Responses of Spectral Indices to Variations in Vegetation Cover and Soil Background

Stella W. Todd and Roger M. Hoffer

Abstract
The primary objective of this study was to evaluate the effects of variations in soil texture and moisture upon the green vegetation index (GVI) and the normalized difference vegetation index (NDVI) for targets with specific vegetation cover amounts and varying soil backgrounds. The second objective was to understand the difference in information provided between NDVI and GVI relative to estimating vegetation cover. The third objective was to investigate the information contained within the wetness/brightness plane in relation to soil background characteristics and variations in percent canopy cover. Brightness and wetness were estimated using the Tasseled Cap brightness index (BI) and wetness index (WI). A simple two-component model of soil and green vegetation reflectance was used to simulate the effects of three soil texture types (sand, silt, and clay) and two soil moisture classes on greenness, brightness, and wetness values.

The results indicated that, for the same vegetation percent cover class, targets with more moist soil backgrounds displayed higher NDVI values than did targets with more dry soil backgrounds. In contrast, GVI values were much less influenced by soil background variation. WI values increased as green vegetation cover increased for all soil backgrounds. The largest increase was for dry soil backgrounds. BI values either increased or decreased as green vegetation cover increased, depending on soil background brightness. BI and WI provided complimentary spectral information.

Introduction
One of the most promising applications of remote sensing imagery is for the estimation of aboveground plant biomass and/or plant cover across multiple geographic scales. For global or continental scales, the Advanced Very High Resolution Radiometer (AVHRR) is currently the only realistic option for biomass estimation. Its large spatial extent, daily temporal coverage, and low cost facilitate seasonal and yearly estimates of biomass production. Limitations include a relatively large spatial resolution (1 km) and few spectral reflectance channels (one visible and one near-infrared). Biomass across large geographic areas has primarily been estimated using the normalized difference vegetation index (NDVI), which is based on the ratios of red and near-infrared channels (Rouse *et al.*, 1973). The NDVI formulation is identical for AVHRR, the Multispectral Scanner (MSS), and the Thematic Mapper (TM) satellite sensors, with the only variation being the width of visible and near-infrared wavebands.

For small geographic regions, sensors other than AVHRR can be employed for biomass estimation, which overcome some of AVHRR's spatial and spectral resolution limitations. The MSS with its smaller spatial resolution (80 m) and increased spectral reflectance resolution (two visible and two near-infrared) expanded the capacity of satellite sensors to characterize physical scene reflectance characteristics. Vegetation and soil indices utilizing four spectral channels were now possible. The four-band Tasseled Cap orthogonal linear transformation, developed by Kauth and Thomas (1976), produced a plane of data in which the primary axis aligned with soil reflectance variation (brightness) and the secondary axis aligned with green vegetation (greenness) variation. Virtually all of the soil variation observed is arranged in a long cigar-shaped cloud centered along the brightness axis for MSS data.

The TM satellite further increased the spatial (30 m) and spectral resolution (three visible, one near-infrared, and two mid-infrared) for characterizing physical object reflectances. The mid-infrared TM bands are coincident with the water absorption regions of the spectrum (Hoffer, 1978). Mid-infrared band reflectances are incorporated into the Tasseled Cap dimension of total scene reflectance (brightness). They are also contrasted with the near-infrared bands to form the dimension of scene moisture (wetness). In TM space, soil variation is represented by both the brightness and wetness axes, creating a two-dimensional plane (Crist, 1983; Crist and Cicone, 1984). The wetness axis is sensitive to both soil moisture and vegetation moisture (Crist and Cicone, 1984).

We were interested in determining which spectral indices would be useful for characterizing variation in green vegetation biomass across small regions with heterogenous soil background characteristics. We therefore focused on TM indices for this study. One of the major problems in determining the quantity of green vegetation using satellite sensors is that the spatial resolution of the sensors is generally larger than the vegetation objects. This is true for TM as well as for MSS and AVHRR. Therefore, pixel measurements represent an integration of subpixel reflectance components of soil, vegetation, the reflectance interaction between soil and vegetation, and shadows, all modified by atmosphere (Richardson and Weigand, 1990; Jasinski and Eagleson, 1989).

Several research results have been reported concerning the effects of soil background on ratio-based and orthogonal vegetation index values (Elvidge and Lyon, 1985; Gardner and Blad, 1986; Huete and Jackson, 1987; Huete *et al.*, 1984; Huete *et al.*, 1985; Tueller, 1987). Previous studies showed that backgrounds containing dark colored soils and other low reflecting soils displayed higher TM ratio-based vegetation index values (NDVI) than did light colored soils or other high reflecting soils, given the same vegetation cover (Elvidge and Lyon, 1985; Huete *et al.*, 1985; Huete and Jackson, 1987; Huete and Jackson, 1988; Heilman and Boyd, 1986). Conversely, previous research showed that TM GVI values were

Department of Forest Sciences, Colorado State University, Fort Collins, CO 80523 (stellat@lamar.colostate.edu).

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lower for backgrounds containing dark colored or low reflecting soils than for light colored or high reflecting soils, given the same vegetation cover (Huete *et al.*, 1985).

Soil reflectance properties depend on numerous soil characteristics. Field soil reflectance is reduced, particularly in the visible portion of the spectrum, when organic matter, iron oxides, or moisture content is high (Hoffer, 1978). The near-infrared and mid-infrared regions of the spectrum are also affected. Soil has an easily distinguishable characteristic reflectance pattern in the visible, near-infrared and mid-infrared wavelengths. Soil reflectance patterns are generally linear with increasing reflectance as wavelengths increase from visible to mid-infrared.

The characteristic soil reflectance pattern is easily distinguishable from green vegetation (Bartolucci, 1977). Green vegetation reflectance is low for the visible bands (particularly red), with a sharp increase in reflectance in the near-infrared portion of the spectrum. Reflectance is also low in the mid-infrared regions associated with water absorption. Physical vegetation properties vary with plant species, environmental stress, and phenology (Hoffer, 1978). Pigmentation and moisture content change as a plant senesces. A loss of chlorophyll pigmentation produces higher visible reflectance, particularly in the red region of the spectrum (Hoffer, 1978). Plant drying also increases visible and mid-infrared reflectance.

Some of the soil induced effects on vegetation indices have been attributed to additional NIR irradiance underneath and in-between canopies due to NIR scattering and transmission properties of the canopy, with intermediate canopies displaying the largest effect (Huete, 1988). Canopy scattering is small with low vegetation cover while the soil signal is small with high vegetation cover. Soil reflects some of the scattered and transmitted NIR flux back toward the sensor, depending upon the soil's reflectance properties.

NIR absorbtance, transmittance, scattering, and reflectance can be modeled based on the physical properties of plant canopies and soil (Suits, 1972; Verhoeff and Bunnik, 1981; Verhoef, 1984; Verhoef, 1985). These models were developed for homogeneous plant canopies assuming fixed (Suits model) or arbitrarily (SAIL model) inclined leaves (Suits, 1972; Verhoeff and Bunnik, 1981). In a comparative study, the Suits and SAIL models were poorly to moderately correlated, respectively, with observed reflectance measurements for homogeneous crops (Badhwar *et al.*, 1985). Modeling heterogeneous canopies would require even greater complexity than homogeneous canopies.

Another approach to modeling canopy reflectance conceptualizes clumps of vegetation as three-dimensional geometric elements against a flat soil background (Jasinski and Eagleson, 1989). This type of model assumes that soil and vegetation are independent contributors to spectral reflectance. In addition, the effects of canopy shadows can be modeled based on plant size, shape, and geometric distribution. The simplest case is at the nadir view angle where the shadow component drops out. The geometric model can be applied to landscapes using statistical plant distribution patterns (Li and Strahler, 1985).

Previous studies have described methods to minimize soil background effects given *a priori* knowledge about canopy cover (Huete, 1988) or soil background characteristics (Jackson, 1983). Canopy cover information is often unknown. Realistically, real-time soil background reflectance information is not available. Soil moisture conditions are dynamic and spatially variable even within a small region. Therefore, vegetation indices which are insensitive to differing soil backgrounds are desirable for determining vegetation biomass and/or vegetation cover on small fields or across regions.

While a study by Huete *et al.* (1985) provided some insights into the limitations of NDVI and GVI for estimating vegetation cover, it focused only on soil brightness variation. Within TM data, soil reflectance characteristics are distributed in a plane defined by wetness as well as brightness. Therefore, normalization to minimize soil related influences on vegetation indices should be based on the more expanded soil plane information (Huete and Tucker, 1991). Understanding the relationship of both soil type and moisture content with brightness and wetness dimensions and their interaction with greenness values for pixels containing both vegetation and soil components should precede the development of soil normalization applications. This study will investigate wetness as well as brightness characteristics in relation to vegetation index responses to variations in green vegetation canopy cover as well as variations in soil type and moisture content, using a simple two component model of soil and vegetation.

Objectives

The first objective of this study was to evaluate the effects of variations in soil texture and moisture upon the green vegetation index (GVI) and the normalized difference vegetation index (NDVI) for targets with specific vegetation cover amounts and varying soil backgrounds. The second objective was to understand the difference in information provided between NDVI and GVI relative to estimating vegetation cover. The third objective was to investigate the information contained within the wetness and brightness axes in relation to soil background characteristics and variations in percent canopy cover.

Methods

A composite reflectance (soil and green vegetation) was estimated using a simple two-component model, assuming that observations were from nadir, the sun was near zenith, and vegetation and soil components contributed proportionately to the total reflectance. Vegetation and soil components were modeled as linear, non-interacting mixtures. Variation in soil type and moisture content produced variations in soil reflectance properties. Vegetation reflectance properties were those of green healthy vegetation only. Variations in reflectances due to vegetation senescence, soil color or organic matter, and radiative scattering and shadows produced by vegetation were not considered. This model is based upon a simple two component geometric model used and described by Jasinski and Eagleson (1989), and is formulated as follows:

$$R(l) = mR_c(l) + (1-m)R_s(l)$$

where l is the wavelength, m is the percentage of pixel covered with canopy, $1-m$ is the percentage of pixel occupied by soil background, $R_c(l)$ is the average reflectance of vegetation of a given pixel, and $R_s(l)$ is the average reflectance of soil background of a given pixel.

Reflectance values were generated from vegetation and soil spectral reflectance curves described by Hoffer (1978). The basic soil and vegetation curves of Bartolucci (1977) were used, in addition to reflectance curves for soils with low and high moisture contents: Chelsea sand at 0 to 4 percent and 22 to 32 percent moisture, Pembroke clay at 2 to 6 percent and 35 to 40 percent moisture (Hoffer and Johannsen, 1969), and Newtonia silt loam at 0.8 percent and 20.2 percent moisture content (Bowers and Hanks, 1965). Although it is arguable that utilizing published reflectance curves is less accurate than obtaining field measurements, this method provided an inexpensive way to estimate the variation in reflectance values expected from a variety of soil backgrounds. This was adequate for our purpose of modeling the effects of diverse soil background reflectances on vegetation indices. We assumed that percent reflectance was a relative estimator of DN values. The actual relationship between DN values and percent reflectance will be impacted by atmospheric properties, sun angle, and detector response functions. DN values were generated for 8-bit data so that spectral indices would produce values in ranges typical of actual TM data. Reflectance values were multiplied by 255 for this purpose. Table 1 shows the simulated TM DN values that were calculated from the soil and vegetation percent reflectance curves using the TM wavelength regions.

After DN values were simulated for all canopy covers, values for the normalized difference vegetation index (NDVI), the brightness index (BI), the green vegetation index (GVI), and the wetness index (WI) were generated from the following equations:

$$\mathrm{NDVI} = (\mathrm{TM4} - \mathrm{TM3})/(\mathrm{TM4} + \mathrm{TM3})$$

$$\mathrm{BI}^*(\text{Landsat 5}) = 0.2909(\mathrm{TM1}) + 0.2493(\mathrm{TM2}) + 0.4806(\mathrm{TM3}) + 0.5568(\mathrm{TM4}) + 0.4438(\mathrm{TM5}) + 0.1706(\mathrm{TM7}).$$

$$\mathrm{GVI}^*(\text{Landsat 5}) = -0.2728(\mathrm{TM1}) - 0.2174(\mathrm{TM2}) - 0.5508(\mathrm{TM3}) + 0.7221(\mathrm{TM4}) + 0.0733(\mathrm{TM5}) - 0.1648(\mathrm{TM7}).$$

$$\mathrm{WI}^*(\text{Landsat 5}) = 0.1446(\mathrm{TM1}) + 0.1761(\mathrm{TM2}) + 0.3322(\mathrm{TM3}) + 0.3396(\mathrm{TM4}) - 0.6210(\mathrm{TM5}) - 0.4186(\mathrm{TM7}).$$

*(Crist *et al.*, 1986)

Results

BI Response

Moist sand, silt, and clay soils were associated with low BI values. Silt at 0.8 percent moisture content displayed the highest BI value for all vegetation covers up to 80 percent. Brightness and wetness indices exhibited a discernable response pattern relative to variations in vegetation cover. Brightness values either increased or decreased with increasing vegetation cover depending on the initial bare soil's brightness values. For example, BI noticeably decreased as percent cover increased for high reflecting, drier soils (sand, 0 to 4 percent moisture; silt, 0.8 percent moisture; and clay, 2 to 6 percent moisture), because the brightness value of the vegetation was much less than that of the underlying soil (Figures 1 and 2). For low reflecting, moist sand and clay, BI increased slightly as vegetation cover increased, indicating these soils were duller than vegetation (Figures 1 and 2). Moist silt displayed BI values similar to green vegetation (Figures 1 and 2).

WI Response

Moist sand, silt, and clay soils were associated with high (less negative) WI values. Wetness index values consistently increased as vegetation cover increased over all six soil combinations: three soils, at two moisture contents each (Figures 3 and 4). Dry soils responded most markedly (Figures 3 and 4). The moist silt displayed a lower wetness value than either sand or clay for vegetation covers up to 80 percent (Figures 3 and 4). Differences in soil type were generally less important than differences in soil moisture, in their impact on WI.

Table 1. Simulated TM Waveband DN Values for Different Vegetation and Soil Characteristics (percent reflectance * 255)

	wavebands*					
Veg/soil Parameter	blue	green	red	NIR	MIR	MIR
Basic Veg	5.30	10.63	8.49	97.74	43.55	32.95
Basic Soil	20.15	27.54	37.18	63.75	98.81	86.06
Sand 0-4%	40.06	23.69	60.10	74.69	119.65	131.43
Sand 22-32%	8.11	19.89	21.85	29.12	41.90	30.96
Silt 0.8%	38.25	53.22	73.19	95.04	155.32	157.64
Silt 20.2%m	16.40	21.85	30.14	42.89	75.40	60.97
Clay 2-6%m	21.57	40.37	72.24	80.76	131.76	93.51
Clay 35-40%m	7.85	16.68	29.76	31.00	40.37	16.68

*(blue 0.45-0.52μm, green 0.52-060μm; red 0.63-0.69μm, NIR 0.76-090μm, MIR 1.55-1.75μm, MIR 2.08-2.35μm)

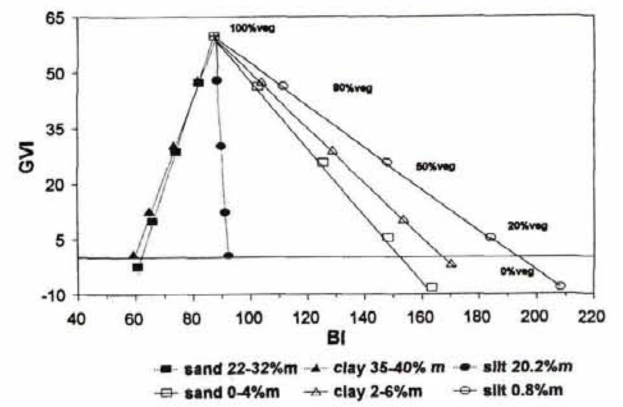

Figure 1. Simulated green vegetation index (GVI) values and brightness index (BI) values as a function of 0, 20, 50, 80, and 100 percent vegetation cover. Lines display changes in BI values as well as GVI values as vegetation cover increases from 0 to 100 percent.

GVI Response

GVI values increased with increasing vegetation cover (Figure 5). GVI values became less variable as percent vegetation cover increased. At 0 percent vegetation cover, dry sand and silt produced the lowest GVI values. The highest initial GVI values were for moist sand and silt. Variation in GVI values decreased as vegetation cover increased. At 80 percent cover, GVI values for the six combinations of three soils at two moisture contents were almost identical. Variations in soil

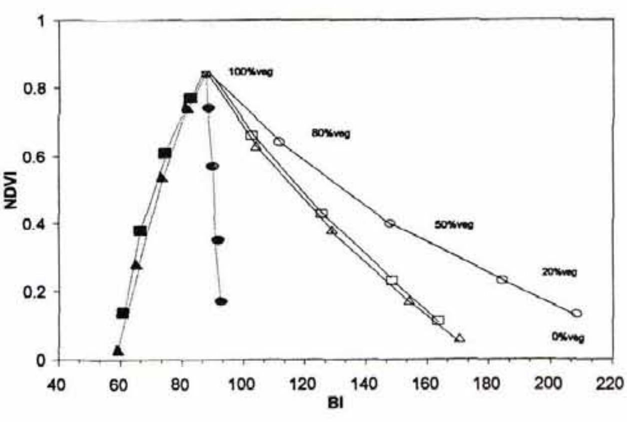

Figure 2. Simulated normalized difference vegetation index (NDVI) values and brightness index (BI) values as a function of 0, 20, 50, 80, and 100 percent vegetation cover. Lines display changes in BI values as well as NDVI values as vegetation cover increases from 0 to 100 percent.

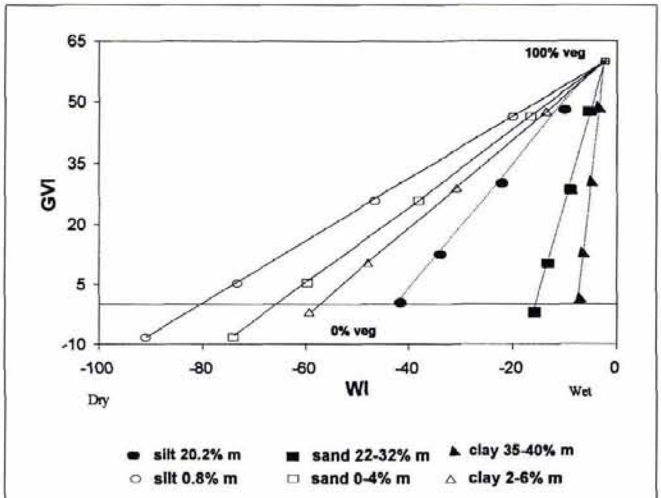

Figure 3. Simulated green vegetation index (GVI) values and wetness index (WI) values as a function of 0, 20, 50, 80, and 100 percent vegetation cover. Lines display changes in WI values as well as GVI values as vegetation cover increases from 0 to 100 percent.

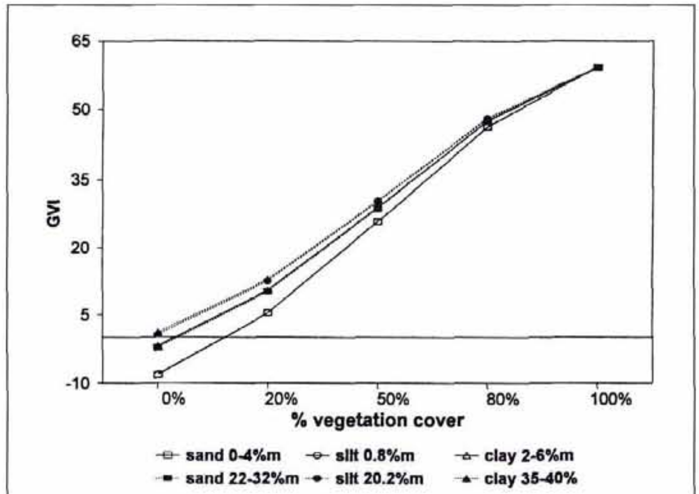

Figure 5. Simulated TM green vegetation index (GVI) values for sand, silt, and clay at two moisture contents, for 0, 20, 50, 80, and 100 percent vegetation cover, using a two-component model of soil and vegetation. Lines display changes in GVI for the same soil type and moisture content, with increasing percent vegetation cover.

background had only a minor effect on GVI values, which were generally distributed parallel to both the brightness and wetness axis for all vegetation cover values (Figures 6 and 7). For low vegetation covers, bright or dry soil backgrounds depressed GVI values slightly given the same vegetation cover. This depression was most evident for silt soils and least evident for clay soils.

NDVI Response

As expected, NDVI increased with increasing percent vegetation cover (Figure 8). The variation in NDVI values increased as percent vegetation cover increased from 0 percent to 20 percent. For vegetation covers between 20 percent and 80 percent, NDVI values were higher for the more moist soils than for the drier soils at the same percent vegetation. Variations in NDVI were lowest for either high or low canopy covers. NDVI values associated with low reflecting soils were elevated compared with those associated with high reflecting, brighter soils (Figure 9). NDVI increased substantially as WI increased, for the same vegetation cover (Figure 10). Differences in soil type were less important than differences in soil moisture, in their impact on NDVI.

Soil effects on the NDVI were most evident for 20 percent to 80 percent vegetation cover. There obviously were no observable soil effects at 100 percent vegetation cover in the

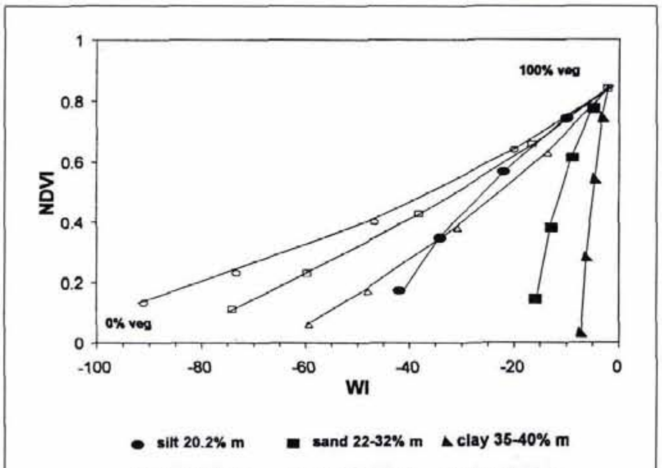

Figure 4. Simulated normalized difference vegetation index (NDVI) values and wetness index (WI) values as a function of 0, 20, 50, 80, and 100 percent vegetation cover. Lines display changes in WI values as well as NDVI values as vegetation cover increases from 0 to 100 percent.

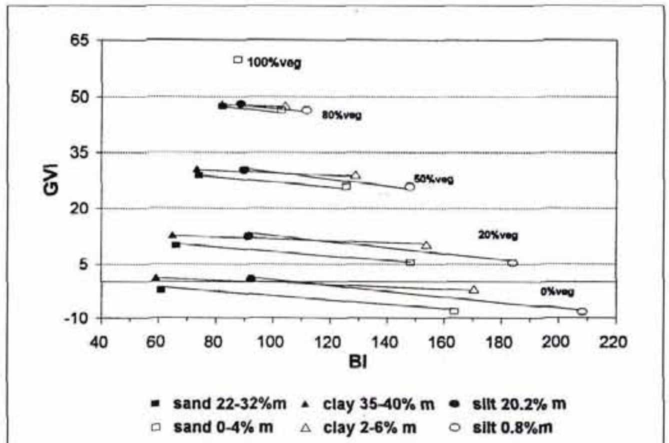

Figure 6. Simulated green vegetation index (GVI) values for sand at 0 to 4 percent and 22 to 32 percent moisture contents, silt at 0.8 percent and 20.2 percent moisture contents, and clay at 2 to 6 percent and 35 to 40 percent moisture contents, as a function of 0, 20, 50, 80, and 100 percent vegetation cover, and associated brightness index (BI), modified from Todd and Hoffer (1993). Lines display differences in index values for the same soil type at two different moisture contents.

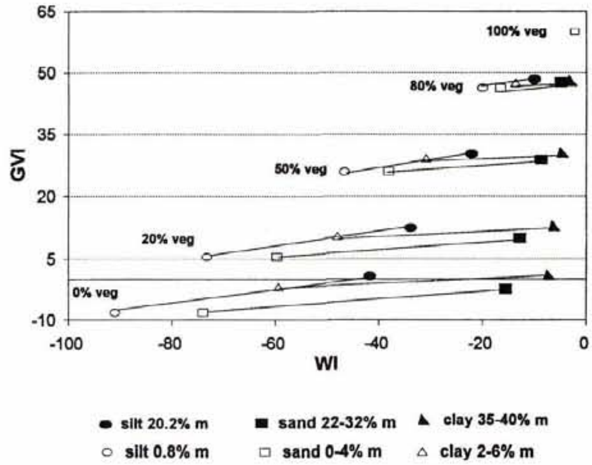

Figure 7. Simulated green vegetation index (GVI) values for sand at 0 to 4 percent and 22 to 32 percent moisture contents, silt at 0.8 percent and 20.2 percent moisture contents, and clay at 2 to 6 percent and 35 to 40 percent moisture contents, as a function of 0, 20, 50, 80, and 100 percent vegetation cover, and associated soil wetness index (WI). Lines display differences in GVI and WI for the same soil type at two different moisture contents.

simple mixed component model in that soil was not a component of the signature at 100 percent vegetation cover. Soil background characteristics noticeably affected NDVI values.

Discussion

GVI was less variable than NDVI in predicting green vegetation cover when soil backgrounds varied by type and moisture content, when using a simple two-component model. GVI appears more stable for predicting green vegetation cover with variations in soil type and soil moisture. The need for soil background normalization appears to be minimal for GVI as compared to NDVI. For the same percentage of vegetation cover, NDVI values decreased with highly reflecting soil back-

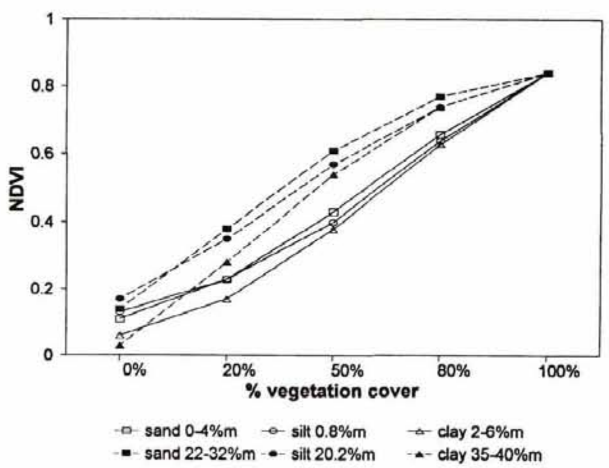

Figure 8. Simulated TM normalized difference vegetation index (NDVI) values for sand, silt, and clay at two moisture contents, at 0, 20, 50, 80, and 100 percent vegetation cover, using a two-component model of vegetation and soil. Lines display changes in NDVI for same soil type and moisture content, with increasing percent vegetation cover.

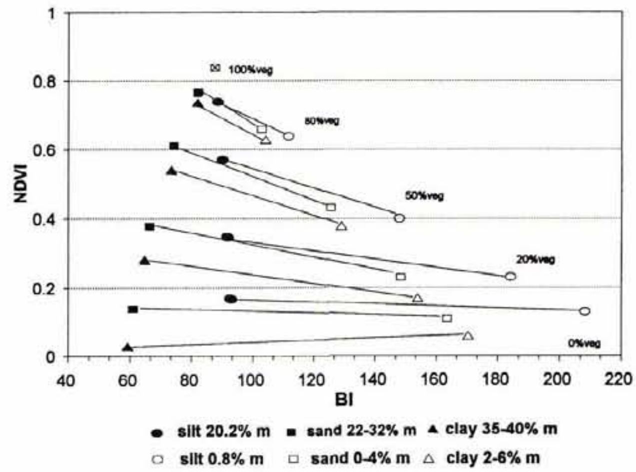

Figure 9. Simulated normalized difference vegetation index (NDVI) values for sand at 0 to 4 percent and 22 to 32 percent moisture contents, silt at 0.8 percent and 20.2 percent moisture contents, and clay at 2 to 6 percent and 35 to 40 percent moisture contents, as a function of 0, 20, 50, 80, and 100 percent vegetation cover, and associated brightness index (BI). Lines display differences in NDVI and BI for the same soil type at two different moisture contents.

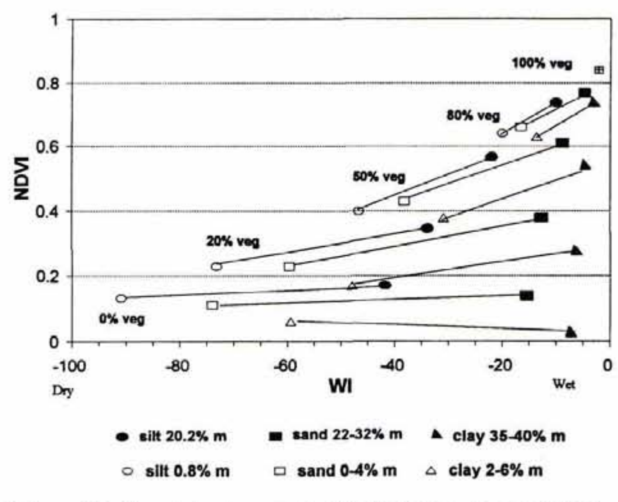

Figure 10. Simulated normalized difference vegetation index (NDVI) values for sand at 0 to 4 percent and 22 to 32 percent moisture contents, silt at 0.8 percent and 20.2 percent moisture contents, and clay at 2 to 6 percent and 35 to 40 percent moisture contents, as a function of 0, 20, 50, 80, and 100 percent vegetation cover, and associated wetness index (WI). Lines display differences in NDVI and WI for the same soil type at two different moisture contents. Drier soils were consistently associated with more negative WI values than were wetter soils of the same soil type.

grounds while GVI values remained generally parallel to brightness and wetness axes.

The six-band GVI contains more spectral information than does the two-band NDVI. BI and WI provide unique, complimentary information about spectral features. Wetness and brightness axes provide information not only relevant to soil background characteristics, but also to vegetation cover. Healthy green vegetation absorbs mid-infrared radiation and therefore produces high wetness values. It's low visible and mid-infrared reflectance also produces relatively low brightness values. Because the GVI directly responds to changes in green vegetation percent cover and does not appear to be overly affected by soil background reflectance, it is preferable to brightness or wetness for estimating vegetation cover percentage.

Soil background reflectance information can be derived from WI and BI if target pixels containing only soil can be located. But obtaining real-time soil background information is more problematic. Soil moisture content was much more important than soil type in determining soil reflectance characteristics. Therefore, information about the soil moisture, which is both dynamic and spatially heterogeneous, would be useful in estimating soil background reflectance characteristics.

The information content of the three Tasseled Cap indices is complimentary. The GVI, along with BI and WI, characterize important scene features: greenness, brightness, and wetness. The use of the three Tasseled Cap indices provides opportunities to better understand the dynamics of spectral variation across landscapes in relation to heterogeneous soil and vegetation components than does a single index of greenness.

Our modeled results for GVI were different from those observed in a field study using a single plant species with varying vegetation cover (Huete *et al.*, 1985). Using field measurements of reflectance, Huete *et al.* (1985) found higher six-band GVI values for vegetation targets which had a background of high reflecting soils. The soil-induced effects increased up to 60 percent vegetation cover. They suggested that soil background spectral responses may be dependent upon the transmittance or scattering properties of NIR radiation by the overlying canopy. An increase in total NIR reflectance without an accompanying decrease in RED reflectance should theoretically elevate GVI values based on the coefficient values for RED and NIR wavebands. NDVI values should also theoretically increase under the same circumstances based on the NDVI formula. But, in fact, the opposite effect is observed for NDVI in field studies, as well as in the present modeling study, so canapy and soil interactions do not explain NDVI behavior.

The impact of soil background on NDVI values found in the present study were similar to those of other investigators who found NDVI values decreasing with highly reflecting soil backgrounds: Elvidge and Lyon (1985), Huete and Jackson (1987), Huete and Jackson (1988), and Heilman and Boyd (1986). The similarity between the results of these studies and ours suggest that a simple two-component geometric model such as was used in the present study may help explain the observed soil effects for NDVI in field studies.

The simple two-component model of proportional soil and vegetation reflectances used in the present study assumed that vegetation and soil components behaved as non-interacting objects. This model was useful for understanding how select spectral indices mathematically behave for a limited number of soil and vegetation physical characteristics. Our study did not consider soil color or organic matter, vegetation senescence, or shadows. We focused on the signals produced by green vegetation and soil and ignored the "noise" produced by vegetation canopy scatter. Canopy scatter can be estimated with radiative transfer models if extensive information about canopy and soil structure is known. But, these models are still being refined for homogeneous canopies, and their application to landscapes with heterogeneous plant canopies is untested. We need to better understand the relative impact of canopy scatter on spectral indices of landscape features at different spatial scales and for different plant communities.

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