Hyperspectral Remote Sensing of Forest Condition: Estimating Chlorophyll Content in Tolerant Hardwoods

Paul H. Sampson, Pablo J. Zarco-Tejada, Gina H. Mohammed, John R. Miller, and Thomas L. Noland

ABSTRACT. To develop practical and objective measures of forest condition, the Bioindicators of Forest Sustainability Project has used a physiological, remote sensing approach that emphasizes identifying early warning measures of stress effects in forests. While stress indicators exist at the leaf level (e.g., chlorophyll fluorescence, pigment levels), developing reliable indicators at the canopy level is a challenge. Hyperspectral sensors, such as the Compact Airborne Spectrographic Imager (CASI), may be useful in remotely detecting vegetation stress effects. In this study, an inverse modeling approach demonstrated that the CASI could be used to map chlorophyll content (root mean square errors ranging from 12.6 to 13.0 mg/cm²) following different silvicultural treatments in a tolerant hardwood (sugar maple [*Acer saccharum* M.]) forest. This capability could be readily applied to operationally assessing forest physiological strain and in classifying forest condition based on chlorophyll content. A change analysis study was also conducted to evaluate chlorophyll estimation across seasons for a range of sites. The implications of these findings and recommendations for a prototype system to monitor forest condition are presented. For. Sci. 49(3):381–391.

Key Words: Bioindicators, CASI, change analysis, MERIS, MODIS, radiative transfer, physiology, silviculture, sugar maple, *Acer saccharum*.

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Acknowledgments: The authors gratefully acknowledge the financial support provided for this research through the Ontario Ministry of Natural Resources, the Centre for Research in Earth and Space Technology (CRESTech), and Geomatics for Informed Decisions (GEOIDE)—a Canadian Centre of Excellence. They also acknowledge their colleagues for their valuable contributions: John Harron (CRESTech) for the development of leaf measurement apparatus; Lawrence Gray, Paul Shepherd, Phil Brasher, and Heidi Beck whose dedication and skill made the airborne CASI field campaigns a success; and Denzil Irving, Brian Brown, Maara Packalen, Nick Seymour, and Desmond Hickie at the Ontario Forest Research Institute (OFRI), who planned and executed complex site sampling campaigns. They are indebted to lan Morrison, Al Cameron, Tom Weldon, and Robert Fleming at the Canadian Forest Service for providing LAI data and offering exceptional cooperation. A note of appreciation is extended to Paul Treitz and Valerie Thomas at Queen's University, our Technical Advisory Team, Ontario's Forest Growth and Yield Program, and Dave McLaughlin, Ministry of Environment and Energy. Lastly, the authors thank Abigail Obenchain and Lisa Buse (OFRI Transfer) and the constructive input of three anonymous reviewers.

Manuscript received Dec. 7, 2000, accepted Dec. 26, 2001. Copyright © 2003 by the Society of American Foresters

EMOTE SENSING DATA used in forestry studies range from coarse-resolution weather satellite data (>1 km) to high spatial and spectral resolution data acquired with airborne sensors. Presumably, this range of data and resolutions would satisfy the diverse needs of the forestry community. But Holmgren and Thuresson (1998) concluded that satellite remote sensing data is unsuitable for many applications in forestry planning. This criticism may in part be overcome by satellites with high spectral resolution (i.e., many narrow spectral bands). Field and laboratory studies have shown that high spectral resolution is needed to discern changes in vegetation condition and amount (see review by Treitz and Howarth 1999). Optical indices derived from the red edge (the region of rapid transition between red and near infra-red reflectance) are especially useful because they are sensitive to both chlorophyll content (chl_{a+b}) and canopy structure.

Developing spectral features related to chlorophyll or other pigments is useful in identifying whether forests are healthy or are stressed to the point where productivity of the resource may be constrained. Several investigators have related changes in chl_{a+b} to a shift in position of the spectral red edge (e.g., Horler et al. 1983, Vogelmann et al. 1993, and Gitelson et al. 1996). This shift has been associated with plant stress, forest decline, and leaf development (e.g., Rock et al. 1988, Boochs et al. 1990, Miller et al. 1991, Hoque and Hutzler 1992).

Traditional visual assessments can be subjective and do not directly measure tree vigor (Ferretti 1997). In contrast, a nonvisual method that allows tracking of pigment concentrations (e.g., chlorophyll) may provide an objective, early warning indicator of stand condition. Early detection could help to identify stands requiring remedial or salvage action before damage is visible and, potentially, before biomass loss occurs. Stress can affect other physiological features such as leaf water content. However, leaf water content changes are less sensitive than those of chl_{a+b}, because they are measurable only under severe dehydration events (Carter 1993).

Foliar chl_{a+b} has been positively correlated with foliar nitrogen (N) in western red cedar (*Thuja plicata* D.) (Radwan and Harrington 1986), big leaf maple (*Acer macrophyllum* P.) (Yoder and Pettigrew-Crosby 1995) sugar maple (*Acer saccharum* M.) (Ellsworth 1999), and balsam fir (*Abies balsamea* L.) (Luther and Carrol 1999). Nitrogen deficiency is the second greatest factor limiting tree growth, next to water stress (Kramer and Kozlowski 1979). Foliar chl_{a+b} has also been positively correlated with shoot growth rate in western red cedar (Radwan and Harrington 1986) and balsam fir (Luther and Carrol 1999) and with photosynthetic rate in sugar maple (Ellsworth 1999); thus it is likely a sensitive indicator of tree physiological condition.

Recent advances in technology, data processing, and scientific application of findings have made physiologically based remote sensing approaches more practical. New satellite systems are being launched with spatial and spectral resolutions comparable to those of airborne sensors (Fritz 1996, Treitz and Howarth 1999, Ustin and Trabucco 2000). Airborne hyperspectral technologies themselves have progressed markedly, offering improved data capture and processing capabilities along with fine spectral and spatial detail. For example, the Compact Airborne Spectrographic Imager (CASI) has been used in various forestry applications, which include conducting land classification (e.g., Zarco-Tejada and Miller 1999), inventorying forests (e.g., Davison et al. 1999a, 1999b), assessing forest management practices (Sampson et al. 2001), detecting root rot (e.g., Reich and Price 1999), and identifying insect damage (e.g., Leckie et al. 1989).

We examined the use of CASI technology to estimate ch_{a+b} in a managed tolerant hardwood forest in the Algoma Region of Ontario, Canada. One objective was to determine if chlorophyll content could be predicted following different harvesting practices. Second, we endeavored to estimate ch_{a+b} across seasons (i.e., conduct change detection analysis) on a range of maple sites. The overall aim is to develop a prototype system for monitoring forest physiological condition; thus, we considered the steps and challenges in designing such a system.

Data Description and Methods

The first objective was addressed by examining CASI imagery and accompanying ground truth data for the Turkey Lakes Harvesting Impacts Project (TLHIP), which allowed us to test our ability to estimate chlorophyll levels in a managed tolerant hardwood forest. The second objective was addressed by conducting change detection analysis of CASI imagery and leaf-based measurements obtained in 1998–1999 from a range of maple sites in the Algoma Region. The study sites and experimental data are described separately. Chlorophyll content (chl_{a+b}) estimation was conducted in the same manner for both objectives.

Turkey Lakes Harvesting Impacts Project

The TLHIP covers approximately 10 km^2 (1,090 ha), at 47°03'N and 84°25'W, within the Algoma Region, Ontario. The forest is an uneven-aged, generally mature-toovermature tolerant hardwood community, more than 90% of which is comprised of sugar maple and yellow birch (*Betula alleghaniensis* Britton) (Table 1). The TLHIP is a single-factor randomized block field experiment with four blocks comparing alternative silvicultural systems: selection, shelterwood, clearcut, and control. The clearcut system (i.e., removal of most, if not all stems) is not recommended for tolerant hardwood management but was included to allow us to analyze a maximal response to canopy removal and site disturbance (Morrison et al., 1999). Treated areas ranged from 6 to 66 ha. The operation was completed over a 6 week period in fall 1997.

The CASI was installed in a light aircraft (Piper Navajo Chieftain) and flown over the TLHIP study area on July 31, 1998, between 19:52 and 22:09 GMT at 2,000 m above sea level. Conditions were considered excellent: average aerosol optical depth of 0.06 at 550 nm under clear skies, a light breeze, and a temperature of 23°C. The sensor was configured to optimize its high spatial resolution features, and a

	Mean	Mean canopy		Mean	Mean	Mean gross		
	stocking	opening	Mean	diameter	basal area	total volume	Percent c	composition
Treatment	$(\text{stems} \cdot \text{ha}^{-1})$	(%)	LAI	(DBH _{ob} -cm)	$(m^2 \cdot ha^{-1})$	$(m^3 \cdot ha^{-1})$	Acer spp.	Betula spp.
Control	1375a	9.0c	4.20a	13.5ab	27.0a	203.6a	94.8a	6.8a
	(±130)	(± 0.6)	(±0.85)	(± 1.48)	(±2.56)	(±20.20)	(±5.18)	(±6.13)
Clearcut	408c	72.9a	1.13d	9.76b	5.2c	30.0c	83.9a	9.54a
	(±123)	(±3.1)	(±0.41)	(± 1.41)	(±2.44)	(±19.20)	(±4.93)	(±5.84)
Selection	746b	25.0b	2.54c	15.5a	23.6ab	170.3ab	86.4a	22.4a
	(±117)	(±2.6)	(±0.60)	(±1.34)	(±2.31)	(± 18.20)	(±4.67)	(±5.53)
Shelterwood	784b	23.4b	2.86b	13.5ab	18.4b	122.6b	80.3a	26.3a
	(±123)	(±2.3)	(±0.50)	(± 1.40)	(±2.43)	(±19.20)	(±4.92)	(±5.82)

Table 1. Forest mensurational data by treatment. Means followed by the same letter within a column are not significantly different (P = 0.05).

seven channel bandset was selected (Figure 1). Flight lines were oriented parallel to the solar azimuth at $65-67^{\circ}$ true north to minimize bidirectional reflectance effects. The sensor was pointing at nadir (vertically downward).

The 12 bit radiometric resolution data collected by the CASI was processed to at-sensor radiance using calibration coefficients derived in the laboratory by the Centre for Research in Earth and Space Technology (CRESTech). Aerosol optical depth at 550 nm was estimated using a Micro-Tops III sunphotometer at the time data were acquired. This measurement was used to process image data to ground-reflectance using the CAM5S atmospheric correction model (O'Neill et al. 1997). Images were geocorrected using on-board gyroscopes and ground control points, with the resulting root mean square error (RMSE) of 4 m. Images were mosaicked using PCI (1997).

In this study, the CASI images had rectangular pixel dimensions due to the integration period of the CASI sensor. The spectral reflectance of the low altitude imagery was regularized over an instantaneous field of view



Figure 1. The wavelengths of Compact Airborne Spectrographic Imager (CASI) channels used in this study sumperimposed on a typical vegetation reflectance spectrum. The seven band spatial mode data are shown in green and the 72 band hyperspectral mode data are shown in dark blue. The wavelengths of the MERIS sensor (to be launched by ESA in 2002) are shown in red. The bands centered at 705 nm, 742 nm, and 753 nm indicate the red-edge bands used to estimate pigment content for the sugar maple sites.

area of 1.90 m \times 1.10 m in the cross- and along-track directions, respectively. The images were resampled to 1 m \times 1 m using the nearest neighbor algorithm.

Physiological condition was assessed on the ground by measuring spectral reflectance and biochemical constituents of leaves. Samples were collected August 4-6, 1998, under full leaf expansion prior to senescence. Trees were randomly selected from permanent sample plots used in forest growth and yield assessments. Upper canopy foliage (i.e., sun leaves) was sampled by shooting down a branch from each of 24 trees per treatment for a total of 96 trees (4 treatments \times 4 blocks x 6 trees). At least ten leaves per tree were collected: six of these leaves were immediately sealed in bags and placed on dry ice for biochemical analyses, and the remaining samples were placed in sealed bags containing moist paper and held on ice for same-day measurements of reflectance (Sampson et al. 2001). Leaf pigment content was assessed on the same sample plots as described in Zarco-Tejada et al. (2000a, 2000b). Leaf area index (LAI) was measured (August 11-17, 1999) using a PCA Li-Cor 2000 equipped with a 180° view-cap and sampled at two heights (0.5 and 2.0 m), with the combined average reported here (Table 1). Additional mensurational data (e.g., crown openings, stocking) were collected as in Sampson et al. (2001).

Change-Detection Analysis

CASI airborne hyperspectral data were acquired in 3 deployments (1997, 1998, and 1999) over 12 sugar maple sites in the Algoma Region. Study sites were selected in 1997 from existing provincial plot networks and represented a range of productivity and decline. Six permanent sample plots were chosen from Ontario's Forest Growth and Yield Program (Anon 1993) to investigate the effects of stand productivity on hyperspectral features of maple. Another six plots were selected from the provincial hardwood forest health network (McLaughlin et al. 1992) to represent a gradient in maple forest decline. Detailed stand records exist for these sites, which are considered representative of tolerant hardwood forests in the Algoma Region.

Each CASI deployment consisted of two missions, each with a specific sensor mode: (1) the *mapping mission*, with 0.5 m spatial resolution and 7 spectral bands and (2) the *hyperspectral mission*, with 2×4 m spatial resolution and 72 channels (Figure 1). Reflectance data were

georeferenced using GPS data collected onboard the aircraft. The hyperspectral mode imagery was registered to the CASI mapping-mission imagery by visually identifying ground-referenced 1 m white targets that were used to identify site locations.

Mean reflectance values per plot were calculated from the imagery from each 20×20 m study site. CASI data were acquired in the hyperspectral reflectance mode, with 2–4 m spatial resolution and 72 spectral channels (7.5 nm spectral bandwidth). Mean reflectance per plot was calculated from the 25% of pixels with highest reflectance in the near-infrared region, thereby targeting crowns while minimizing the influence of shadows, canopy openings, and direct understory reflectance.

Field samples for biochemical analysis of leaf chl_{a+b} , along with leaf reflectance and transmittance, were collected concurrently with field data. Sampling was done in June and July of 1998 and 1999, collecting from the top of crowns at each of the 12 sugar maple study sites. Four leaves from the tops of crowns (n = 5 trees per site) were sampled for chl_{a+b} , reflectance and transmittance. LAI measurements were acquired for all the plots using a PCA Li-Cor 2000 instrument at 1.3 m with a 180° view-cap. A total of 440 leaf samples per year were collected for biochemical analysis and measurement of leaf chl_{a+b} . Leaf pigment content was determined as described in Zarco-Tejada et al. (2000a, 2000b), and single leaf reflectance and transmittance were measured according to Zarco-Tejada et al. (2001).

Chlorophyll Content (chl_{a+b}) Estimation

Chlorophyll content (chl_{a+b}) was estimated by radiative transfer (RT) model inversion (Zarco-Tejada et al. 2001). The formulation and solution of RT theory have been improved significantly in the last decade, resulting in models that can enhance our understanding of the light regime in complex vegetation canopies (Asner and Wessman 1997). The RT model approach used in this work can be easily adapted to couple canopy reflectance models and leaf RT models, thus linking canopy reflectance directly to foliar biochemicals. This approach is based on the assumption that an analytical model describes spectral variation of canopy reflectance as a function of canopy structure (with inputs such as LAI), leaf optical properties (leaf reflectance and transmittance), soil background reflectance, and a set of parameters to describe the viewing geometry (solar zenith and azimuth angle, viewing angle).

As shown in Figure 2, three consecutive steps are required to estimate chl_{a+b} in a coupled leaf and canopy model. The estimation is based on inverting the coupled models using an iterative optimization technique. The steps are as follows: (1) estimating leaf reflectance and transmittance (r, t) from a set of leaf model input parameters, such as the parameter to be estimated, chl_{a+b} , and other leaf structural parameters; (2) estimating canopy reflectance from leaf level model-estimated r, t and a set of canopy model parameters that define canopy structure and viewing geometry; and (3) calculating the error from comparing the estimated canopy reflectance r^* to the at-



Figure 2. Calculating error between the estimated canopy reflectance (r^*) to the at-sensor measured reflectance (r_m) by using a numerical model-inversion technique. The steps include: (1) estimating leaf reflectance and transmittance (r, t) from a set of leaf model input parameters; (2) estimating canopy reflectance from leaf level model and a set of canopy model parameters that define canopy structure and viewing geometry; and (3) calculating the error from comparing r^* to r_m . Estimation of the optimum set of input parameters is derived through iterative optimization.

sensor measured reflectance r_m . Calculating the error involves determining the set of parameters $P = (N, \text{Chl}_{a+b}, C_w, \text{LAI}, \theta_s...)$ that minimize a merit function Δ^2 over the whole spectrum or using a spectral transform calculated from the simulated and measured reflectance. The merit function can be expressed as:

$$\Delta^2 = \sum_n [r_m(\lambda_i) - r^*(\lambda_i, P)]^2 \tag{1}$$

where

 $r_m(\lambda_i)$ is the measured canopy spectral reflectance, and

 $r^*(\lambda_i, P)$ is the modeled canopy spectral reflectance with a

set of P parameters.

Different merit functions for calculating the error in the numerical model inversion can be built as described in Zarco-Tejada et al. (2001). The choice of function greatly influences the estimation of the parameter for which the inversion is made. Equation (2) shows a merit function based on the red-edge ratio R_{750}/R_{705} (where R_{750} and R_{705} represent reflectance at 750 and 705 nm) presented in Zarco-Tejada et al. (2001) for the Medium Resolution Imaging Spectrometer (MERIS) sensor onboard ENVISAT, which was launched March 2002 by the European Space Agency and used here to estimate pigment content with CASI data.

$$\Delta^{2} = \left[\left(\frac{R750}{R705} \right)_{m} - \left(\frac{R750}{R705}, P \right)_{*} \right]^{2}$$
(2)

where

$$\left(\frac{R750}{R705}\right)_m$$

is the optical index calculated from measured canopy reflectance, and

$$\left(\frac{R750}{R705}, P\right)_{*}$$

is the optical index calculated from modelled canopy reflectance for a given set of input parameters *P*.

For the first study objective, total chlorophyll content (chl_{a+b}) was estimated from RT model inversion of CASI data carried out for 32 plots in the TLHIP using different methods. The PROSPECT (Jacquemond and Baret 1990) leaf RT model was coupled to the Hapke infinite reflectance (R_{m}) (Hapke 1993) and SAILH (Verhoef 1984) canopy reflectance models to estimate chl_{a+b} using numerical model inversion and the red-edge optical index (R_{750}/R_{705}) in the merit function [Equation (2)] (Zarco-Tejada et al. 2001). This analysis considers viewing geometry (sensor viewing angle, solar azimuth, and zenith angles) and canopy structural characteristics (e.g., LAI, leaf angle distribution function (LADF), and soil reflectance). A nominal value of LAI = 3, plagiophile LADF for maple, and soil reflectance collected from the sites was used to estimate chl_{a+b} . For comparison, chl_{a+b} was also estimated using the PROSPECT and infinite reflectance (R_{∞}) models without viewing geometry or canopy structural parameters.

When followed over time, chlorophyll content may be a useful indicator of physiological status and a non-specific indicator of damage. Thus, the second study objective was to determine chl_{a+b} by model inversion using the coupled PROS-PECT leaf and SAILH canopy reflectance models over 2 seasons for several (n = 12) maple sites. Scaling-up approaches (Zarco-Tejada et al. 2001) based on statistical relationships obtained at the leaf level and coupled to the SAILH model were also used for these same sites to examine possible changes in chl_{a+b}. The objective was to study whether leaf-measured changes in chl_{a+b} (per site) from 1998 to 1999 could be accurately detected from canopy reflectance data, thereby demonstrating the potential of chlorophyll estimation as a monitoring tool.

Results

Turkey Lakes Harvesting Impacts Project

The first RT model inversion approach used to estimate ch_{a+b} for each treatment area required viewing geometry (sensor viewing angle, solar azimuth, and zenith angles) and canopy structural characteristics (e.g., LAI, LADF, and soil reflectance). The results of this analysis yielded an $r^2 = 0.43$



Figure 3. Estimating leaf total chlorophyll content (chl_{a+b}) for the Turkey Lakes Harvesting Impact Project (TLHIP) plots by model inversion coupling PROSPECT to Hapke R_{∞} model (a) and to the SAILH CR model (b).

(P < 0.001) and an RMSE of 13 µg/cm² (Figure 3). When chl_{a+b} was estimated *without* using viewing geometry or canopy structural parameters results were comparable: r² = 0.43 (P < 0.001) and RMSE = 12.6 µg/cm² (Figure 4). Thus, detailed structural and viewing geometry parameters are likely not essential to estimating chl_{a+b}. In addition to being more straightforward, the predictive (i.e., low RMSE) nature of this approach lends itself to other sites where classes of chl_{a+b} could be applied.

Change Analysis

The relationship between ground-measured and remotely estimated chl_{a+b} percent change from 1998 to 1999 resulted in an $r^2 = 0.55$ (P = 0.0028) for the scaling-up method and $r^2 = 0.46$ (P = 0.0077) for the model inversion technique (Figure 5). Field data estimates for chl_{a+b} over the same study area in 1998 and 1999 were 34.3 µg/cm² and 45.8 µg/cm², respectively. In comparison, model inversion estimates were 35 µg/cm² (1998) and 41.5 µg/cm²



Figure 4. Estimating leaf total chlorophyll content (chl_{a+b}) for the Turkey Lakes Harvesting Impact Project (TLHIP) plots by model inversion coupling PROSPECT to Hapke R_{\odot} model with R_{750}/R_{705} .



Figure 5. Relationship between percent change of total chlorophyll content (chl_{a+b}) measured over 12 sugar maple plots from 1998 to 1999 and percent change estimated by scaling-up (solid pink) and model inversion (blue) through SAILH CR model using a rededge R_{750}/R_{710} optical index.

(1999), indicating a modest difference of 0.7 μ g/cm² and 4.3 μ g/cm², respectively, for the study sites over time (Figure 6). We therefore conclude that a red-edge index such as R_{750}/R_{710} can be used to monitor seasonal changes in chl_{a+b} with reasonable accuracy. In a practical setting, classes of total chlorophyll (μ g/cm²) could be considered. Figure 6 shows a map where: (1) < 20 (very low chlorophyll), (2) 20–25 (low chlorophyll, suspected decline condition), (3) 25–30 (below average, possible decline symptoms), (4) 30–35 (average chlorophyll, usually healthy), (5) 35–40 (average to above-average chlorophyll, trees healthy).

Discussion

Turkey Lakes Harvesting Impacts Project

Interpreting the findings of the TLHIP study requires some understanding of the likely factors affecting chl_{a+b} estimation. For instance, the wide range of LAI values (from 1.1 to 4.2) and the fairly narrow range of chl_{a+b} (from 26 to 56 µg/cm²) are likely reasons for the RMSE being higher and the correlations lower than those found in a previous study using the same approach for sugar maple (Zarco-Tejada et al. 2001). When tree crowns are not dense (e.g., LAI values are less than 2), the spectral effect of underlying soil and vegetation can mask the condition of foliage (Guyot et al. 1989).

Canopy geometry also influences the ratio of shadowed surfaces to illuminated surfaces (i.e., bidirectional aspects). Zarco-Tejada et al. (2001) showed that chlorophyll estimates in closed maple stands (i.e., LAI greater than two) are not significantly affected by shadowed components when appropriate inversion methods are used. However, other species with open canopies and/or different canopy architectures (e.g., conical shape) could influence these predictions. To address these potential challenges, researchers are studying optimum view angles in different species and collecting airborne and field data on wellcharacterized sites using optically based methods (e.g., Chen 1996).

Spectral Indices

Another challenge in estimating chl_{a+b} is choosing a spectral index. Evidence from both leaf and canopy scale experiments demonstrate that relationships exist between pigment concentrations and narrow band reflectance, but many indices developed at the leaf level do not work at the canopy level since the leaf and canopy media have different optical properties. The large number of optical indices developed at the leaf level also makes it difficult to decide which to use (Blackburn 1999). Most proposed spectral indices have been developed empirically, typically by combining stress-sensitive and insensitive bands. The advantage of this approach is that insensitive bands function as baselines that factor out variability due to causes other than variation in leaf chl_{a+b}. Similarly, spectral derivatives have important advantages over spectral reflectance; for example, they can reduce variability due to changes in illumination or background reflectance (Elvidge and Chen 1995). Recently, Myneni et al. (1995) tried to quantify possible physical reasons for these observed correlations.

The spectral index (R_{750}/R_{705}) used here was selected after examining several indices for estimating chlorophyll in sugar maple at the leaf and canopy levels (Zarco-Tejada et al. 2001). A notable advantage of this red-edge index is its applicability to the MERIS sensor (Figure 2). However, the implications of the 300 m spatial resolution of MERIS must be evaluated further. Widely used indices for pigment estimation, such as the Normalized Difference Vegetation Index (NDVI), primarily track canopy structural changes and thus are considered insensitive to subtle changes in pigment content. The spectral index (R_{750}/R_{705}) offers a means to track chl_{a+b} semi-empirically (i.e., without detailed modeling) or, as demonstrated here, predictively using model inversion.

Sensor Calibration

A third possible factor affecting spectral response is sensor calibration. While calibration issues should not be discounted, many external factors can be determined easily (e.g., sun elevation, inclination of the view axis) (Guyot et al. 1989). The aerosol optical depth and solar zenith angle were obtained in our study using a Micro-Tops III sunphotometer-a portable and technically simple device to use. As well, due to reported levels of accuracy in retrieving above-canopy reflectance are quite high [e.g., 0.006 absolute error in the visible (Gray et al. 1997)], and, therefore, internal factors will likely influence pigment extraction to a greater degree. The larger spatial coverage for satellite sensors will mean, however, that a single measure of optical characteristics using a sun photometer will not be sufficient to capture the spatial variation in atmospheric properties. Thus proposed image-based cor-



Figure 6. Estimating total chlorophyll content (chl_{a+b}) for the same 500 m × 500 m study area in 1998 (upper figure) and 1999 (lower figure), where leaf field measurements showed pigment increased from 34.3 μ g/cm² (1998) to 45.8 μ g/cm² (1999) for the 20 m × 20 m plot (in white box). Similar results were achieved by model inversion using PROSPECT and SAILH models (nominal LAI = 4 and N = 1.3), with chl_{a+b} estimated at 35 μ g/cm² (1998) and 41.5 μ g/cm² (1999). Six classes of total chlorophyll (μ g/cm²) are shown, where (1) < 20 (very low chlorophyll), (2) 20⁹–25 (low chlorophyll, suspected decline condition), (3) 25–30 (below average, possible decline symptoms), (4) 30–35 (average chlorophyll, usually healthy), (5) 35–40 (average to above-average chlorophyll, trees healthy) and (6) >40 (above-average chlorophyll, trees healthy).

rection schemes (e.g., Zagoloski et al. 1999) with some degradation of correction accuracy will likely be needed.

Spatial Resolution

A final consideration in estimating chl_{a+b} is defining the optimal spatial, spectral and temporal resolutions since these are generally not known (Treitz and Howarth 2000). This issue can be viewed from two perspectives. The more common view is to use that the spatial resolution that will capture the spatial variability of the scene should be used. The spatial variability is a function of the type of environment being studied and the type of information required (Woodcock and Strahler 1987). But selecting an appropriate scale for vast forested areas is a challenge; Ontario alone has 39 million ha of productive forest. This challenge was illustrated by an examination of natural forest environments at various scales, where Marceau et al. (1994) concluded that there is no unique spatial resolution at which all geographic entities could be discriminated. A second, equally important, perspective is that a spatial resolution should be chosen that ensures that the assumptions made in the remote sensing interpretation methodologies are valid. For example, at very high spatial resolution, crown reflectance and canopy reflectance must be distinguished in parameter retrieval results.

For the study areas investigated here, Sampson et al. (2001) showed that an appropriate resolution (as derived by semivariogram analysis) is either approximately 5 m or approximately 9 m, depending on whether physiological or structural parameters are being examined. Similarly, optimal spatial resolutions for several boreal forest species were shown to be in the order of 3 to 7 m (Treitz and Howarth 2000). Extending these suggested resolutions to other environments may not be possible given the potential influences of factors such as terrain and sensor characteristics. However, the results do provide some guidance in considering the suitability of existing data sets and in developing sampling strategies in these forest types.

Change Analysis

Baseline thresholds are needed to interpret spectral responses. To derive these thresholds, hyperspectral imagery must be obtained over established forest sites to provide an ongoing database of average responses and to serve as a database for detecting physiological change. The latter is seen as the real strength of a change analysis system, because it allows evaluation of forest responses over time, rather than of single snapshots, which are susceptible to natural fluctuations. However, to develop a change analysis system, factors affecting spectral response must first be considered and, consequently, addressed here in the following sections.

Chlorophyll Content (chl_{a+b})

Chlorophyll content, including the ratio of chlorophyll a/b, may be affected by a range of intrinsic and extrinsic factors and is subject to considerable natural and stressinduced variation (Kozlowski and Pallardy 1997a). For instance, chlorophyll content is higher in sun-adapted foliage than in shade leaves. It is influenced by genetic factors, which produce plants ranging from albinos, devoid of chlorophyll, to those showing various degrees of striping or mottling. Flooding or drought may induce chlorosis, and chlorophyll synthesis may be inhibited by leaf diseases. Chlorophyll content is also affected by seasonal cycles (Vogg et al. 1998, Rosenthal and Camm 1997) and by extreme air and soil temperatures (Kozlowski and Pallardy 1997b). In addition, both chronic and acute injury from atmospheric pollutants may be manifested as chlorosis and then leaf senescence, with symptoms more conspicuous in angiosperms than gymnosperms, in seedlings rather than older trees, and in immature rather than mature foliage (Treshow and Pack 1970).

Because of its non-specific nature, reflectance should be used with caution when attempting to diagnose a stress. It may, however, be combined with other analytical methods to pinpoint causal factors. For instance, the decline phenomenon in sugar maple found in Canada and the United States has been often been correlated with nutrient stress, especially calcium (Ca) and magnesium (Mg) (Bernier and Brazeau 1988, Horsley et al. 2000). Our results show positive correlations (significant in all but one case) between foliar chl_{a+b} and Ca and Mg content of leaves in both the change analysis sites and the TLHIP plots (Table 2). Thus, the differences in chlorophyll content appear to relate somewhat to the nutrient stress status of the sugar maple stands. Incorporating spatial data such as soil type, terrain, and insect or disease surveys may offer greater insight into why chlorophyll changes are evident.

Monitoring Approach

The wide variety of factors producing chlorosis suggests that it can be caused by general disturbances of metabolism as well as by deficiency (or toxicity) of a specific mineral element (Kozlowski and Pallardy 1997a). To account for these factors, a diagnostic approach could be used to integrate various types of information (e.g., climatic, terrain, and vegetation), with chlorophyll sampling data over several seasons to assess trends. A similar strategy would be to target a specific pest problem (such as root rot disease, e.g., Armillaria ostoyae) that causes chlorosis and then to allow its spread and extent to be monitored. Alternatively, with a bioindicator approach (e.g., Sampson et al. 2000), the causal agents influencing chlorosis are not directly of interest, but rather attention is placed on identifying deviations from the "normal" chlorophyll range. All these strategies have merit, and the choice depends on management objectives and overall feasibility. See Ferretti (1997) for a discussion of issues related to sampling strategies, monitoring intensity, and concepts behind defining appropriate indicators.

In our study, samples were collected under full leaf expansion prior to senescence on sites that included many scientific interests. The rationale was to minimize early and late season phenological changes that influence spectral response while targeting sites of long-term research importance. In addition, the stand level assessments was emphasized because, as described by others (e.g., Mohammed et al. 1997, Colombo and Parker 1999):

- Stands are the basic operational management units in a forest ecosystem.
- Stands are land units that can be readily identified from existing databases.
- Stands have some uniformity of tree species and age, facilitating comparison of physiological attributes among similar ecosystem units.
- Stands provide a means to examine spatial variability of larger land units such as the landscape.

As satellite sensors that could estimate chl_{a+b} become available (e.g., MERIS, MODIS), target stands may still be used, but it may also be possible to explore regional patterns of variation. The red-edge index (R_{750}/R_{705}) will be useful because it provides a link between satellite and airborne platforms. This robust measure of chl_{a+b} minimizes the confounding influences of structure in tolerant hardwoods yet is sensitive to subtle changes in optical properties at both the leaf and canopy levels.

Conclusion

Predicting chl_{a+b} or any other canopy biophysical parameter from airborne or satellite canopy reflectance is essential to many aspects of forest management. Although statistical relationships have been widely used in estimating biophysical features, no predictive estimates can be inferred from these studies, since these locally derived relationships are affected by species, canopy structure, and solar-viewing geometry. To advance the predictive capability for chl_{a+b} , it has been shown here that RT simulation for leaf and canopy levels with red-edge indices such as R_{750}/R_{710} and R_{750}/R_{705} can be used in models that are both predictive and simplistic. The practical implications of these findings are in providing an early warning measure of condition without needing ground data collection. This approach has several advantages over traditional ground surveys, which primarily rely on structural measures and subjective vigor estimates.

While our research findings are encouraging, the robustness of algorithms and approaches needs to be addressed. In particular, applying this method in open canopies and for different species needs to be investigated. Moreover, if chlorophyll estimates are to be used as a monitoring tool, the factors affecting response need to be more fully understood. Our results and others have provided insight into several of these factors (e.g., calibration, size of view area, structure, and optical properties). The question of operational feasibility remains. The cost and limitations of airborne hyperspectral imagery must be considered; however, its utility increases when one considers its broad applicability to many aspects of forest management, such as forest health monitoring and forest mapping and inventory. It would be helpful if hyperspectral data now obtained via aircraft became available at a reasonable cost via satellites. Ready access to satellite-based pigment estimates of a well-known scene would also help us answer questions about its potential, as well as factors limiting its retrieval. In future studies, the potential of spaceborne platforms and the suitability of the method described here will be investigated.

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Table 2. Correlation coefficients of foliar chlorophyll content (chl_{a+b}) with leaf nutrient content.

	Change	analysis plots	Turkey Lakes harvesting impact project plots				
	(<i>n</i> =	= 36 trees)	(1	(n = 96 trees)			
Sample date	July 98	July 99	Aug 98	July 99			
Ca	0.625*	0.353	0.158	0.340			
	< 0.0001	P = 0.006	P = 0.124	P = 0.018			
Mg	0.517	0.408	0.221	0.448			
	P < 0.0001	P = 0.001	P = 0.03	P = 0.0014			

* *r* value of Pearson correlation test and probability value.

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