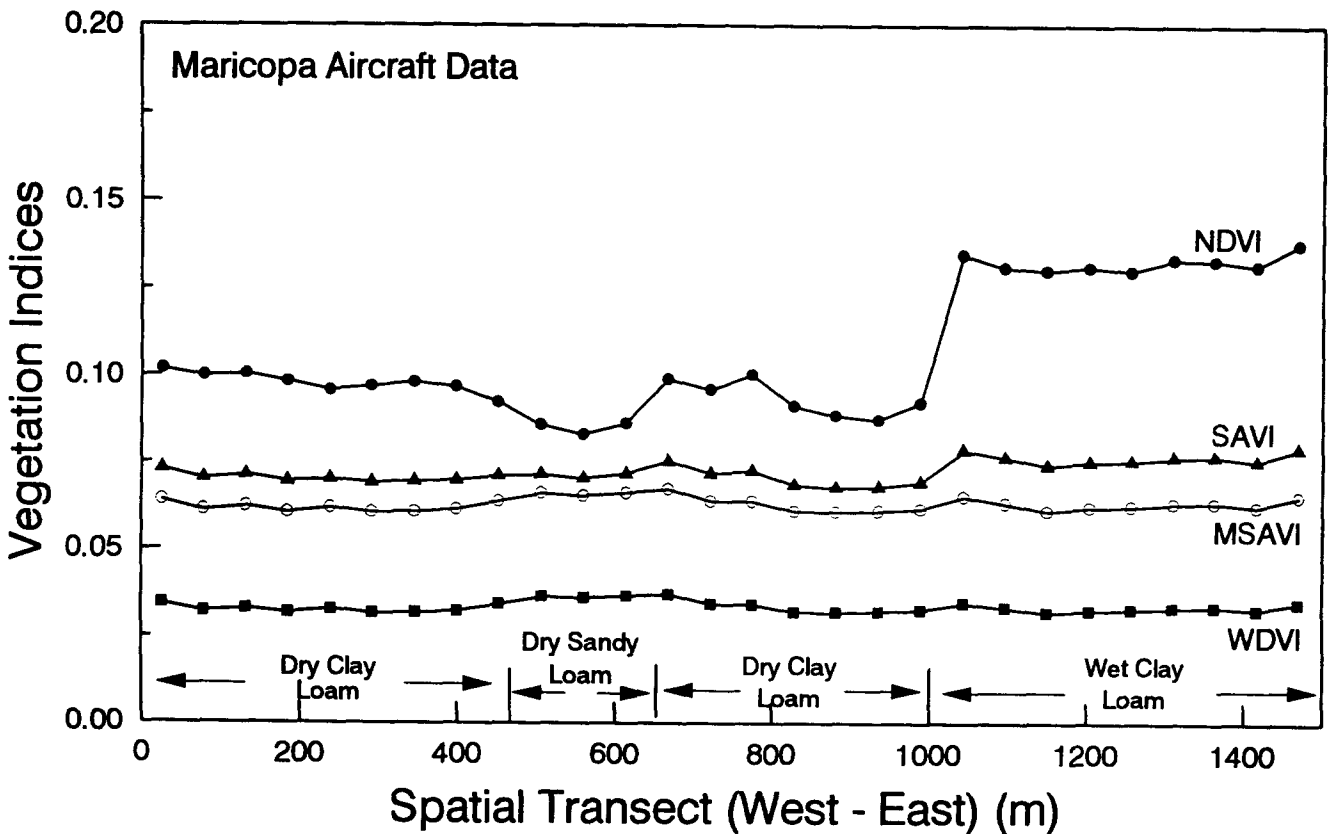


Figure 6. Demonstration of soil background influences on the MSAVI, SAVI, WDV, and NDVI using MAC aircraft data.

the SAVI for the two data sets. The MSAVI reached almost the maximum value of 1 for the MAC aircraft data, while NDVI, SAVI, and WDV reached only 0.9, 0.78, and 0.62, respectively. Once again, in Figure 7, one can see an “apparent” greater sensitivity of the NDVI to green vegetation, similar to that encountered in Fig. 2b. The saturation of the NDVI at higher amounts of vegetation is also evident at day of year (DOY) 200, whereas all other indices continue to rise for at least two more weeks. This was also evident in Figure 2b.

DISCUSSION AND CONCLUSIONS

In conclusion, the aircraft and ground-based data sets collected over cotton showed a greater dynamic range

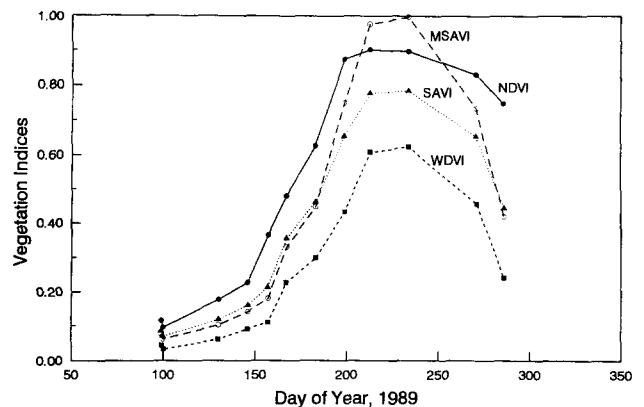
response by the MSAVI as well as a lowered sensitivity to the soil background spatial and temporal variations. By raising the vegetation signal and simultaneously lowering soil-induced variations, the MSAVI can be said to be a more sensitive indicator of vegetation amount over that of SAVI as well as other indices presented here. Both the dynamic range and “noise” related effects are important to consider in the evaluation and improve-

Table 1. Dynamic Ranges of Vegetation Indices Using Two Cotton Data Sets

VIs	Huete et al. (1985) Cotton Data			MAC (1989) Aircraft Data		
	Min	Max	δ^a	Min	Max	δ^a
NDVI	0.13	0.89	0.76	0.10	0.90	0.80
SAVI	0.06	0.75	0.69	0.07	0.78	0.71
WDVI	0.03	0.63	0.60	0.03	0.62	0.59
MSAVI	0.05	0.92	0.87	0.06	0.99	0.94

^a δ = max - min.

Figure 7. Temporal dynamic responses of the MSAVI, SAVI, WDV, and NDVI to cotton growth using MAC aircraft data.



ment of vegetation indices, particularly for large scale (and global) studies that encompass considerable soil spatial and temporal variations unrelated to the vegetation signal.

The MSAVI is a modified version of the SAVI, which replaces the constant soil adjustment factor, L , with a self-adjusting L . Although the L factor does not appear in the second version of the MSAVI, an iterative L function was used in the derivation of the MSAVI₂. Consequently, both MSAVI and SAVI use soil-adjustment factors. The difference is that SAVI uses a manual-adjustment L , while the MSAVI uses a self-adjustment L . The former requires a prior knowledge about vegetation densities in order to use an optimal L value in SAVI equation, while the latter automatically adjusts its L values to optimal.

The signal to noise ratio was higher for the MSAVI than that of other vegetation indices (including the original version of SAVI). This suggests that the use of the L functions not only increased the vegetation dynamic responses, but also further reduced the soil background variations. At higher vegetation covers, L approaches 0, and the MSAVI behaved like the NDVI, while at low vegetation covers, the L approaches 1, and the MSAVI behaved like PVI or WdVI. For intermediate vegetation cover, the MSAVI is similar to the SAVI.

The use of the product of NDVI and WdVI in the empirical L expression may not be the best function and may not work well for other canopy types. At low vegetation covers, the WdVI is less affected by soil background, while the NDVI is strongly affected. The product in the L function may, therefore, inherit more soil noise than if WdVI were used alone. At high vegetation cover, the use of NDVI alone may be better, since the NDVI is much less affected than the WdVI at high vegetation density. However, the inherited noise in L (if not canceled out by the product) would become secondary when used as an adjustment factor in the MSAVI. L may also be derived by induction that works quite well over a wide range of vegetation types and conditions.

The inductive L has boundary conditions of 0 and 1 and the resulting MSAVI is only a function of the reflectances. The dynamic range of the inductive MSAVI was slightly lower than that of the empirical L function due to the difference in the L boundary conditions. However, both versions of the MSAVI proved to be satisfactory with respect to the vegetation sensitivity and soil noise reduction.

Finally, the MSAVI was validated using ground and aircraft-based radiometric measurements only. It needs to be validated further with other remote sensing data, particularly with satellite data. In addition, only soil background effects were examined here. The sensitivi-

ties to other external factors such as sensor viewing angles, atmospheric conditions, and solar illumination conditions ought to be tested thoroughly in order to evaluate the MSAVI on vegetation monitoring. Further work will be needed to ensure these effects are accounted for when interpreting the results of the MSAVI.

This work was completed in the frame work of an EOS interdisciplinary investigation. It was a joint effort of the exchange student programs of the EOS-Hydrology project. One author (J. Q.) was funded by NASA Project NAWG-1949, Eos-NAWG-2425, MODIS Contract NAS5-31364, and LERTS, and another (A. C.) was funded by LERTS and the University of Arizona Hydrology and Water Resources Department. The authors greatly appreciated Dr. Ray Jackson for his encouragement and advice and Dr. M. S. Moran for her advice and comments. J. Q. was grateful to LERTS and the Soil and Water Science Department of the University of Arizona for the working environments.

REFERENCES

- Asrar, G., Fuchs, M., Kanemasu, E. T., and Hatfield, J. L. (1984), Estimating absorbed photosynthetic radiation and leaf area index from spectral reflectance in wheat, *Agron. J.* 76:300-306.
- Baret, F., and Guyot, G. (1991), Potentials and limits of vegetation indices for LAI and APAR assessment, *Remote Sens. Environ.* 35:161-173.
- Baret, F., Guyot, G., and Major, D. (1989), TSAVI: A vegetation index which minimizes soil brightness effects on LAI or APAR estimation, in *12th Canadian Symposium on Remote Sensing and IGARSS'90*, Vancouver, Canada, 10-14 July.
- Clevers, J. G. P. W. (1988), The derivation of a simplified reflectance model for the estimation of leaf area index, *Remote Sens. Environ.* 25:53-70.
- Huete, A. R. (1988), A soil-adjusted vegetation index (SAVI), *Remote Sens. Environ.* 25:295-309.
- Huete, A. R. (1989), Soil influences in remotely sensed vegetation-canopy spectra, in *Theory and Applications of Optical Remote Sensing* (G. Asrar, Ed.), pp 107-141.
- Huete, A. R., Jackson, R. D., and Post, D. F. (1985), Spectral response of a plant canopy with different soil backgrounds, *Remote Sens. Environ.* 17:37-53.
- Jackson, R. D., and Huete, A. R. (1991), Interpreting vegetation indices, *J. Preventative Vet. Med.* 11:185-200.
- Major, D. J., Baret, F., and Guyot, G. (1990), A ratio vegetation index adjusted for soil brightness, *Int. J. Remote Sens.* 11(5): 727-740.
- Qi, J., Huete, A. R., Moran, M. S., Chehbouni, A., and Jackson, R. D. (1993), Interpretation of vegetation indices derived from multi-temporal SPOT images, *Remote Sens. Environ.* 44:89-101.
- Richardson, A. J., and Wiegand, C. L. (1977), Distinguishing vegetation from soil background information, *Photogramm. Eng. Remote Sens.* 43:1541-1552.
- Wiegand, C. L., Richardson, A. J., Escobar, D. E., and Gerbermann, A. H. (1991), Vegetation indices in crop assessments, *Remote Sens. Environ.* 35:105-119.