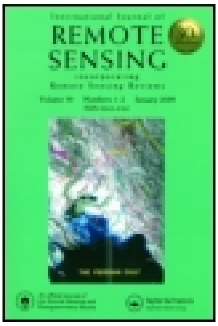

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R. Darvishzadeh [a] , C. Atzberger [b] , A. K. Skidmore [c] & A. A. Abkar [d]

[a] RS and GIS Department, Faculty of Earth Sciences , Shahid Beheshti University, Evin Street , Tehran, Iran

[b] Joint Research Centre of the European Commission , TP 266, Via Enrico Fermi 1, 21020, Ispra, (VA), Italy

[c] International Institute for Geo-information Science and Earth Observation (ITC) , Hengelosestraat 99, PO Box 6, Enschede, 7500, AA, The Netherlands

[d] Faculty of Environment , University of Tehran , Tehran, Iran

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Leaf Area Index derivation from hyperspectral vegetation indices and the red edge position

R. DARVISHZADEH*†, C. ATZBERGER‡, A. K. SKIDMORE§ and A. A. ABKAR¶

†RS and GIS Department, Faculty of Earth Sciences, Shahid Beheshti University, Evin Street, Tehran, Iran
‡Joint Research Centre of the European Commission, TP 266, Via Enrico Fermi 1, 21020 Ispra (VA), Italy
§International Institute for Geo-information Science and Earth Observation (ITC), Hengelosestraat 99, PO Box 6, Enschede 7500 AA, The Netherlands
¶Faculty of Environment, University of Tehran, Tehran, Iran

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The aim of this study was to compare the performance of various narrowband vegetation indices in estimating Leaf Area Index (LAI) of structurally different plant species having different soil backgrounds and leaf optical properties. The study uses a dataset collected during a controlled laboratory experiment. Leaf area indices were destructively acquired for four species with different leaf size and shape. Six widely used vegetation indices were investigated. Narrowband vegetation indices involved all possible two band combinations which were used for calculating RVI, NDVI, PVI, TSAVI and SAVI2. The red edge inflection point (REIP) was computed using three different techniques. Linear regression models as well as an exponential model were used to establish relationships. REIP determined using any of the three methods was generally not sensitive to variations in LAI ($R^2 < 0.1$). However, LAI was estimated with reasonable accuracy from red/near-infrared based narrowband indices. We observed a significant relationship between LAI and SAVI2 ($R^2 = 0.77$, RMSE = 0.59 (cross validated)). Our results confirmed that bands from the SWIR region contain relevant information for LAI estimation. The study verified that within the range of LAI studied ($0.3 \leq \text{LAI} \leq 6.1$), linear relationships exist between LAI and the selected narrowband indices.

1. Introduction

Leaf Area Index (LAI) measures one half of the total leaf area of the vegetation per unit area of soil (background) surface. It can be used to infer processes such as photosynthesis, transpiration and evapotranspiration and is closely related to net primary production of terrestrial ecosystems (Running *et al.* 1989, Bonan 1993). Measuring LAI on the ground is difficult and requires a great amount of labour and hence cost (Gower *et al.* 1999). Therefore, many studies have sought to discover relationships between LAI and remote sensing data for its cost-effective, rapid, reliable and objective estimation. To minimize the variability due to external factors such as underlying soil brightness, leaf angle

*Corresponding author. Email: darvish@itc.nl; r_darvish@sbu.ac.ir

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distribution and leaf optical properties, remote sensing data have been transformed and combined into various vegetation indices (VI).

Spectral vegetation indices are usually calculated as combinations of near-infrared and red reflectance. In many studies, these broadband VIs have shown to be well correlated with canopy parameters related to chlorophyll and biomass abundance such as green Leaf Area Index and absorbed photosynthetically active radiation (e.g. Elvidge and Chen 1995). Two common classes of indices have been the subject of considerable research: (1) ratio based indices such as the Ratio Vegetation Index (RVI) (Pearson and Miller 1972) and the Normalized Difference Vegetation Index (NDVI) (Rouse *et al.* 1974); (2) soil line related indices such as the Perpendicular Vegetation Index (PVI) (Richardson and Wiegand 1977) and the Transformed Soil Adjusted Vegetation Index (TSAVI) (Baret *et al.* 1989). A large number of relationships have been discovered between these vegetation indices and canopy variables including LAI (Elvidge and Chen 1995, Rondeaux and Steven 1995, Broge and Leblanc 2001, Schlerf *et al.* 2005, Wang *et al.* 2005).

Developments in the field of hyperspectral remote sensing and imaging spectrometry have opened new ways for monitoring plant growth and estimating biophysical properties of vegetation. They have promoted a new group of vegetation indices based on the shape and relative position of the spectral reflectance curve. These include the red edge of the vegetation spectrum, which is the sharp slope between the low reflectance in the visible region and the higher reflectance in the near-infrared region, around 670–780 nm. The red edge inflection point (REIP), i.e. the wavelength which has maximal slope in the red edge, and the shape of the red edge have been investigated in several studies and have demonstrated a good correlation with biophysical parameters such as LAI, while simultaneously being less sensitive to spectral noise due to soil background and/or atmospheric effects (Demetriades-Shah *et al.* 1990, Baret *et al.* 1992). The blue and red shift of the red edge inflection point (REIP) has been related to plant growth conditions in many studies (Horler *et al.* 1983, Gilabert *et al.* 1996, Blackburn 1998). REIP depends on the amount of chlorophyll seen by the sensor and is strongly correlated with foliar chlorophyll content, presenting a very sensitive indicator of vegetation stress (Dawson and Curran 1998; Rossini *et al.* 2007). The chlorophyll amount present in a vegetation canopy is characterized by the chlorophyll concentration of the leaves and the Leaf Area Index (Schlerf *et al.* 2005).

Danson and Plummer (1995) found a strong correlation between LAI and REIP in coniferous forests and suggested complementary use of REIP with NDVI. Kodani *et al.* (2002) concluded that the red edge position was strongly correlated with LAI in a deciduous beech forest, thus being a good estimator of LAI as well as canopy chlorophyll content. In the study of Hansen and Schjoerring (2003) using winter wheat, the red edge responded linearly to LAI and chlorophyll content. Lee *et al.* (2004) concluded that spectral channels in the red edge and SWIR regions are generally very important for predicting LAI in four different biomes of row-crop agriculture, tall grass prairie and mixed conifer forest. Pu *et al.* (2003) studied the relationship between forest LAI and two red edge parameters: red edge position (REP) and red well position (RWP) and found good correlations between forest LAI and red edge parameters calculated from four point interpolation methods. Clevers (1994) showed that Leaf Area Index and leaf chlorophyll concentration of crops are the main parameters determining the value of the red edge index.

In contrast, Broge and Leblanc (2001) indicated that REIP measures relate poorly to LAI according to a simulation analysis using a combined PROSPECT and SAIL radiative transfer model. Gong *et al.* (1992) used imaging spectrometer data to investigate the relationship between the LAI of ponderosa pine stands and their spectral response. They found that the magnitude of the red edge slope was not strongly correlated with LAI. Schlerf *et al.* (2005) used HyMap data for highly managed conifer stands and discovered a relatively close linear relationship between forest LAI and REIP only for a subset of their data. Imanishi *et al.* (2004) found that REIP was neither a good indicator of drought status nor of LAI for two tree species, *Quercus glauca* and *Quercus serrata*. Blackburn (2002) found no relationship between REIP and LAI using CASI data in coniferous forests.

From the above literature it is evident that many of the conclusions drawn for similar vegetation types are contradictory. Moreover, many studies focus on single plant species and/or structurally similar plant types. Hence, there is a need to further investigate the relationship between LAI and narrowband indices including the REIP. The investigation should involve structurally widely different plant species with varying leaf chlorophyll concentration and should be measured above contrasting backgrounds. The objectives of this study were to examine the relationship between the LAI of structurally different vegetation canopies and the hyperspectral reflectance data, narrowband VI and REIP. The laboratory study was designed to test two hypotheses: (i) REIP is controlled primarily by canopy LAI and is a good predictor for LAI, and (ii) the narrowband VI is more responsive than REIP and broadband VI for estimation of canopy LAI. The study is based on canopy spectral reflectances measured during a laboratory experiment using canopy species with different leaf sizes and leaf shapes.

2. Materials and methods

2.1 *Experimental set-up*

Four different plant species with different leaf shapes and sizes were selected for sampling: *Asplenium nidus*, an epiphytic fern which has apple green leaves of about 50 cm length and 20 cm width; *Halimium umbellatum*, a Mediterranean procumbent shrub which has crowded leaves at the apex of branchlets, the leaves being linear and about 25 mm in length; *Schefflera arboricola Nora*, a shrub with palm shaped leaves, dark green in colour and palmately compound with 7–9 leaflets each about 5–7 cm long; and *Chrysalidocarpus decipiens*, a single trunked or clustering palm with slightly plumose leaves, each about 25 cm long with a width of 2 to 3 cm. A total of 24 plants were used for the study, 6 plants per species. The plants were maintained in a greenhouse with a day temperature of 25°C and night temperature of 21°C. Photos taken from nadir (figure 1) show the four plant species and illustrate their variability in leaf size and shape.

Canopy spectral reflectance in visible and mid infrared regions is affected by many factors such as LAI, pigment concentration, canopy architecture and soil brightness (Jackson and Pinter 1986, Gitelson *et al.* 2003). In order to artificially generate a wide variability within each species, we artificially induced variations in LAI and canopy chlorophyll content as well as variations in background brightness. To obtain differences in leaf optical properties (e.g. leaf chlorophyll concentration), the plants (from each species) were randomly divided into two equal groups (three plants per species in each group) on 8 March 2005. One group (12 plants) was placed in a nutrient-rich soil (soil enriched with ammonium nitrate) and the other group (12 plants) was placed in a very poor soil (soil mainly consisting of peat) to induce nutrient shortage and thus to reduce the amount of chlorophyll in the leaves. After four weeks, a SPAD-502 Leaf

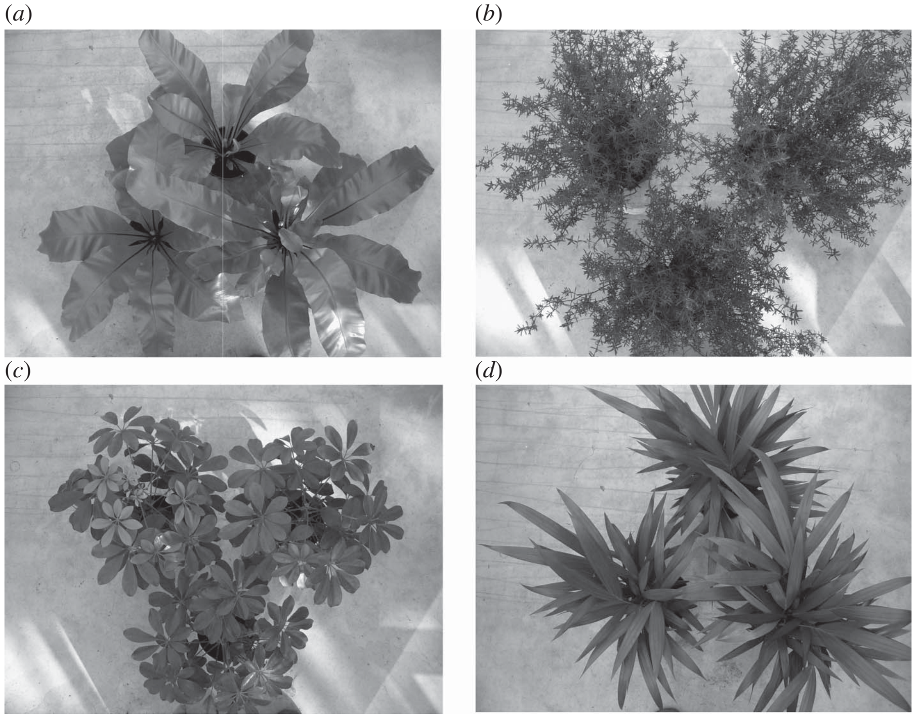

Figure 1. The four plant types at maximum coverage. (*a*) *Asplenium nidus*, (*b*) *Halimium umbellatum*, (*c*) *Schefflera arboricola Nora* and (*d*) *Chrysalidocarpus decipiens*.

Chlorophyll Meter (MINOLTA, Inc., The Netherlands) was used to measure relative chlorophyll concentration in the leaves and to verify that the goal of creating differences in leaf chlorophyll concentration was achieved.

2.2 *Spectral measurements*

Spectra were measured in a remote sensing laboratory with all walls and the ceiling coated with black material in order to avoid any ambient light or reflection, therefore minimizing the effect of diffuse radiation and lateral flux. A GER 3700 spectroradiometer (Geophysical and Environmental Research Corp., New York, USA) was used for the spectral measurements. The wavelength range is 350–2500 nm, with a spectral sampling of 1.5 nm in the 350–1050 nm range, 6.2 nm in the 1050–1900 nm range, and 9.5 nm in the 1900–2500 nm range. The fibre optic, with a field of view (FOV) of 25°, was placed in a pistol and mounted on an arm of a tripod and positioned 90 cm above a 50 cm × 50 cm soil bed at nadir position. In the setting, the spectrometer had a FOV with a diameter of 40 cm on the soil surface with the nadir point being the centre of the circle. We prepared two beds with two different soil types. One bed was filled with dark soil (peat) and one with light soil (sand silica). Three empty pots were fixed in each soil bed such that their centres were positioned on the border of the FOV and a line drawn from centre to centre would form an equal-distance triangle. Figure 2 shows the arrangement of the pots in the experiment.

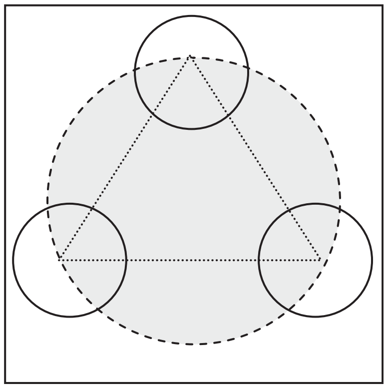

Figure 2. Schematic representation of the position of the pots in our field of view (dashed circle).

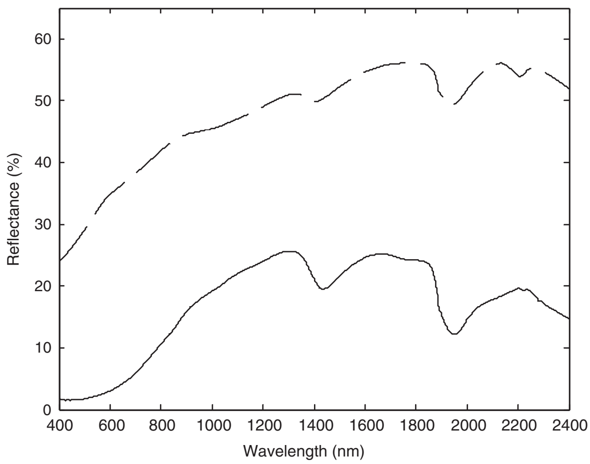

Figure 3. Spectral reflectance characteristics of the light (dashed line) and dark (solid line) soils. Each curve represents the average of 64 bare soil reflectance measurements.

Spectral measurements of bare (and air-dried) soils were acquired each time before starting the canopy reflectance measurements of one group of species. Mean reflectance spectra associated with the two soil types are shown in figure 3. Further the spectral measurements continued by placing three plants (with the same species and treatment) in their predefined positions in one of the soil beds directly under the sensor and the halogen lamp (235 W) positioned next to it, while the centre of the soil bed was made to coincide with the centres of the light and the sensor's FOV. We made sure that the FOV of the sensor was fully covered by the plants. In this manner we achieved a constant illumination, but a variable reflectance as determined by leaf area and differences in leaf shape of the various species. The soil beds were rotated by 45° after every spectral measurement in order to average out differences in canopy orientation. Next the plants were moved to the other soil bed to repeat the measurements in the other soil type. The readings were calibrated by means of a white (barium sulphate, $BaSO_4$) reference panel (50 cm × 50 cm) of known reflectivity. Reference measurements were taken after every eight target measurements. As the halogen lamp was relatively close to the plants and was not fully collimated, the incoming flux density of the various leaf layers depended on the distance to the light source. However, care was given in the selection of the plants, so that the investigated plants had more-or-less the same height (about 45 cm). Our main objective was to compare the performance of different VIs in estimating LAI of structurally different plant types having different soil backgrounds. Hence, the absolutely correct canopy reflectance (with fully collimated light source) was not of primary importance.

To create variations in LAI, the leaves on the inner side of the plants were harvested in six steps. At each step, approximately 1/6 of the total canopy (total leaves) was harvested. The leaves for removal were selected from different layers of the canopy. Each time we separated a leaf or a portion of the leaves we measured its surface area with a LI-3100 scanning planimeter. The LI-3100 (LICOR, NE, USA) is a commercial leaf area meter which makes use of a fluorescent light source and a solid-state scanning camera to 'sense' the area of leaves as they move through the instrument. The calibration of the instrument was checked each time with a metal circle of known surface. The measured surface area of the leaves was then divided by the ground area to calculate the Leaf Area Index (LAI, $m^2 m^{-2}$).

2.3 *Method*

2.3.1 Pre-processing of spectra. An average spectrum was calculated from every eight replicated measurements. A moving Savitzky-Golay filter (Savitzky and Golay 1964) with a frame size of 15 (second degree polynomial) was applied to the reflectance spectra to eliminate sensor noise.

2.3.2 Hyperspectral vegetation indices. Narrowband vegetation indices were computed from the averaged, smoothed spectra using all possible two wavelength combinations involving 584 wavelengths between 400 nm and 2400 nm. Additionally the red edge inflection point (REIP) was calculated using three different methods, i.e. first derivative, linear interpolation and inverted Gaussian model.

2.3.2.1 The narrowband indices. The most common indices are generally ratio indices and soil based indices which are based on discrete red and NIR bands. This is due to the fact that vegetation reveals distinctive reflectance properties in these bands. Ratio based vegetation indices are often preferred over soil based indices as the required soil line parameters are often unavailable or influenced by soil variability (Broge and Mortensen 2002). The soil line originally defined by Richardson and Wiegand (1977) is a linear relationship between the NIR and red reflectance of bare soils and is defined by the slope and intercept of this line. In this study, the soil line parameters (slope '*a*' and intercept '*b*') were calculated from spectral measurements of the two soils. We assumed that the soil line concept, originally defined for the red-NIR feature space, can be transferred into other spectral domains (Thenkabail *et al.* 2000, Schlerf *et al.* 2005). The narrowband indices were systematically calculated for all possible 584 × 584 = 341 056 wavelength combinations. The narrowband RVI, NDVI, PVI, TSAVI and SAVI2 were computed according to the equations in table 1.

2.3.2.2 Red edge inflection point. In the literature, several techniques are proposed to calculate the REIP. For this study, the REIP was calculated using three different approaches which are widely used in the literature, namely first derivative (Dawson

Table 1. Vegetation indices formulas used in the study. ρ denotes reflectance, λ_1 and λ_2 are wavelengths and a and b are the soil line coefficients for λ_1 and λ_2 respectively.

Acronym	Name	Vegetation index	Reference
RVI	Ratio Vegetation Index	$\mathrm{RVI} = \rho_{\lambda_1}/\rho_{\lambda_2}$	(Pearson and Miller 1972)
NDVI	Normalized Difference Vegetation Index	$\mathrm{NDVI} = \frac{\rho_{\lambda_1}-\rho_{\lambda_2}}{\rho_{\lambda_1}+\rho_{\lambda_2}}$	(Rouse *et al.* 1974)
TSAVI	Transformed Soil- Adjusted Vegetation Index	$\mathrm{TSAVI} = \frac{a(\rho_{\lambda_1}-a\rho_{\lambda_2}-b)}{a\rho_{\lambda_1}+\rho_{\lambda_2}-ab}$	(Baret *et al.* 1989)
SAVI2	Second Soil- Adjusted Vegetation Index	$\mathrm{SAVI2} = \frac{\rho_{\lambda_1}}{\rho_{\lambda_2}+(b/a)}$	(Major *et al.* 1990)
PVI	Perpendicular Vegetation Index	$\mathrm{PVI} = \frac{\rho_{\lambda_1}-a\rho_{\lambda_2}-b}{\sqrt{1+a^2}}$	(Richardson and Wiegand 1977)

and Curran 1998), linear interpolation (Guyot and Baret 1988) and inverted Gaussian model (Bonham-Carter 1988).

A first difference transformation of the reflectance spectrum was derived according to equation (1) (Dawson and Curran 1998):

$$\mathrm{FDiff}_{\lambda(i)} = (R_{\lambda(j+1)} - R_{\lambda(j)})/\Delta\lambda \tag{1}$$

$$\mathrm{REIP}_{\mathrm{FDiff}} = \lambda_{\max}(\mathrm{FDiff}) \tag{2}$$

where FDiff is the first difference transformation at a wavelength i midpoint between wavebands j and $j + 1$. $R_{\lambda(j)}$ is the reflectance at the jth waveband, $R_{\lambda(j+1)}$ is the reflectance at the $(j + 1)$th waveband and $\Delta\lambda$ is the difference in wavelength (λ) between j and $j + 1$. The REIP is simply the wavelength where the first difference is greatest.

The linear interpolation, as described by Guyot and Baret (1988), assumes that the spectral reflectance at the red edge can be simplified to a straight line centred on a midpoint between (a) the reflectance in the near-infrared shoulder at about 780 nm and (b) the reflectance minimum of the chlorophyll absorption feature at about 670 nm. The reflectance value is estimated at the inflection point. It applies a linear interpolation procedure for the measurements at 700 nm and 740 nm estimating the wavelength corresponding to the estimated reflectance value at the inflection point. The REIP is determined using the following equations:

$$R_{\mathrm{red-edge}} = (R_{670} - R_{780})/2 \tag{3}$$

$$\mathrm{REIP}_{\mathrm{linear}} = 700 + 40\left[\frac{R_{\mathrm{red\text{-}edge}} - R_{700}}{R_{740} \quad - R_{700}}\right] \tag{4}$$

where the constants 700 and 40 result from interpolation between the 700–740 nm intervals, and R_{670}, R_{700}, R_{740} and R_{780} are, respectively, the reflectance values at 670, 700, 740 and 780 nm.

The inverted Gaussian method (Bonham-Carter 1988) fits a Gaussian normal function to the measured reflectance data points between 670 and 800 nm to determine the REIP. The fitting involves iterative techniques to determine the parameters of interest:

$$R_{\mathrm{estimated}}(\lambda) = R_{\mathrm{s}} - (R_{\mathrm{s}} - R_{\mathrm{O}})\exp\left(\frac{-(\lambda_{\mathrm{o}}-\lambda)^2}{(2\sigma)^2}\right) \tag{5}$$

$$REIP_{\mathrm{IGM}} = \lambda_{\mathrm{O}} + \sigma, \tag{6}$$

where σ is the Gaussian shape parameter, measured in nanometres, R_s is the (maximum) shoulder reflectance, usually 780–800 nm, R_o is the minimum reflectance, usually at about 670–690 nm and λ_o is the wavelength at the point of minimum reflectance. The measured reflectance data points are fitted by adjusting the values of R_s, R_o, λ_o and σ in such a way that the RMSE is minimized (Mathworks 2007).

2.4 *Regression models*

We used two approaches for modelling the relationship between LAI and predictor variables (i.e. narrowband vegetation indices and REIP): (i) simple linear regression models; and (ii) a more flexible exponential model, initially suggested by Baret and Guyot (1991). The latter is a modified version of Beer's law expressing the variation in vegetation index (V) as a function of the LAI measurements (equation (7)).

$$V = V_\infty + (V_g - V_\infty)\exp^{(-K_V(\mathrm{LAI}))}. \tag{7}$$

The exponential model assumes the canopy to be a homogenous body of green plant material with an optical thickness given by the LAI. The dynamic range of the vegetation index is expressed as the difference between the bulk vegetation index (V_∞) and the index value corresponding to bare soil (V_g). The K_V parameter is equivalent to the extinction coefficient in Beer's law and characterizes the relative increase in vegetation index due to an increase in LAI. Previous studies (Wiegand *et al.* 1992, Atzberger 1995, 1997, Broge and Mortensen 2002) have confirmed the effectiveness of this model to relate vegetation indices to biophysical variables particularly to Leaf Area Index. Thus we also used this model to evaluate the relationships between narrowband vegetation indices/REIP and LAI.

2.5 *Validation*

To validate the regression models, a cross validation procedure (also called the leave-one-out method) was used. In cross validation, each sample is estimated by the remaining samples. Benefits of the cross validation method are its aptitude to detect outliers (Schlerf *et al.* 2005) and its capability for providing nearly unbiased estimations of the prediction error (Efron and Gong 1983). This implied that for each regression variant we developed 95 individual models, each time with data from 94 observations. The calibration model was then used to predict the observation that was left out. As the predicted samples are not the same as the samples used to build the models, the cross validated RMSE is a good indicator for the accuracy of the model in predicting unknown samples.

3. Results and discussion

3.1 *Variation in LAI and spectral reflectance*

The experimental protocol ensured a wide range of variation in LAI (table 2). LAI ($m^2\ m^{-2}$) varied between 0.3 and 6.1 with an average of 1.69. Due to the different leaf sizes and shapes, and different canopy architectures, as well as variations caused by nutrient stress and differences in soil brightness, canopy reflectance measurements showed a large variability (figure 4).

Table 2. Description of the data acquired during the experiment (n = 95).

Canopy species	Min LAI ($m^2\ m^{-2}$)	Mean LAI ($m^2\ m^{-2}$)	Max LAI ($m^2\ m^{-2}$)	Standard deviation LAI	SPAD	Standard deviation SPAD	No. of observations
Asplenium nidus	0.87	3.28	6.11	1.93	34.7	4.6	11
*Asplenium nidus**	0.34	2.02	3.70	1.26	31.7	6.3	12
Halimium umbellatum	0.49	1.11	1.63	0.43	44.2	3.6	12
*Halimium umbellatum**	0.42	1.09	1.73	0.48	40.0	4.6	12
Schefflera arboricola Nora	0.41	1.15	1.78	0.53	59.1	2.8	12
Schefflera arboricola Nora*	0.54	1.75	2.92	0.92	49.2	6.7	12
Chrysalidocarpus decipiens	0.30	0.85	1.64	0.50	41.5	5.9	12
*Chrysalidocarpus decipiens**	0.62	2.27	3.66	1.11	33.5	8.8	12
All combined	0.30	1.69	6.11	1.19	41.7	10.2	95

*indicates the samples placed in poor soils to reduce the leaf chlorophyll content. SPAD is the average SPAD (relative chlorophyll measure) reading for 30 randomly selected leaves in each canopy species.

Canopy reflectances of all plant types with an approximate LAI of 1.5 are shown in figure 4(*a*) to illustrate the influence of canopy architecture and leaf optical properties; like any other green vegetation spectrum, they all have a high reflectance in the near-infrared and low reflectance in the visible regions. However, their red and near-infrared reflectance values vary significantly. This variability can be attributed to variations in optical properties of the foliage (i.e. canopy chlorophyll contents) and differences in canopy architecture (Jackson and Pinter 1986, Gitelson *et al.* 2003). The canopy reflectance of *Asplenium nidus* with an approximate LAI of 1.5 is shown in figures 4(*b*) and 4(*c*). Spectral reflectance of canopy with nutrient stress shows lower absorption peaks in the visible region but along the red edge (~700 nm) it stayed relatively stable (figure 4(*b*)).

Our two investigated soils mainly differed in overall albedo. Consequently, for a given LAI and plant species (figure 4(c)), soil background variations translated into simple reflectance offsets in the measured canopy reflectance spectra. As expected, canopy LAI variation had a strong influence on the reflectance spectra (figure 4(*d*)). The most distinct effects were found in the NIR and the smallest effects in the VIS region. As LAI increased within a canopy, a clear deepening of the two water absorption features within the NIR (~1000 nm and 1200 nm) were observed in the reflectance spectras (Asner 1998).

3.2 *REIP and LAI*

Figure 5 shows box plots of the red edge positions calculated using the three methods. The red edge positions calculated using the inverted Gaussian model and the first derivative show a (too) wide dynamic range and have a tendency toward shorter wavelengths while the REIP calculated using the linear interpolation varies only between 715 nm and 726 nm. It is apparent from figure 5 that the result of REIP

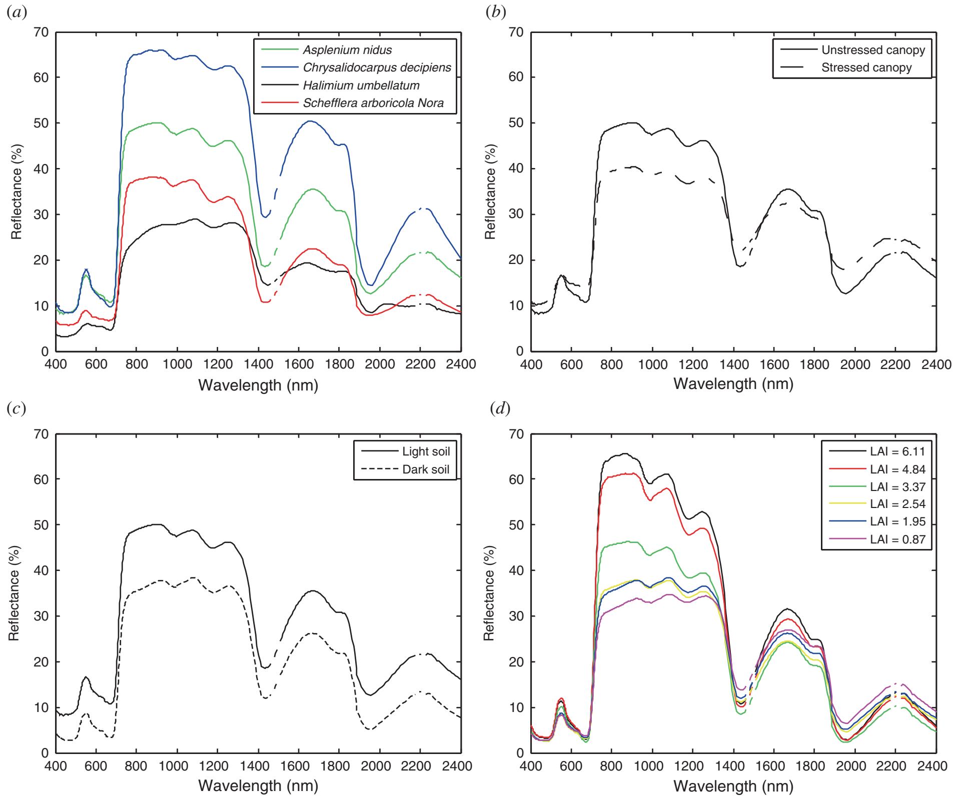

Figure 4. (*a*) Spectral reflectance of different canopy species with an LAI of 1.5. (*b*) Spectral reflectance of *Asplenium nidus,* with an LAI of 1.5, stressed and unstressed. (*c*) Spectral reflectance of *Asplenium nidus*, with an LAI of 1.5, in dark and light soil. (*d*) Spectral reflectance of *Asplenium nidus* corresponding to LAI between 0.87 and 6.11.

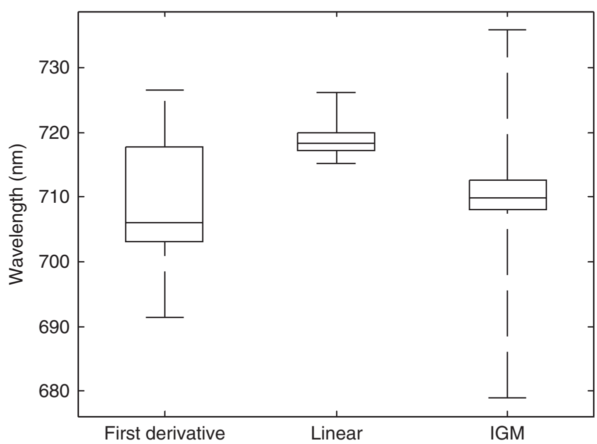

Figure 5. Box plots showing the median, lower and upper quartile values, and extent of the rest of the red edge position (REIP) calculated using three different methods (first derivative, linear interpolation and an inverted Gaussian model).

calculations from the three methods yield very dissimilar results and are highly dependent on the choice of methodology (Broge and Leblanc 2001, Cho and Skidmore 2006). In the case of the first derivative method, part of the outliers is probably due to the remaining noise in reflectance measurements (Broge and Leblanc 2001). In a recent study, Cho and Skidmore (2006) demonstrated that double peaks in the first derivative reflectance could cause discontinuities in the data and hence lead to poor relationships between LAI and REIP.

REIP calculated via either of the three methods did not show a close relation to variations in LAI. The coefficient of determination (R^2) calculated between LAI and REIP was very low ($R^2 < 0.1$) when measurements of the different plant species were pooled together.

Examples of these confusing relationships are shown in figure 6 for REIP determined using the first derivative. As is evident from figure 6, REIP was not sensitive to variations in LAI.

We also evaluated the correlation between REIP derived from different methods and LAI of each individual canopy (not shown). The results varied somewhat, but confirmed that REIP is not a good variable to estimate LAI. Consequently, we had to reject our first hypothesis that 'REIP is controlled primarily by canopy LAI and is a good predictor of LAI'.

Our findings are supported by results obtained from other studies. Blackburn (2002) found no relation between REIP and LAI for coniferous stands using CASI data, while Broge and Leblanc (2001) indicated a poor relationship between REIP and LAI. Attempts by Schlerf *et al.* (2005) to relate LAI to REIP for Norway spruce forest stands were only successful for a subset of their data. Further, our results are confirmed by the findings of Imanishi *et al.* (2004), who verified that there is no significant relationship between REIP and LAI for two deciduous and evergreen tree species. However, our results contradict the results of Broge *et al.* (1997) as well as Hansen and Schjoerring (2003) and Kodani *et al.* (2002), who showed REIP to be better than NDVI for estimation of LAI for a single species. Also, Danson and Plummer (1995) found a strong, nonlinear correlation between LAI and REIP for Sitka spruce using a helicopter-borne spectroradiometer. We conclude that at canopy

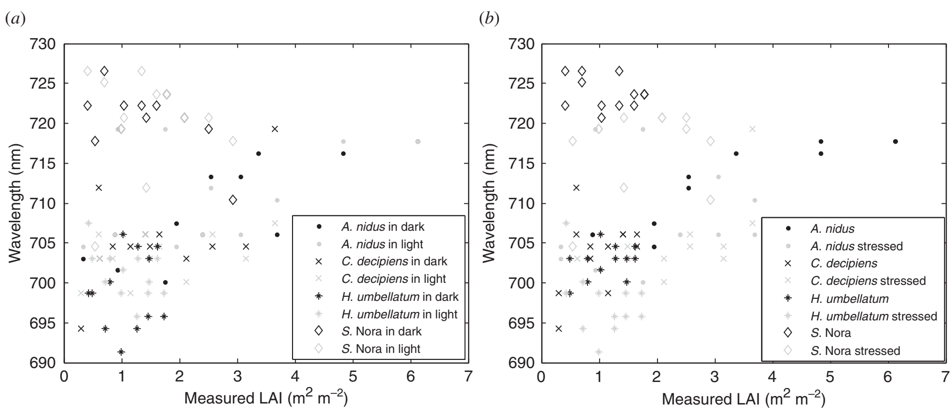

Figure 6. The relationship between LAI of different canopies and REIP calculated using first derivative. Different symbols indicate different plant species and different shades show different soil backgrounds (*a*) and different nutrient status (*b*).

level, REIP is not an appropriate variable to be considered for LAI estimations if several contrasting species are pooled together, though it may be appropriate for single species. Note that successful studies with REIP did not use destructive sampling for LAI retrieval, as was the case in this study.

Many studies have found relationships between REIP and vegetation characteristics at leaf level. As such, REIP has been used as a means to estimate changes in foliar chlorophyll concentration and also as an indicator of vegetation stress (Horler *et al.* 1983, Curran *et al.* 1995, Lamb *et al.* 2002, Rossini *et al.* 2007).

3.3 *Narrowband indices*

For both types of indices (ratio and soil based indices), the optimal narrowband vegetation index was determined using two approaches. First, the coefficients of determination (R^2) of all possible two-band combinations of vegetation index and LAI were computed. An illustration of these results is shown in the 2D correlation plot in figure 7(*a*). The meeting point of each pair of wavelengths corresponds to the R^2 value of LAI and the vegetation index calculated from the reflectance values in those two wavelengths. In the second approach (figure 7(*b*)), all possible two-band combinations of vegetation indices were calculated and used to estimate the LAI using an exponential model. The 2D plot shows the coefficients of determination (R^2) between measured and estimated LAI.

For both approaches, band combinations that formed the best indices for estimating LAI were recognized based on the R^2 values in the 2D correlation plots. The coefficient of determination (R^2) and the band positions of the best performing indices are tabulated in tables 3(*a*) and 3(*b*). In figure 8, 'hot spot' regions with relatively high R^2 values ($R^2 > 0.7$), are highlighted for all vegetation indices.

Although the near-infrared region has been the keystone of the omnipresent vegetation indices (NDVI, RVI), our results show that for most indices, bands from

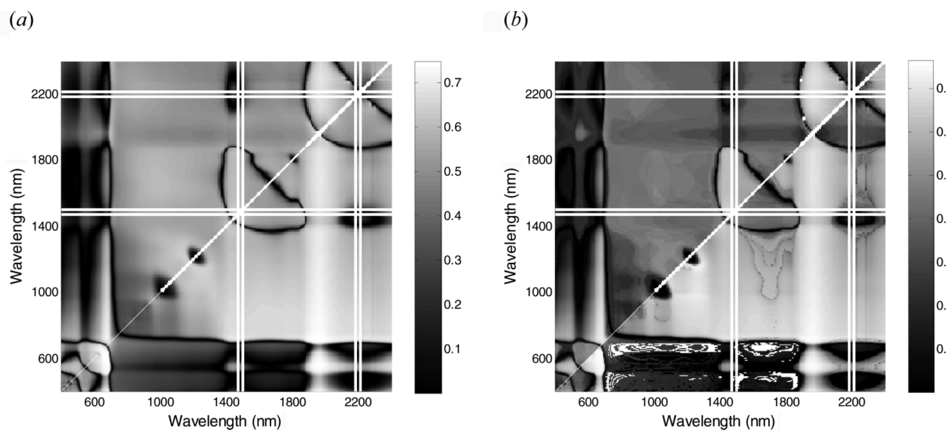

Figure 7. (*a*): 2D correlation plot representing the coefficient of determination (R^2) of narrowband RVI values and LAI. (*b*): 2D correlation plot that illustrates the coefficient of determination (R^2) of estimated LAI (using an exponential model) and measured LAI for narrowband RVI. Please note that the plots are not symmetrical. The *y*-axis is the nominator and the *x*-axis is the denominator, respectively.

Table 3. The wavelength positions (λ) and the coefficient of determination (R^2) of (*a*) the best performing narrowband indices and LAI (linear model); and (*b*) the best estimated LAI and measured LAI (exponential model).

VI	λ_1 (nm)	λ_2 (nm)	R^2
(*a*)			
RVI	718	1943	0.749
NDVI	651	653	0.745
PVI	1132	1238	0.741
TSAVI	700	1966	0.707
SAVI2	718	1966	0.775
(*b*)			
RVI	651	653	0.765
NDVI	650	658	0.755
PVI	731	1717	0.768
TSAVI	703	1955	0.751
SAVI2	719	1966	0.775

the SWIR region contain most information relevant to canopy LAI (figure 8). As is clear from figure 8, the 'hot spots' with high R^2 values mostly occur in this region.

These results support findings from studies by Brown *et al.* (2000), Cohen and Goward (2004), Lee *et al.* (2004), Nemani *et al.* (1993) and Schlerf *et al.* (2005), that suggest a strong contribution by SWIR bands to the strength of relationships between spectral reflectance and LAI. Considering that the SWIR bands were important for most vegetation indices in this study, vegetation indices that do not include this spectral region may be less satisfactory for LAI estimation (Lee *et al.* 2004). A number of other studies have recognized this region of the reflectance spectrum as potentially important for tracking vegetation properties (Asner 1998, Eklundh *et al.* 2001, Cohen *et al.* 2003).

In the next step of the analysis, for the best performing narrowband index of all vegetation indices, cross validated R^2 and RMSE were computed using linear regression and the exponential model of Baret and Guyot (1991). The results are reported in table 4. As can be observed from the table, the linear model gave relatively lower RMSE values for all indices compared to the exponential model. This is probably due to the fact that in the exponential model, at high LAI values, small reflectance variations cause (too) large variations in the estimated LAI and hence lead to increased RMSE.

The best narrowband indices for predicting LAI were identified from their RMSE values (table 4). Comparison between different narrowband vegetation indices revealed that the narrowband SAVI2 (Major *et al.* 1990) followed by the narrowband RVI (Pearson and Miller 1972) were the best overall choices as estimator of LAI based on R^2 and RMSE values if the reflectance measurements of the plant species were pooled together. This result is in agreement with those of Broge and Mortensen (2002), who defined SAVI2 as the best estimator for green canopy area index. Further, SAVI2 has been proven to be relatively insensitive to external factors such as background reflectance and atmospheric effects (Broge and Leblanc 2001).

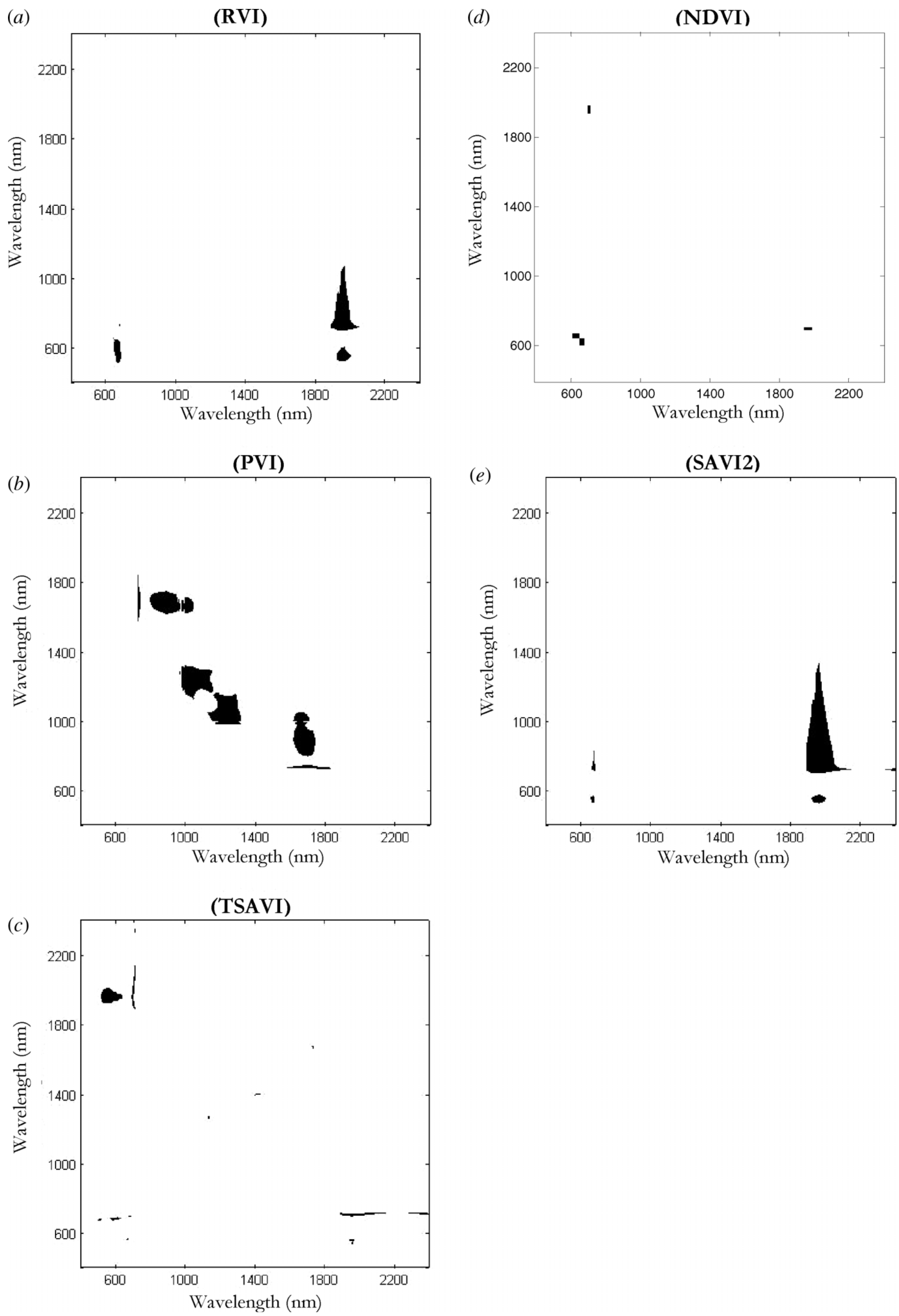

Figure 8. ‘Hot spot’ regions with relatively high values of the coefficient of determination (R^2 > 0.7) between narrowband VI and LAI. (*a*) RVI; (*b*) PVI; (*c*) TSAVI; (*d*) NDVI; (*e*) SAVIZ. Note that for TSAVI, black regions correspond to R^2 values greater than 0.6 (R^2 > 0.6).

Table 4. Cross validated R^2 and RMSE for estimation of LAI using a linear and an exponential model. $NDVI_{typical}$ is the typical NDVI (680 nm, 833 nm) vegetation index.

Narrow band VI	R^2 and RMSE (cross validated)	Linear model	Exponential model
RVI	R^2	0.729	0.754
	RMSE	0.625 (718 nm, 1943 nm)	0.686 (651 nm, 653 nm)
NDVI	R^2	0.728	0.71
	RMSE	0.628 (651 nm, 653 nm)	0.74 (650 nm, 658nm)
PVI	R^2	0.725	0.714
	RMSE	0.629 (1132 nm, 1238 nm)	0.757 (731 nm, 1717 nm)
TSAVI	R^2	0.686	0.684
	RMSE	0.672 (700 nm, 1966 nm)	0.806 (703 nm, 1955 nm)
SAVI2	R^2	0.768	0.766
	RMSE	0.590 (718 nm, 1966 nm)	0.672 (719 nm, 1966 nm)
$NDVI_{typical}$	R^2	0.354	0.586
	RMSE	0.965	0.988

Vegetation indices have been frequently correlated with LAI through linear or exponential models, depending on the existence of the saturation effect. VIs exhibit decreasing sensitivity to LAI at increasing greenness measurements (LAI values). To overcome the saturation problem, previous studies have confirmed the effectiveness of the exponential model developed by Baret and Guyot (1991) to relate vegetation indices to biophysical variables, particularly to Leaf Area Index (Wiegand *et al.* 1992, Atzberger 1995, Broge and Mortensen 2002). However, in some studies vegetation indices tend to be almost linearly related to canopy greenness without saturation (Hinzman *et al.* 1986, Goel 1989, Broge and Mortensen 2002, Chen *et al.* 2002, Schlerf *et al.* 2005). The scatter plots between best band combinations of SAVI2 and LAI illustrate a linear relationship (figure 9). Also evident from the scatter plot is that even at relatively high values of LAI (LAI = 6) saturation did not yet occur.

In the next step of the analysis, the best narrowband NDVI (651 nm, 653 nm, R^2 = 0.745) was compared to a typical NDVI (680 nm, 833 nm) (Hurcom and Harrison 1998,

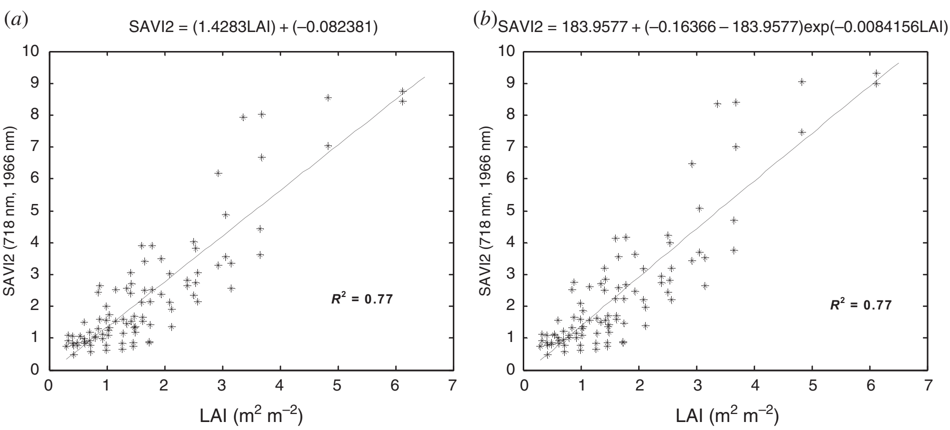

Figure 9. Relationships between best narrowband SAVI2 and LAI (*a*) using a simple linear model, and (*b*) using an exponential relationship (Baret and Guyot 1991).

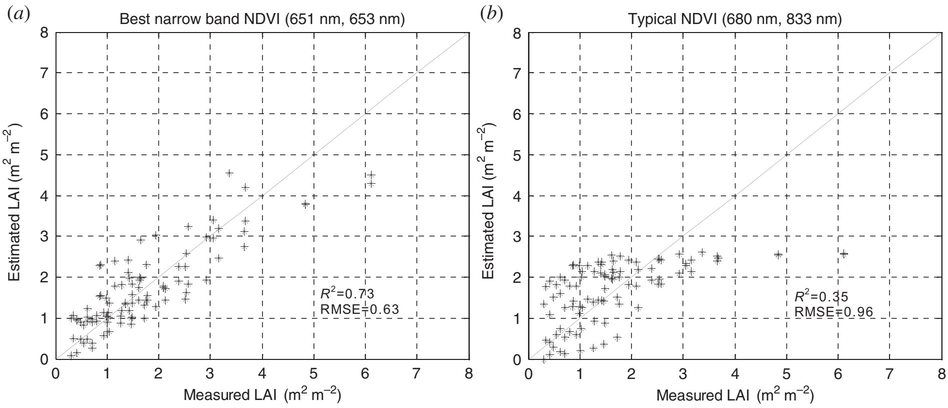

Figure 10. The relationship between measured and estimated LAI for best narrowband NDVI (*a*) and typical NDVI (*b*) using a linear regression model. Note that the values of R^2 and RMSE are cross validated.

Mutanga and Skidmore 2004), to see if narrowband vegetation indices would improve the prediction accuracy of LAI. The analysis of the LAI-NDVI in linear and exponential relationships showed that the best selected narrowband NDVI more accurately predicted LAI (table 4). Cross validated RMSE and R^2 values revealed that best narrowband NDVI (651 nm, 653 nm) is a better predictor for LAI than typical NDVI (680 nm, 833 nm). Figure 10 illustrates the relationship between measured and estimated LAI for typical NDVI and best narrowband NDVI using the linear regression model. It can be observed that LAI saturates very early (around 4) for the typical NDVI. Using the best narrowband NDVI, saturation occurs later (around an LAI of 6). This confirms previous findings by Lee *et al.* (2004) and Schlerf *et al.* (2005), who showed that narrowband vegetation indices are better predictors of vegetation biophysical variables, such as LAI, compared to broadband vegetation indices.

4. Conclusions

This paper has investigated the relationship between LAI and narrowband spectral indices, based on a laboratory experiment. Three types of narrowband vegetation indices, namely ratio based, soil based and REIP, were compared for their effectiveness in estimating LAI. The following conclusions were drawn from this study:

- REIP determined using any of the three investigated methods had a very poor relationship with LAI, in particular when the plant species were pooled together.
- LAI of vegetation canopies was estimated with reasonable accuracy from red/near-infrared based narrowband indices.
- Narrowband SAVI2 based on wavelengths in the near-infrared and SWIR proved to be the best index, in both exponential and linear models, for estimating LAI.
- Spectral channels in the SWIR regions (and those in the near-infrared) were important for predicting LAI.
- The linear model gave a better estimation of LAI than the exponential model.
- Narrowband vegetation indices were better predictors of LAI than broadband typical vegetation indices.

Although in our pooled dataset we used a relatively wide range of canopy spectral reflectances, we recommend that further studies should investigate datasets covering more species to show the relationships between biophysical variables and narrowband vegetation indices more clearly. Furthermore the number of plants within the scene should be increased to ensure that the reflected flux is representative of an infinitely extended canopy. Likewise, more care should be taken to uniformly illuminate the target by using fully collimated light sources. The latter two points will be particularly important if physically based canopy reflectance models are investigated in similar laboratory settings.

This study investigated laboratory measured reflectance data. So the findings should be applicable to real-world measurements: representative bandwidths and band settings of existing airborne or satellite based hyperspectral sensors should be used.

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