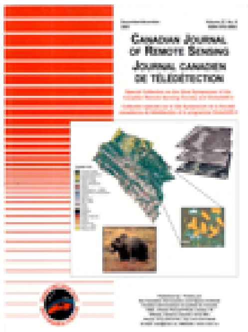

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A Comparison of Spectral Mixture Analysis and Ten Vegetation Indices for Estimating Boreal Forest Biophysical Information from Airborne Data

by D.R. Peddle • S.P. Brunke • F.G. Hall

RÉSUMÉ

L'analyse des spectres mixtes (ASM) permet de dériver le pourcentage de couronnes ensoleillées, de fond et d'ombre à l'intérieur d'un pixel d'une image de télédétection. Il a été démontré que l'information à l'échelle du sous-pixel peut fournir de façon continue des estimations significativement améliorées d'information biophysique sur la forêt comme la biomasse, l'indice de surface foliaire (LAI) et la production primaire nette (NPP) comparativement aux estimations de NDVI (Normalised Difference Vegetation Index) utilisant des images aéroportées ou satellitales. Toutefois, un certain nombre d'indices de végétation ont été proposés à titre d'amélioration au NDVI. Dans cet article, dix indices de végétation différents ont été utilisés pour prédire les paramètres biophysiques de la forêt et les résultats ont été comparés avec les résultats obtenus par analyse des spectres mixtes utilisant les données multispectrales aéroportées du projet COVER de la NASA, dans la Superior National Forest du Minnesota, aux États-Unis. Cet ensemble de données a été acquis à travers une gamme d'angles solaires zénithaux à la limite de résolution spatiale et dans les bandes spectrales du capteur Thematic Mapper de Landsat. Les indices de végétation suivants ont été dérivés des données de télédétection : NDVI, SR, MSR, RDVI, WDVI, GEMI, NLI et trois autres indices de végétation ajustés en fonction du sol (SAVI, SAVI-1, SAVI-2). Des résultats ont été obtenus à des angles solaires zénithaux de 30°, 45° et 60° pour la biomasse, LAI, NPP, DBH, la densité de tiges et la fraction de surface terrière. Dans tous les cas, les fractions d'ombre dérivées de l'analyse des spectres mixtes ont fourni des résultats significativement meilleurs que tout autre indice de végétation, avec une amélioration de l'ordre de 20% comparativement aux meilleurs résultats obtenus par les indices de végétation. Dans la plupart des cas, un ou plusieurs des nouveaux indices de végétation ont apporté une amélioration variant de faible à modérée comparativement au NDVI, WDVI et SAVI-1 ayant la meilleure performance parmi les indices de végétation grâce probablement à l'inclusion de la réflectance de fond. En conclusion, quoique les différents indices de végétation puissent apporter une amélioration par rapport au NDVI, ceux-ci apparaissent comme fonctionnellement équivalents et fondamentalement semblables en termes de statistiques de premier ordre quant à leur potentiel à prédire les paramètres biophysiques de la forêt, potentiel qui est surpassé par les approches basées sur la décomposition des images à l'échelle du sous-pixel comme l'analyse des spectres mixtes et la modélisation de la réflectance optique du couvert.

SUMMARY

Spectral Mixture Analysis (SMA) provides the capability 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 net primary productivity (NPP) compared to that provided by the normalized difference vegetation index (NDVI) using airborne and satellite imagery. However, a number of vegetation indices (VIs) have been proposed as an improvement to NDVI. In this paper, ten different VIs were used to predict forest biophysical parameters, and then compared with results obtained from SMA using airborne multispectral data from the NASA COVER Project, Superior National Forest, Minnesota USA. This data set was acquired over a range of solar zenith angles at the spatial resolution and spectral bands of the Landsat Thematic Mapper sensor. The following vegetation indices were derived from the remotely sensed data: NDVI, SR, MSR, RDVI, WDVI, GEMI, NLI, and three different soil-adjusted vegetation indices (SAVI, SAVI-1, SAVI-2). Results were obtained at solar zenith angles of 30°, 45° and 60° for biomass, LAI, NPP, DBH, stem density, and basal fraction. In all cases, SMA shadow fraction provided significantly better results than any vegetation indices, with improvements on the order of 20% compared to the best vegetation index results. In most cases, one or more of the new vegetation indices provided a small to moderate improvement compared to NDVI, with WDVI and SAVI-1 performing best amongst the VIs, likely due to the inclusion of background reflectance. It is concluded that while different VIs can provide some improvements over NDVI, these appear to be functionally equivalent and fundamentally similar in a first-order sense in terms of their ability to predict forest biophysical parameters, which is surpassed by approaches based on sub-pixel image decomposition such as spectral mixture analysis and canopy optical reflectance modelling.

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Introduction

Remote sensing imagery has become a critical source of information on vegetation for use in a broad range of climatic, ecological and terrestrial monitoring studies at local to global scales (USGCRP, 1999). A key requirement is the need to maximize remote sensing information extraction of important vegetation parameters and biophysical variables (Wulder, 1998) for direct use in these studies and for input to models of terrestrial carbon stocks, forest and agricultural productivity, ecological change, climatic variability, and others. Vegetation indices (VIs) have been developed with the goal to provide this information, for which a large body of work has resulted over the past three decades as well as extensive literature, as reviewed by Bannari *et al.* (1995) and Baret and Guyot (1991). These indices, in general, are formulated as the ratio of red (or visible) and near-infrared (NIR) measurements, based on the fact that plants reflect less visible light but more NIR radiation when compared with non-vegetated surfaces (Bannari *et al.*, 1995; Chen, 1996). The Normalized Difference Vegetation Index (NDVI) is one of the earliest and perhaps most popular vegetation indices. However, a number of fundamental problems have been identified with vegetation indices such as NDVI (Lathrop and Pierce, 1991). A significant issue is that band ratios are based on measurements of the entire pixel field of view, and therefore do not account explicitly for non-vegetated components and mixtures at sub-pixel scales (Jasinski and Eagleson, 1989; Shimabukuro and Smith, 1991; Adams *et al.*, 1993). These include shadows, background soils, and understory vegetation, each of which may contribute a significant portion of the overall remote sensing signal (Elvidge and Lyon, 1985; Huete, 1989; Spanner *et al.*, 1990), both in low density forests or crops where the background surface dominates the signal, and also in high density canopies where shadows are quite prevalent (Li and Strahler, 1992; Huguenin *et al.*, 1997). VIs also have no formal mechanism to account for canopy geometry, yet this can be a strong controlling factor of reflected radiation used as a basis for deriving vegetation information (Guyot *et al.*, 1989). Another limitation is that VIs are based on a small number of spectral bands, usually two, and thus do not utilize new and potentially important information in other channels, particularly given the emergence of higher dimensional and hyperspectral remote sensing instruments. Vegetation indices have also been less effective with canopies at higher leaf areas, in which band ratios tend to saturate beyond a certain LAI (Spanner *et al.*, 1990).

To address these problems, research has been conducted to provide:

(i) improved vegetation indices, and

(ii) different approaches to the problem.

In our work, we have adopted the second approach, pursuing a more direct solution to the sub-pixel mixing problem using spectral mixture analysis (SMA), and later, optical reflectance models. Both are rooted in the derivation of sub-pixel scale fractions (*e.g.*, percent sunlit canopy, shadow, background), with canopy geometry dealt with explicitly. In comparisons with NDVI, we have found SMA shadow fractions provide significantly improved predictions of parameters such as leaf area index (LAI), biomass, and net primary productivity (NPP) in boreal forest (Hall *et al.*, 1995; Peddle *et al.*, 1999a), montane forests in the Canadian Rockies (Peddle and Johnson, 2000) and agricultural sites (Peddle *et al.*, 1999b) using both airborne and satellite image data. However, there have been a number of vegetation indices developed as improvements to NDVI which have yet to be considered in our forestry research. As a result, consideration of additional VIs is important since vegetation indices are more straightforward to compute, compared to the use of SMA and optical reflectance models that involve different inputs and more sophisticated algorithms. Accordingly, in this paper we identify a set of major VIs and perform a more comprehensive comparison with SMA for predicting forest biophysical variables. Further, we expand the scope of forestry information from our previous work (Hall *et al.*, 1995; Peddle *et al.*, 1999a) which considered only LAI, biomass and NPP to now also include three additional forest parameters. Here, we consider a total of 10 individual VIs, and compare these to SMA shadow fraction for predicting LAI, biomass, and NPP, as well as basal fraction, stem density, and tree diameter at breast height (DBH). In the next section, the study area and data set are described, after which the methods based on vegetation indices and spectral mixture analysis are outlined. Results from the ten VIs and SMA are then reported and discussed.

Data Set

The 4800 km^2 study area is located at 48°N, 92°W in the Superior National Forest (SNF) in Minnesota USA, near the southern limit of the North American boreal forest, and encompasses stands of black spruce, jack pine, and trembling aspen over a range of densities, successional stages, age classes, and rates of productivity. Field and airborne remote sensing data were acquired during the summers of 1983 and 1984 as part of the NASA COVER Project. Quantitative measurements and estimates of biomass (BMS), LAI (projected), NPP, DBH, basal fraction (BF, the ratio of bole area to surface area), and stem density (SD) were obtained by relating dimension analysis of sacrificed trees to plot measurements based on standard allometric techniques (Woods *et al.*, 1985, 1991; Hall *et al.*, 1992, 1995). The study comprised 31 stands of black spruce (*picea mariana*), the most common boreal forest dominant, based on 80 × 80m plots with a full range of stand densities. A full presentation of the biophysical data for these stands was given in Hall *et al.* (1995), from which the following ranges were derived: biomass ranged from 0.68-15.14 kg/m^2; NPP: 0.039-0.572 kg/m^2; LAI: 0.48-5.42; DBH: 3.94-14.52 cm; SD: 0.148-1.074 stems/m^2; and BF: 0.00032-0.00487. Spectral data were acquired at nadir view angle using a helicopter-mounted Modular Multi-band Radiometer (MMR) at Landsat Thematic Mapper bands with a nominal 30-metre spatial resolution. A total of 149 spectral measurements were acquired over a variety of solar zenith angles (SZA) categorized into three 7°

SZA ranges centered at 30°, 45° and 60°, with all values converted to reflectance based on simultaneous spectral ground measurements of calibration reference targets. In addition to airborne data, spectral measurements of individual canopy components and leaf optical properties were acquired on the ground. More detailed descriptions of the forest measurements and remote sensing data are contained in Hall *et al.* (1992, 1995) and Peddle *et al.* (1999), and are not repeated here.

Vegetation Indices and Spectral Mixture Analysis

Vegetation Indices

Ten vegetation indices were selected for comparison in this paper, as identified by Chen (1996), which represent the major VIs that are among the most commonly used in forestry applications. These are: Normalized Difference Vegetation Index (NDVI), Simple Ratio (SR), Modified Simple Ratio (MSR), Re-normalized Difference Vegetation Index (RDVI), Weighted Difference Vegetation Index (WDVI), three different Soil Adjusted Vegetation Indices (SAVI, SAVI-1, SAVI-2), Global Environment Monitoring Index (GEMI), and the Non-Linear Index (NLI). However, we note that this is by no means a full or exhaustive set of VIs, for example, some 35 to 40 vegetation indices were reviewed by Bannari *et al.* (1995) in a comprehensive review of the literature for a variety of applications. Instead, in this paper, it is our intention to compare some of the more commonly used vegetation indices in forestry with new results obtained by SMA. Each VI used in this study is reviewed briefly in this section, with full equations provided in **Table 1**. For a more complete discussion of these VIs the reader is referred to Chen (1996); while for a more complete treatment of vegetation indices, the reader is referred to Bannari *et al.* (1995), Baret and Guyot (1991), and other original works referenced therein.

Simple Ratio (Birth and McVey, 1968; Jordan, 1969) and the Normalized Difference Vegetation Index (Rouse *et al.*, 1974) were among the earliest vegetation indices developed for multispectral data, and both are still in use today, particularly NDVI. SR is simply the ratio of NIR reflectance (ρ_r) to red reflectance (ρ_r). Occasionally, however, when ρ_r approaches zero, SR becomes unbounded at very large values (Chen, 1996). NDVI was designed to avoid this problem by normalizing the difference between ρ_n and ρ_r with their sum, thus creating a fixed range of values from 0 to 1. NDVI and SR are fundamentally the same, since they can be derived directly from each other, although SR is sometimes preferred since it can be more linear with biophysical parameters compared to NDVI (Chen, 1996). However, an assumption of both SR and NDVI which is often not met for vegetated surfaces is that ρ_n and ρ_r should vary simultaneously in the same proportion (Chen, 1996). However, due to factors such as background effects and multiple scattering in the near infrared, this assumption can be violated. For example, when plotted in red-NIR space, lines of fixed values of SR and NDVI would converge at the origin. However, due to soil background effects, this convergence point often occurs at negative red-NIR coordinates, from which the Soil Adjusted Vegetation Index (Huete, 1988) was developed to reduce or remove this effect by introducing a parameter L into the NDVI equation according to the location of the convergence point. In SAVI, the convergence point is assumed to be fixed, and a constant L value is used. The importance of background effects was recognized by Clevers (1989), who implemented the Weighted Difference Vegetation Index in which the spectral response of background material in the red and NIR was integrated into the calculation. WDVI is also based on the distance between constant-index lines in red-NIR space, assuming these lines are parallel (Chen, 1996). SAVI was later refined by Qi *et al.* (1994), who showed the convergence point is not fixed, and instead provided an equation to compute L as a function of NDVI and WDVI (SAVI-1), as well as a different, more involved derivation (SAVI-2). Often, the relationship between VIs and surface biophysical parameters is not linear (Chen, 1996). This led to the development of the Non-Linear Index (Goel and Qin, 1994) and the Re-normalized Difference Vegetation Index (Roujean and Breon, 1995), both of which attempt to linearize this relationship through different formulations applied to the NDVI equation. The Global Environment Monitoring Index (Pinty and Verstraete, 1992) is also a non-linear index designed to reduce atmospheric effects in satellite imagery at the global scale. GEMI is not linear with ρ_n and ρ_r since atmospheric effects vary considerably by wavelength. GEMI may be less applicable in this study, owing to the reduced atmospheric attenuation with airborne data compared to satellite imagery. Based on an evaluation of these indices, Chen (1996) proposed the Modified Simple Ratio as an improved version of RDVI for providing a more linear relationship with biophysical parameters. With this improved linearity, MSR also retains the fundamental basis of SR in which red and NIR values are ratioed, thus reducing sensitivity to noise which is proportional in these wavelengths, as compared to other indices which do not ratio these values and therefore may retain or even amplify these errors (Chen, 1996).

Each of these VIs was derived for each set of red and NIR airborne spectral measurements in the data set and used to predict each of the six biophysical parameters using linear regression analysis. WDVI also required red and NIR background reflectance values - these were determined by field spectroradiometer measurements. The analysis was done for each data subset corresponding to each SZA range, as well as for the full set of data.

Spectral Mixture Analysis

Spectral Mixture Analysis (Adams *et al.*, 1993) involves the systematic decomposition of spectral data to determine the percent area within a pixel which may be attributed to individual scene components, or endmembers. In the forestry context, component endmembers such as sunlit canopy, sunlit background, and shadow are important, for which SMA computes the corresponding sub-pixel scale fractions C, B, and

Table 1.
Equations for ten vegetation indices: ρ_n is NIR reflectance, ρ_r is red reflectance (after Chen, 1996).

NDVI: Normalized Difference Vegetation Index	$\frac{\rho_n - \rho_r}{\rho_n + \rho_r}$
SR: Simple Ratio	$\frac{\rho_n}{\rho_r}$
MSR: Modified Simple Ratio	$\frac{\frac{\rho_n}{\rho_r} - 1}{\sqrt{\frac{\rho_n}{\rho_r}} + 1}$
RDVI: Re-normalized Difference Vegetation Index	$\frac{\rho_n - \rho_r}{\sqrt{\rho_n + \rho_r}}$
WDVI: Weighted Difference Vegetation Index	$\rho_n - a \cdot \rho_r, a = \frac{\rho_{n,soil}}{\rho_{r,soil}}$
SAVI: Soil Adjusted Vegetation Index	$\frac{(\rho_n - \rho_r)(1+L)}{(\rho_n + \rho_r + L)}, L = 0.5$
SAVI 1: Soil Adjusted Vegetation Index 1	$\frac{(\rho_n - \rho_r)(1+L)}{(\rho_n + \rho_r + L)}, L = 1 - 2.12 \cdot NDVI \cdot WDVI$
SAVI 2: Soil Adjusted Vegetation Index 2	$\rho_n + 0.5 - \sqrt{\left(\rho_n + 0.5\right)^2 - 2\left(\rho_n - \rho_r\right)}$
GEMI: Global Environment Monitoring Index	$\frac{\eta\left(1 - 0.25 \cdot \eta\right) - \left(\rho_r - 0.125\right)}{1 - \rho_r}$, $\eta = \frac{2\left(\rho_n^2 - \rho_r^2\right) + 1.5\rho_n + 0.5\rho_r}{\rho_n + \rho_r + 0.5}$
NLI: Non-Linear Index	$\frac{\rho_n^2 - \rho_r}{\rho_n^2 + \rho_r}$

S, respectively. The inputs to SMA are the spectral reflectances of each endmember (ρ_c,ρ_b,ρ_s) in each band, and the overall pixel band reflectance values (ρ_8) to be "unmixed". To ensure consistency in comparison with 2-band vegetation indices, only red (λ_1) and NIR (λ_2) spectral bands were analyzed by SMA in this study, using the following general system of equations:

$$\rho_8(\lambda_1) = C\rho_c(\lambda_1) + B\rho_b(\lambda_1) + S\rho_s(\lambda_1),$$

$$\rho_8(\lambda_2) = C\rho_c(\lambda_2) + B\rho_b(\lambda_2) + S\rho_s(\lambda_2).$$

This system of equations was solved using a constrained least-squares approach (Shimabukuro and Smith, 1991) to compute the endmember scene fractions (C,B,S) for each pixel. In terms of endmember inputs, red and NIR ρ_b and ρ_s values were obtained in this study by spectral measurement of ground targets (the same ρ_b values were also used with WDVI), with ρ_c derived using a spheroid-based geometric optical reflectance model (Li and Strahler, 1992). This method allowed for different values of ρ_c to be obtained for the solar zenith angles at 30°, 45° and 60° corresponding to the MMR SZA categories, owing to the reflectance anisotrophy for nadir observations of conifer forest stands (Syrén, 1994). A detailed study of variations due to different SZA and reflectance models was reported in Peddle *et al.* (1999a), and is not repeated here. However, the ability to provide SZA-specific ρ_c inputs represents an important capability which is possible using SMA. In the following comparisons, SMA and VI results are evaluated at three individual SZAs, as well as using the full data set integrated over all SZAs.

The SMA output fractions were used as predictors of the forest biophysical-structural parameters using separate linear regression analyses of each of the three data subsets for the SZA ranges, and for the full data set (as with the VI analysis). A confidence level of 95% was used for all regressions reported in this study, with the magnitude of the coefficient of determination (r^2) and the standard error (SE) used to evaluate results. Since shadow fraction has been shown to provide better predictions of forest biophysical information compared to sunlit canopy and background fractions in our previous SNF study (Peddle *et al.*, 1999a), shadow fraction (SMA-S) was used for predicting the six biophysical parameters in the comparison with the full set of vegetation indices, presented next.

Results of SMA and VI Comparisons

Comparison by SZA

The regression results using spectral data acquired within a 7° SZA range centered at 30° are shown in **Table 2**. Overall, SMA shadow fraction had the best results, with the highest r^2 value found with five of the six parameters. In terms of the best absolute predictive capabilities found for each parameter, biomass, NPP, LAI and BF had r^2 values from SMA which ranged from 0.73 to 0.76, with a standard error (SE) of 2.16 kg/m^2, 0.07 kg/m^2/yr, 0.57 and 0.00, respectively (LAI and BF are unitless; all BF SE values were 0.00, since all bole-to-surface area ratios were very small). In comparison, the best VIs were between 5% and 13% lower. The best results for DBH and SD were somewhat lower, at r^2 = 0.49 (SE=2.03cm) and 0.32 (0.17 stems/m^2) from SMA and WDVI, respectively. Of the vegetation indices, WDVI had the highest results in all six cases, and was the best overall predictor of stem density. WDVI is the only vegetation index to include a more explicit treatment of background effects, in which the ratio of NIR and red reflectance is incorporated as a correction factor into the equation (**Table 1**). This lends additional support to a fundamental rationale for spectral mixture analysis, in which background (and other) components are treated explicitly.

The results from spectral data acquired at a nominal SZA=45° (**Table 3**) were similar to those at SZA=30°: SMA shadow fraction was best for all but one biophysical parameter, with r^2 results ranging from 0.82 to 0.86, with the exception of SD for which the best overall r^2 value was only 0.10. Using SMA shadow fraction as the predictor, BMS, NPP, LAI and BF were estimated with SE=1.73 kg/m^2, 0.05 kg/m^2/yr, 0.46 and 0.00. The only case where shadow fraction did not produce the best result was for DBH, where GEMI was best (r^2=0.77, SE=1.65cm), with SMA ranked second (r^2=0.67). The best VI

Table 2
Linear regression results (r^2 coefficient of determination; standard error SE) for predicting six forest parameters using vegetation indices and SMA shadow fraction for airborne image data acquired at a nominal SZA=30° (±3.5°).

SZA=30	Biomass			NPP			LAI			DBH			Stems/m^2			Basal Fraction		
	Rank	r^2	SE	Rank	r^2	SE	Rank	r^2	SE	Rank	r^2	SE	Rank	r^2	SE	Rank	r^2	SE
1	SMA	0.73	2.16	SMA	0.76	0.07	SMA	0.76	0.57	SMA	0.49	2.03	WDVI	0.32	0.16	SMA	0.75	0.00
2	WDVI	0.60	2.65	WDVI	0.71	0.08	WDVI	0.71	0.62	WDVI	0.34	2.32	NDVI	0.31	0.16	WDVI	0.66	0.00
3	GEMI	0.44	3.12	GEMI	0.54	0.10	SAVI 1	0.54	0.78	RDVI	0.28	2.41	SAVI 2	0.31	0.16	GEMI	0.48	0.00
4	SAVI 1	0.43	3.16	SAVI 2	0.54	0.10	SAVI 2	0.54	0.78	GEMI	0.21	2.53	SAVI	0.30	0.16	SAVI 1	0.47	0.00
5	SAVI 2	0.40	3.24	NDVI	0.53	0.10	NDVI	0.54	0.79	SAVI 1	0.21	2.53	MSR	0.29	0.16	SAVI 2	0.47	0.00
6	NDVI	0.39	3.25	SAVI 1	0.53	0.10	GEMI	0.54	0.79	SAVI 2	0.18	2.58	SAVI 1	0.28	0.16	NDVI	0.47	0.00
7	SAVI	0.36	3.35	SAVI	0.50	0.11	SAVI	0.50	0.82	NDVI	0.17	2.59	SR	0.28	0.16	SAVI	0.43	0.00
8	MSR	0.30	3.50	MSR	0.43	0.11	MSR	0.44	0.87	SAVI	0.15	2.62	GEMI	0.24	0.17	MSR	0.36	0.00
9	RDVI	0.26	3.60	SR	0.38	0.12	SR	0.39	0.90	MSR	0.11	2.69	SMA	0.24	0.17	SR	0.32	0.00
10	SR	0.26	3.60	RDVI	0.17	0.14	RDVI	0.16	1.06	NLI	0.11	2.69	NLI	0.05	0.19	RDVI	0.21	0.00
11	NLI	0.04	4.10	NLI	0.00	0.15	NLI	0.00	1.16	SR	0.09	2.72	RDVI	0.00	0.19	NLI	0.01	0.00

Table 3
Results from image data acquired at nominal 45 ° SZA. See Table 2 caption for details.

SZA=45	Biomass			NPP			LAI			DBH			Stems/m^2			Basal Fraction		
	Rank	r^2	SE	Rank	r^2	SE	Rank	r^2	SE	Rank	r^2	SE	Rank	r^2	SE	Rank	r^2	SE
1	SMA	0.83	1.73	SMA	0.86	0.05	SMA	0.82	0.46	GEMI	0.77	1.65	SMA	0.10	0.16	SMA	0.84	0.00
2	GEMI	0.81	1.91	SAVI 1	0.78	0.07	SAVI 1	0.75	0.56	SMA	0.67	1.92	SAVI 1	0.08	0.16	SAVI 1	0.75	0.00
3	SAVI 1	0.74	2.23	GEMI	0.73	0.07	GEMI	0.68	0.63	SAVI 1	0.63	2.10	WDVI	0.06	0.16	GEMI	0.75	0.00
4	WDVI	0.58	2.85	WDVI	0.62	0.09	WDVI	0.60	0.70	WDVI	0.51	2.40	MSR	0.04	0.16	WDVI	0.61	0.00
5	SR	0.52	3.04	SR	0.54	0.10	SR	0.52	0.78	SR	0.49	2.46	SR	0.04	0.16	SR	0.52	0.00
6	MSR	0.51	3.09	MSR	0.52	0.10	MSR	0.51	0.78	MSR	0.47	2.50	NDVI	0.04	0.16	MSR	0.51	0.00
7	NDVI	0.44	3.11	NDVI	0.46	0.10	NDVI	0.44	0.82	NDVI	0.42	2.61	SAVI 2	0.04	0.16	NDVI	0.47	0.00
8	SAVI 2	0.42	3.34	SAVI 2	0.45	0.11	SAVI 2	0.43	0.84	SAVI 2	0.39	2.68	SAVI	0.03	0.16	SAVI 2	0.44	0.00
9	SAVI	0.41	3.38	SAVI	0.43	0.11	SAVI	0.42	0.85	SAVI	0.38	2.70	RDVI	0.02	0.16	SAVI	0.42	0.00
10	RDVI	0.13	4.10	RDVI	0.12	0.13	RDVI	0.11	1.05	RDVI	0.02	0.16	GEMI	0.02	0.16	RDVI	0.12	0.00
11	NLI	0.01	4.38	NLI	0.01	0.14	NLI	0.01	1.11	NLI	0.01	3.41	NLI	0.00	0.16	NLI	0.01	0.00

results were between 2% and 9% lower than SMA, however, unlike the results at SZA=30° in which WDVI was the best VI, here SAVI-1 was the best VI in three cases, GEMI in two cases, with GEMI and SAVI-1 tied in one case (BF). It is difficult to explain these differences amongst the vegetation indices, although we note that SAVI-1 includes background reflectance values and WDVI in its formulation (WDVI itself was lower than SAVI-1 by 12% or more in all cases except SD). Again, a strong predictive capability was observed with SMA for all parameters except stem density, which showed a weak relationship similar to that found with SZA=30°.

For the airborne data acquired at SZA=60° (**Table 4**), SMA shadow fraction was best in four of six cases, with r^2 results ranging from 0.65 to 0.79 for BMS, NPP, LAI and BF (SE= 2.53 kg/m^2, 0.07 kg/m^2/yr, 0.61 and 0.00, respectively). VIs were best only for DBH and stem density, (r^2=0.59, SE=1.48cm; and r^2=0.36, SE=0.23 stems/m^2, respectively). Of the vegetation indices, WDVI, SAVI, and SAVI-2 performed best, with NDVI tied with these three as best VI for basal fraction. As with the two other SZA ranges considered, an acceptable level of predictive capability was found using SMA shadow fraction for BMS, NPP, LAI and BF, whereas the other two parameters (DBH and SD) were somewhat lower.

Comparison of Full Data Set

To further assess these data, independent of the effects of SZA, a series of regression analyses was performed on the full data set using all spectral data from all SZA. The results of these regressions are shown in **Table 5** and summarized in **Figure 1**. SMA shadow fraction had the best result for all six of the biophysical structural parameters: biomass was estimated with r^2=0.74 (SE=2.14 kg/m^2), NPP r^2=0.80 (SE=0.06 kg/m^2/yr), LAI r^2=0.79 (SE =0.55), and BF r^2=0.78 (SE=0.00). These results were over 20% higher than the best VI results (BMS, NPP, LAI, BF: r^2=0.53, 0.59, 0.59, 0.57 respectively). For DBH and stem density, SMA still provided the best results compared to all vegetation indices; however, the r^2 values were only 0.50 and 0.22, respectively, and had less improvement over VIs (increases of 13% and 2%, respectively). It would appear that biomass, NPP, LAI and basal fraction can be predicted well, but DBH (r^2=0.50) and, particularly SD (r^2=0.22), may not.

Although the best results were obtained by SMA, it is useful to also compare individual vegetation index results, given the number of different VIs compared in this study. Of the 10 VIs, WDVI appeared to perform the best overall, followed by SAVI-1, NDVI and SAVI-2. From **Table 5**, we also note that WDVI and SAVI-1 were the two highest ranking VIs for all six

Table 4.
Results from image data acquired at nominal 60° SZA. See Table 2 caption for details.

SZA = 60	Biomass			NPP			LAI			DBH			Stems/m^2			Basal Fraction		
	Rank	r^2	SE	Rank	r^2	SE	Rank	r^2	SE	Rank	r^2	SE	Rank	r^2	SE	Rank	r^2	SE
1	SMA	0.65	2.53	SMA	0.77	0.07	SMA	0.79	0.61	SAVI	0.59	1.48	WDVI	0.36	0.23	SMA	0.76	0.00
2	SAVI 2	0.61	2.97	SAVI 2	0.67	0.10	WDVI	0.68	0.84	SAVI 2	0.58	1.50	SMA	0.34	0.22	SAVI 2	0.67	0.00
3	SAVI	0.61	2.97	SAVI	0.66	0.10	SAVI 2	0.67	0.86	RDVI	0.57	1.51	SAVI 1	0.32	0.23	NDVI	0.67	0.00
4	WDVI	0.59	3.03	WDVI	0.66	0.10	SAVI	0.65	0.88	MSR	0.56	1.53	NDVI	0.30	0.24	WDVI	0.67	0.00
5	MSR	0.57	3.10	MSR	0.62	0.11	SAVI 1	0.62	0.92	SR	0.55	1.55	SAVI 2	0.30	0.24	SAVI	0.67	0.00
6	SR	0.56	3.16	SR	0.60	0.11	MSR	0.62	0.92	WDVI	0.52	1.60	SAVI	0.28	0.24	MSR	0.63	0.00
7	SAVI 1	0.53	3.24	SAVI 1	0.59	0.12	NDVI	0.60	0.83	SAVI 1	0.48	1.67	RDVI	0.27	0.24	SR	0.61	0.00
8	NDVI	0.37	3.41	NDVI	0.56	0.10	SR	0.60	0.94	SMA	0.32	2.61	MSR	0.27	0.24	SAVI 1	0.60	0.00
9	GEMI	0.27	4.04	GEMI	0.30	0.15	GEMI	0.33	1.21	GEMI	0.31	1.92	SR	0.25	0.25	GEMI	0.31	0.00
10	NLI	0.12	4.45	RDVI	0.11	0.17	RDVI	0.18	1.34	NLI	0.23	2.04	GEMI	0.16	0.26	RDVI	0.12	0.00
11	RDVI	0.08	4.55	NLI	0.10	0.17	NLI	0.04	1.45	RDVI	0.02	2.29	NLI	0.01	0.28	NLI	0.09	0.00

Table 5.
Overall results from all image data over full range of solar zenith angles.

	ALL SZA	Biomass		NPP			LAI			DBH			Stems/m^2			Basal Fraction		
	Rank	r^2	SE	Rank	r^2	SE	Rank	r^2	SE	Rank	r^2	SE	Rank	r^2	SE	Rank	r^2	SE
1	SMA	0.74	2.14	SMA	0.80	0.06	SMA	0.79	0.55	SMA	0.50	2.19	SMA	0.22	0.18	SMA	0.78	0.00
2	WDVI	0.53	2.91	WDVI	0.59	0.10	WDVI	0.59	0.75	WDVI	0.37	2.35	SAVI 1	0.20	0.18	WDVI	0.57	0.00
3	SAVI 1	0.49	3.02	SAVI 1	0.55	0.10	SAVI 1	0.56	0.78	SAVI 1	0.33	2.43	WDVI	0.18	0.18	SAVI 1	0.53	0.00
4	NDVI	0.40	3.26	NDVI	0.47	0.11	NDVI	0.47	0.85	NDVI	0.28	2.51	MSR	0.15	0.19	NDVI	0.44	0.00
5	SAVI 2	0.39	3.30	SAVI 2	0.45	0.11	SAVI 2	0.45	0.87	SAVI 2	0.28	2.52	NDVI	0.15	0.19	SAVI 2	0.43	0.00
6	MSR	0.38	3.33	MSR	0.44	0.11	MSR	0.45	0.87	MSR	0.26	2.55	SR	0.15	0.19	MSR	0.42	0.00
7	SAVI	0.37	3.35	SAVI	0.43	0.11	SAVI	0.43	0.88	SAVI	0.26	2.55	SAVI 2	0.15	0.19	SAVI	0.41	0.00
8	SR	0.36	3.38	SR	0.43	0.11	SR	0.43	0.89	GEMI	0.25	2.56	SAVI	0.14	0.19	SR	0.40	0.00
9	GEMI	0.35	3.41	GEMI	0.37	0.12	GEMI	0.39	0.91	SR	0.24	2.57	GEMI	0.13	0.19	GEMI	0.37	0.00
10	RDVI	0.15	3.91	RDVI	0.12	0.14	RDVI	0.13	1.09	RDVI	0.11	2.80	RDVI	0.03	0.20	RDVI	0.14	0.00
11	NLI	0.01	4.23	NLI	0.00	0.15	NLI	0.01	1.17	NLI	0.00	2.96	NLI	0.00	0.20	NLI	0.01	0.00

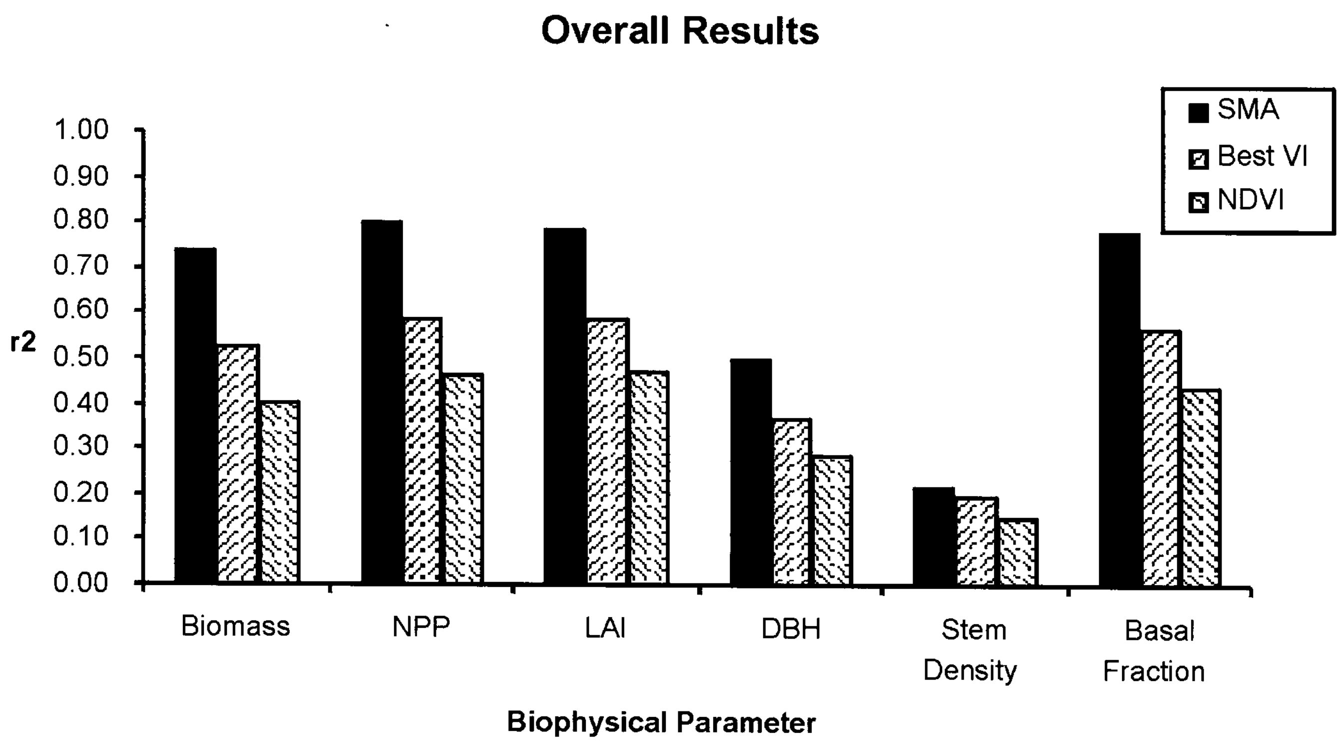

Figure 1.
Summary of results from the full data set (all SZA) for predicting six biophysical structural parameters. Results shown from spectral mixture analysis (SMA), the best vegetation index (VI) result of the ten VIs tested, and NDVI. Full results shown in Table 5.

parameters, with WDVI the best in five of six cases. WDVI and SAVI-1 are the only VIs which consider individual background reflectance in their formulation. As shown in **Table 1**, WDVI includes the ratio of NIR and red background reflectance, while SAVI-1 includes WDVI in its equation. This would seem to lend additional support to the premise of spectral mixture analysis, that of isolating individual scene components such as background (and others), using their reflectance values as input, and computing their individual fractions. NDVI, the long-standing and popular vegetation index, ranked a respectable third amongst VIs (fourth overall when SMA is included), and was on the order of 10% lower than the best vegetation index (**Figure 1**). However, there was not much difference amongst the fourth through ninth ranks (NDVI, SAVI-2, MSR, SAVI, SR, GEMI), which all had r^2 values between 0.37 and 0.31. The remaining VIs, RDVI and NLI, had poor results (r^2 ranged from 0.03 to 0.15, and from 0.00 and 0.01, respectively). It is difficult to know why some vegetation indices performed poorly. Further, the variability in results from different vegetation indices and for different biophysical parameters is also unclear. By comparison, with SMA the same variable was used in all cases (shadow fraction), and the results were consistent in their ability to provide good biophysical estimates.

Conclusion

Spectral mixture analysis was shown to provide significantly better predictions of forest biophysical and structural information compared to ten different vegetation indices derived from an airborne remote sensing data set acquired at the spectral and spatial resolution of Landsat Thematic Mapper imagery. Using SMA shadow fraction, the biophysical structural parameters biomass, NPP, LAI and basal fraction were predicted with r^2 values ranging from 0.74 to 0.80 using the full data set. This was 20% better than the best vegetation index results in each case. DBH and stem density were marginally or poorly predicted by all of the methods tested, suggesting these may be difficult to estimate or may require more sophisticated analytical or modelling strategies. Parameters such as biomass, NPP and LAI may be considered the most important for input to ecological and climatic models - good results were obtained for each using SMA.

The results from the analyses at SZA=30°, 45° and 60° showed that SMA was a better predictor of forest biophysical and structural parameters compared to the vegetation indices. For six biophysical parameters over three SZA ranges, SMA shadow fraction was ranked ahead of all ten vegetation index results in 14 of 18 instances (differences ranged from 2% to 15%), and was ranked second in two other cases. Of the vegetation indices, different VIs performed best at different SZA (WDVI at 30°, GEMI and SAVI-1 at 45°, SAVI-2, SAVI and WDVI at 60°). No explanation for these differences in VIs was made, other than to note that WDVI includes background reflectance in its formula, and WDVI is included in the SAVI-1 equation (**Table 1**). Given these results, it is difficult to recommend what the best vegetation selection is if this is the only processing option, whereas with SMA, the same variable (shadow fraction) was used in all cases, as recommended from previous studies, and provided overall superior results to VIs.

From these results, we conclude that using sub-pixel scale fractions appears to represent a more appropriate approach for predicting forest information compared to vegetation indices. The basis for this is that SMA accounts explicitly and directly for the influence of background and shadows on overall pixel reflectance, while vegetation indices do not. These influences are complex and often non-linear in red-NIR space, and ratio-based and other indices cannot adequately account for this. Using SMA, scene components such as shadow fraction provide a physically based surrogate for stand characteristics and canopy dimension. Furthermore, canopy optical reflectance models can be used with SMA to further increase the ability to account for sub-pixel scale components as well as canopy geometry.

Of the vegetation indices, the ones which performed best were primarily WDVI and SAVI-1, which both included some consideration of background reflectance. This may further indicate the merits of treating individual components separately in new vegetation indices, as in SMA. Overall, many of the VI results were rather similar. This, plus analysis of the VI equations, would suggest that these vegetation indices could be considered functionally and fundamentally similar, at least in a first-order sense. Differences in VIs provide altered orientations of red-NIR distributions and various levels of linearity (or otherwise) with respect to forest biophysical-structural measures; however, these differences did not result in large changes in predictive ability.

Although we have not tested all possible or available vegetation indices in the present study, this more comprehensive treatment of some of the major VIs provides additional evidence beyond that obtained in our previous evaluations wherein only NDVI was used (Hall *et al.*, 1995; Peddle *et al.*, 1999). Although improved VI results were found compared to NDVI in this study, the SMA results are still considerably higher. This serves to justify the additional inputs and computation involved with SMA, compared to simple VI methods. These results also lend further support for our research involving canopy reflectance models within the context of a physically based approach to regional and global scale land classification and biophysical estimation (Hall *et al.*, 1997). These models provide sub-pixel scale fractions together with canopy dimension and form information, as well as a more robust setting for coupling advanced classification and biophysical estimation algorithms (Peddle, 1999). We continue to find this sub-pixel scale framework provided by SMA to be both theoretically and empirically superior to vegetation indices.

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