Remote Estimation of Crop Chlorophyll Content Using Spectral Indices Derived From Hyperspectral Data

Driss Haboudane, Nicolas Tremblay, John R. Miller, and Philippe Vigneault

Abstract—This paper examines the use of simulated and measured canopy reflectance for chlorophyll estimation over crop canopies. Field spectral measurements were collected over corn and wheat canopies in different intensive field campaigns organized during the growing seasons of 2004 and 2005. They were used to test and evaluate several combined indices for chlorophyll determination using hyperspectral imagery (Compact Airborne Spectrographic Imager). Several index combinations were investigated using both PROSPECT–SAILH canopy simulated spectra and field-measured reflectances. The relationships between leaf chlorophyll content and combined optical indices have shown similar trends for both PROSPECT–SAILH simulated data and ground-measured data sets, which indicates that both spectral measurements and radiative transfer models hold comparable potential for the quantitative retrieval of crop foliar pigments. The data set used has shown that crop type had a clear influence on the establishment of predictive equations as well as on their validation. In addition to generating different predictive equations, corn and wheat data yielded contrasting agreement between estimated and measured chlorophyll contents even for the same predictive algorithm. Among the set of indices tested in this paper, index combinations like Modified Chlorophyll Absorption Ratio Index/ Optimized Soil-Adjusted Vegetation Index (OSAVI), Triangular Chlorophyll Index/OSAVI, Moderate Resolution Imaging Spectrometer Terrestrial Chlorophyll Index/Improved Soil-Adjusted Vegetation Index (MSAVI), and Red-Edge Model/MSAVI seem to be relatively consistent and more stable as estimators of crop chlorophyll content.

Index Terms—Chlorophyll content, chlorophyll estimation, combined indices, crop-type effect, hyperspectral, leaf area index (LAI), precision agriculture.

I. INTRODUCTION

The assessment of crop canopy health status and vigor is central to the understanding of the functioning of agro-ecosystems and the exchanges occurring at the atmosphere/biosphere interface in agricultural landscapes. Hence, monitoring crop development patterns is a crucial component of farm management since yield maximization requires that crop plants optimize nutrient supply and to remain under favorable environmental conditions [1]. Moreover, measurement of crop canopy variables during the growing season is required for understanding the intra- and inter-annual changes in agro-ecosystems, as well as for improving yields and quality by site-specific application of fertilizers. The most important variables in this context are leaf area index (LAI), biomass [2], [3], and leaf chlorophyll content [6]. Indeed, crop chlorophyll measurement provides information on the plant physiological status [4], [5] because leaf chlorophyll concentration is linked to nitrogen content and therefore to photosynthesis [7]–[9]. An accurate assessment of the spatial distribution is of great importance for regional and global studies of carbon dynamics and nitrogen availability. Chlorophyll concentration in vegetation depends on soil nitrogen availability and crop nitrogen uptake, which are important management factors in precision agriculture; it changes throughout different stages of plant development and is affected when crop plants are exposed to various kinds of natural and anthropogenic stresses [10]. This explains its use by agronomists and farmers to make important management decisions at critical stages (e.g., nitrogen supply and pesticide application).

Direct field measurements of chlorophyll content over large areas require a tremendous commitment of labor and are thereby expensive. Indeed, chlorophyll content can vary significantly both spatially and temporally, and its ground sampling is not amenable to frequent coverage of large heterogeneous areas. To avoid laborious and time-consuming destructive sampling and laboratory wet chemistry sampling methods, field measurements of leaf chlorophyll concentrations require the use of special optical techniques with handheld devices such as SPAD-502 (Minolta Osaka Company, Ltd., Japan). SPAD readings are nondestructive and fairly reliable, but they are still time consuming and expensive, particularly when they are used for monitoring purposes over large heterogeneous areas [9], [11]. In contrast, remote-sensing techniques, particularly the use of satellite imagery, offer a great potential for frequent chlorophyll estimation at the regional and local scale [12]–[14]. Consequently, remote sensing is seen as an important tool to complement missing or inappropriate information and achieve sustainable and efficient agricultural practices. The amount and condition of photosynthetic activity of crop green foliage...
can be captured through remote-sensing measurements in the optical portion of the electromagnetic spectrum. These measurements can then be combined and used to determine key crop canopy parameters, such as crop pigment content. In precision agriculture, the assessment and monitoring of crop chlorophyll status and spatial distribution are of importance for addressing crucial issues, such as crop growth monitoring, vegetation stress, forecasting, and management practices. Furthermore, farmers are concerned with the spatial variability within agricultural fields, aiming to improve farm productivity and to reduce input (fertilizer) costs. For this purpose, various precision agriculture technologies and tools have been developed [15]. Their primary goal is to help scientists and farmers to better manage agricultural fields through the use of spatially variable application rates that are based on localized plant growth requirements [16]. Hence, crop chlorophyll status at any particular stage in the growth cycle can be a consequence of several crop and soil variables, such as soil condition, nutrient imbalances, and pests. Its spatial heterogeneity can be used as an indicator of the crop condition resulting from vegetation response to soil properties and specifically nutrient availability under the given weather conditions.

In this paper, we discuss the use of forward model simulations and ground-measured data (biophysical and spectral) to establish predictive equations to estimate chlorophyll concentration from hyperspectral data and imagery. The specific objectives of this paper are the following: 1) to use ground-measured spectra and corresponding laboratory-measured chlorophyll concentrations, i.e., from corn and wheat canopies, to establish chlorophyll predictive equations based on spectral indices ratios; 2) to assess the dependency of the prediction relationships on the crop type (corn and wheat); and 3) to validate and compare the indices’ prediction capability using Compact Airborne Spectrographic Imager (CASI) hyperspectral images and ground truth measurements collected over fields different from those used to collect ground spectra.

II. BACKGROUND

Using laboratory analysis, field measurements, and remotely sensed data, scientists have made tremendous progress in developing approaches and methodologies to estimate chlorophyll content at both leaf and canopy levels, and over diverse vegetation species [12], [14], [17]–[20]. While some studies have used the inversion of physically based models [13], [20]–[23], others have expended considerable effort to improve the relationships between chlorophyll concentration and a variety of optical spectral indices [5], [9], [24]–[26], with Haboudane et al. [12] focusing on simulations from physically based models to develop robust relationships between chlorophyll concentration and optical spectral indices. Physically based models alone are not site, sensor, or season specific; they are based on the simulation of canopy reflectance and the creation of quantitative relationships between remotely sensed data and canopy attributes (from satellite/airborne imagery) for inversion purposes. In contrast, index-based approaches rely on semi-empirical relationships whose basis can be derived from simulations with physically based models to give a predictive ability or simply represent the semi-empirical relationship between laboratory-measured chlorophyll concentrations and observed spectral reflectances; in either case, their strength lies in the fact that spectral indices are computationally fast and require little expertise, especially when based on physically explainable principles.

When the emphasis is solely on a semi-empirical relationship, one can find that, despite satisfactory relationships obtained between some of these spectral indices and leaf pigments, indices can also be very sensitive to other vegetation variables such as canopy cover, LAI, and absorbed photosynthetically active radiation, as has been demonstrated in previous studies [9], [12], [27]–[29]. Indeed, the combined effects of chlorophyll concentration and LAI variation strongly influence the abrupt changes affecting the vegetation reflectance of the “red-edge” region. This confounding phenomenon is shown in Fig. 1 using spectra simulated with the SAILH radiative transfer model. It shows that chlorophyll interactions with the radiation are limited to the optical domain ranging from 400 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 increases contribute to the shift of the red-edge position (REP, Fig. 1).

The relative spectral differences are generated between the spectra representing various chlorophyll contents and the spectrum corresponding to 70 $\mu g/cm^2$. Wavelength regions that are most sensitive to leaf pigment variability are centered on 550 nm in the green edge and 715 nm in the red edge. The narrow peak observed at 715 nm seems to be shifted to a longer wavelength when the 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 [30]. In fact, an increase of chlorophyll content induces a broadening of chlorophyll absorption feature in the red (670–680 nm) and therefore moves the REP to longer wavelengths, as seen in Fig. 1. In contrast, major LAI effects on canopy reflectance occur in two broad bands of around 685 and 780 nm. Unlike chlorophyll concentration, LAI generates weak variations of the reflectance spectrum at 550 and 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 in connection with the influence of non-photosynthetic materials and dry biomass on canopy reflectance when the green biomass is represented in weak proportions. The major variations induced by LAI in the near infrared are due to the canopy structural development and the multiple scattering, which is particularly important at these wavelengths.

Consequently, to meet the requirements related to prediction accuracy and consistency, there is a need for the design of specific spectral indices that are sensitive exclusively to a vegetation/canopy descriptor of interest, such as green LAI or chlorophyll content. For instance, [9] and [12] have suggested an index-based approach to estimate leaf chlorophyll content with minimal confounding effects due to LAI, while [31] used radiative transfer models (PROSPECT and SAILH) to develop methods for minimizing the effect of leaf chlorophyll content on the prediction of green LAI and to suggest spectral indices that adequately predict the LAI of crop canopies.
Most studies based on spectral indices have sought to establish semi-empirical relationships between laboratory-measured leaf pigments and remotely sensed data measured on the ground or extracted from satellite/airborne imagery [17], [24], [25]. These relationships were generally developed under given environmental conditions and for specific crops or forest stands. Their application under different circumstances and for different crop/forest species needs extensive research to take into account the effects of other structural/biochemical canopy attributes. For this purpose, two main approaches have been presented: scaling-up strategies based on model inversion techniques [32], and the study of prediction power and stability of spectral indices on the basis of forward model simulations with radiative transfer models [9], [27], [31]. In a previous study, leaf and canopy models (PROSPECT and SAILH) were employed to simulate chlorophyll and LAI effects on crop canopy reflectance to develop a combined index that is sensitive to chlorophyll content changes but resistant to LAI variations [12]. Based on simulated data, the suggested index [TCARI/ Optimized Soil-Adjusted Vegetation Index (OSAVI)] has a unique relationship with the chlorophyll content over a wide range of LAI values (0.3–8), thereby allowing the determination of a predictive equation for corn chlorophyll content estimation from hyperspectral imagery. Furthermore, predictive equations built on TCARI/OSAVI scaled-up through radiative transfer simulation were successfully used to estimate chlorophyll content over open (orchards) [33] and row-structured discontinuous canopies (vineyards) [14].

So far, the ratios Modified Chlorophyll Absorption Ratio Index MCARI/OSAVI and TCARI/OSAVI are the only combinations of indices that have been used to provide predictive relationships for chlorophyll estimations in precision agriculture, namely in closed-corn canopies [12], open-tree canopy orchards [33], and row-structured canopy vineyards [14]. The predictive relationships were established from simulated data according to predefined structural/biochemical attributes of the studied canopy. Hence, each study uses physical models at leaf and canopy levels to scale-up optical indices to infer a unique predictive equation that takes into account the effects of canopy structure, viewing geometry, and background. However, no studies have investigated the use of different indices combinations nor evaluated the use of predictive equations established from laboratory- and ground-measured data (pigments and spectra).

III. Experiments and Data Sets
A. Study Site

The study area is located near Montreal at the Horticultural Research and Development Centre of Agriculture and Agri-Food Canada, St-Jean-sur-Richelieu, Quebec, Canada. It is known as the L’Acadie Experimental Research Sub-station, where prior knowledge of the field management and plant stress patterns helped in selecting ground truth sites of contrasting productivity. Over two years (2004 and 2005), various crops (corn, wheat, beans, and peas) were grown on different experimental fields as well as on fields managed by private producers. These commercial sites were chosen to better understand the respective influence of soil factors and nitrogen supply on crop growth.

Hence, intensive field campaigns were organized during the growing seasons of 2004 and 2005 to collect ground spectra and corresponding leaf chlorophyll content values as well as crop growth measures. Acquisition dates were planned to coincide with different phenological development stages to monitor temporal changes in crop biophysical attributes. Nitrogen fertilization treatments were supplied in two applications: one at the time of seeding and the other at topdressing a few weeks later. Four to five nitrogen rate treatments were established in each field and randomized within four blocks. Nitrogen rates varied between 0 and 150 kg N/ha for wheat and from 0 to 437 kg N/ha for corn.

B. Biophysical and Spectral Measurements

Within each field, georeferenced points were established on representative sections of each nitrogen treatment. These
locations were used to monitor crop biophysical parameters during the growing season, particularly during intensive field campaigns coinciding with hyperspectral image acquisition. Indeed, simultaneous with imagery acquisition with the CASI, flown by the Earth Observations Laboratory at York University, a set of field and laboratory data was collected for biochemical and geochemical analysis, along with optical and biophysical measurements. Ground truth measurements included the following: 1) collection of leaf tissue for laboratory determination of leaf chlorophyll concentration; 2) chlorophyll meter (SPAD) measurements; 3) LAI measurements using the Plant Canopy Analyzer (Li-Cor model LAI-2000); 4) field spectroradiometric measurements; and 5) crop growth measures. Details on field in situ instrumentation, measuring approaches, and laboratory analysis are presented in [57] and [58].

To establish prediction relationships between leaf chlorophyll content and spectral indices, spectral reflectance data were carried out using the ASD spectroradiometer (Analytical Spectral Devices, Boulder, CO). A white Spectralon reference panel (Labsphere, North Sutton, NH) was used to calibrate the spectroradiometer spectral radiance measurements to reflectance by measurements of the reference panel under the same illumination conditions as the ground targets. Reflectances were calculated and corrected for the nonideal properties of the reference panel, as described in [34]. In all experiments, spectroradiometric data were collected close to solar noon so that changes in illumination conditions (solar zenith angle) were minimized.

C. CASI Airborne Images

During the two growing seasons, CASI hyperspectral images were collected in different deployments using two modes of operation: the multispectral mode with 1-m spatial resolution and seven spectral bands selected for sensing vegetation properties (489.5, 555.0, 624.6, 681.4, 706.1, 742.3, and 776.7 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 the different phenological development stages, which provides image data covering the earliest, middle, and latest periods of the growth season.

IV. METHODS

A. Radiometric and Atmospheric Corrections

The hyperspectral digital images collected by CASI were processed at-at sensor radiance using calibration coefficients determined in the laboratory by the Earth Observations Laboratory, York University. Subsequently, the CAM5S atmospheric correction model [35] 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 records and ground Global Positioning System measurements.

Reflectance curves derived from processed CASI images showed the presence of spectral anomalies that are associated with the atmospheric absorption features at specific wavelengths. Although we applied model-based atmospheric corrections, the calculated reflectances were still affected by spectrally specific errors due mostly to an undercorrection of some atmospheric component effects (oxygen and water vapor absorption). The flat field calibration is a correction technique used to remove the residual atmospheric effects from hyperspectral reflectance image cubes. Its aim is to improve the overall quality of spectra and provide apparent reflectance data that can be compared with laboratory spectra [36]. 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 compensate for the residual 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 the observed residual features were successfully removed (Fig. 2).

B. Simulated Data

The leaf optical properties were simulated using the PROSPECT model [37], [38], 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 $N$, chlorophyll $a + b$ content $C_{ab}$ (in micrograms per square centimeter), equivalent water thickness $C_w$ (in centimeters), and leaf dry matter content $C_m$ (in grams per square centimeter) to determine the leaf reflectance and transmittance signatures in the optical domain.

The input parameters $C_w$ and $C_m$ were assigned the nominal values of 0.0015 cm and 0.0035 g · cm$^{-2}$, respectively. The $N$ parameter was estimated by inverting the PROSPECT model on corn leaf reflectance and transmittance spectra measured in the laboratory using an integrating sphere coupled to a
spectrometer. The mean value of 1.41 was thereby obtained and is in agreement with the value ($N = 1.4$) used for corn plants in [20]. We have also used $N = 1.55$ as an average value for various crops, including corn, soybean, and wheat. With these inputs, the reflectance and transmittance spectra were generated for chlorophyll content varying from 5 to 100 $\mu$g · cm$^{-2}$ for the purpose of simulating corn canopy reflectance (SAILH model) for a wide range of chlorophyll concentrations. Canopy reflectance spectra were simulated using a variant of the Scattering by Arbitrary Inclined Leaves (SAIL) model [39] called SAILH. It was adapted to take into account the hotspot effect or the multiple scattering in the canopy [40]. 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. Discussions and mathematical formalisms of SAIL and SAILH are provided in [39], [41]–[43], and [32]. Typical SAILH inputs were presented and discussed in previous publications (e.g., [9] and [31]): canopy architecture defined by the LAI and the leaf angle distribution function (LADF), leaf reflectance and transmittance spectra for the given chlorophyll content per unit area, underlying soil reflectance, and the illumination and viewing geometry (solar zenith and sensor viewing angles). The following input variables were used for simulations with SAILH: simulated leaf reflectance and transmittance (PROSPECT) for various chlorophyll content, from 5 to 100 $\mu$g · cm$^{-2}$; a reflectance spectrum of a bare soil pixel extracted from CASI imagery; a spherical distribution for LADF, a sun zenith angle of 35°; a sensor viewing angle of 0° (nadir); and LAI values of 0.1, 0.3, 0.5, 1, 1.5, 2, 2.5, 3, 4, 5, 6, 7, 8, 9, 10, 11, and 12.

C. Vegetation and Chlorophyll Indices

Based on the differences in reflectance between stressed and healthy vegetation in the visible and red-edge spectral regions, a number of spectral indices were widely and successfully used to estimate chlorophyll concentration from leaf optical properties [22], [44], [45]. Unfortunately, they are not appropriate for chlorophyll prediction at the canopy level because canopy spectral signatures are strongly influenced by the changes in soil background optical properties and the variations of LAI at different growth stages. On the other hand, some optical indices, which are known as traditional vegetation indices, have shown low relationships with vegetation pigments, less sensitivity to soil optical properties, but acceptable performance in predicting LAI. Hence, ratios involving indices sensitive to chlorophyll variations and traditional vegetation indices have been proposed to minimize LAI and soil background effects while maximizing the sensitivity to canopy chlorophyll content [9], [12].

In this section, we present a brief review of some representative chlorophyll and vegetation indices. This review is not meant to gather all published chlorophyll and vegetation indices; its aim is only to discuss the indices that were selected for use in this paper.

1) Chlorophyll Indices:

Indices related to the depth of chlorophyll absorption at 760 nm: Indices that incorporate bands in the green and red-edge parts of the solar spectrum were developed to measure the light absorption by chlorophyll in the red region (760 nm) (Table I). Kim et al. [46] developed the Chlorophyll Absorption Ratio Index (CARI) that measures the depth of chlorophyll absorption at 670 nm relative to the green reflectance peak at 550 nm and the reflectance 700 nm. The ratio ($R_{700}/R_{670}$) was introduced to minimize the combined effects of the underlying soil reflectance and the canopy nonphotosynthetic materials. This ratio is the slope of the spectrum when the canopy contains no green biomass. Nevertheless, MCARI is still sensitive to background reflectance properties so that it is difficult to interpret at low LAI [9]. To improve its sensitivity to low chlorophyll values, Haboudane et al. [12] suggested a modified MCARI version, i.e., the transformed CARI. As

### TABLE I

<table>
<thead>
<tr>
<th>Index</th>
<th>Formula</th>
<th>Reference</th>
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<tbody>
<tr>
<td>Chlorophyll indices</td>
<td>$[(R_{700} - R_{670}) - 0.2*(R_{700} - R_{550})]/(R_{700} + R_{670})$</td>
<td>Daughtry et al. (2000)</td>
</tr>
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<td></td>
<td>$3*(R_{700} - R_{670}) - 0.2*(R_{700} - R_{550})/R_{700}$</td>
<td>Haboudane et al. (2002)</td>
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<td></td>
<td>$[R_{750} - R_{510}]/(R_{710} - R_{680})$</td>
<td>Dash and Curran (2004)</td>
</tr>
<tr>
<td></td>
<td>$(R_{750} - R_{720}) - (R_{350} - R_{670})$</td>
<td>Le Maire et al. (2004)</td>
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<tr>
<td></td>
<td>$(R_{750}/R_{720}) - 1$</td>
<td>Gitelson et al. (2005)</td>
</tr>
<tr>
<td></td>
<td>$[1.2*(R_{700} - R_{550}) - 1.5*(R_{700} - R_{550})]/(R_{700} - R_{670})$</td>
<td>This study</td>
</tr>
<tr>
<td>Vegetation indices</td>
<td>$[(R_{660} - R_{570})/ (R_{660} + R_{570})]$</td>
<td>Rouse et al. (1974)</td>
</tr>
<tr>
<td></td>
<td>$(R_{660} - R_{570})/ (R_{660} + R_{570})$</td>
<td>Rougean and Breon (1995)</td>
</tr>
<tr>
<td></td>
<td>$(1+0.5) * (R_{660} - R_{570})/(R_{660} + R_{570} + 0.5)$</td>
<td>Hucle (1988)</td>
</tr>
<tr>
<td></td>
<td>$(1+0.16) * (R_{660} - R_{570})/(R_{660} + R_{570} + 0.16)$</td>
<td>Rendeaux et al. (1996)</td>
</tr>
<tr>
<td></td>
<td>$0.5 * 2 * R_{660} + 1 - (2 * R_{900} + 1)^2 - 8 * (R_{660} - R_{570})$</td>
<td>Qi et al. (1994)</td>
</tr>
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</table>

** : In order to have indices values in the same range, scaling factors of 2, 3, 2, 0.05, 2, and 0.2 were applied to MCARI, TCARI, TCI, MTI, DD, and R-M, respectively.
a part of this paper, we developed a modified version of the Triangular Vegetation Index (TVI) [27] that is suitable for chlorophyll estimation from remote-sensing data. The general idea behind this modification was to render TVI more sensitive to chlorophyll effects rather than being responsive to vegetation vigor or green LAI variations. For this reason, we introduced the ratio \( \frac{R_{700}}{R_{670}} \) in the TVI formula to reduce the combined effects of the underlying soil reflectance and the canopy nonphotosynthetic materials, and integrated the red-edge wavelength (700 nm) to increase its sensitivity to chlorophyll changes. Consequently, a variant of the TVI, which is called Triangular Chlorophyll Index (TCI), is obtained. Indeed, changes in chlorophyll concentration will cause a red shift of the red-edge reflectances, which will introduce changes in the reflectance at 700 nm that represent the transition between the red and infrared spectral regions.

**Indices related to changes along the red-edge region:** Recently, new chlorophyll indices, which are based on wavelengths in the “red-edge” region, were developed (Table I). Dash and Curran [47] proposed the Moderate Resolution Imaging Spectrometer (MERIS) Terrestrial Chlorophyll Index (MTCI) that appeared to be the most suitable index for the retrieval of chlorophyll content from MERIS data. MTCI showed strong correlation with the REP with enhanced sensitivity to high values of chlorophyll content. It became an official MERIS level-2 product of the European Space Agency [47]. Le Maire et al. [5] have conducted a thorough study on estimating the chlorophyll content of broad leaf from hyperspectral data. They developed the double difference index (DD) that yielded the best results on a large simulated database. It is expected to give good results on a large experimental database [5]. We have selected DD to assess its performance with canopy reflectance of crops and with SAILH simulated spectra. One of the most recent developments was reported by Gitelson et al. [48]. They developed a conceptual model for chlorophyll estimation in crop canopies; it is a technique that uses red-edge wavelengths for the accurate assessment of the total chlorophyll content of crop canopies. A simplified form of their red-edge model, which is termed here as “R-M,” is tested in this paper on simulated and measured spectra of crop canopies.

**2) Vegetation Indices:** The most known and widely used vegetation index is the normalized difference vegetation index (NDVI) developed by Rouse et al. [49]. It exploits the contrast between the maximum absorption in the red due to chlorophyll pigments and the maximum reflection in the infrared caused by the leaf cellular structure. NDVI approaches a saturation level in cases of dense and multilayered canopy, and shows a nonlinear relationship with the biophysical parameters such as biomass and green LAI [50], [51]. To address these issues, improved indices like the renormalized difference vegetation index (RDVI, [52]) were proposed and tested.

To compensate for soil background influences, soil-adjusted indices that minimize the background effects have been developed. The leading index in such an improvement is the soil-adjusted vegetation index (SAVI; [53]), which includes a canopy background adjustment factor \( L \). The value of the factor \( L \) is critical in the minimization of soil optical property

![Fig. 3](image-url)
effects on vegetation reflectance. Huete [53] suggested an optimal value of $L = 0.5$ to account for first-order soil background variations. Attempting to improve SAVI with regard to the differences in soil background, Qi et al. [54] developed an improved SAVI (MSAVI) with a self-adjustment factor $L$ that does not appear in the formulation of MSAVI. The index OSA VI [55] belongs to the SAVI family. It is selected for its easy use in operational observations on agricultural landscapes. Its determination needs no information on soil optical properties, and it offered the best overall performance for most agricultural crops [55]. Additionally, using CASI airborne data, Haboudane et al. [12] found that OSA VI has similar behavior and trends as transformed SAVI [56], whose determination requires knowledge of the soil line parameters.

V. RESULTS AND ANALYSIS

A. Indices Correlation With Crop Biophysical Variables: Measured Data

The good performance of optical indices on simulated canopy spectra might not be as good on measured canopy reflectances. Indeed, it has been demonstrated that some indices perform very well on PROSPECT simulated data but yield very poor results when applied on experimental data [5]. Consequently, one of the main objectives of this paper is to study the behavior of chlorophyll indices as determined from field-measured canopy reflectance. The latter is the result of complex interactions of solar radiation with leaf pigments, canopy structure (LAI), and to some extent the underlying soil properties. Consequently, chlorophyll indices are very sensitive not only to changes in leaf pigments but also to LAI variability. The relationship between each chlorophyll index (MCARI, TCARI, TCI, MTCI, DD, and R-M) and foliar chlorophyll is influenced by LAI variation and/or other canopy attributes. To understand this influence, the chlorophyll indices used in this paper were plotted against measured chlorophyll concentrations on optical indices, and derive unique relationships between chlorophyll content and combined indices. In an attempt to compare the performances of various combinations of optical indices in terms of their sensitivity to LAI changes, we have determined them from ground spectra measured over the corn canopy. Then, we selected the best ratios and plotted them as a function of foliar chlorophyll concentration [Fig. 4(a) and (b)]. Indices measuring the depth of chlorophyll absorption performed very well in combination with OSAVI, while indices measuring the change in the “red-edge” region yielded better performances with MSAVI.

The most important information revealed in Fig. 3(a) and (b) is the strength of the relationships between chlorophyll indices and biophysical variables of the corn canopy. Indices measuring the depth of chlorophyll absorption (MCARI, TCARI, TCI) have, on one hand, a moderate relationship with chlorophyll content ($0.47 \leq R^2 \leq 0.55$) and, on the other hand, an extremely weak relationship with LAI ($R^2 \leq 0.09$). In contrast, indices measuring the change in the red edge (MTCI, DD, R-M) show a strong correlation with chlorophyll content ($0.70 \leq R^2 \leq 0.81$) but with significant relationship with green LAI ($0.45 \leq R^2 \leq 0.55$). Similar behaviors were found in the case of the wheat canopy but with weak to moderate correlations, as shown in Table II. The latter reveals that, for both corn and wheat, the indices MTCI, DD, and R-M are very sensitive to LAI and strongly correlated with the variable LAI$^\ast$Chl (Chl = chlorophyll).

To address the issue of high sensitivity to LAI and LAI$^\ast$Chl, and based on previous studies [9], [12], we have combined (ratioed) these chlorophyll indices with selected vegetation indices. The objective was to uncouple the effects of LAI and chlorophyll concentrations on optical indices, and derive unique relationships between chlorophyll content and combined indices. In an attempt to compare the performances of various combinations of optical indices in terms of their sensitivity to LAI changes, we have determined them from ground spectra measured over the corn canopy. Then, we selected the best ratios and plotted them as a function of foliar chlorophyll concentration [Fig. 4(a) and (b)]. Indices measuring the depth of chlorophyll absorption performed very well in combination with OSAVI, while indices measuring the change in the “red-edge” region yielded better performances with MSAVI.

As a result, and as expected, all index ratios clearly combine, to some extent, the abilities of indices responding to chlorophyll variations and those minimizing the LAI effects. The combination of MCARI, TCARI, and TCI with OSAVI has substantially improved their relationships with corn chlorophyll content [Fig. 4(a)], with determination coefficients ($R^2$) increasing from a range of 47–55 to a range of 74–80. At the same time, responsivity to LAI changes has slightly increased and reached reasonable levels ($R^2$ of 0.29 for MCARI and 0.33 for TCI). The ratio TCARI/OSAVI seems slightly more sensitive to LAI with a determination coefficient ($R^2$) of 0.46 [Fig. 4(a)]. Regarding the indices MTCI and R-M, their ratios with MSAVI yielded improved resistance to LAI changes with $R^2$ values of 0.27 and 0.37, respectively. In contrast, the combination with MSAVI has slightly increased the DD

### TABLE II

<table>
<thead>
<tr>
<th>Indices</th>
<th>CORN</th>
<th>WHEAT</th>
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<tr>
<td></td>
<td>Chl</td>
<td>LAI</td>
</tr>
<tr>
<td>MCARI</td>
<td>0.47</td>
<td>0.04</td>
</tr>
<tr>
<td>TCARI</td>
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<td>TCI</td>
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<td>MTCI</td>
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</tr>
<tr>
<td>DD</td>
<td>0.70</td>
<td>0.47</td>
</tr>
<tr>
<td>R-M</td>
<td>0.77</td>
<td>0.45</td>
</tr>
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sensitivity to LAI ($R^2$ changing from 0.47 to 0.51) but has significantly strengthened its relationship with the chlorophyll content [Fig. 4(b)].

The above findings based on a relatively limited experimental database were corroborated by the use of a larger simulated database built using PROSPECT and SAILH radiative transfer models. This is illustrated in Fig. 5, where spectral indices and corresponding ratios were plotted against chlorophyll concentrations as a function of LAI. For each index (and corresponding ratio), the curves represent LAI values varying as follows: 0.3, 0.5, 1, 2, 3, 4, 5, 6, 7, and 8. Lower curves correspond to low LAI values (e.g., 0.3) and higher ones to high LAI values (e.g., 8) for MCARI, TCI, DD, R-M, and corresponding ratios, while they represent high and low LAI values, respectively, for TCARI, MTCI, and corresponding ratios.

As expected, Fig. 5 shows that LAI exerts a strong influence on the relationship between the indices and the foliar pigments, especially in the case of indices DD and R-M. The latter exhibits a considerable scatter caused by the LAI for almost the whole range of chlorophyll values. Therefore, there is no unique relationship between these indices and the simulated chlorophyll content because their sensitivity to LAI changes. This high responsivity to LAI variations was significantly reduced when DD and R-M were combined (ratioed) with MSAVI (Fig. 5, center right and bottom right). Striking distinct behaviors are observable in Fig. 5: indices measuring the depth of chlorophyll absorption are more sensitive to LAI changes at low chlorophyll content ($\leq 30 \mu g/cm^2$); conversely, indices measuring the change in the red-edge region are more responsive to LAI variations at medium to high chlorophyll concentrations ($30 \mu g/cm^2$). These conditions represent the major source of uncertainty for predicting crop chlorophyll status. The latter estimation is the most time-critical information needed by farmers and agricultural managers for it is an indicator of plant physiological status (health and stress) at a time when management decisions can still be made and implemented.

Regarding the improvements due to the combined use of MSAVI or OSAVI with chlorophyll indices, one may note that the ratios show limited sensitivity to LAI changes with almost unique relationships between combined indices and simulated chlorophyll concentrations (Fig. 5), especially for the most observable chlorophyll concentrations (15–60 $\mu g/cm^2$). This is probably an advantage because a candidate index to estimate crop chlorophyll content should be less sensitive but not insensitive to LAI changes. Of course, the ratio DD/MSAVI seems to be an exception for it is still significantly influenced by LAI variability (Fig. 5, center right).

**B. Effect of Crop Type: Measured Data**

The major problem in the use of optical indices arises from the fact that canopy reflectance in the visible and near infrared is strongly dependent on the structural (e.g., $N$ parameter, LAI, LADF) and biochemical properties (e.g., chlorophyll) of the canopy as well as on the underlying soil properties, illumination conditions, and viewing geometry [20], [22], [42], [59]. To assess the possible effect of the canopy structural attributes...
Fig. 5. Spectral indices and combined spectral ratios plotted as a function of chlorophyll concentrations 10–80 µg/cm² for various LAI values (0.3, 0.5, 1, 2, 3, 4, 5, 6, 7, and 8). The trends are based on simulation with PROSPECT–SAILHIPROSP–SAILH for the following spectral indices and ratios: (top left) MCARI and MCARI/OSAVI, (top right) MTCI and MTCI/MSAVI, (center left) TCARI and TCARI/OSAVI, (center right) DD and DD/MSAVI, (bottom left) TCI and TCI/OSAVI, and (bottom right) R-M and R-M/MSAVI. Arrows indicate the increase of LAI for spectral indices (bold arrows) and combined spectral ratios (thin arrows). Scaling factors of 2, 3, 2, 0.05, 2, and 0.2 were applied to MCARI, TCARI, TCI, MTCI, DD, and R-M, respectively, to facilitate performance comparisons.

on the combined indices, we used field-measured spectra and laboratory-measured leaf chlorophyll concentrations of two crop species, i.e., corn and wheat; the leaves and canopies of these crops have different structural parameters (N, LAI, LADF). Corn chlorophyll measurements range from low to high values (24.00–63.78 µg/cm²), while those of wheat vary only from intermediate to high (41.92–69.68 µg/cm²). The lack of low chlorophyll concentrations for wheat impedes getting an accurate and precise appreciation of crop-type effects on the optical indices. Even so, the available data set was judged sufficient to investigate and compare index performances as a function of crop type.

First, we have plotted the ratios TCI/OSAVI and DD/MSAVI against measured leaf chlorophyll concentrations of corn and wheat (Fig. 6) to illustrate the general trends. One may note that the points representing corn and those corresponding to wheat are organized in two distinct clouds although some overlapping is observed for both ratios. In contrast, for any given MCARI/OSAVI value, the measured wheat chlorophyll content is higher than in corn (Fig. 6, top). Overall, corn and wheat data sets showed parallel trends, and the best fits were obtained for linear, exponential, and logarithmic functions with almost the same values of determination coefficients ($R^2$). The latter were 0.75 (corn) and 0.49 (wheat) for TCI/OSAVI, and 0.80 (corn) and 0.27 (wheat) for DD/MSAVI when a logarithmic fit is used.

Second, using the same experimental data set, we compared the performance of different combined indices. We have observed that the behavior differences were mainly generated by chlorophyll indices and slightly by vegetation indices.
Therefore, to avoid duplication and for clarity purposes, we have selected only the combinations that yielded the best correlations between measured chlorophyll and measured biophysical variables of crops used, i.e., corn and wheat. As shown in Table III, there is a clear effect of the crop type on the performance of the combined ratios. Indeed, the corn data set revealed strong correlations between combined indices and chlorophyll content \((0.73 \leq R^2 \leq 0.80)\) with some noticeable sensitivity to LAI influence \((0.27 \leq R^2 \leq 0.51)\). In contrast, the wheat data set showed relatively lower correlation level between the ratios and chlorophyll content \((0.26 \leq R^2 \leq 0.49)\) but with almost no responsibility to LAI variability \((0.00 \leq R^2 \leq 0.33)\) except for DD/MSAVI.

C. Measured Versus Simulated Trends

Under certain circumstances, the PROSPECT database may show substantial discrepancies in leaf reflectance simulations compared to experimental results [5]. Thus, one can expect that the canopy reflectance simulation with SAILH could lead to even more important differences with the measured canopy reflectances. We examined the shape of the measurement-based relationships between the optical indices and the foliar chlorophyll, and compared them to the relationships established from PROSPECT–SAILH-simulated spectra. For clarity purposes, only a few index combinations were reported in Fig. 7, and the others exhibit similar behaviors. Although our measured data set does not cover the same range of chlorophyll concentrations as the PROSPECT–SAILH simulations (e.g., 10–80 \(\mu g/cm^2\)), it clearly shows that there is a great similarity between simulation-based and measurement-based trends (Fig. 7). The major difference resides in the accuracy of predicting chlorophyll content using a trend-line based on PROSPECT–SAILH spectra: it seems reasonable to assume that, in general, the leaf chlorophyll content would be slightly overestimated for corn and underestimated for wheat with ratios using indices measuring the depth of chlorophyll absorption (MCARI, TCARI, TCI). In fact, clouds of points representing corn and wheat fall slightly below and above, respectively, the cloud corresponding to simulated data (Fig. 7, top, center, and bottom left). This appears not to be the case for ratios R-M/MSAVI, the points of which fall into the cloud of simulated data (Fig. 7, bottom right). Such a result can be explained by the fact that for simulated data, ratios involving R-M show a noticeable scatter of their relationship with chlorophyll due to an LAI effect even at intermediate to high chlorophyll concentrations (40–80 \(\mu g/cm^2\)). Conversely, MTCI/MSAVI tends to overestimate the wheat chlorophyll content (Fig. 7, top right) while DD/MSAVI seems to yield an overestimation of chlorophyll for both corn and wheat (Fig. 7, center right).

In conclusion, there is an obvious concordance between the trends established from simulated spectra and those determined from reflectance measurements. Of course, plots representing measured data sets are more scattered than those corresponding to simulations. The reason is that field-measured data integrate other extraneous effects related to canopy structure, illumination conditions, and soil optical properties. Moreover, given wheat plants’ health status, laboratory measurements found no chlorophyll concentrations below 40 \(\mu g/cm^2\). This will indeed introduce a bias in the corresponding predictive equation.

D. Estimation of Crop Chlorophyll Content and Validation

Through the analyses discussed above, it is reasonable to assume that index ratios offer a great potential for photosynthetic pigment determination from remotely sensed data. Hence, predictive equations for the assessment of chlorophyll status over crop canopies (corn and wheat) were established for various combined indices. The best fits were obtained with logarithmic, exponential, and linear functions separately from simulated data, corn-measured spectra, wheat-measured spectra, as well as both corn and wheat reflectances. Their application to CASI airborne hyperspectral images has enabled maps of chlorophyll status over large fields of corn and wheat (Fig. 8) to be generated. From these maps, we extracted predicted chlorophyll values to compare them to corresponding ground truth measurements collected at the time of image acquisitions. Then, linear regressions were carried out in an attempt to evaluate the predictive power of ratios used. Results in terms of determination coefficients and corresponding root mean square errors (RMSE) are summarized in Table IV for three predictive equations determined from simulated spectra. The table shows contrasting results in many respects, e.g., the index ratio involved and the crop-type effect at application/validation time.
TABLE III

<table>
<thead>
<tr>
<th>Ratios</th>
<th>CORN</th>
<th>WHEAT</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Chl</td>
<td>LAI</td>
</tr>
<tr>
<td>MCARI/OASAVI</td>
<td>0.74</td>
<td>0.29</td>
</tr>
<tr>
<td>TCARI/OASAVI</td>
<td>0.80</td>
<td>0.46</td>
</tr>
<tr>
<td>TC/OSAVI</td>
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</tr>
<tr>
<td>MT/MSAVI</td>
<td>0.73</td>
<td>0.27</td>
</tr>
<tr>
<td>DD/MSAVI</td>
<td>0.79</td>
<td>0.51</td>
</tr>
<tr>
<td>R-M/MSAVI</td>
<td>0.78</td>
<td>0.78</td>
</tr>
</tbody>
</table>

Fig. 7. Similarity between the trends based on field/laboratory measurements (corn/wheat spectra and measured chlorophyll) and the trends based on simulation with PROSPECT–SAILH for the following spectral ratios: (top left) MCARI/OASAVI, (top right) MT/MSAVI, (center left) TCARI/OASAVI, (center right) DD/MSAVI, (bottom left) TC/OSAVI, and (bottom right) R-M/MSAVI. Scaling factors of 2, 3, 2, 0.05, 2, and 0.2 were applied to MCARI, TCARI, TC, MT, DD, and R-M, respectively, to facilitate performance comparisons.

The effect of the index ratio that was used to establish predictive equations had a significant impact on the degree of agreement in terms of $R^2$ between estimated and measured chlorophyll contents. Indeed, the three combined ratios have yielded different $R^2$ values for both corn and wheat. Nevertheless, MCARI/OASAVI and TC/OSAVI have given approximately similar results over wheat fields with good $R^2$ values of 0.49, and 0.47, respectively. However, they yielded very good agreement with ground truth over corn fields with $R^2$ values of 0.54 and 0.64, respectively. As for predictions from...
Indeed, previous investigations have reported the following predictions in terms of RMSE. This crop-type effect is confirmed by the agreement expressed in terms of RMSE for corn fields (Table IV). This test-type effect is confirmed by the prediction accuracy expressed in terms of RMSE: for example, for corn fields and moderate to good agreement (Table IV). This test-type effect is confirmed by the prediction accuracy expressed in terms of RMSE for corn fields and moderate to good agreement (Table IV). This test-type effect is confirmed by the prediction accuracy expressed in terms of RMSE for corn fields and moderate to good agreement (Table IV).

Conversely, the application of the equations to different crops has led to very contrasting agreements between the estimations and the ground truth. Thus, depending on the combined index, the agreements were good to very good ($R^2 = 0.52$–0.74) over corn fields and moderate to good ($R^2 = 0.29$–0.49) over wheat fields (Table IV). This test-type effect is confirmed by the prediction accuracy expressed in terms of RMSE: for example, using MCARI/OSAVI and TCI/OSAVI, the resulting RMSE values for corn were slightly better than those obtained for wheat. As a reference for RMSE values, it is worth mentioning that the published ranges of RMSE are also highly variable. Indeed, previous investigations have reported the following values: $4.35$ $\mu g/cm^2$ for corn canopies [12], $8.10$ $\mu g/cm^2$ for conifer canopies [33], $11.50$ $\mu g/cm^2$ for vineyard canopies [14], $11.70$ $\mu g/cm^2$ for olive canopies [33], and $10.27$ to $11.32$ $\mu g/cm^2$ for wheat leaves using different chlorophyll indices [60]. Consequently, the results obtained seem to be within the published literature ranges (RMSE $= 5.72$–12.17 $\mu g/cm^2$).

Of course, it is important to mention that based on our actual data set, the degree of agreement is crop-type dependant. This seems to strongly argue that at the present state of understanding for the operational mapping of chlorophyll content, crop speciation is required prior to applying species-specific algorithms for optimal accuracy in the retrieval of maps of leaf pigment content.

The corresponding spatial distribution of chlorophyll status is best illustrated by a map, as shown in Fig. 8, where corn plots are discriminated with respect to their chlorophyll level and variability. The map texture illustrates the spatial pattern caused by the differences in nitrogen supply (numbers on the map are in kilograms per hectare), soil properties, and drainage conditions. For instance, in the eastern part of the field, low chlorophyll content (reddish tones) is independent of nitrogen supply (30, 82, and 135 kg/ha). They are the result of poor drainage conditions due to a high clay percentage in the soil. The 16 plots of the field were horizontally (east–west) separated by three stripes used as reference plots. The reddish stripe (low chlorophyll content) along the middle grand axis of the field represents no-nitrogen fertilization effect, while the bluish ones (high chlorophyll content) correspond to overfertilized plots (Fig. 8).

This patterning has important consequences for the understanding of plant productivity and its dependence on the spatial variability of soil physical and chemical properties. It expresses a time-specific status of the complex soil–crop conditions. Moreover, such information is of great importance for effective crop management that targets both profitability optimization and environment protection during the growing season. It will help farmers in balancing the competing goals of supplying enough nitrogen to the crops while limiting its loss to the environment.

These results reveal the potential of hyperspectral reflectance data for detecting and characterizing the spatial heterogeneity of pigment content in corn canopies at the meter spatial scale using the CASI sensor. Estimates using modeling and indices-based approach have shown that chlorophyll content had responded to the spatial changes in soil nitrogen availability. Thus, characterization of the spatial distribution of crop canopy hyperspectral reflectance could form a basis for developing techniques for variable nitrogen supply in agricultural fields in the sense that leaf chlorophyll content is an indicator of both soil nitrogen availability and plant nitrogen status.

### VI. CONCLUSION

In conclusion, this paper has focused on testing a remote-sensing approach for chlorophyll estimation over crop canopies with minimum effects from the canopy LAI. Based on simulated and measured data sets, we compared several combined indices that are both sensitive to chlorophyll content variations and relatively resistant to the variations of LAI. Their application to CASI hyperspectral reflectance data generated images of predicted leaf chlorophyll content. Evaluation showed that chlorophyll variability over crop plots with various levels of nitrogen revealed contrasting agreement with ground truth: leaf chlorophyll content estimates from CASI hyperspectral data were more or less similar to leaf chlorophyll content measurements in the laboratory from plot field sampling. In fact, the agreement between estimated and measured chlorophyll was very good for corn fields but moderate over wheat fields. Based on the relatively limited data set used in this paper, we can draw conclusions regarding the following aspects: simulation versus measurements-based relationships, indices behavior and

### TABLE IV

<table>
<thead>
<tr>
<th>Ratios</th>
<th>CORN</th>
<th>WHEAT</th>
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<tbody>
<tr>
<td></td>
<td>$R^2$</td>
<td>RMSE</td>
</tr>
<tr>
<td>MCARI/OSAVI</td>
<td>0.54</td>
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<tr>
<td>TCARI/OSAVI</td>
<td>0.73</td>
<td>11.8</td>
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<tr>
<td>TCI/OSAVI</td>
<td>0.64</td>
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</table>

**Fig. 8.** Map of chlorophyll status determined from a CASI hyperspectral image of summer 2005, for corn fields. Chlorophyll estimations have been performed through the relationship between chlorophyll concentration and the ratio TCARI/OSAVI. Numbers 30, 82, 135, and 187 represent nitrogen supply in kilograms per hectare. Chlorophyll content ranges from (red tones) $9 \mu g/cm^2$ to (blue tones) $72 \mu g/cm^2$. It is worth noting that the published ranges of RMSE are also highly variable.
performances, and crop-type effect on the prediction/validation processes.

Through the analysis of the relationships between leaf chlorophyll content and combined optical indices, we have found that PROSPECT–SAILH simulation-based trends are similar to the trends determined on measured data sets over corn and wheat canopies. This denotes that both spectroradiometric measurements and radiative transfer models hold comparable unique potential to quantitatively retrieve crop biophysical attributes such as foliar pigments.

Regarding the performances of indices, the analysis of combined index behaviors either as related to simulated/measured chlorophyll contents or as chlorophyll estimators has allowed the following conclusions to be drawn.

— Combined indices using OSAVI or MSAVI revealed more consistent relationships with chlorophyll content than those involving NDVI, RDVI, or SAVI.
— The ratio TCARI/OSAVI seems to be the best estimator of leaf chlorophyll content for corn canopies.
— The combined indices MCARI/OSAVI and TCI/OSAVI seem to be relatively consistent and more stable as estimators of crop chlorophyll content because they yielded relatively good determination coefficients for both corn and wheat.

Based on our limited data set, it is obvious that crop type had a clear influence on the establishment of predictive equations as well as on their validation. Indeed, in addition to generating different predictive equations, corn and wheat showed contrasting agreement between estimated and measured chlorophyll contents even for the same predictive algorithm.

For future studies, improvements to the proposed analysis may include the following.

— A larger database of spectral and corresponding foliar chlorophyll measurements, with more crop types and various levels of vegetation stress to get the whole relevant range of chlorophyll variations in vegetation tissues: from low to high concentrations.

— Advanced versions of radiative transfer models, namely a new calibrated version of PROSPECT. They should represent in a more realistic and detailed manner the link between remote-sensing measurements and biophysical (chemical and structural) vegetation parameters.

REFERENCES


Nicolas Tremblay received the B.S.A. degree in bio-agronomy and the Ph.D. degree in plant science from Laval, respectively. Since 1985, he has been a Research Scientist with Agriculture and Agri-Food Canada, St-Jean-sur-Richelieu, QC, where he has developed a comprehensive program on the management of nitrogen fertilization based on remote sensing for stress detection and growth assessment of crops, nitrogen accounting, and quick diagnosis methods of nitrogen deficiency. He is an Agronomist and an Adjunct Professor with Laval University, Quebec City, and the Université du Québec à Chicoutimi, Chicoutimi, QC, Canada. He also cosupervises students at the Université de Montréal, Montréal, QC, Canada. He heads a team of four professional assistants and one postdoctoral fellow (Dr. Zhijie Wang). He has served two terms (1997–2003) as Associate Editor for the Canadian Journal of Plant Science.

John R. Miller received the B.E. degree in physics and the M.S.c. and Ph.D. degrees in space physics from the University of Saskatchewan, Saskatoon, SK, Canada, in 1963, 1966, and 1969, respectively. He spent two years on a postdoctoral fellowship with the Herzberg Institute, National Research Council, Ottawa, ON, Canada. Since 1972, he has been with York University, Toronto, ON, Canada, where he is currently a Professor of physics and earth and space science. His remote-sensing interests include atmospheric correction and extraction of biophysical surface parameters through radiative transfer models from water color reflectance and from canopy reflectance for forestry and agriculture applications. Over the past two decades, his primary focus has been on the application of reflectance spectroscopic techniques in remote sensing using imaging spectrometer sensors.

Philippe Vigneault received the B.Sc. degree in geography from Montreal University, Montreal, QC, Canada, in 1996. From 1996 to 1999, he was a research professional with the Remote Sensing Laboratory, Montreal University. Since 1999, he has been a Remote Sensing Specialist with the Horticulture Research Centre, Agriculture and Agri-Food Canada, St-Jean-sur-Richelieu, QC, Canada. His research interests include remote sensing, precision farming, plant physiology, vegetation indices, spatial analyst, geostatistics, geomorphology, glacial geomorphology, and geology.