Comparisons among Vegetation Indices and Bandwise Regression in a Highly Disturbed, Heterogeneous Landscape: Mount St. Helens, Washington

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Spectral vegetation indices have been used extensively to predict ecological variables, such as percent vegetation cover, above-ground biomass, and leaf-area index. We examined the use of various vegetation indices and multiple linear regression using raw spectral bands for predicting vegetation cover in a landscape characterized by high variability in vegetation cover and soil properties. We were able to improve the explanatory value of several vegetation indices by using regression fitting techniques including log transformations and polynomial regressions. We expected soil-adjusted indices to perform better than nonadjusted indices. However, soil-adjusted vegetation indices based on a ratio of red and near-infrared bands explained 55–65% of the variability in vegetation cover, while two nonadjusted indices each explained 70%. An index using six spectral bands explained 40%. The best multiple regression model used the red and near-infrared bands and explained 75% of the variability in vegetation cover. Among the soil-adjusted indices, an index which used a computed soil line performed best. Ratio-based vegetation indices were less sensitive to shadow influences, but this influence was outweighed by the advantages of multiple regression against original bands. ©*Elsevier Science Inc., 1998*

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INTRODUCTION

On 18 May 1980, Mount St. Helens in the State of Washington erupted with catastrophic, landscape-scale effects (Lipman and Mullineaux, 1981). In a mere 10 min, an area of approximately 500 sq km was devastated, with destruction of substantially all above-ground vegetation (Frenzen, 1992). The ensuing debris, mud, and pyroclastic flows further transformed the landscape from one of lush Pacific Northwest forests into a seemingly barren expanse.

The Mount St. Helens eruptions and subsequent recovery have gathered world-wide public attention. Mount St. Helens National Volcanic Monument remains one of the most visited natural wonders in the Pacific Northwest. The attention from scientists has been at least as great. A compendium published in 1994 listed 637 publications and 69 research abstracts related to the eruptions and their aftermath (Frenzen et al., 1994). However, the research opportunities afforded by Mount St. Helens have gone essentially overlooked by the remote sensing community. The research reported in this article is part of a program designed to exploit some of the remote sensing opportunities afforded by this site.

Mount St. Helens provides a nearly unique opportunity to address some of the more perplexing problems in remote sensing. Since the early days of satellite remote sensing, scientists have sought to use multispectral imagery to measure assorted ecological variables related to vegetation amount. Much of this research has attempted to formulate vegetation indices that can be related to ecological variables such as vegetation cover, biomass, leaf area index, and fraction of absorbed photosynthetically active radiation. Considerable success has been achieved in this area. However, several problems have

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continued to plague remote sensing scientists. Two of these problems that are relevant to Mount St. Helens are: 1) As percentage of vegetation cover decreases vegetation reflectance signals become increasingly contaminated by soil reflectance noise; and 2) Variation in soil reflectances increase the difficulty in adjusting for soil reflectance influences.

The area devastated by the eruption of Mount St. Helens provides the opportunity to address both of these problems in a relatively small landscape. The eruption and subsequent recovery have created substantial heterogeneity both in substrates and vegetation cover amounts. Thus, we have been able to formulate and test hypotheses related to these issues within a range of conditions that might otherwise require regional analysis.

The specific purposes of this study were twofold. First, we sought to formulate and test hypotheses regarding the relative strength of various vegetation indices that either have been widely used or were specifically designed to account for substrate influences. Second, we attempted to determine whether the use of vegetation indices to measure ecological variables has advantages over the use of multiple regression against raw, nonindexed spectral bands. We did not attempt to assess the utility of vegetation indices for other purposes, such as data visualization and data compression.

OVERVIEW OF VEGETATION INDICES AND FORMULATION OF HYPOTHESES

The distinctive spectral properties of green vegetation have long been used by remote sensing scientists to map ecological variables of interest. Jordan (1969) is credited with first combining near-infrared and red spectral responses into a ratio that was then shown to correlate highly with leaf-area index. Since that pioneering work, a vast number of spectral band combinations have been studied as measures of vegetation. These vegetation indices have been variously proposed, modified, analyzed theoretically, compared, summarized, categorized, and criticized. Although it is not our intent to repeat those efforts here, we will review certain vegetation indices to the extent necessary to formulate hypotheses regarding which indices should perform relatively better under the heterogeneous vegetation and substrate conditions found within the Mount St. Helens devastated area.

We have generally divided vegetation indices into two categories, although other categorizations might be appropriate for other purposes. The first type consists of ratio-based indices. The most commonly used of these indices exploit the characteristic chlorophyll absorption by vegetation in the red portion of the spectrum and high reflectance by vegetation in the near-infrared portion (Tucker, 1979). Ratio-based indices include the simple ratio (SR) developed by Jordan (1969), the normalized difference vegetation index (NDVI) developed by Rouse et al. (1973), and various modified versions of NDVI designed to address its sensitivity to factors such as soil variability and atmospheric conditions. The formula for each vegetation index discussed in this article is presented in Table 1.

A second type of indices are soil-line based or orthogonal indices. These indices are based on there being a line in spectral space (assuming two dimensions, a plane in three dimensions, or a hyperplane in higher dimensions) along which bare soils of differing brightness will lie. Vegetation increases perpendicularly to the soil line. Kauth and Thomas (1976) developed their "Tasseled Cap" transformation for Landsat MSS data, the second component of which has become known as the greenness index, which is sometimes called the green vegetation index (GVI). Crist and Cicone (1984) have extended the analysis to six bands of Landsat Thematic Mapper (TM) data (excluding the thermal infrared band). We used the version of this index currently implemented in the Imagine 8.2 image processing software (ERDAS, 1995).

The reader is referred to the original works cited above for more detail on the theory and derivation of these vegetation indices, as well as several excellent reviews contained in the literature (e.g., Rondeaux et al., 1996; Qi et al., 1994; Perry and Latenschlager, 1984). Specific properties of the indices relevant to our study will be discussed below in connection with hypothesis development.

Ratio-Based Indices

The two most widely used ratio-based indices are SR and NDVI. These indices have performed well in many applications, showing high correlations to vegetation cover, above-ground biomass (Tucker, 1979; Elvidge and Lyon, 1985; Anderson et al., 1993), leaf-area index (Running et al., 1986; Spanner et al., 1990), and other ecological variables (e.g., Cihlar et al., 1991; Myneni and Williams, 1994; Yoder and Waring, 1994; Wiegand et al., 1991). Coefficients of determination (R^2) between these variables and ratio-based indices ranging from 0.60 to 0.90 have been reported in many studies (although some studies have had lesser or greater degrees of success). Based on a rational theory for the correlation of SR and NDVI to green vegetation cover, as well as the empirical success of other studies, we formulated a baseline hypothesis:

Hypothesis 1: Vegetation cover within the Mount St. Helens devastated area is significantly correlated to SR and NDVI.

We called this our baseline hypothesis because it referred to the simplest of the vegetation indices, and we formed our further hypotheses relative to Hypothesis 1.

Notwithstanding the observed success of SR and NDVI, these indices were found to have limitations be-

Table 1. Formulae for Vegetation Indices Used in This Article[a]

Index	*Formula*
SR	$SR=\frac{Band\ 4}{Band\ 3}$
NDVI	$NDVI=\frac{Band\ 4-Band\ 3}{Band\ 4+Band\ 3}$
SAVI	$SAVI=1.5\frac{Band\ 4-Band\ 3}{Band\ 4+Band\ 3+0.5}$
OSAVI	$OSAVI=1.16\frac{Band\ 4-Band\ 3}{Band\ 4+Band\ 3+0.16}$
TSAVI	$TSAVI=\frac{a*(Band\ 4-(a*Band\ 3)-b)}{Band\ 3+(a*(Band\ 4-b))+(0.08*(1+a^2))}$ where a=the slope of the soil line and b=the intercept of the soil line
$MSAVI_2$	$MSAVI_2=\frac{(2*Band\ 4)+1-\sqrt{((2*Band\ 4)+1)^2-(8*(Band\ 4-Band\ 3))}}{2}$
GVI	$GVI=-(0.2848*Band\ 1)-(0.2435*Band\ 2)-(0.5436*Band\ 3)+(0.7243*Band\ 4)+(0.0840*Band\ 5)-(0.1800*Band\ 7)$

[a] Band designations are for Landsat TM bands—Band 1=0.45–0.52 μm, Band 2=0.52–0.60 μm, Band 3=0.63–0.69 μm, Band 4=0.76–0.90 μm, Band 5=1.55–1.75 μm, Band 7=2.08–2.35 μm. Band 6, used in the bandwise regression analysis, is 10.4–12.5 μm.

cause of their sensitivity to different substrates (Huete, 1988). Several modified versions of NDVI have been developed, with increasing complexity, to reduce the inherent sensitivity of NDVI to varying substrates. The soil-adjusted vegetation index (SAVI) (Huete, 1988) incorporates an adjustment factor, based on the amount of vegetation, from 0 (for high vegetation) to 1 (for low vegetation). In the absence of extrinsic knowledge, an intermediate adjustment factor of 0.5 has been suggested and generally applied. Our study area is highly variable with respect to vegetation amount, with substantial areas low in vegetation. Therefore, if the rationale behind SAVI is sound, it should perform better than NDVI for Mount St. Helens.

A minor, but potentially important, variation to SAVI has been proposed by Rondeaux et al. (1996). An approach to optimizing the adjustment factor for general applications resulted in a recommended adjustment factor of 0.16, rather than 0.5. The optimized soil-adjusted vegetation index (OSAVI) is the same as SAVI with an adjustment factor of 0.16. Once again, if the rationale behind OSAVI is accepted, we expect OSAVI to out perform SAVI throughout the range of vegetation covers present at Mount St. Helens. However, because of the relatively low average vegetation within the study area, we hypothesized that the higher adjustment factor of SAVI might result in better performance at Mount St. Helens than OSAVI.

Rather than using a universal adjustment factor, the transformed soil-adjusted vegetation index (TSAVI) uses the slope and intercept of the specific soil line of the study area (Baret et al., 1989). Although the adjustment to NDVI is based on the soil line, rather than vegetation amount, the effect is similar in moving the assumed location of the soil line and how vegetation varies from the soil line. TSAVI specifically adjusts to a given study area. As a result, we can expect it to perform better than the "universally" adjusted SAVI and OSAVI. However, we also note that TSAVI assumes that there is a well-defined soil line. With the substrate variability present at Mount St. Helens, this may not be true.

The final ratio-based index we examined was the modified soil-adjusted vegetation index (MSAVI) (Qi et al., 1994). MSAVI is designed to correct a weakness in SAVI in how vegetation responds as it moves away from the soil line. MSAVI has the same conceptual basis as SAVI. However, with MSAVI vegetation isolines (lines of equal vegetation) cross the soil line at varying points. This is believed to more accurately reflect how vegetation spectral responses actually behave. Because of this improvement over SAVI, we expect MSAVI to perform better than SAVI, OSAVI or TSAVI. (For this study, we used the second of the proposed versions, $MSAVI_2$, which does not require an empirically determined soil line.)

Based on the theory presented for each soil-adjusted index and the results observed by the developers of these indices, we can present a second, multi-part hypothesis.

Hypothesis 2: For the Mount St. Helens devastated area, soil-adjusted vegetation indices a) are highly correlated to vegetation cover, b) explain more variation in vegetation cover than nonadjusted indices, and c) perform in increasing ability in the order OSAVI, SAVI, TSAVI, and $MSAVI_2$.

ORTHOGONAL INDICES

Widely used orthogonal vegetation indices are based on a universally predetermined soil line, rather than the inherently assumed soil line underlying NDVI. Therefore, orthogonal indices have not been subject to modifications similar to the soil-adjusted versions of NDVI. The most widely used orthogonal index is the tasseled cap greenness index, or green vegetation index (GVI). By using six bands, rather than the two used in ratio-based indices, the Landsat Thematic Mapper version of GVI has the potential for making greater distinctions in vegetation. In certain cases, perpendicular indices have been found superior in correlations to vegetation variables than ratio-based indices (Huete and Jackson, 1988). However, much of the variability in vegetation versus soil occurs in the red and near-infrared portions of the spectrum, while variation in soil types is often detected in middle infrared bands (Lillesand and Kiefer, 1994). Thus, we postulated that, under conditions of low vegetation cover and substrate heterogeneity, GVI might be more sensitive to soils than ratio-based indices, resulting in reduced ability to distinguish differences in vegetation cover. This leads us to our third hypothesis.

Hypothesis 3: GVI will explain less variability in vegetation cover within the Mount St. Helens devastated area than ratio-based indices.

MULTIPLE REGRESSION APPROACH

Vegetation indices have been advocated for vegetation analysis because they provide a standardized approach to analysis. Although this argument has some appeal, we question its validity when there is a need to estimate or predict ecological variables (as opposed to using indices for data visualization purposes, for example). Rather, if the study requires knowledge of an ecological variable of interest (e.g., above-ground biomass), the researcher must ultimately analyze the relationship between the spectral index used and the ecological variable, generally through a regression analysis. For example, several studies have found high correlations between NDVI and leaf-area index (LAI) (e.g., Running et al., 1986; Spanner et al., 1990; Chen and Cihlar, 1996). However, the nature of the relationship varies with each study so that we cannot say that a certain NDVI generally equals a certain LAI. For example, when we used the two regression formulae published by Spanner et al. (1990) for two different years, and assumed an NDVI value of 0.5, the estimated LAI differed by 5.5% between the two scenes. Chen and Cihlar (1996) showed that the regression formula can differ between seasons.

The use of vegetation indices would seem to unnecessarily constrain the regression analysis. For example, many studies using NDVI or SR fit both a simple linear model (of the form $y=\beta_0+\beta_1 x$, where y=an ecological variable of interest and x=a spectral vegetation index) and test for a curvilinear relationship by using a log-transformed response variable [presented either as $\log(y)=\beta_0+\beta_1 x$ or $y=\beta_0 e^{\beta x}$]. However, these models using vegetation indices are not able to independently model the red and near-infrared responses. Thus, if the red response is curvilinear and the near-infrared is not, a compromise fit is necessary. Further, regression model fitting using band interactions, polynomial terms, and other data transformations are similarly constrained because any function performed on the index affects both bands proportionately and simultaneously. At least one study has found regression on individual bands to explain more variability than regression against NDVI (Ripple, 1994), although the causes of this effect have not been explored. This leads us to our fourth, and final, hypothesis.

Hypothesis 4: Multiple linear regression on individual bands will explain as much or more of the variability in vegetation cover within the Mount St. Helens devastated area than any vegetation index.

STUDY AREA

The 1980 eruptions of Mount St. Helens may be the most heavily documented volcanic eruptions in history. In one sense, the 18 May eruption may be viewed as a single catastrophic event. However, for most ecological purposes it is best viewed as a related suite of disturbance events that resulted in a complex mosaic of disturbed patches. Although minute-by-minute accounts of the events have been presented (e.g., Lipman and Mullineaux, 1981), one paragraph by Franklin et al. (1985, p. 201) provides a thumbnail sketch:

> The 18 May 1980 eruption began at 0832 PDT when a large earthquake triggered a massive avalanche of debris involving the entire upper portion of the mountain. Movement of this mass unroofed the core of the mountain where superheated groundwater flashed to steam, unleashing a blast of steam and rock debris in a 180° arc to the north. Mudflows rampaged through the valley-bottom forests to the west and southeast. Volcanic ash rained from the sky to the northeast of the mountain from the morning of 18 May into the next day. In early afternoon of 18 May and during the subsequent eruptions, pumiceous pyroclastic flows (flows of hot gases and pumice) spilled northward out of the newly formed crater across the deposits left by the avalanche.

The effects were clearly devastating throughout the affected area. Disturbed areas were generally well defined depending on the type of disturbance affecting them. Thus, the resulting landscape is a mosaic of deposits from the debris avalanche, pyroclastic flows, mudflows, downed timber, scorched vegetation, and airfall tephra. Each of these deposits has distinctive characteristics regarding thickness, deposit temperature, and substrate composition (Franklin et al., 1988). As a result, potential spectral properties of the substrate and potential rates of vegetative recovery vary significantly throughout the area.

The specific selection of our study area was dictated by the larger study of which this research is a part. The larger study is examining the natural recovery of the area devastated by the 1980 eruptions. Therefore, the study area was limited to that portion of the devastated area that has not been reforested following the eruption. Large water bodies within the area were also excluded. Figure 1 is a false color composite of the study area using the TM image acquired for this study. The study area consisted of approximately 25,400 ha, or approximately 42% of the area devastated by the eruption.

Vegetation structure and types are not readily summarized for the study area because plant cover is highly variable, within site plant diversity is often high, and successional changes are, in some cases, rapid, making previous reports rapidly obsolete. Early reports of vegetation in blowndown forests reported 0.2% mean canopy cover in 1981, with dominant species primarily herbaceous, including pearly everlasting (*Anaphalis margaritacea*), thistle (*Cirsium* spp.), fireweed and willowweeds (*Epilobium* spp.), ryegrass (*Lolium* spp.), and groundsel (*Senecio* spp.) (Franklin et al., 1985). By 1992, these species had completely covered portions of the landscape (Frenzen, 1992). In subalpine study sites, substantially different results have been reported (del Moral and Bliss, 1993). Recovery has varied depending on the nature of the disturbance, with less than 1% cover reported on pyroclastic flows, under 5% on mudflows, and over 40% on adjacent tephra covered sites. Although there is significant overlap in species composition among these sites, dominance varies greatly. Most abundant species in order of importance in 1990 included on tephra sites bentgrass (*Agrostis diegoensis*), prairie lupine (*Lupinus lepidus*), spreading phlox (*Phlox diffusa*), and Newberry fleeceflower (*Polygonum newberryi*), and on a mudflow Newberry fleeceflower, prairie lupine, and Cardwell's penstemon (*Penstemon cardwelli*). However, there was significant change in the relative importance of species on the mudflow site between 1988 and 1990, emphasizing the rapid changes taking place within the area. Although tree species are not yet of significant influence within the Mount St. Helens devastated area, in some areas late snowpacks at the time of the eruption protected mountain hemlock (*Tsuga mertensiana*), and Pacific silver fir (*Abies amabilis*), scattered alder (*Alnus* spp.), and Douglas-fir (*Pseudotsuga menziesii*) have appeared throughout the area, and some roots of willows (*Salix* spp.) and black cottonwood (*Populus trichocarpa*) that were up-rooted by mudflows and the debris avalanche happened to come to rest at the surface and resprout (Frenzen, 1992).

METHODS

Data Acquisition

The study area was extracted from a 19 August 1995 TM scene (path 46, row 28). We received the data rectified to a Universal Transverse Mercator (UTM) grid using a cubic convolution resampling method.

The study area was subset using a mask created from four GIS layers. The Gifford Pinchot National Forest (GPNF) provided a layer defining the boundaries of the Mount St. Helens National Volcanic Monument (the Monument). Areas outside the Monument were subject to reforestation and were masked from the study area. A stand data layer provided by GPNF was used to exclude the few stands within the Monument that were reforested. A disturbance map prepared by the USGS (Lipman and Mullineaux, 1981) was manually digitized and used to delineate those areas within the Monument that were devastated by the eruptions. Finally, an unsupervised classification of the study area portion of our Landsat scene, using the ISODATA algorithm (ERDAS, 1995), was used to identify large water bodies and exclude them from the study area. The resulting study area image is shown in Figure 1.

Reference data were provided by interpretation of true color aerial photographs (1:15,840) loaned to us by the Monument. The aerial photographs were acquired in late June through late July 1995. Ground visits to the study area were conducted with copies of aerial photographs during summer 1996. During these visits, we delineated examples of different cover conditions on the aerial photographs as an aid to aerial photo interpretation.

Sampling Procedure

Prior to sampling the data, we determined the number of samples necessary to detect differences in vegetation indices of significance. We intended to estimate vegetation cover from the aerial photos in increments of 10%. Therefore, we needed sufficient samples to detect, with 95% confidence, half-width differences of this increment, or 5%. Using the procedures outlined in Montgomery (1991), we determined that 95 sample points would be adequate for all the vegetation indices we examined. This sample size was confirmed by applying the same procedures to our estimates of vegetation cover after our aerial photo interpretation was completed. We acquired 200 sample points to account for the possibility of having to screen out some points and potential curvi-

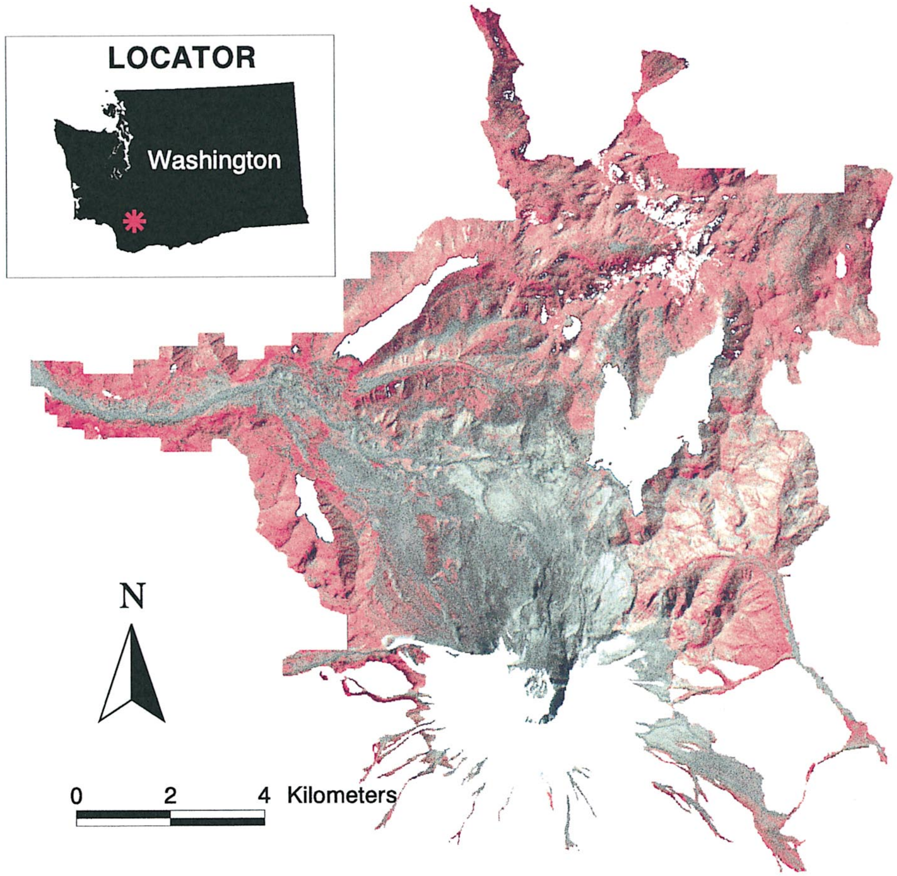

Figure 1. False color composite of study area from Landsat TM image. Band 4 (near infrared) is displayed in red, Band 3 (red) is displayed in green, and Band 2 (green) is displayed in blue. White portions represent areas excluded because they were either 1) outside the devastated area, 2) reforested following the eruption, 3) water, or 4) covered by snow, ice, or fog in an image used in our Mount St. Helens studies.

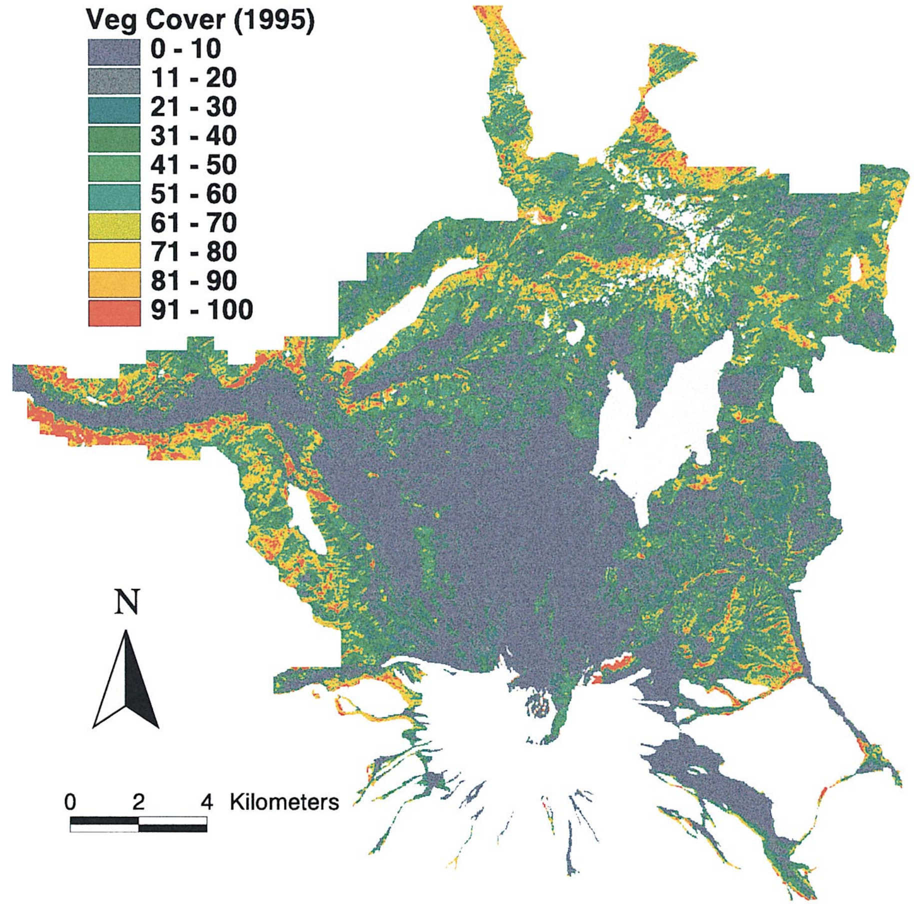

Figure 3. Estimated vegetation cover for the study area based on the application of the final bandwise regression model: Percent vegetation cover=106.00−5.50 (Band 3)+0.048 (Band 3)^2+1.36 (Band 4)−0.0051 (Band 4)^2. p-value<0.0001. Multiple R^2=0.75.

linear relationships between indices or raw TM bands and vegetation cover.

A random set of sample points was generated for the Landsat image using Imagine 8.2 image processing software's accuracy assessment program (ERDAS, 1995). Actual sample plots included a 3×3 pixel area with the sample point at its center. We selected this plot size because we were confident we could accurately locate plots of this size on the 1:15,840 scale aerial photos. We eliminated 32 points for the following reasons: 1) 17 points because they were affected by snow cover, generally within the volcano's crater; 2) eight points because they were too close to the edge of the study area to obtain a three-by-three pixel plot; 3) five points because the aerial photograph was missing; 4) one point because the plot was partially covered by a pond; and 5) one point because it duplicated another point. The final set of 168 points was used for all statistical analysis reported in the article.

For each sample plot we recorded the average digital number (DN) values for each TM spectral band. SR, NDVI, and GVI were computed from these DN values. For the soil-adjusted indices, DN values were transformed to exoatmospheric reflectance units prior to computing index values (Markham and Barker, 1986).

Each sample plot was located on the aerial photos using landmarks identifiable on both the photos and the Landsat image. Plots were marked, labeled, and interpreted. For each plot, we made visual estimates of the percentage of the plot covered by 1) green vegetation and 2) shadow. All estimates were made in 10% increments because we felt this was the reasonable limit of differentiation possible with visual interpretation. Thus, estimates of 1–10% cover were classified as 5%, 11–20% as 15%, and so on. In addition, estimates of 0% cover were recorded.

Statistical Analysis

Prior to performing any regression analysis, and to assist in the selection of regression models, we examined exploratory graphs of the data. Boxplots (Fig. 2) of NDVI, soil-adjusted indices, and GVI showed no significant departures from symmetry. Both SR and percentage of green vegetation cover (Veg Cover) as interpreted from the aerial photos showed some degree of skewing, indicating the potential advantages of data transformation, such as a log transformation. Plots of Veg Cover versus individual bands and indices revealed no unexpected trends, other than some possible curvilinear relationships.

Simple linear regression was used to initiate analyses of individual vegetation indices. For each index, analysis of residual plots and exploratory data plots was used to guide potential improvements in the regression fits. Extra-sum-of-squares *F*-tests were used to evaluate the significance of additional predictor variables, and coefficients of determination (R^2) were examined to determine the amount of variability explained by the best fitting models. To avoid infinite values, for log transformations of variables containing 0 values, a value was added to the variable equal to 0.01 times the smallest incremental value of the variable. (For example, for vegetation cover, which was recorded in integer increments, a value of 0.01 was added to each entry, so that, for a sample plot with no vegetation, we used a value of log 0.01).

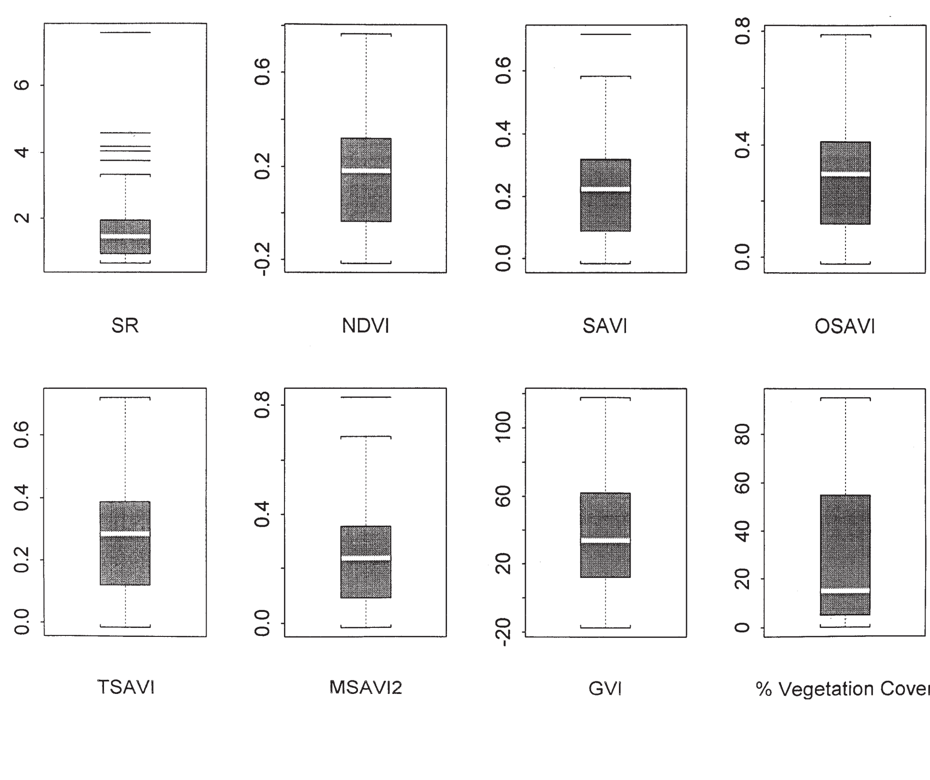

Figure 2. Boxplots for vegetation indices used in this study and percent of green vegetation cover as interpreted from aerial photographs. Plots do not show substantial deviations from symmetry, except for SR and percent of vegetation cover, which are skewed toward lower values, indicating possible advantages of data transformations.

Forward and backward stepwise regression was used with all seven TM bands to provide guidance as to which bands might be significant in predicting Veg Cover. As with vegetation indices, residual and exploratory data plots were used to guide further regression analysis and select the best fit.

RESULTS

Vegetation Indices

Regression models for the vegetation indices using simple linear regression and models with a log-transformed response variable (log-transformed models), as has been traditionally used in vegetation index studies (e.g., Anderson et al., 1993; Chen and Cihlar, 1996; Friedl et al., 1995; Jordan, 1969; Spanner et al., 1990; Yoder and Waring, 1994), were all statistically highly significant (p-values$<$ 0.0001). Table 2 sets forth R^2 for each of these models. NDVI performed best (best R^2=0.65), followed by TSAVI (best R^2=0.62), SR (best R^2=0.60), OSAVI (best R^2= 0.59), $MSAVI_2$ (best R^2=0.55), and SAVI (best R^2=0.55). GVI performed substantially worse (best R^2=0.40).

We found that we could improve on several of these models by including polynomial terms in the final regression models. Other transformations, including additional log, inverse, and square-root transformations, did not improve model results. Table 3 sets forth for Veg Cover regressed against each vegetation index the final regression model selected and the multiple R^2 representing the amount of variation explained by the model. Although some of the final models selected may be more complex than may be desirable for the additional amount of variation explained over the simple models, only by fitting the best regression model can the indices be objectively compared. Choosing a simpler model involves subjective judgments as to what level of model complexity is worthwhile and compromises an objective comparison. The extra-sum-of-squares F-test is a rigorous standard for the addition of predictor variables and only allows the addition of variables that are significant when considered with other variables already in the model.

Table 2. Results of Linear and Log-Transformed Regressions of Percentage of Vegetation Cover against Vegetation Indices[a]

Index	*Linear Regression* R^2	*Log-Transformed Regression* R^2
SR	0.6002	0.3502
NDVI	0.6539	0.5900
SAVI	0.5515	0.5001
OSAVI	0.5912	0.5535
TSAVI	0.6184	0.5796
$MSAVI_2$	0.5546	0.4782
GVI	0.3261	0.4025

[a] Log transformations did not improve any regressions, except for GVI. NDVI explained the most variation (65%) and GVI explained the least (40%).

All final regression models were statistically highly significant (all p-values$<$0.0001). R^2 for the final regression models for the ratio-based vegetation indices ranged from 0.55 to 0.70. Final models for SAVI and $MSAVI_2$ were simple linear regressions. OSAVI and TSAVI included third-degree polynomials, while NDVI included a fourth-degree polynomial. SR was the most complex model and included a log transformation of SR and a third-degree polynomial.

The final regression model for GVI explained substantially less variation than the ratio-based indices, with an R^2 of 0.40. This model included a log-log transformation and no polynomial terms.

Bandwise Regression Models

Simple linear and log-transformed regressions of individual bands against Veg Cover were performed to determine the basic relationships between our variable of interest and the bands. Table 4 sets forth the slopes, p-values, and R^2 for these regressions. Veg Cover varied inversely with all bands except Bands 4 (near-infrared) and 5 (middle-infrared). Each band individually in a simple regression was able to explain at least one-forth of the variation in Veg Cover, except Band 6 (thermal infrared), which explained 18% of the variability, and Bands 5 and 7 (middle-infrared), which explained 2% and 6% of the variability, respectively. Only Band 5 performed better in a log-transformed model, with 11% of variability explained.

Forward stepwise regression on all seven TM spectral bands against nontransformed Veg Cover resulted in a model including Bands 3 (red), 4 (near-infrared), and 6 (thermal infrared). All three bands were highly significant (all p-values$<$0.01), the model was highly significant (p-value$<$0.0001), and the multiple R^2 was 0.69. However, a review of the residual plots from the regression showed potential curvature in the fit. Review of residual plots, exploratory data plots, and stepwise regression including polynomial terms was used to guide further model fitting. The final fitted bandwise regression model was:

$$\text{Veg Cover}=106.00-5.50\ (\textit{Band3})+0.048\ (\textit{Band 3})^2 +1.36\ (\textit{Band 4})-0.0051\ (\textit{Band 4})^2.$$

The regression model and each model term were highly significant (all p-values=0.0135), and the multiple R^2 was 0.75.

Effect of Shadows

We regressed each vegetation index and the final bandwise regression model against the percent of shadow cover in each plot from our aerial photo interpretation to determine the relative sensitivity to shadow influence.

Table 3. Final Regression Models for Percentage of Vegetation Cover Estimated from Aerial Photos against Individual Vegetation Indices[a]

Index	*Regression Model*	*Multiple R^2*
SR	Veg Cover=29.53+312.63 (log SR)+33.18 (log SR)^2−64.12 (log SR)^3	0.6982
NDVI	Veg Cover=9.78+45.35 $NDVI$+105.11 $NDVI^2$+510.84 $NDVI^3$−725.10 $NDVI^4$	0.7040
SAVI	Veg Cover=−1.91+143.77 $SAVI$	0.5515
OSAVI	Veg Cover=3.86−20.50 $OSAVI$+436.40 $OSAVI^2$−327.86 $OSAVI^3$	0.6166
TSAVI	Veg Cover=3.34−33.74 $TSAVI$+540.63 $TSAVI^2$−423.81 $TSAVI^3$	0.6476
$MSAVI_2$	Veg Cover=−0.68+124.65 $MSAVI_2$	0.5546
GVI	log (Veg Cover)=−0.73+0.066 log (GVI)	0.4025

[a] Variables were tested for significance using extra-sum-of-squares F-tests. Ratio-based indices that have not been soil adjusted (SR and NDVI) explained the most variation (70%), followed by soil-adjusted indices (55–65%). GVI explained substantially less variation (40%).

Most shadows were the result of topography and standing dead trees. Live vegetation was rarely tall enough to cause substantial shadowing. Shadow was not significant for any of the ratio-based indices (all p-values>0.5). However, percent of shadow was marginally significant for GVI (p-value=0.13) and highly significant for the bandwise model (p-value=0.003). Of our 168 plots, 44 had at least 5% shadow coverage.

DISCUSSION

Ratio-Based Indices—Hypotheses 1 and 2

As predicted in Hypotheses 1 and 2a, all ratio-based indices were significantly correlated to vegetation cover. This result was expected based on the known biophysical relationships between red and near-infrared reflectance and green vegetation. Further, the variation explained by the best of these individual indices was substantial (65–70%) and well within the range found by previous studies. We expected, in addition to soil variability, several sources of unexplained variation would prevent higher R^2 values, including 1) the estimation of vegetation cover in 10% increments incorporated variation within these ranges, 2) phenologic changes in vegetation during the 1–2 months between aerial photo and satellite image acquisition were not accounted for, and 3) vegetation cover amounts with differing leaf-area indices (LAI) were treated as equal, although it is known that higher leaf-area indices can affect spectral responses.

This last source of variability illustrates an important limitation of the accuracy of vegetation indices. For example, two plots might each have 50% vegetation cover. Within the portion of the plot covered by vegetation, one plot might have an LAI of 2 while the other has an LAI of 4. Because the deeper canopy reflects more near-infrared and absorbs more red, the second plot will have a higher vegetation index, all other factors being equal. We expect this variability might be especially noticeable at high cover amounts, where LAI can continue to increase while increases in percent cover are limited.

All ratio-based indices except SAVI and $MSAVI_2$ incorporated polynomial terms in their best regression fits. It has been found in previous studies that vegetation indices often have a curvilinear fit to LAI because the spectral response saturates beyond a certain point (Ripple, 1985). We believe that the effect of varying leaf areas also results in curvature in our study. We hypothesize that, as vegetation cover increases, leaf area within patches of vegetation also tends to increase. For example, as vegetation initially invades a barren site, most patches are made up of annuals or juvenile plants. Further occupation of the site may include new invaders, but will also result from the expansion and aging of plants already present. This in turn leads to deeper canopies and, especially in the red band, greater absorption for the amount of vegetation cover. For example, percent vegetation cover might increase within a sample plot from 20% to 40%, while in-patch LAI increases from 2

Table 4. Results of Linear and Log-Transformed Regressions of Percentage of Vegetation Cover against Individual Spectral Bands[a]

	Linear Regression			*Log-Transformed Regression*		
TM Band	*Slope*	*p-Value*	*R^2*	*Slope*	*p-Value*	*R^2*
Band 1	−1.69	<0.0001	0.4281	−0.17	<0.0001	0.3605
Band 2	−2.64	<0.0001	0.3343	−0.25	<0.0001	0.2495
Band 3	−1.80	<0.0001	0.4363	−0.16	<0.0001	0.3070
Band 4	0.75	<0.0001	0.2729	0.079	<0.0001	0.2517
Band 5	0.19	0.06843	0.01974	0.050	<0.0001	0.1118
Band 6	−1.81	<0.0001	0.1769	−0.16	<0.0001	0.1120
Band 7	−0.70	0.001375	0.05964	−0.019	0.4342	0.003667

[a] Signs of slope terms indicate positive correlations with Bands 4 and 5 and negative correlations with all other bands. Linear relations provide better fits with all bands except Band 5.

to 4. In this case, the sample plot LAI increases from 0.4 to 1.6, a four times increase in LAI with a two times increase in percent vegetation cover. The response is, therefore, curvilinear.

The simple linear, log-transformed, and final models do not support Hypothesis 2b, but do partially support Hypothesis 2c. Both SR and NDVI explained more variability than any of the soil-adjusted indices. TSAVI did better than SAVI and OSAVI, as hypothesized, but $MSAVI_2$ did not. Finally, OSAVI performed better than SAVI, contrary to expectations.

We believe that our results are explained by the particular soil line present in our study. We estimated the soil line for the soil-adjusted indices to have an intercept of -0.02 and a slope of 1.1. Reflectance values used in calculating these indices range from 0 to 1. Thus, the intercept and slope are not substantially different from 0 and 1, respectively. These soil line parameters are the same as inherently assumed for NDVI and SR and might explain the superior performance of these indices. TSAVI uses the computed soil line parameters and, probably for this reason, performed better than other soil-adjusted indices. OSAVI uses a smaller correction (0.16) than our implementation of SAVI (0.50), and thus diverged less from NDVI. We believe that MSAVI might have performed better if we had used $MSAVI_1$, which uses computed soil line parameters.

Although for our study area SR and NDVI explained more variation than soil-adjusted indices, our analysis indicates that the basis underlying soil-adjusted indices is sound. Adjustment of indices in accordance with soil line parameters improved results. In our case, these parameters were not substantially different than those assumed in unadjusted indices. However, these results also point to the importance of using actual soil line parameters. When "universally" applicable parameters were applied, as in SAVI and OSAVI, results were inferior to unadjusted indices.

GVI—Hypothesis 3

GVI was significantly correlated to vegetation cover but, as predicted by Hypothesis 3, explained substantially less variation than ratio-based indices. The relatively poor response of GVI might be explained by the relatively low vegetation cover (and consequent high substrate exposure) in the study area, combined with the inclusion of middle-infrared bands in the calculation of GVI. The middle-infrared portion of the spectrum is known to be sensitive to soil mineral content. Our study area is characterized by a heterogeneous mosaic of soils poor in organic matter. The reflectances of these soils can be expected to be heavily influenced by mineral content and other substrate characteristics, which vary throughout the area (Hoblitt et al., 1981; Ugolini et al., 1991). The influence of this soil variation on the middle-infrared bands probably added significant noise to the predictor variable, thereby interfering with the relationship that we observed with the red and near-infrared bands.

Table 5. Coefficients of Variation for Each Landsat TM Spectral Band for Bare Soil Sample Plots Indicate the Relative Amount of Variability in Soil Reflectance for Each Band[a]

Band	*Coefficient of Variation*
Band 1	0.12
Band 2	0.17
Band 3	0.22
Band 4	0.09
Band 5	0.36
Band 6	0.03
Band 7	0.31

[a] The middle-infrared Bands 5 and 7 show substantially more variability than other bands.

To confirm the effects of soil on different bands, we calculated the coefficients of variation for each band for all sample plots with no vegetation cover. The results are presented in Table 5. The coefficient of variation normalizes the variability for each band and reflects the relative amount of variability in bare soil for each band. Bands 5 and 7 show substantially more variability in soil response than other bands. Therefore, the inclusion of these bands in an index increases the amount of information contained in the index that is not related to vegetation cover.

Bandwise Regression—Hypothesis 4

The results of our regression against the raw, nonindexed bands supports our hypothesis that this approach has the potential for out performing vegetation indices. The regression model was highly significant and explained between 5% and 20% more variation than the ratio-based vegetation indices. Figure 3 displays the estimated percentage of vegetation cover for the study area based on the final bandwise regression model. An examination of the bandwise regression model explains why this approach can be superior to vegetation indices.

The final bandwise regression model includes only Bands 3 and 4, as do the ratio-based vegetation indices. Thus, like the vegetation indices, the bandwise model is a function of these two bands. Further, as with several of the ratio-based models, the bandwise model includes a term reflecting a curvilinear relationship (the squared red and near-infrared bands). However, the relative influence of the bands and their polynomials is markedly different. For example, the red band has over four times the influence of the near-infrared band, and the squared infrared band has about one-tenth the influence of the squared red band. This might be the result of the red band having a much lower spectral asymptote than the near-infrared band (Ripple, 1985). Thus, the bandwise regression approach allows the decoupling of bands and permits the analyst to discover different relationships between the response variable and each band, including different polynomials, coefficients, and transformations. This flexibility is not possible with regression against vegetation indices. Further, because different biophysical mechanisms control different band responses, there is no reason to believe the relation of individual bands to ecological variables will necessarily be the same.

Using bandwise regression did not require substantial additional time when compared to the use of vegetation indices. With both approaches, we had to perform regression analysis to relate spectral responses to our ecological variable of interest. The only additional step required for the bandwise regression was the selection of spectral bands as predictor variables. This step should take a few hours, at most, which we believe is not a significant increase in time for most projects. Further, this additional step can be eliminated if only the red and near-infrared bands are employed. Although the exclusive use of these two bands is not unreasonable, considering our results and those of previous studies, we believe that testing other spectral bands is prudent. The success in other study areas of multiband orthogonal indices, as well as indices using middle-infrared (e.g., Dusek et al., 1985) and thermal infrared bands (Boyd and Ripple, 1997), indicates that the optimal selection of spectral bands might depend on the individual scene and parameter being estimated.

Models that were not ratio-based (GVI and the bandwise model) were more sensitive to shadows than ratio-based indices. However, in spite of a large percentage of our plots with shadow influence, the bandwise model performed better than the ratio-based indices. Thus, any reduced sensitivity of ratio-based indices to shadows appears to be outweighed by the other advantages of bandwise multiple regression.

SUMMARY AND CONCLUSION

Under conditions of high substrate and vegetation heterogeneity, all vegetation indices were found to be highly correlated to green vegetation cover. Among ratio-based vegetation indices, the unadjusted indices (SR and NDVI) performed best because our soil line was not substantially different from that assumed by these indices. As a result, for the soil-adjusted indices, TSAVI, which used a site specific soil line, explained more variability in vegetation cover than other soil-adjusted indices. Indices that incorporated larger soil line adjustments explained progressively less variation. GVI explained substantially less variability, possibly because of the influence of substrate variability on middle infrared bands. Bandwise multiple regression provided superior results to the use of indices because it allows the decoupling of individual bands and the potential for different band responses.

Although substantial success has been achieved through the use of vegetation indices to predict ecological variables, we believe that bandwise multiple regression should achieve equivalent or better results without additional effort. In order to understand the relationship between an index and an ecological variable of interest, it is usually necessary to perform regression or other analysis to establish the relationship. The use of vegetation indices unnecessarily constrains the regression analysis. Instead, we have shown that improved results may be obtained by performing regression on the original bands and using a range of regression techniques (stepwise analysis, individual band transformations, polynomial terms) to fit the best regression model.

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REFERENCES

Anderson, G. L., Hanson, J. D., and Haas, R. H. (1993), Evaluating Landsat thematic mapper derived vegetation indices for estimating above-ground biomass on semiarid rangelands. *Remote Sens. Environ.* 45:165–175.

Baret, F., Guyot, G., and Major, D. (1989), TSAVI: a vegetation index which minimizes soil brightness effects on LAI of APAR estimation. In *12th Canadian Symposium on Remote Sensing and IGARSS '90,* Vancouver, Canada, 10–14 July, 4 pp.

Boyd, D. S., and Ripple, W. J. (1997), Potential vegetation indices for determining global forest cover. *Int. J. Remote Sens.* 18:1395–1401.

Chen, J. M., and Cihlar, J. (1996), Retrieving leaf area index of boreal conifer forests using Landsat TM images. *Remote Sens. Environ.* 55:153–162.

Cihlar, J., St. -Laurent, L., and Dyer, J. A. (1991), Relation between the normalized difference vegetation index and ecological variables. *Remote Sens. Environ.* 35:279–298.

Crist, E. P., and Cicone, R. C. (1984), Application of the Tasseled Cap concept to simulated Thematic Mapper data. *Photogramm. Eng. Remote Sens.* 50:343–352.

del Moral, R., and Bliss, L. C. (1993), Mechanisms of primary succession: insights resulting from the eruption of Mount St. Helens. In: *Advances in Ecological Research* (M. Began and A. Fitter, Eds.), Academic, London, Vol. 24, pp. 1–66.

Dusek, D. A., Jackson, R. D., and Musick, J. T. (1985), Winter wheat vegetation indices calculated from combinations of seven spectral bands. *Remote Sens. Environ.* 18:255–267.

Elvidge, C. D., and Lyon, R. J. P. (1985), Influence of rock-soil spectral variation on assessment of green biomass. *Remote Sens. Environ.* 17:265–279.

ERDAS (1995), *ERDAS Field Guide*, 3rd ed., ERDAS, Atlanta, GA, 628 pp.

Franklin, J. F., MacMahon, J. A., Swanson, F. J., and Sedell, J. R. (1985), Ecosystem responses to the eruption of Mount St. Helens. *Natl. Geogr. Res.* 1:198–216.

Franklin, J. F., Frenzen, P. M., and Swanson, F. J. (1988), Recreation of ecosystems at Mount St. Helens—contrasts in artificial and natural approaches. In *Rehabilitating Damaged Ecosystems* (J. Cairns, Ed.), CRC Press, Boca Raton, FL, pp. 1–37.

Frenzen, P. (1992), Mount St. Helens: a laboratory for research and education. *J. For.* 90:14–18, 37.

Frenzen, P. M., Delano, A. M., and Crisafulli, C. M. (1994), *Mount St. Helens: Biological Responses Following the 1980 Eruptions—An Indexed Bibliography and Research Abstracts (1980–93),* Gen. Tech. Rep. PNW-GTR-342, U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station, Portland, OR, 149 pp.

Friedl, M. A., Davis F. W., Michaelsen, J., and Moritz, M. A. (1995), Scaling and uncertainty in the relationship between NDVI and land surface biophysical variables: an analysis using a scene simulation model and data from FIFE. *Remote Sens. Environ.* 54:233–246.

Hoblitt, R. P., Miller, C. D., and Vallance, J. W. (1981), Origin and stratigraphy of the deposit produced by the May 18 directed blast. In *The 1980 Eruptions of Mount St. Helens, Washington* (P. W. Lipman and D. R. Mulineaux, Eds.), U.S. Government Printing Office, Washington, DC, pp. 401–419.

Huete, A. R. (1988), A soil-adjusted vegetation index (SAVI). *Remote Sens. Environ.* 29:295–309.

Huete, A. R., and Jackson, R. D. (1988), Soil and atmosphere influences on the spectra of partial canopies. *Remote Sens Environ.* 25:89–105.

Jordan, C. F. (1969), Derivation of leaf-area index from quality of light on the forest floor. *Ecology* 50:663–666.

Kauth, R. J., and Thomas, G. S. (1976), The Tasselled Cap—a graphic description of the spectral-temporal development of agricultural crops as seen by Landsat. In *Proceedings of the Symposium on Machine Processing of Remotely Sensed Data,* Purdue University, West Lafayette, IN, pp. 41–51.

Lillesand, T. M., and Kiefer, R. W. (1994), *Remote Sensing and Image Interpretation,* 3rd ed., Wiley, New York, 750 pp.

Lipman, P. W., and Mullineaux, D. R., Eds. (1981), *The 1980 Eruptions of Mount St. Helens, Washington,* U.S. Government Printing Office, Washington, DC, 844 pp.

Markham, B. L., and Barker, J. L. (1986), Landsat MSS and TM post-calibration dynamic ranges, exoatmospheric reflectances and at-satellite temperatures. *Landsat Tech. Notes* 1:3–8.

Montgomery, D. C. (1991), *Design and Analysis of Experiments,* 3rd ed., Wiley, New York, 649 pp.

Myneni, R. B., and Williams, D. L. (1994), On the relationship between FAPAR and NDVI. *Remote Sens. Environ.* 49: 200–211.

Perry, C. R., and Lautenschlager, L. F. (1984), Functional equivalence of spectral vegetation indices. *Remote Sens. Environ.* 14:169–182.

Qi, J., Chehbouni, A., Huete, A. R., Kerr, Y. H., and Sorooshian, S. (1994), A modified soil adjusted vegetation index. *Remote Sens. Environ.* 48:119–126.

Ripple, W. J. (1985), Asymptotic reflectance characteristics of grass vegetation. *Photogramm. Eng. Remote Sens.* 51:1915–1921.

Ripple, W. J. (1994), Determining coniferous forest cover and forest fragmentation with NOAA-9 Advanced Very High Resolution Radiometer data. *Photogramm. Eng. Remote Sens.* 60:533–540.

Rondeaux, G., Steven, M., and Baret, F. (1996), Optimization of soil-adjusted vegetation indices. *Remote Sens. Environ.* 55:95–107.

Rouse, J. W., Haas, R. H., Schell, J. A., Deering, D. W., and Harlan, J. C. (1973), Monitoring the vernal advancement and retrogradation (greenwave effect) of natural vegetation, NASA/GSFC Type III Final Report, Greenbelt, MD.

Running, S. W., Peterson, D. L., Spanner, M. A., and Teuber, K. B. (1986), Remote sensing of coniferous forest leaf area. *Ecology* 67:273–276.

Spanner, M. A., Pierce, L. L., Running, S. W., and Peterson, D. L. (1990), The seasonality of AVHRR data of temperate coniferous forests: relationship with leaf area index. *Remote Sens. Environ.* 33:97–112.

Tucker, C. J. (1979), Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sens. Environ.* 8:127–150.

Ugolini, F. C., Dahlgren, R., LaManna, J, Nuhn, W., and Zachara, J. (1991), Mineralogy and weathering processes in Recent and Holocene tephra deposits of the Pacific Northwest, USA. *Geoderma* 51:277–199.

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.

Yoder, B. J., and Waring R. H. (1994), The normalized difference vegetation index of small Douglas-fir canopies with varying chlorophyll concentrations. *Remote Sens. Environ.* 49:81–91.