

Effects of chlorophyll concentration on green LAI prediction in crop canopies: Modelling and assessment

Driss Haboudane¹, John R. Miller^{1,2}, Elizabeth Pattey³, Pablo J. Zarco-Tejada⁴ and Ian Strachan⁵

1) Centre for Research in Earth and Space Science (CRESS), Petrie Science Building, York University, 4700 Keele St., Toronto - Ontario M3J 1P3, Canada, driss@terra.phys.yorku.ca

2) Department of Physics and Astronomy, York University, Toronto, ON, M3J 1P3, Canada, jrmiller@yorku.ca

3) Agriculture and Agri-Food Canada, Central Experimental Farm, K. W. Neatby room 2091, 960, Carling ave., Ottawa, Ontario, K1A 0C6, Canada, PatteyE@agr.gc.ca

4) Grupo de Optica Atmosferica (GOA-UVA), Escuela Técnica Superior de Ingenierias Agrarias, Campus de La Yutera, Universidad de Valladolid, Avda. de Madrid, 44, Palencia, 34004 Spain, pzarco@iaf.uva.es

5) Department of Natural Resource Sciences, Macdonald Campus of McGill University, 2111 Lakeshore Rd., Ste. Anne de Bellevue, Qc, H9X 3V9, Canada, ian.strachan@mcgill.ca

ABSTRACT—A growing number of studies have focused on evaluating vegetation indices in terms of their sensitivity to vegetation biophysical parameters as well as to external factors affecting canopy reflectance. In this context, leaf and canopy radiative transfer models have provided a basis for understanding the behaviour of such indices, particularly their resistance to external perturbing effects related to soil background, illumination, and atmospheric conditions. But, so far no studies have thoroughly assessed the impact of leaf chlorophyll concentration changes on the ability of spectral indices to predict green leaf area index (LAI). Because the variables LAI and chlorophyll content have similar effects on canopy reflectance in the visible and red edge portions of the solar spectrum, there is a need to uncouple these effects in order to accurately assess each of these variables. In the present work we used PROSPECT and SAILH models to simulate a wide range of crop canopy reflectances which were used to study the sensitivity of a set of vegetation indices to LAI variability. The aim of the paper was to present a method for minimizing the effect of leaf chlorophyll content on the prediction of vegetation green LAI, and to propose an index that adequately predicts the LAI of crop canopies. Accordingly, we have developed new algorithms that proved to be the best predictor of green LAI with respect to potentially confounding leaf chlorophyll concentration effects. The technique has been validated using CASI hyperspectral reflectance images acquired on different dates (1999, 2000, 2001), over fields with various crops (corn, wheat, and soybean) at different growth stages, containing plots with various fertilization treatments. Maps of predicted LAI were generated and corresponding statistics were compared to ground truth data. Evaluation of predictions revealed good agreement with field measurements.

1 INTRODUCTION

Green leaf area index (LAI) is one of the canopy parameters that plays a major role in vegetation physiological processes, and ecosystems functioning; it has been frequently used by agronomists and crop physiologists to assess crop conditions and growth. Its estimation from remote sensing data has motivated the

development of various approaches and techniques for LAI mapping at local, regional, and global scales (Baret and Guyot, 1991; Daughtry et al., 1992; Chen et al., 2002; etc.). While some studies have focused on model inversion (Jacquemoud et al., 2000), and spectral mixture analysis (Hu et al., 2002; Peddle and Johnson, 2000; Pacheco et al., 2001), others have expended considerable effort to develop relationships between green LAI and spectral vegetation indices

(Spanner *et al.*, 1990; Chen and Cihlar, 1996; Fassnacht *et al.*, 1997). Though these indices were well correlated with green LAI, studies have demonstrated that they were as well very responsive to other vegetation descriptors such as canopy cover, chlorophyll concentration and absorbed photosynthetically active radiation (Broge and Leblanc, 2000; Broge and Mortenson, 2002; Daughtry *et al.*, 2000; Gitelson *et al.*, 2001; Haboudane *et al.*, 2002a). Consequently, to meet the requirements related to prediction accuracy and consistency, there is a need for the design of specific spectral indices that are ideally sensitive exclusively to a vegetation/canopy descriptor of interest. For instance, Daughtry *et al.* (2000) and Haboudane *et al.* (2002) have each suggested index-based approaches to estimate leaf chlorophyll content with minimal confounding effects due to LAI.

The objective of the present study is to evaluate the potential of selected spectral indices in terms of quantifying green LAI of crop canopies. Indices were assessed regarding their sensitivity to chlorophyll concentration changes, and their linearity and saturation with green LAI increase. As a part of the study, a new index is suggested and its LAI predictions are compared to ground truth data.

2 DATA COLLECTION AND PROCESSING

The study area is located near Ottawa, Canada at the NCC Research Farm. Over three successive years, different crops (soybean, corn, wheat) were grown on a 30-ha field with a drained clay loam soil as well as on adjacent fields operated by private producers. The experiments consisted of dividing the main field into four regions receiving various nitrogen treatments: 100% of the recommended fertilization (155 kg/ha) over a flat region, 100% of recommended nitrogen over a region with a gentle topographic slope, 60% of the recommended rate, and no nitrogen application (0%). They were thus laid out to promote development of remote sensing techniques for detection of plant stresses in precision agriculture, particularly stresses due to nitrogen deficiency, water deficit, and topographic influence. Within each region, a grid of georeferenced points spaced every 25 m was established on a representative section of 150 m x 150 m. These locations were used to monitor crop biophysical parameters during the growing season, particularly during intensive field campaigns coinciding with image acquisition. Details on the experimental site are presented in Pattey *et al.* (2001).

Hyperspectral images were acquired by the Compact Airborne Spectrographic Imager (CASI), operated by the Centre for Research in Earth and Space Technology (CRESTech). Simultaneously, a set

of field and laboratory data were collected for biochemical and geochemical analysis, along with optical and biophysical measurements. Ground truth measurements included: (i) collection of leaf tissue for laboratory determination of leaf chlorophyll concentration, (ii) crop leaf reflectance and transmittance measurements using an integrating sphere (Li-Cor model 1800-12) coupled with a single mode optical fibre to a spectrometer (GER1500, GER, Millbrook, NY), (iii) chlorophyll meter (Minolta SPAD 502) measurements, (iv) leaf area index (LAI) measurements using the Plant Canopy Analyzer (Li-Cor model LAI-2000) and an area meter (LI-3100, Li-Cor, Lincoln, NE), and (v) crop growth measures.

During 2000 and 2001 growing seasons, CASI hyperspectral images were collected in three different deployments, using two modes of operation: the *multispectral mode*, with 1 m spatial resolution and 7 spectral bands suitable for sensing vegetation properties (489.51, 554.98, 624.63, 681.42, 706.12, 742.31, and 776.69 nm); and the *hyperspectral mode*, with 2 m spatial resolution and 72 channels covering the visible and near infrared portions of the solar spectrum from 408 to 947 nm with a bandwidth of 7.5 nm. Acquisition dates were planned to coincide with different phenological development stages, providing image data covering the earliest, middle and latest periods of the growth season.

The hyperspectral digital images collected by CASI were processed to at-sensor radiance using calibration coefficients determined in the laboratory by CRESTech (Centre for Research in Earth and Space Technology). Then the CAM5S atmospheric correction model (O'Neill *et al.*, 1997) was used to transform the relative at-sensor radiance to absolute ground-reflectance. To perform this operation, an estimate of aerosol optical depth at 550 nm was derived from ground sun-photometer measurements. Data regarding geographic position, illumination and viewing geometry as well as ground and sensor altitudes were derived both from aircraft navigation data recordings and ground GPS measurements.

Reflectance curves derived from processed CASI images showed the presence of spectral anomalies associated with atmospheric absorption features at specific wavelengths. Although we applied model-based atmospheric corrections, the calculated reflectances are still affected by spectrally-specific errors owing mostly to an under-correction of some atmospheric components effects (oxygen and water vapour absorption). These imperfections in reflectance data cube retrieval are a problem common to hyperspectral systems due to limitations in the performance of atmospheric correction models and to variations across the detector array in nominal imager characterisations in spectral registration and

bandwidth. The flat field calibration is a correction technique used to remove the residual calibration-induced noise and atmospheric effects from hyperspectral reflectance image cubes. Its aim is to improve overall quality of spectra and provide apparent reflectance data that can be compared with laboratory spectra (Boardman, and Huntington, 1996). It requires the presence, and identification in images of spectrally-flat uniform areas where the spectral anomalies can be unambiguously attributed, in narrow spectral ranges, to atmospheric effects and the solar spectrum. In CASI images, these features were observed over asphalt and concrete areas within the same image where the reflectance spectra are assumed to be flat or nearly flat over these features. Using signatures of such scene elements, we calculated coefficients that adequately compensated for the effects of atmospheric water and oxygen absorption. After those coefficients were applied to the entire image, but only in the specific spectral ranges affected, we checked the signatures of different components of the image and found that observed residual features have been successfully removed.

3 CANOPY REFLECTANCE SIMULATIONS

Leaf optical properties were simulated using the PROSPECT model (Jacquemoud and Baret, 1990; Jacquemoud *et al.*, 1996), which simulates upward and downward hemispherical radiation fluxes between 400 and 2500 nm, and relates foliar biochemistry and scattering parameters to leaf reflectance and transmittance spectra. It requires the leaf internal structure parameter N , the chlorophyll a + b content C_{ab} ($\mu\text{g}/\text{cm}^2$), the equivalent water thickness C_w (cm), and the leaf dry matter content C_m (g/cm^2) to determine leaf reflectance and transmittance signatures in the optical domain.

Canopy reflectance spectra were simulated using a variant of the SAIL (Scattering by Arbitrary Inclined Leaves) model (Verhoef, 1984) called SAILH. It was adapted to take into account the hotspot effect or the multiple scattering in the canopy (Kuusk, 1985). It is a turbid-medium model that approximates the canopy as a horizontally uniform parallel-plane infinitely-extended medium, with diffusely reflecting and transmitting elements. Typical SAILH inputs are: canopy architecture defined by the leaf area index (LAI) and the leaf angle distribution function (LADF), leaf reflectance and transmittance spectra for given chlorophyll content per unit area, underlying soil reflectance, and the illumination and viewing geometry (solar zenith and sensor viewing angles).

4 LAI AND CHLOROPHYLL EFFECTS ON CANOPY REFLECTANCE

The chlorophyll content effect on canopy reflectance is presented for a preliminary analysis of SAILH simulated spectra in **Figure 1**. It shows reflectance differences induced by changes in leaf chlorophyll concentration ($5 - 70 \mu\text{g}/\text{cm}^2$) for a known medium LAI ($=3$). The relative spectral difference is performed between spectra representing various chlorophyll contents and the spectrum corresponding to $50 \mu\text{g}/\text{cm}^2$. Wavelength regions that are the most sensitive to leaf pigment variability are centered on 550 nm in the green and 715 nm in the red edge. The narrow peak observed at 715 nm seems to be shifted to longer wavelength when leaf chlorophyll concentrations increase. This corresponds to the transition from chlorophyll absorption processes in the red wavelengths to within-leaf scattering in the near-infrared region (Munden *et al.*, 1994). In fact, an increase of chlorophyll content induces a broadening of chlorophyll absorption feature in the red (670-680 nm) and, therefore, moves the red-edge position to longer wavelengths (Daughtry *et al.*, 2000) as seen on **Figure 1**. The relatively wide window of sensitivity to pigment variation in the green is due to the canopy reflectance decrease generated by the increase in leaf chlorophyll concentration.

In contrast, major LAI effects on canopy reflectance occur around 685 nm and beyond 740 nm (**Figure 2**). Unlike chlorophyll concentration, LAI generates weak variations of reflectance spectrum at 550 nm and at 720 nm. It can be seen that high differences in the red region (685-690 nm) are observed only for low LAI values (0.1, 0.5, and 1.0). This phenomenon could be associated with the influence of non-photosynthetic materials and dry biomass on canopy reflectance when green biomass represents a relatively small proportion. The major variations induced by LAI in the near-infrared are due to the canopy structural development and multiple scattering which is particularly important at these wavelengths. Based on these simulations, it can be seen that chlorophyll interactions with radiation are limited to the optical domain ranging from 400 nm to 725 nm, while LAI influences are observed over the red and near-infrared portions. Their combined effects occur over the red edge region where LAI and chlorophyll density increasingly contribute to the shift of the red edge position.

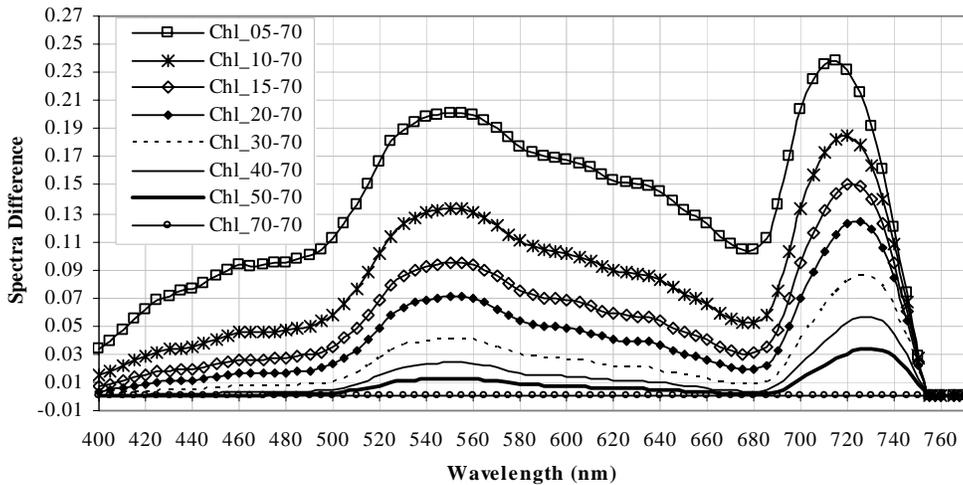


Figure 1 Relative canopy reflectance differences (difference between spectra representing various chlorophyll contents and the spectrum corresponding to 70 $\mu\text{g}/\text{cm}^2$) for an LAI of 3. In the legend, Chl40-70 represents the difference between spectra corresponding to chlorophyll contents 40 and 70 $\mu\text{g}/\text{cm}^2$.

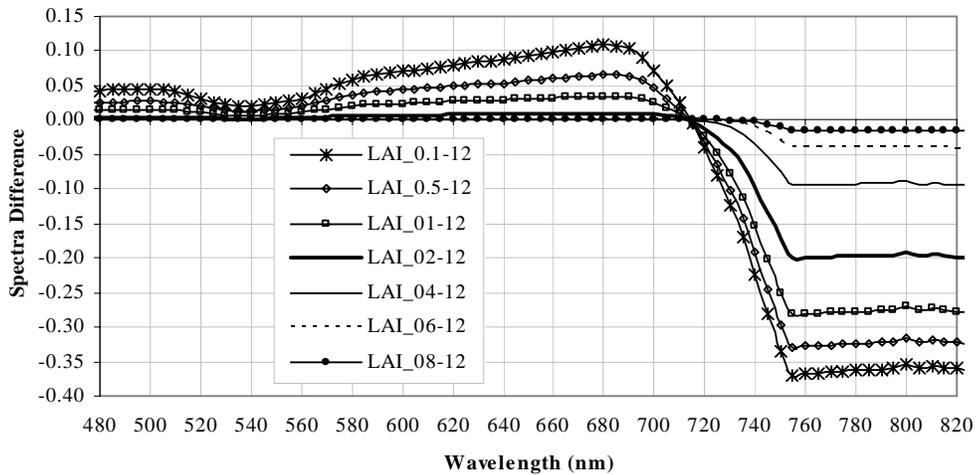


Figure 2 Relative canopy reflectance differences (difference between spectra representing various LAI values and the spectrum corresponding to LAI = 12) for a chlorophyll content of 35 $\mu\text{g}/\text{cm}^2$. In the legend, LAI_04-12 represents the difference between spectra corresponding to LAI values 4 and 12.

5 LAI ESTIMATION: MODELLING AND PREDICTION

Different techniques have been developed in order to improve green LAI estimation over large areas, mainly through the use of spectral indices, model inversions (Jacquemoud et al., 2000), and spectral mixture

analysis (Hu *et al.*, 2002; Peddle and Johnson, 2000; Pacheco *et al.*, 2001). The widely used approach was to establish relationships between ground-measured LAI and vegetation indices (Spanner *et al.*, 1990; Chen and Cihlar, 1996; Fassnacht *et al.*, 1997). Consequently, a large number of relationships were developed, with a wide range of determination coefficients ($0.05 < r^2 < 0.66$) between satellite-

derived spectral indices and LAI (Baret and Guyot, 1991; Chen, 1996; Brown *et al.*, 2000).

Several optical indices have been reported in the literature and have been proven to be well correlated with various vegetation parameters such as LAI, biomass, chlorophyll content, and photosynthetic activity. Efforts focused on improving vegetation indices and rendering them insensitive to variations in illumination conditions, observing geometry, and soil properties. Thus, the performance and the suitability of a particular index are generally determined by its sensitivity to a characteristic of interest. Consequently, only a few of the most common vegetation indices were presented in this paper aiming to study leaf chlorophyll concentration effects on LAI predictions.

Their formulae and references are provided in **Table 1** below where G, R and NIR denote canopy reflectance in the green (550 nm), red (670 nm), and near-infrared (800 nm), respectively. A detailed discussion on some spectral indices can be found in Zarco-Tejada (2000), Broge and Leblanc (2000) and Haboudane *et al.* (2002a).

Evaluation of the performance of these indices was based on canopy reflectance spectra simulated with the radiative transfer models PROSPECT and SAILH. It was conducted with consideration of the following criteria: index sensitivity to chlorophyll effects, its saturation level when LAI increases, and the linearity of its relationship with LAI.

Table 1 Information about the spectral indices evaluated in the present research.

Acronym	Name	Formula	Reference
NDVI	Normalized difference vegetation index	$(NIR - R)/(NIR + R)$	(Rouse <i>et al.</i> , 1974)
MSAVI	Modified second soil-adjusted vegetation index	$\frac{1}{2} \left[2 * NIR + 1 - \sqrt{(2 * NIR + 1)^2 - 8 * (NIR - R)} \right]$	(Qi <i>et al.</i> , 1994)
MCARI1	Modified chlorophyll absorption ratio index	$2 * [(NIR - R) - 0.2 * (NIR - G)]$	(Haboudane <i>et al.</i> , 2002a)
MCARI2	Modified second chlorophyll absorption ratio index	$\frac{1.35 * [1.9 * (NIR - R) - 0.52 * (NIR - G)]}{(0.8 + NIR * NIR + R * R)}$	(Haboudane <i>et al.</i> , 2002a)

6 RESULTS AND ANALYSIS

To understand the chlorophyll effect on LAI estimation from reflectance data, we plotted spectral indices against green LAI as a function of chlorophyll concentration (**Figure 3**). For each index, the number of the curves expresses the variation of chlorophyll content from 10 to 100 $\mu\text{g cm}^{-2}$ with an increment of 5 $\mu\text{g cm}^{-2}$. As a preliminary analysis, it can be seen that all indices behave logarithmically rather than linearly with LAI. NDVI and MSAVI show a similar resistance to chlorophyll content changes, with clear sensitivity only to chlorophyll concentrations in the lower range (10 to 25 $\mu\text{g cm}^{-2}$). The main difference between these two indices is that NDVI reaches a

saturation level when LAI exceeds 2, while MSAVI shows a better dynamic response even extending to high LAI levels (up to 6) (**Figure 3**). The best behaviour in terms of both insensitivity to pigments variation and responsivity to LAI changes is given by MCARI1 and MCARI2. They offer the advantage of being the most resistant to chlorophyll changes and the least sensitive to the saturation phenomena. Indeed, MCARI1 and MCARI2 have almost unique relationships with green LAI independent of chlorophyll content changes. Because it has the advantage of including a soil adjustment term, MCARI2 was used to develop a predictive equation for estimation of canopy green LAI based on these model simulations for use with remotely sensed data.

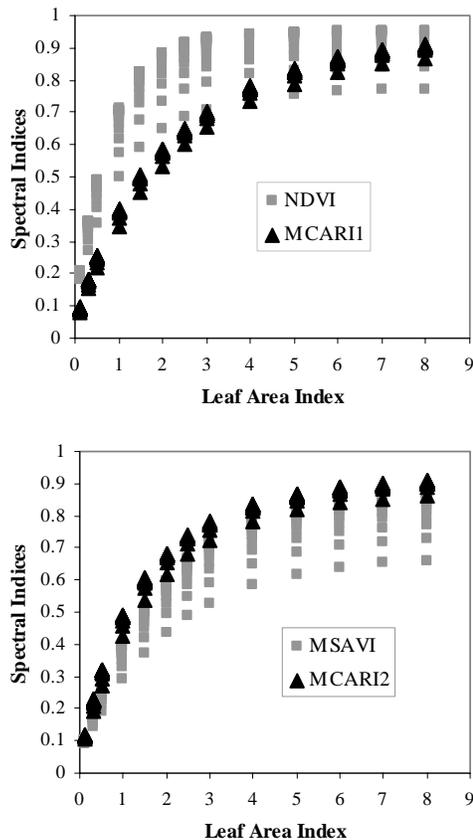


Figure 3 Effects of chlorophyll content on the relationships between spectral indices and green LAI. Application to canopy reflectance simulated using PROSPECT and SAILH. The curves correspond to various chlorophyll contents ranging from 5 to 100 $\mu\text{g}/\text{cm}^2$ in steps of 5 $\mu\text{g}/\text{cm}^2$.

For analyses of the linearity between spectral indices and green LAI, real reflectance data were extracted from CASI hyperspectral images. The latter were acquired in intensive field campaigns carried out in 1999, 2000, and 2001 over soybean, corn and wheat canopies. Indices under evaluation in this study were calculated from these data, then, plotted against the NIR reflectance as shown in **Figure 4**. The choice of NIR reflectance is due to the fact that above-canopy reflectance in the NIR is drastically affected by vegetation structural changes rather than by pigments concentration variations (**Figures 1 and 2**).

As can be seen in **Figure 4**, vegetation indices show different trends when plotted as a function of NIR reflectance. NDVI offered the weaker dynamic

range, and saturated quickly with the increase of NIR reflectance. In contrast, MSAVI and MCARI2 appeared to be more sensitive to NIR reflectance changes, however, their behaviour is characterised by a gentle asymptotic trend at high NIR reflectance values. The overall best linear relationship is offered by MCARI1, but further analyses have shown that it results in an overestimation at high LAI values.

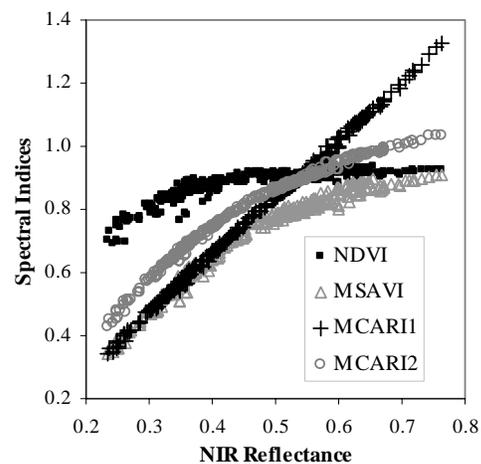


Figure 4 Relationships between evaluated spectral indices and the near-infrared (NIR) reflectance from CASI hyperspectral images collected over various crops.

A predictive relationship has been established to make green LAI estimations as a function of MCARI2 (**Figure 5**). The overall best fit was given by an exponential curve with a coefficient of determination (r^2) exceeding 0.98. One can see that, for a wide range of chlorophyll concentrations (15 to 100 $\mu\text{g}/\text{cm}^2$), there is a unique relationship between MCARI2 and green LAI. A corresponding predictive equation has been retrieved and successfully applied to CASI hyperspectral images to map green LAI status over agricultural fields seeded with corn, wheat, and soybean (**Figure 6**). Results of comparison between estimates using remote sensing and measurements in the field and laboratory are summarised in **Table 2** below.

Table 2 Comparison estimated-measured LAI: determination coefficient and RMSE.

Crop	Determination coeff. (r^2)	RMSE
Corn	0.82	0.87
Wheat	0.92	0.76
Soybean	0.96	0.87

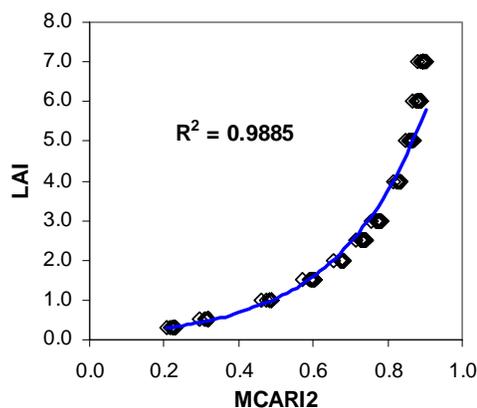


Figure 5 Relationships between Green LAI and MCARI2, for chlorophyll content varying from 15 to 100 $\mu\text{g}/\text{cm}^2$ and green LAI ranging from 0.3 to 7.

Spatial distribution of green LAI in corn, wheat, and soybean canopies is illustrated by the map in **Figure 6**. It represents the early growth stage as observed during the first intensive field campaign in summer 2001 (June 13). It shows two important features: (i) growth differences between fields of corn, wheat, and soybean, and (ii) effects of soil texture, topography, and fertilization on wheat conditions. Indeed, at this early stage, wheat has reached an advanced growth level, with LAI ranging from 0.2 to 7, in comparison to corn and soybean with LAI values not exceeding 0.4. LAI variability within the wheat field is controlled by nitrogen treatments, soil texture, and drainage conditions. Thus, high LAI levels observed in the north-eastern portion of the field (reddish tones) are associated with high nitrogen supply and the presence of a sandy soil, while low LAI values (blue and cyan tones) present in the north-western portion of the field result from topographic effects, in contrast to low LAI levels (cyan, bright green tones) encountered in the south-western portion of the field caused by the lack of nitrogen supply.

7 CONCLUSION

The study presented in this paper has focused on developing a remote sensing approach to estimate green LAI of crop canopies, with minimum effects from chlorophyll concentration variations. Estimates based on modeling (PROSPECT & SAILH) and indices-based approach have shown that the pattern of crop LAI had responded to the spatial variability of various surface attributes such as: soil texture, topography features, soil nitrogen content. The

research has demonstrated the potential of airborne CASI reflectance data for detecting and characterizing the spatial heterogeneity of LAI of interest to precision agriculture. Moreover, it has shown the important role of linked leaf-canopy models (PROSPECT and SAILH used in this case) in developing and testing various spectral indices, as well as understanding effects of key vegetation biochemical and structural parameters on canopy reflectance.

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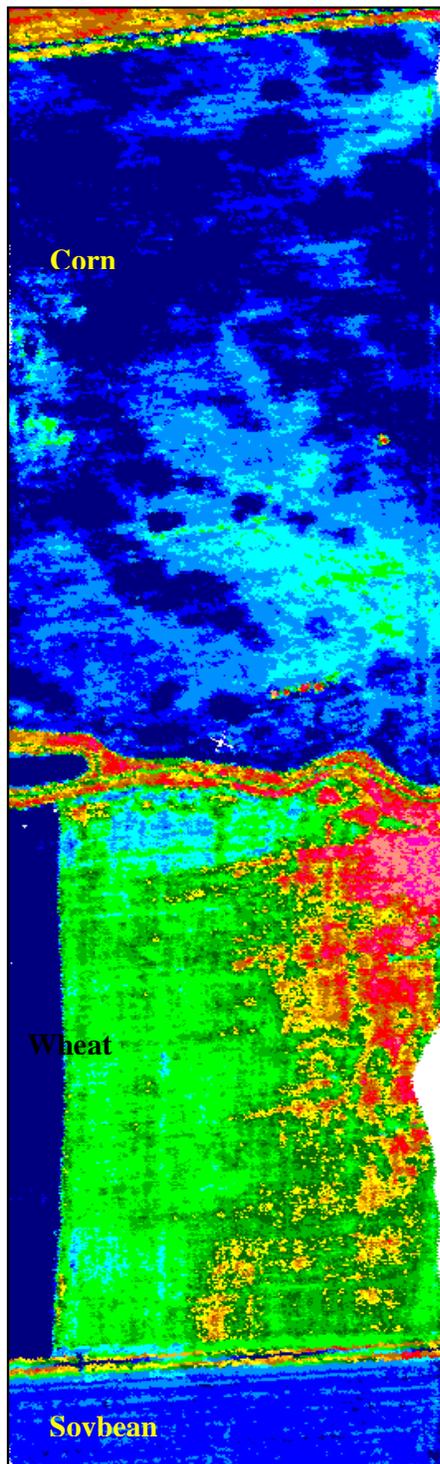


Figure 6 Map of green LAI determined with MCARI2-based algorithm from a CASI hyperspectral image.