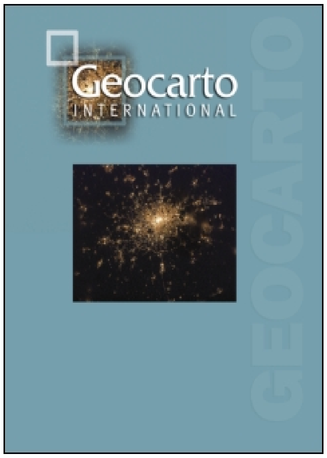

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Vegetation Indices: Advances Made in Biomass Estimation and Vegetation Monitoring in the Last 30 Years

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Vegetation Indices: Advances Made in Biomass Estimation and Vegetation Monitoring in the Last 30 Years

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Abstract

During the last 30 years Vegetation Indices (VI) have been extensively used for tracing and monitoring vegetation conditions, such as health, growth levels, production, water and nutrients stress, etc. In this paper the characteristics of over 20 VIs based on the VNIR spectrum are described in order to provide the reader with adequate material to form a picture of their nature and purpose. It is not, though, a review article due to the fact that a huge volume of work exists all over the world and a simple lining up of the related papers would not contribute to an understanding of the usefulness of VIs. A limited number of review work is included, together with research results from various operational and research applications of VI for wheat damage assessment in Northern Greece.

Introduction

One of the major applications of remote sensing in environmental resources management and decision making is the detection and quantitative assessment of green vegetation. In this sense, vegetation analyses and detection of changes in vegetation patterns and structure are keys to natural resources assessment and monitoring.

Healthy canopies of green vegetation have a very distinct interaction with certain portions of the electromagnetic spectrum. In the visible regions, chlorophyll causes strong absorption of energy, primarily for use in photosynthesis. This absorption peaks in the red and blue areas of the visible spectrum, while the green area is reflected by chlorophyll, thus leading to the characteristic green appearance of most leaves. At the same time, the near-infrared region of the spectrum is strongly reflected through the internal structure of the leaves. It is this strong contrast, particularly between the reflected energy in the red and near-infrared regions of the electromagnetic spectrum that has been the focus of a large variety of attempts to develop quantitative indices of vegetation condition using remotely sensed imagery.

The proposed vegetation indices (VI) are applicable to both low and high spatial resolution multispectral satellite sensors, such as NOAA AVHRR, Terra MODIS, Landsat TM and MSS, SPOT HRV/XS, and all the others that acquire data in the visible and near-infrared regions. They have been used in a variety of contexts to assess green biomass and have also been used as a proxy to overall environmental change, especially in the context of drought and land degradation risk assessment (Kogan, 1990; Tripathy *et al*., 1996; Liu and Kogan, 1996). Consequently, special interest has been focused on the assessment of green biomass in arid environments where soil background becomes a significant component of the signal detected.

A wide review of VIs can be found in several textbooks (Bastiaanssen, 1998; Jensen, 2000; Jensen, 2005). The aim of this paper, however, is not to evaluate the extensive amount of work carried out on VIs, but rather to provide the reader with a clear understanding of their nature and usefulness. With this in mind, a description is provided of the characteristics of over 20 VIs used on the VNIR spectrum. A limited amount of review work, together with the research results of various operational and research applications using VIs have been included in this paper.

Classification of Vegetation Indices

Jackson and Huete (1991) classify VIs into two groups: (1) *slope-based* and (2) *distance-based* VIs. To appreciate this distinction, it is necessary to consider the position of vegetation pixels in a two-dimensional graph (or *bi-spectral plot*) of red versus infrared reflectance (Figure 1). The slope-based VIs are simple arithmetic combinations that focus on the contrast between the spectral response patterns of vegetation in the red and near-infrared portions of the electromagnetic spectrum. In contrast to the slope-based group, the distance-based group measures the degree of vegetation present by gauging the difference of any pixel's reflectance from the reflectance of bare soil. A key concept here is that a plot of the positions of bare soil pixels of varying moisture levels in the bi-spectral plot will tend to form a line (known as a *soil line*). As vegetation canopy cover increases, this soil background will become progressively obscured, with vegetated pixels showing a tendency towards increasing perpendicular distance from this soil line. All of the members of this group (such as the Perpendicular Vegetation Index-PVI) thus require that the slope and intercept of the soil line be defined for the image under consideration.

To these two groups of vegetation indices, a third group can be added, namely *orthogonal transformation* VIs. Orthogonal indices undertake a transformation of the available spectral bands to form a new set of uncorrelated bands within which a green vegetation index band can be defined. The Tasseled Cap transformation is perhaps the most well-known of this group.

The Slope-Based VIs

Slope-based VIs are combinations of the visible red and the near infrared bands and are widely used to generate vegetation indices. Their values indicate both the state and abundance of green vegetation cover and biomass. The slope-based VIs include the RATIO, NDVI, SAVI, RVI, NRVI, TVI, CTVI, TTVI, and EVI (Table 1).

The Ratio Vegetation Index (RATIO) was originally described by Birth and McVey (1968). It is calculated by simply dividing the reflectance values of the near infrared band by those of the red band. The result clearly captures the contrast between the red and infrared bands for vegetated pixels, with high index values being produced by combinations of low red (because of absorption by chlorophyll) and high infrared (as a result of leaf structure) reflectance. In addition, because the

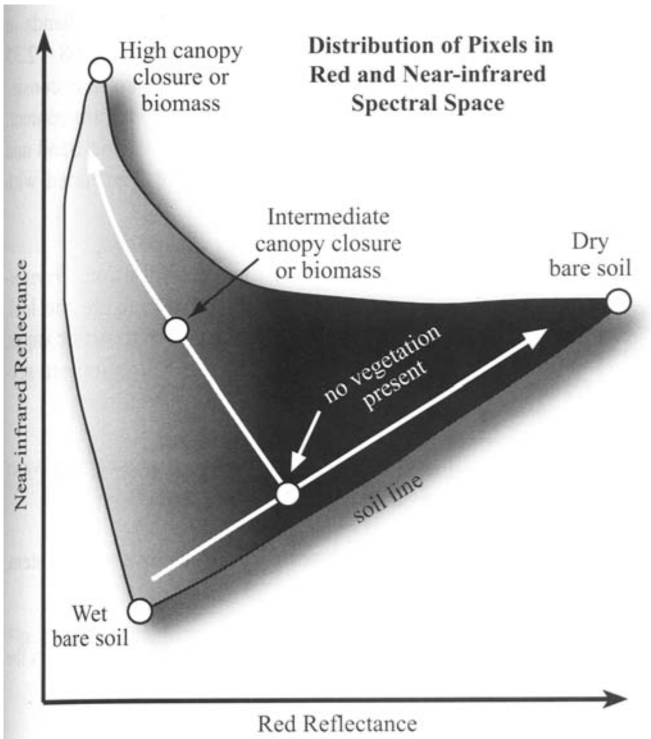

Figure 1 Bi-spectral plot in the near-infrared and red domain of all pixels in a scene. All pixels are found in the grey shaded area. Bare soil fields are located along the soil line. The greater the biomass and/or canopy cover, the greater the near-infrared

index is constructed as a ratio, problems of variable illumination as a result of topography are minimized. However, the index is susceptible to division by zero errors and the resulting measurement scale is not linear. A study regarding its efficiency has been published by Vaiopoulos *et al*. (2004).

The Normalized Difference Vegetation Index (NDVI) was introduced by Rouse *et al*. (1974) in order to produce a spectral VI that separates green vegetation from its background soil brightness using Landsat MSS digital data. It is expressed as the difference between the near infrared and red bands normalized by the sum of those bands. It is the most commonly used VI as it retains the ability to minimize topographic effects while producing a linear measurement scale. In addition, division by zero errors are significantly reduced. Furthermore, the measurement scale has the desirable property of ranging from -1 to 1, with 0 representing the approximate value of no vegetation, and negative values non-vegetated surfaces.

The Soil-Adjusted Vegetation Index (SAVI) was proposed by Huete (1988). It is intended to minimize the effects of soil background on the vegetation signal by incorporating a constant soil adjustment factor L into the denominator of the NDVI equation. L varies with the reflectance characteristics of the soil (e.g., colour and brightness). The author provides a graph from which the values of L can be extracted. The L factor chosen depends on the density of the vegetation one wishes to analyse. In cases of very low vegetation, the use of an L factor of 1.0 is suggested, for intermediate 0.5, and for high densities 0.25. Eastman (2003) suggests that the best L value to select is where the difference between SAVI values for dark and light

Table 1 Slope-based Vegetation Indices

SLOPE BASED VEGETATION INDICES	Explanation of symbols	Author
$RATIO = \frac{NIR}{R}$	NIR = near infrared, R = red, B = blue, L = Soil adjustment factor, C_1 and C_2 are constants, G is a gain factor	Birth and McVey (1968)
$NDVI = \frac{NIR-R}{NIR+R}$		Rouse *et a*l. (1974)
$SAVI = \frac{NIR-R}{(NIR+R)}(1+L)$		Huete (1988)
$TVI = \sqrt{\frac{(NIR-R)}{NIR+R}} + 0.5$		Deering *et a*l. (1975)
$CTVI = \frac{NDVI+0.5}{ABS\ (NDVI+0.5)} \times \sqrt{ABS\ (NDVI+0.5)}$		Perry and Lautenschlager (1984)
$TTVI = \sqrt{ABS\ (NDVI+0.5)}$		Thiam (1997)
$RVI = \frac{R}{NIR}$		Richardson and Wiegand (1977)
$NRVI = \frac{RVI-1}{RVI+1}$		Baret and Guyot (1991)
$EVI = G\frac{NIR-R}{NIR+C_1R-C_2B+L}(1+L)$		Huete *et a*l. (1999)

soil is minimal. For L = 0, SAVI equals NDVI. For L = 1, SAVI approximates PVI.

The Transformed Vegetation Index (TVI) (Deering *et al*., 1975) modifies NDVI by adding a constant of 0.5 to all its values and taking the square root of the results. The constant 0. 5 is introduced in order to avoid operating with negative NDVI values. The calculation of the square root is intended to correct NDVI values that approximate the Poisson distribution and introduce a normal distribution. Moreover, there is no technical difference between NDVI and TVI in terms of image output or active vegetation detection.

The Corrected Transformed Vegetation Index (CTVI) was proposed by Perry and Lautenschlager (1984) to correct the TVI. Clearly adding a constant of 0.5 to all NDVI values does not always eliminate the negative values in the square root, as NDVI can be as low as -1. Thus, the CTVI is intended to resolve this situation by dividing the term [NDVI + 0.5] by its absolute value [ABS(NDVI + 0.5)] and multiplying the result by the square root of the absolute value [SQRT(ABS (NDVI + 0.5))]. This suppresses the negative NDVI. Given that the correction is applied in a uniform manner, the output image using CTVI should have no difference with the initial NDVI image or the TVI whenever TVI properly carries out the square root operation. The correction is intended to eliminate negative values and generate a VI image that is similar to, if not better than, the NDVI.

However, Thiam (1997) indicates that the resulting image of the CTVI can be very “noisy” due to an overestimation of the greenness. He suggests ignoring the first term of the CTVI equation in order to obtain better results. This is done by simply taking the square root of the absolute values of the NDVI in the original TVI expression to have a new VI called **Thiam’s Transformed Vegetation Index (TTVI)**.

The simple **Ratio Vegetation Index** (RVI) was suggested by Richardson and Wiegand (1977) as graphically having the same strengths and weaknesses as the TVI (see above), while computationally being more simple. RVI is clearly the inverse of the standard Ratio Vegetation Index (RATIO).

The Normalized Ratio Vegetation Index (NRVI) is a modification of the RVI by Baret and Guyot (1991) whereby the result of [RVI - 1] is normalized over [RVI + 1]. This normalization is similar in effect to that of the NDVI, i.e., it reduces topographic, illumination and atmospheric effects and creates a statistically desirable normal distribution.

The Enhanced Vegetation Index (EVI) was developed by the MODIS Land Discipline Group for use with MODIS data. It is a modified NDVI with a soil adjustment factor L and two coefficients C_1 and C_2, which describe the use of the blue band in correction of the red band for atmospheric aerosol scattering. This VI has improved sensitivity to high biomass regions and reduced atmospheric influence (Huete *et al*., 1999).

The Distance-Based VIs

This group of vegetation indices is derived from the Perpendicular Vegetation Index (PVI) discussed in detail below. The main objective of these VIs is to cancel the effect of soil brightness in cases where vegetation is sparse and pixels contain a mixture of green vegetation and soil background. This is particularly important in arid and semi-arid environments.

The procedure is based on the soil line concept as outlined earlier. The soil line represents a description of the typical signatures of soils in a red/near-infrared bi-spectral plot (Figure 1). It is obtained through linear regression of the near-infrared band against the red band for a sample of bare soil pixels. Pixels falling near the soil line are assumed to be soil, while those far away are assumed to be vegetation. Distance-based VIs (Table 2) using the soil line require the slope (b) and intercept (a) of the line as inputs to the calculation.

Unfortunately, there has been a remarkable inconsistency in the logic with which this soil line has been developed for

Table 2 Distance-based Vegetation Indices

SLOPE BASED VEGETATION INDICES	Explanation of symbols and author
$PVI = \sqrt{(Rgg5 - Rp5)^2 + (Rgg7 - Rp7)^3}$	Where Rp is the reflectance at a vegetation spot for Landsat bands MSS5 and MSS7, and Rgg is the reflectance of soil background (Richardson and Wiegand, 1977)
$PVI1 = \frac{(bNIR\text{-}R) + a}{\sqrt{b^2 + 1}}$	NIR = reflectance in the near infrared band R = reflectance in the visible red band a = intercept of the soil line b = slope of the soil line (Perry and Lautenschlager, 1984)
$PVI2 = \frac{(NIR\text{-}a) * (R + b)}{\sqrt{1 + a^2}}$	Similar to PVI (Bannari *et al*., 1996)
$PVI3 = apNIR - bpR$	pNIR = reflectance in the near infrared band pR = reflectance in the visible red band a = intercept of the soil line b = slope of the soil line (Qi *et al*., 1994)
$DVI = gMSS7 - MSS5$	g = the slope of the soil line MSS7 = reflectance in the near infrared 2 band MSS5 = reflectance in the visible red band (Richardson and Wiegand, 1977)
$AVI = 2.0\ MSS7 - MSS5$	Similar to DVI (Ashburn, 1978)
$TSAVI1 = \frac{a(NIR - a)\ (R - b)}{R + a * NIR - a*b}$	NIR = reflectance in the near infrared band (expressed as reflectances) R = reflectance in the visible red band (expressed as reflectances) a = slope of the soil line b = intercept of the soil line (Baret *et al*., 1989)
$TSAVI2 = \frac{a(NIR - aR - b)}{R + aNIR - ab + 0.08\ (1 + a^2)}$	Similar to TSAVI1 (Baret and Guyot, 1991)
$MSAVI1 = \frac{NIR - R}{NIR + R + L}(1 + L)$	NIR = reflectances in the near infrared band R = reflectances in the visible red band L = 1 -2 NDVI * WDVI (Qi *et al*., 1994)
$MSAVI2 = \frac{2pNIR + 1 - \sqrt{(2pNIR + 1)^2 - 8(pNIR - pR)}}{2}$	pNIR = reflectance of the near infrared band pR = reflectance of the red band (Qi *et al*., 1994)
$WDVI = pNIR - \gamma pR$	pNIR = reflectance of near infrared band p*R* = reflectance of visible red band γ = slope of the soil line (Richardson and Wiegand, 1977; Clever, 1988)

specific VIs. One group requires the red band be the independent variable and the other requires the near-infrared band be the independent variable for the regression.

The Perpendicular Vegetation Index (PVI) suggested by Richardson and Wiegand (1977) is the parent index from which this entire group is derived. The PVI uses the perpendicular distance from each pixel coordinate to the soil line (Figure 1). Attempts to improve the performance of the PVI have yielded three other indices suggested by Perry and Lautenschlager (1984), Bannari *et al*., (1996), and Qi *et al*. (1994).

PVI1 was developed by Perry and Lautenschlager (1984) who argued that the original PVI equation is computationally intensive and does not discriminate between pixels that fall to the right or left side of the soil line (i.e., water from vegetation). Given the spectral response pattern of vegetation in which the infrared reflectance is higher than the red reflectance, all vegetation pixels will fall to the right of the soil line.

PVI2 Bannari *et al*., (1996) weights the red band with the intercept of the soil line, similar to **PVI3**, presented by Qi *et al*. (1994).

The Difference Vegetation Index (DVI) is also suggested by Richardson and Wiegand (1977) as an easier vegetation index calculation algorithm. The particularity of the DVI is that it weights the near-infrared band by the slope of the soil line. Similar to the PVI1, zero values of DVI indicate bare soil, negative values indicate water, and positive values indicate vegetation.

The Ashburn Vegetation Index (AVI) (Ashburn, 1978) is presented as a measure of green growing vegetation. The values in MSS7 are multiplied by 2 in order to scale the 6-bit data values of this channel to match with the 8-bit values of MSS5. This scaling factor would not apply if both bands were either 7-bit or 8-bit; in this case, the equation is rewritten as a simple subtraction.

The Transformed Soil-Adjusted Vegetation Index (TSAVI-1) was defined by Baret *et al.* (1989) who argued that the SAVI concept is exact only if the constants of the soil line are *a=1* and *b=0*. Because this is not generally the case, the authors transformed SAVI. By taking into consideration the PVI concept, a first modification of TSAVI, designated as TSAVI-1, was proposed. With some resistance to high soil moisture, TSAVI-1 was specifically designed for semi-arid regions and does not perform well in areas with full vegetation cover.

TSAVI was readjusted a second time by Baret and Guyot (1991) with an additional correction factor of 0.08 to minimize the effects of the background soil brightness. The new version was named **TSAVI-2**.

The Modified Soil-Adjusted Vegetation Indices (MSAVI-1 and **MSAVI-2)** suggested by Qi *et al*. (1994) are based on a modification of the *L* factor of the SAVI. Both are intended to better correct the soil background brightness in different vegetation cover conditions. With MSAVI-1, *L* is selected as an empirical function due to the fact that *L* decreases with a decrease of vegetation cover, as is the case in semi-arid lands (Qi, *et al*., 1994). In order to cancel or minimize the effect of the soil brightness, *L* is set to be the product of NDVI and WDVI (described below). Therefore, it displays the opposite trends of NDVI and WDVI.

The second modified SAVI, MSAVI-2, uses an inductive *L* factor to: (i) remove the soil "noise" that was not cancelled out by the product of NDVI by WDVI, and (ii) correct values greater than 1 that MSAVI-1 may have due to the low negative value of [NDVI*WDVI]. Thus, its use is limited for high vegetation density areas.

The Weighted Difference Vegetation Index (WDVI) has been attributed to Richardson and Wiegand (1977) and Clevers (1988). Although simple, WDVI is as efficient as most of the slope-based VIs. The effect of weighting the red band with the slope of the soil line is maximization of the vegetation signal in the near-infrared band and minimization of the effect of soil brightness.

The Orthogonal Transformations

The derivation of vegetation indices has also been approached through orthogonal transformation techniques such as the PCA, the GVI of the Kauth-Thomas Tasseled Cap Transformation and the MGVI of the Wheeler-Misra orthogonal transformation. The link between these three techniques is that they all express green vegetation through the development of their second component.

Principal Components Analysis (PCA) is an orthogonal transformation of *n*-dimensional image data that produces a new set of images (components) that are uncorrelated with one another and ordered with respect to the amount of variation (information) they represent from the original image set.

PCA is typically used to uncover the underlying dimensionality of multivariate data by removing redundancy (evident in inter-correlation of image pixel values), with specific applications in GIS and image processing ranging from data compression to time series analysis. In the context of remotely sensed images, the first component typically represents albedo (in which the soil background is represented), while the second component most often represents variation in vegetative cover. For example, the second component generally has positive loadings on the near-infrared bands and negative loadings on the visible bands. As a result, the green vegetation pattern is highlighted in this component (Singh and Harrison, 1985; Fung and LeDrew, 1988; Thiam, 1997).

The Green Vegetation Index (GVI) of the Tasseled Cap is the second of the four new bands that Kauth and Thomas (1976) extracted from raw MSS images. The GVI provides global coefficients that are used to weight the original MSS digital counts to generate the new transformed bands. The expression of the green vegetation index band, GVI, is written as follows for MSS or TM data:

GVI = [(-0.386 MSS4) + (-0.562 MSS5) + (0.600 MSS6) + (0. 491 MSS7)]

GVI = [(-0.2848 TM1) + (-0.2435 TM2) + (-0.5436 TM3) + (0.7243 TM4) + (0.0840 TM5) + (-0.1800 TM7)]

The negative weights of the GVI on the visible bands tend to minimize the effects of the background soil, while its positive weights on the near infrared bands emphasize the green vegetation signal.

Applications

Selected publications, which are evidence of the extensive use of VIs in the last decades in various applications employing a wide range of sensors and VIs, are explored in this section.

Payero *et al*. (2004) compared 11 vegetation indices in order to estimate plant height and develop its quantitative relationship with VIs. Among the VIs used were NDVI, IPVI (Infrared Percentage Vegetation Index), TVI and RATIO.

Steven *et al*. (2003) used NDVI and SAVI from a range of earth observation satellites currently in operation, such as AVHRR, ATSR-2, Landsat MSS, TM and ETM+, SPOT-2 and SPOT-4 HRV, IRS, IKONOS, SeaWiFS, MISR, MODIS, POLDER, QuickBird, and MERIS. Spectroradiometric measurements were made over a range of crop canopy densities, soil backgrounds and foliage colour. The reflected spectral radiances were convoluted with the spectral response functions of the satellite instruments to simulate their responses. The results indicated that vegetation indices could be interconverted to a precision of 1-2%.

Ferreira and Huete (2004) used MQUALS (light aircraft-based Modland Quick Airborne Looks package, consisting of a spectroradiometer and digital camera), MODIS, AVHRR and Landsat ETM+ in order to investigate VI's ability to differentiate the physiognomies in the Brazilian Cerrado and monitor their seasonal dynamics.

Fensholt (2004) identified and validated net primary production (NPP) model variables from the MODIS sensor, focusing on the semi-arid ecosystem. Two MODIS VIs were evaluated against the NOAA AVHRR NDVI to exploit the improvement of the MODIS sensor quality and also to examine the possibility of establishing an empirical relation in order to reap the full benefit of 20 years' availability of NOAA AVHRR data.

Price *et al*. (2002) evaluated the use of raw Thematic Mapper (TM) band combinations and several derived VIs to determine optimal vegetation indices and band combinations for discriminating among six grassland management practices in eastern Kansas. Tasselled Cap Brightness Index, GVI, Wetness Index, the first three components from Principle Component Analysis (PCA1, 2, 3), NDVI, GR (Green Ratio) and MR (MIR Ratio) were used as VIs.

Huete *et al*. (2002) performed an initial analysis of the MODIS NDVI and EVI performances from both radiometric and biophysical perspectives, using MODIS, airborne radiometric measurements, Landsat ETM+ and in situ field biophysical data collected over four validation test sites. The results showed good correspondence between airborne-measured, top-of-canopy reflectances and VI values with those from the MODIS sensor at four intensively measured test sites.

Gilabert *et al*. (2002) introduced a generalized soil-adjusted vegetation index (GESAVI), theoretically based on a simple vegetation canopy model.

Peddle *et al*. (2001) compared ten vegetation indices for estimating boreal forest biophysical information from airborne data. The authors used Landsat-TM images to test the hypothesis that Spectral Mixture Analysis (SMA) is able to derive the percentage of sunlit crowns, background, and shadows within a remote sensing image pixel. This sub pixel scale information has been shown to consistently provide significantly improved estimates of forest biophysical information such as biomass, leaf area index (LAI) and NPP compared to that provided by NDVI using airborne and satellite imagery. To accomplish the work, ten different VIs were used to predict forest biophysical parameters, the results of which were compared with those obtained from SMA using airborne multispectral data from the NASA COVER Project (Superior National Forest, Minnesota, USA). In all cases, SMA shadow fraction provided significantly better results than those of any VI, with improvements in the order of 20% compared to the best VI result. In most cases, one or more of the new vegetation indices provided a small to moderate improvement compared to NDVI, with NDVI and SAVI-1 performing best among the VIs, possibly due to the inclusion of background reflectance.

Eklundhe *et al.* (2001) investigated the relationship between Landsat ETM+ sensor data and leaf area index in a boreal conifer forest. The authors used Landsat ETM+ and detailed field data from a coniferous forest area, dominated by Norway spruce and Scots pine. A forest canopy reflectance model was used to simulate stand reflectances in the Landsat ETM+ wavelengths bands in order to investigate the theoretical response to LAI changes. The analysis showed that the response to changes in LAI was the strongest in the visible wavelength bands, particularly in band 3, whereas only a weak response was noted in the near-infrared band and for some vegetation indices (RATIO and NDVI). Statistical relationships between LAI and observed ETM+ reflectances were strongest in band 7.

Based on these examples, it is clear that remote sensing has presented a significant opportunity to study and monitor vegetation and vegetation dynamics. The application of various VIs in a test site located in Northern Greece is shown in Figure 2. Visual interpretation of the VI images can reveal differences in their performances.

Silleos *et al*. (2002) carried out the first operational work to assessing crop damage using space remote sensing techniques (Figure 3). A linear regression model was used to compare remote sensing estimations with field observations. The results of the model application for all the studied fields showed an agreement in 60% of cases, with a deviation of about 10%.

In Figure 4, the orthogonal VIs, namely the Tasseled Cap, Principal Components Analysis, and the decorrelation stretch of the original bands, were produced in order to extract new bands. In all these orthogonal transformations, a green band that was free of soil background effects was produced. This was due to the fact that almost all soil characteristics were ascribed to a brightness band. The results are displayed in a perspective view in order to facilitate visual interpretation.

An important issue to be considered when using VIs is the pre-processing of the images. Radiometric calibration is usually a standard procedure performed by the image distribution companies. Atmospheric correction is essential when biophysical parameters (e.g. biomass, LAI, percent vegetation cover) are extracted from the VIs as final products. Erroneous VI estimations could result in misleading information, often with severe consequences (Jensen, 2005). Also, atmospheric correction is needed when VIs are to be compared with measurements obtained at different times, such as for multi-temporal change detection (Lu *et al*., 2004). On the other hand, the demanding and complex algorithms used for atmospheric correction can be avoided in case of single date dataset (Song *et al*., 2001).

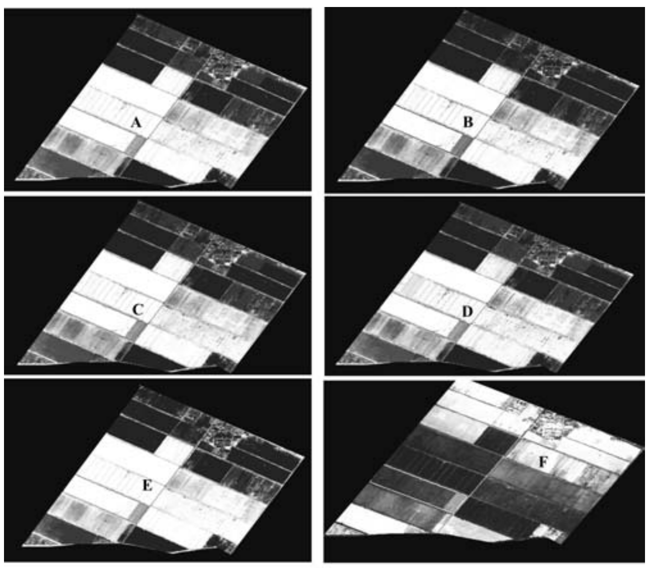

Figure 2 The following indices were estimated in a group of large fields in a test site in Northern Greece: NDVI (A), RVI (band 4/band3) (B), SQRT(IR/R) (C), VI (band4 - band 3) (D), TNDVI (Sqrt NDVI + 0.5) (E), and Iron Oxide (band3/band 1) (F). Bare land, corn and cotton were the main land cover types.

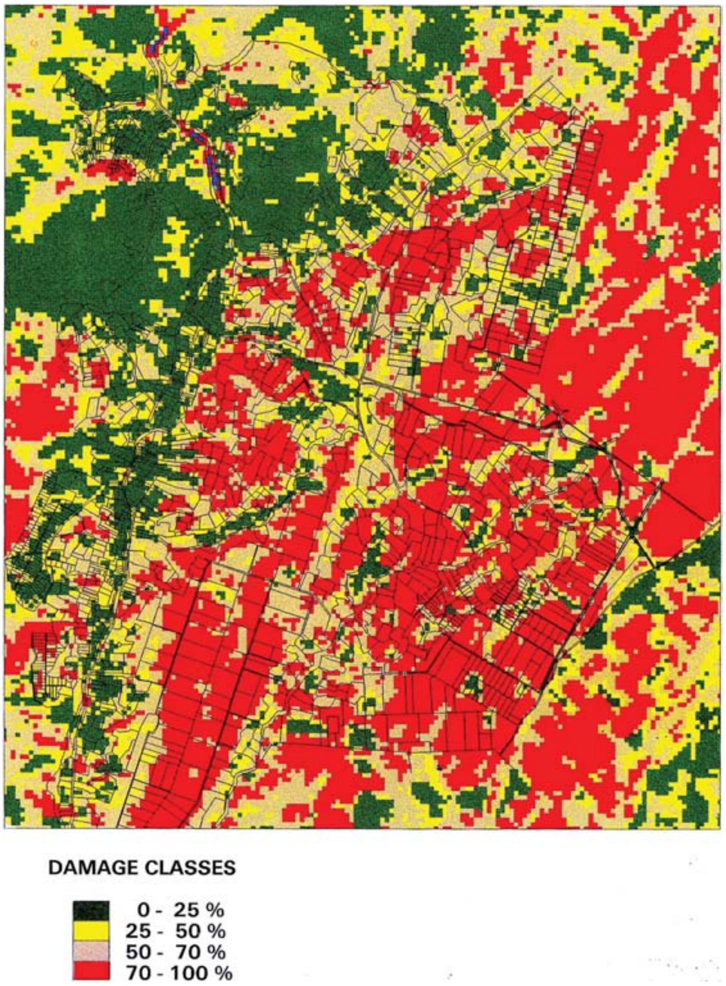

Figure 3 Assessment of damage caused by frost to wheat crops in Northern Greece. The Normalized Difference Vegetation Index (NDVI) was used as main input image in the estimation model. Class 0-25% (green) refers to very low damage, Class 25-50% (yellow) refers to low damage, Class 50-70% (pink) refers to moderate damage, and Class 70-100% (red) refers to severe damage. Source: Silleos *et al*., 2002.

Discussion

The use of any of these transformations depends on the objective of the investigation and the general geographic characteristics of the studied area. In theory, any of these can be applied to any geographic area, regardless of their sensitivity to various environmental components that might limit their effectiveness. In this respect, one might consider applying the slope-based indices, as they are simple to use and yield numerical results that are easy to interpret. However, it is important to note that all slope-based indices, excluding SAVI, have the major weakness of not being able to minimize soil background effects. This means that a certain proportion of their values, negative or positive, represent the background soil brightness. The effect of the background soil is a major limiting factor in certain statistical analyses geared towards the quantitative assessment of above-ground green biomass.

Although there exist indices whose extremes may be much lower and higher than those of the more familiar NDVI, the distance-based VIs have the advantage of being able to minimize the effects of background soil brightness by combining the input bands with the slope and intercept of the soil line. This represents an important quantitative and qualitative improvement in the significance of the indices for all types of applications, particularly for those dealing with arid and semi-arid environments. Despite the large number of vegetation indices currently in use, it is clear that much more needs to be carried out into how these procedures can be applied in different environments.

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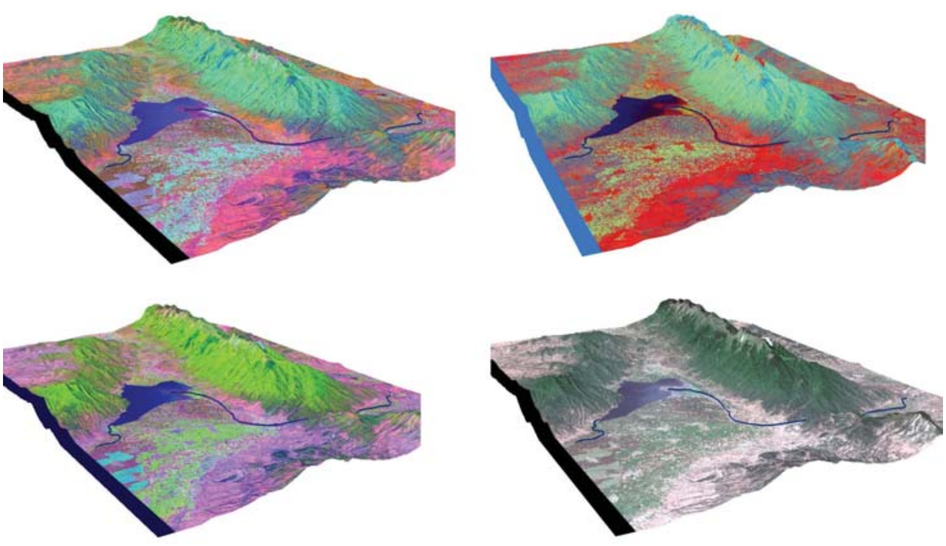

Figure 4 Principal Components Analysis (upper left), Tasseled Cap (upper right), Decorrelation stretch (lower left) and Natural colour (lower right) of a SPOT-5 image in 3D representation of Kerkini wetland in North Greece.

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