HYPERSPECTRAL VEGETATION INDICES FOR ESTIMATION OF LEAF AREA INDEX

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ABSTRACT:

Spectral vegetation indices are frequently used to estimate vegetation biophysical/biochemical characteristics. In general they have been proposed to reduce spectral effects caused by external factors such as the atmosphere and the soil background. This study evaluated narrow band vegetation indices for estimation of vegetation leaf area index. The study takes advantage of using a dataset collected during a laboratory experiment. The spectral measurements have been carried out using a GER spectroradiometer. Leaf area indices were destructively acquired at the same time. Vegetation types sampled included four different types and sizes of leaves. For predicting leaf area index, five widely used vegetation indices were investigated. Narrow band vegetation indices involving all possible two band combinations of RVI, NDVI, PVI, TSAVI, and SAVI2 were computed. Cross-validation procedures were used to assess the predictive power of the regression model. We observed a significant relationship between the narrow band SAVI2 and the leaf area index (R^2 =0.78, RMSE=0.57). All other narrow band indices respectively: RVI, NDVI, PVI and TSAVI had relatively lower R^2 values ($0.65 \leq R^2 \leq 0.75$) and higher RMSE values compared to SAVI2. Our results showed that bands from the SWIR region contain relevant information regarding to canopy LAI and are important for LAI estimation. The study demonstrates that hyperspectral data can be used to quantify leaf area index with a high accuracy.

1. INTRODUCTION

Leaf area index (LAI) is a key biophysical variable influencing land surface processes such as photosynthesis, transpiration, and energy balance and is a required input for various ecological model (Bonan, 1993). It measures one half of the total surface leaf area of the vegetation per unit area of soil (background) surfaces. In situ measurements of LAI can be time-consuming, expensive and often unfeasible. This leads to the striking possibility of using remote sensing data to estimate LAI (Wang et al., 2005). Moreover developments in the field of hyperspectral remote sensing and imaging spectrometry have allowed new ways for monitoring plant growth and estimating vegetation biophysical properties as such LAI.

To minimize the variability due to external factors such as underlying soil, remote sensing data have been transformed and combined into various vegetation indices. Spectral vegetation indices are usually calculated as combination of near infrared and red reflectance. These broad-band vegetation indices have shown to be well correlated with canopy parameters related to chlorophyll and biomass abundance such as green leaf are index and absorbed photosynthetically active radiation (Elvidge and Chen, 1995). Two common classes of indices have been the subject of considerable research : (1) ratio based indices such as 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 perpendicular vegetation index (PVI) (Richardson and Wiegand, 1977) and transformed soil adjusted vegetation index (TSAVI) (Baret et al., 1989). A large number of relationships have been established between these vegetation indices and canopy variables including leaf area index (LAI) (Broge and Leblanc, 2000; Elvidge and Chen, 1995; Rondeaux and Steven, 1995; Schlerf et al., 2005; Wang et al., 2005). While most of these relationships have been established between broadband vegetation indices and canopy LAI, less research has been done on investigating these relationships with hyperspectral vegetation indices.

The overall aim of the work was to evaluate the information content of hyperspectral reflectance measurements for the estimation of LAI. The specific objectives were (i) to determine the spectral narrow band vegetation indices that are best suited for estimating LAI, and (ii) to determine spectral region which are containing relevant information for LAI estimation. The study is based on canopy spectral reflectances measured during a laboratory experiment.

2. MATERIALS AND METHODS

2.1 Experimental Setup

Four different types of natural vegetation with different leaf shapes and sizes were selected for the study. From each species six pots were grown and examined. The plants were namely "Asplenium nidus": an epiphytic fern which has apple green leaves that will reach up to about 50 cm long by 20 cm wide, "Halimium umbellatum": a Mediterranean procumbent shrub which has crowded leaves at apex of branchlets, the leaves are linear and about 25mm long, "Schefflera arboricola Nora": a shrub with palm shaped leaves, which are dark green and are palmately compound with 7-9 leaflets. The individual leaflets are sometimes about 7.5 cm long, and "Chrysalidocarpus decipiens": a single trunked or clustering palm to about 20m high which has slightly plumose leaves.

In order to generate a wider range of canopy spectra from each species, the effects of variation in LAI, soil brightness and canopy chlorophyll content were considered. The latter was achieved, by dividing the pots (from each species) randomly into two equal groups (3 pots in each group) on 8th March 2005. One group (12 pot) were placed in the reach nutrient soil and the other group (12 pots) were placed in a very poor soil in order to reduce the nutrient and thus to reduce the amount of chlorophyll. After four weeks, according to the SPAD readings (SPAD-502 Leaf Chlorophyll Meter, MINOLTA, Inc.), the latter was achieved. .
Spectral measurements with GER 3700 Spectroradiometer (Geophysical and Environmental Research Corp.) were taken in a remote sensing laboratory where all the walls and ceiling were coated with black material in order to avoid any ambient light or reflection. The measurements started by placing three pots of same species in a 50cm x 50cm soil bed, such a way, that they would form a homogenous canopy in the sensor's field of view . The readings were normalized to bi-directional reflectance by means of a spectralon reference panel (50cm x 50cm) of known reflectivity. Reference measurements were taken after every eight target measurements.
In order to manipulate a variation in LAI, the leaves in the inner side of the pots were harvested in 6 steps. In each step, after every eight replicate of spectral measurements from the canopy, we harvested approximately 1/6 of the total canopy (total leaves). Each time that we separated a leaf or a portion of the leaves we measured its surface area with the LI-3100 scanning planimeter. The measured surface area of the leaves was divided by the ground area to calculate the leaf area index (LAI, m^2 m^{-2}).

2.2 METHOD

An Average spectrum was calculated from every eight replicate measurements. A moving Savitzky-Golay filter (Savitzky and Golay, 1964) of 15 nm wide was applied to the reflectance spectra to eliminate sensor noise (2nd degree polynomial). Cubic interpolation of the data into 1 nanometer interval ensured detailed investigation on the spectrum and made the rest of the calculations smoother.
Narrow band vegetation indices were computed using all possible two wavelengths combinations involving 2000 wavelengths between 400 nm and 2400 nm (2000 x 2000=4 x 10^6 wavelengths combinations). The soil line parameters (slope "a" and intercept "b") were calculated from the soil spectral measurements. We assumed that the soil line concept, originally defined for the red-NIR feature space can be transferred into other spectral domains (Schlerf et al., 2005; Thenkabail et al., 2000). So it was thought that the soil line is present between all wavelengths. The narrow band RVI, NDVI, PVI, TSAVI and SAVI2 were computed according to table one.

ACRONYM	NAME	VI		REFERENCE
RVI	Ratio vegetation index	$RVI = \rho_{\lambda 1} / \rho_{\lambda 2}$	(1)	(Pearson and Miller, 1972)
NDVI	Normalized difference vegetation index	$NDVI = \frac{\rho_{\lambda 1} - \rho_{\lambda 2}}{\rho_{\lambda 1} + \rho_{\lambda 2}}$	(2)	(Rouse et al., 1974)
TSAVI	Transformed soil-adjusted vegetation index	$TSAVI = \frac{a(\rho_{\lambda 1} - a\rho_{\lambda 2} - b)}{a\rho_{\lambda 1} + \rho_{\lambda 2} - ab}$	(3)	(Baret et al., 1989)
SAVI2	Second soil- adjusted vegetation index	$SAVI2 = \frac{\rho_{\lambda 1}}{\rho_{\lambda 2} + (b/a)}$	(4)	(Major et al., 1990)
PVI	Perpendicular vegetation index	$PVI = \frac{\rho_{\lambda 1} - a\rho_{\lambda 2} - b}{\sqrt{1+a}^{2}}$	(5)	(Richardson and Wiegand, 1977)

Table 1. Vegetation indices formulas used in the study. *ρ* denotes reflectance, *λ1* and *λ2* are wavelengths and *a* and *b* are the soil line coefficients.

2.3 Regression and validation

Vegetation indices are often correlated with LAI through a linear or exponential model, depending on the existence of saturation effect. Most vegetation indices exhibit decreasing sensitivity followed by saturation with increasing greenness measures. However, some vegetation indices tend to be almost linearly related to canopy greenness with no saturation (Broge and Mortensen, 2002; Chen et al., 2002; Goel, 1989; Hinzman et al., 1986; Schlerf et al., 2005). We used linear regression approach for modeling the relationship between LAI and narrow band vegetation indices. Cross validation procedure was used to validate the regression models. This implied that for each regression variant, (where n = 95) 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 pointer of the accuracy of the model in predicting unknown samples.

3. RESULTS AND DISCUSSION

As expected, the measured spectra reflected a wide range of variation in LAI (table. 2). LAI varied between 0.3 m^2 m^{-2} and 6.11 m^2 m^{-2} with an average of 1.69 m^2 m^{-2}.

Total samples	Min LAI m^2 m^{-2}	Mean LAI m^2 m^{-2}	Max LAI m^2 m^{-2}	STDev LAI
95	0.30	1.69	6.11	1.19

Table 2. Summery statistics of the data acquired during the experiment.

Canopy reflectances of all plant types with an approximate LAI of 1.5 are shown in figure one; like any other green vegetation spectra, 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 significantly vary among each other. This variability can be attributed to variations in foliar optical properties (i.e. canopy chlorophyll contents) and differences of canopy architectures (Gitelson et al., 2003; Jackson and Pinter, 1986).

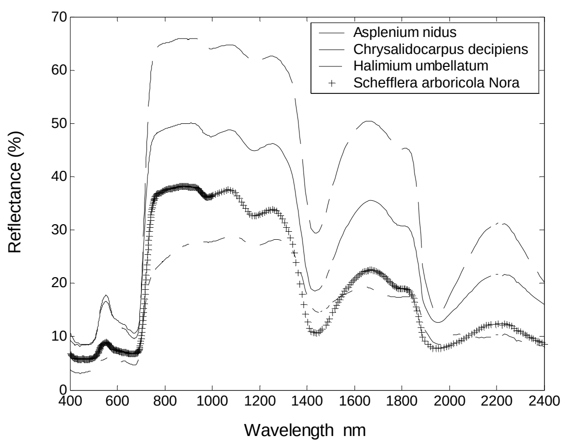

Figure 1. Spectral reflectance of different canopy species with an LAI of 1.5.

For both, the ratio indices and soil based indices, to determine the optimal narrow band vegetation index, the coefficient of determination (R^2) between all possible two band combination of vegetation index and LAI were computed. An illustration from these results is shown in 2-D correlation plot in figure two.

Band combinations that formed the best indices for determining LAI were recognized based on the R^2 values in the 2-D correlation plot (table 3). In figure three the regions where relatively high values of coefficient of determination R^2 (R^2>0.7) exist are highlighted for all vegetation indices.

VI	λ1 (nm)	λ2 (nm)	R^2
RVI	652	653	0.749
NDVI	652	653	0.748
PVI	1132	1241	0.741
TSAVI	1940	1968	0.681
SAVI2	727	1967	0.786

Table 3. The wavelength positions and the coefficient of determination (R^2) between the best performing narrow band indices and LAI.

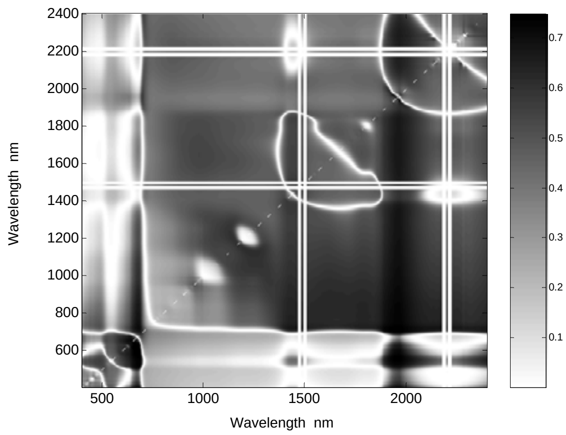

Figure 2. 2D correlation plot that illustrates the correlation of determination (R^2) between narrow band RVI values and LAI.

Although the near infrared region has been the keystone of the ubiquitous vegetation indices (NDVI, RVI), but our results show that for most indices, bands from the SWIR region contain more information relevant to canopy LAI than of red and near infrared bands and are important for LAI estimation (figure 3). As it is clear from figure three the "hot spots" are mostly have occurred in this region.

These results support findings of previous studies by (Brown et al., 2000; Cohen and Goward, 2004; Lee et al., 2004; Nemani et al., 1993; Schlerf et al., 2005), that suggested a strong contribution of SWIR bands to the strength of relationships between spectral reflectance and LAI. Considering that the SWIR bands were important for most of VI 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 vegetative properties (Asner, 1998; Cohen et al., 2003b; Eklundh et al., 2001).

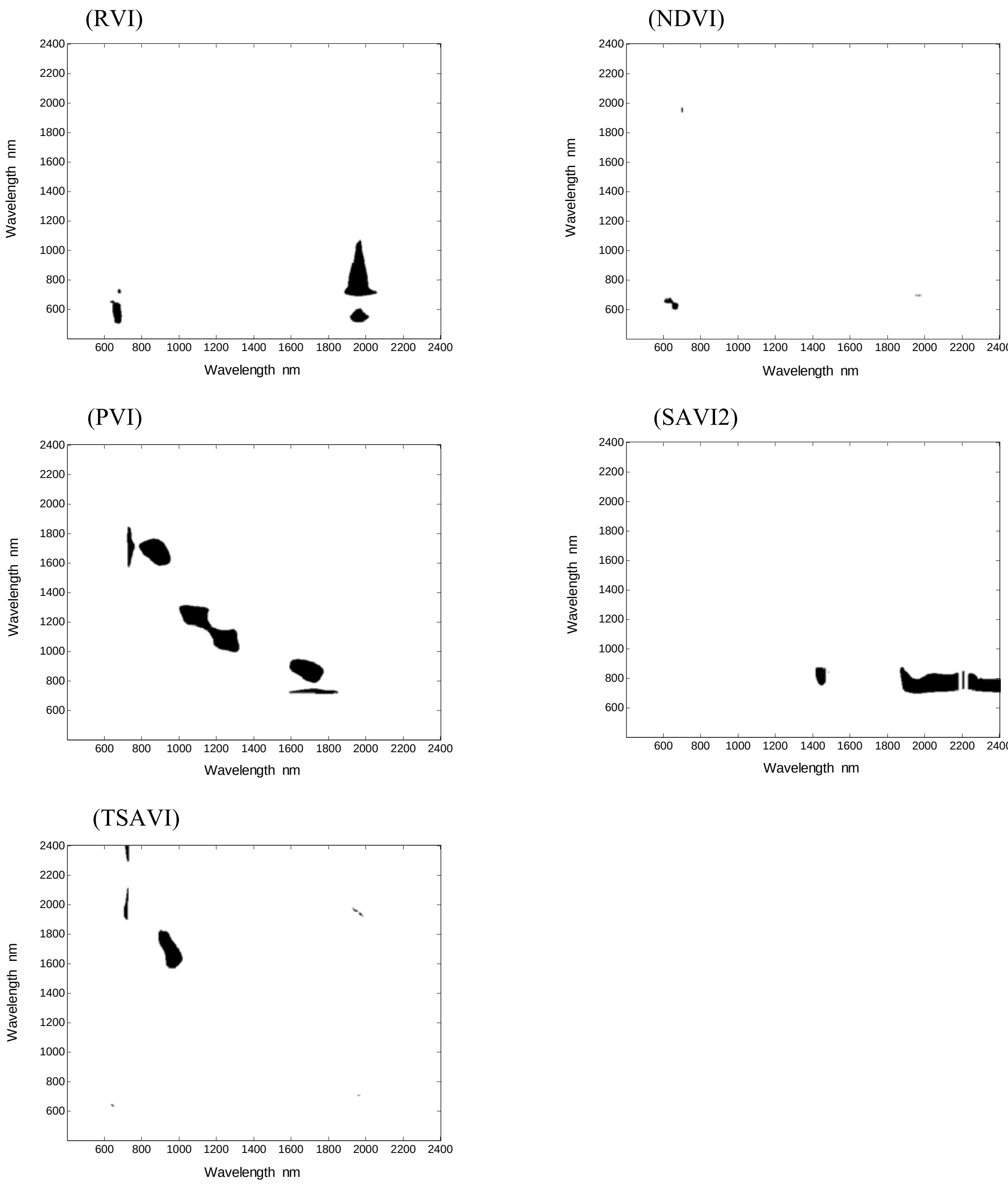

Figure 3. The "hot spot" regions where there are relatively high values of coefficient of determination R^2 (R^2>0.7) between band combinations and LAI. Note that only in case of TSAVI the R^2 value is greater than 0.6 (R^2>0.6).

For the best performing narrow band index of all vegetation indices, cross validated R^2 and RMSE between measured and estimated LAI were computed. Comparison of R^2 and RMSE values between different narrow band vegetation indices revealed that the narrow band SAVI2 followed by narrow band RVI index which were proposed by (Major et al., 1990) and (Pearson and Miller, 1972), respectively, seemed to be the best overall choices as estimator of LAI. Figure four illustrates the relationships between LAI and narrow band SAVI2 obtained from linear model. This result is in agreement with those of recent study by (Broge and Mortensen, 2002) which defined SAVI2 as an best estimator for green canopy area index (a derivative variable from LAI).

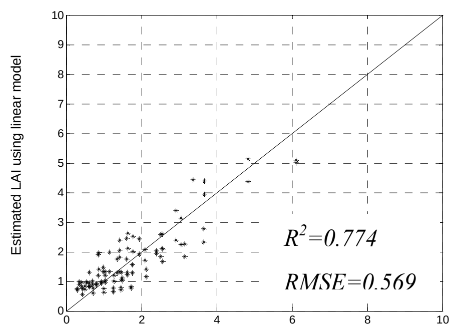

Figure 4. Cross validated, estimated LAI versus measured LAI using narrow band SAVI2.

The scatter plots between best band combination SAVI2 and LAI illustrate their linear relationship (figure 5). Also it is evident from the scatter plot that even at relatively high values of LAI no saturation has happened.

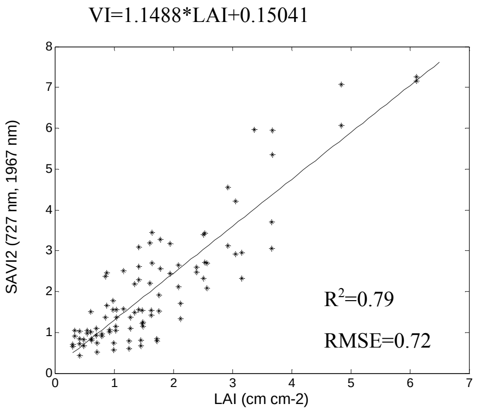

Figure 5. Relationships between best narrow band SAVI2 and LAI.

4. CONCLUSIONS

The study has investigated the relationship between LAI and narrow band spectral indices, based on a laboratory experiment. Two types of narrow band vegetation indices, namely ratio based and soil based were compared for estimation of LAI. The following conclusions were drawn from this study:

-Vegetation LAI was estimated with a good accuracy from red/ near infrared based narrow band indices.

-Narrow band SAVI2 based on wavelengths in near infrared and SWIR was performed as the best index, for estimation of LAI.

-Spectral channels in the SWIR regions are important as well as those in the near infrared for predicting LAI.

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