Extraction of Vegetation Biophysical Parameters by Inversion of the PROSPECT + SAIL Models on Sugar Beet Canopy Reflectance Data. Application to TM and AVIRIS Sensors

S. Jacquemoud,*,†† F. Baret,† B. Andrieu,‡ F. M. Danson,§ and K. Jaggard**

The PROSPECT leaf optical properties and SAIL canopy reflectance models were coupled and inverted using a set of 96 AVIRIS (Airborne Visible/Infrared Imaging Spectrometer) equivalent spectra gathered in a field experiment on sugar beet plots expressing a large range in leaf area index, chlorophyll concentration, and soil color. In a first attempt, the model accurately reproduced the spectral reflectance of vegetation, using six variables: chlorophyll a + b concentration (C_{ab}), water depth (C_w), leaf mesophyll structure parameter (N), leaf area index (LAI), mean leaf inclination angle (θ_l), and hot-spot size parameter (s). The four structural parameters (N, LAI, θ_l, and s) were poorly estimated, indicating instability in the inversion process; however, the two biochemical parameters (C_{ab} and C_w) were evaluated reasonably well, except over very bright soils. In a second attempt, three of the four structure variables were assigned a fixed value corresponding to the average observed in the experiment. Inversions performed to retrieve the remaining structure variable, leaf area index, and the two biochemical variables showed large improvements in the accuracy of LAI, but slightly poorer performance for C_{ab} and C_w. Here again, poor results were obtained with very bright soils. The compensations observed between the LAI and C_{ab} or C_w led us to evaluate the performance of two more-synthetic variables, canopy chlorophyll content or canopy water content; for these the inversions produced reasonable estimates. The application of this approach to Landsat TM (Thematic Mapper) data provided similar results, both for the spectrum reconstruction capability and for the retrieval of canopy biophysical characteristics.

INTRODUCTION

The retrieval of the Earth's surface properties from remote sensing data is a long-term research goal, given the multiplicity of information sources and the complexity of the phenomena brought into play (Verstraete et al., 1994). The last 10 years have been characterized by the development and intensive use of empirical or semiempirical methods to relate simple vegetation indices to single, biophysical characteristics of canopies such as the leaf area index (LAI) or the absorbed fraction of photosynthetically active radiation. These vegetation indices are combinations of the reflectances or radiances

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*Joint Research Centre, Institute for Remote Sensing Applications, Advanced Techniques, Ispra, Italy

†Institut National de la Recherche Agronomique, Station de Bioclimatologie, Montfavet, France

‡Institut National de la Recherche Agronomique, Station de Bioclimatologie, Thiverval Grignon, France

§University of Salford, Department of Geography, Salford, United Kingdom

**Brooms Barn Experimental Station, Higham, Bury St. Edmunds, Suffolk, United Kingdom

††Permanent affiliation: LAMP / OPGC, Université Blaise Pascal, Aubière, France.

Address correspondence to Stephane Jacquemoud, Univ. of California, Dept. of Land, Air, and Water Resources, Davis, CA 95616.

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655 Avenue of the Americas, New York, NY 10010

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observed in several broad wavelength bands. The limited use of physical principles in the construction of these indices has restricted their robustness and portability to targets and conditions similar to those that prevailed during the original experiments. Thus, inversion of canopy reflectance models that incorporate current understanding of the radiative transfer inside canopies seems to be an attractive and alternative approach (Myneni and Ross, 1991).

The process of inverting a model means determining those parameters that minimize the differences between the measured and simulated data. In remote sensing studies, such an approach has been applied to infer properties of the atmosphere and terrestrial targets such as soil, vegetation, or water areas. In plant canopy studies, most effort has concentrated on the use of directional reflectance data which were already available. It is very important to choose an appropriate model; for example, the reflectance properties of homogeneous and heterogeneous (row, sparse or mixed crops) canopies are seldom governed by the same equations. Also, some models may be incapable of providing the information which is required about the reflecting surface. Goel (1987) distinguished several types of plant canopy reflectance model, some of which have been inverted. Thus Goel and Thompson (1984a,b) and Deering et al. (1992) retrieved the LAI and, less accurately, the mean leaf inclination angle by inverting, respectively, the SAIL (Verhoef, 1984; 1985) and TRIM (Goel, 1989) models using directional data. However, to do this, they had to know the leaf reflectance and transmittance, soil reflectance, and the fraction of solar radiation which was diffuse. Otterman (1987) assumed canopy structure and inverted a protrusion model to determine the leaf reflectance for several wavelength bands and zenith view angles. Later, the same author (Otterman, 1990) tried to infer the leaf orientation as well, but found difficulty separating leaf reflectance from leaf orientation or LAI. Pinty et al. (1990; 1991), Kuusk (1991b), and Privette et al. (1994) estimated the leaf optical properties as well as the spatial distribution of scatterers in the canopy by inverting analytical models of bidirectional reflectance. All these studies have been performed using data acquired at ground level because such directional measurements cannot be easily collected at the same date by current satellite sensors. Multitemporal data may be used, but this implies that the target does not change from one measurement to another and that corrections for atmospheric disturbances can be applied with great accuracy.

Following these attempts to retrieve surface characteristics by inversion of radiative transfer models on directional data, the introduction of high spectral resolution sensors has contributed to the development of similar methods to extract information from reflectance spectra. A spectra matching technique was applied by Gao and Goetz (1990) with a simple model to the 1.5–1.74 μm region of AVIRIS spectra; these authors asserted that the vegetation spectrum in this wavelength region was driven by liquid water and dry vegetation components. However, this work has not been thoroughly validated. Schmuck et al. (1993) described the vegetation reflectance with a Kubelka–Munk formula containing chlorophyll $a+b$ and water specific absorption coefficients; this model was used to measure the residues at 1.7 μm, thought to be a signature of the canopy biochemical components. In a theoretical study based on simulated spectra, Jacquemoud (1993) tried to evaluate the use of AVIRIS data for determining canopy biophysical properties of agronomic interest [leaf mesophyll structure (N), chlorophyll $a+b$ concentration (C_{ab}), water depth (C_w), leaf area index (LAI), and mean leaf inclination angle (θ_l)] by inversion of the PROSPECT leaf optical properties model (Jacquemoud and Baret, 1990) coupled with the SAIL canopy reflectance model: Chlorophyll and water seemed to be obtained with good accuracy, but it was difficult to separate LAI from θ_l. Here, again, a validation was needed. Kuusk (1994) was the first to attempt to invert his fast canopy reflectance (FCR) model both on directional and spectral data. Results from soybean and corn crops were promising; they offer new prospects to interpret remote sensing measurements acquired by current satellites.

Already, several conclusions can be drawn from these studies. First, inverting a canopy reflectance model on remote sensing data is not easy: operational use of this approach requires a compromise between simple equations that cannot take into account the multiple scattering due to canopy architecture (distortion of the biochemical signal), and complex models whose inversion is difficult and time-consuming. Second, the interdependence of some parameters prevents them from being extracted separately. Third, with current sensors it is not possible to acquire enough reflectance data to describe the bidirectional and spectral features of plant canopies. Thus, the radiometric information to invert models is often restricted. Finally, measurement of the spectral variation of canopy reflectance at a given time and location is, from a technological point of view, the easiest way to get radiometric information from a satellite or airborne platform. Therefore, most of this article will focus on the use of spectral information.

The main aim is to evaluate the possibility of infering canopy biophysical variables by inversion of a simple radiative transfer model using canopy reflectance spectra acquired in the field with a high spectral resolution radiometer. Before discussing the scope of the model to provide valuable information on vegetation, the field experiment is described, and the choice of model and of inversion procedure is justified. A basic criticism of the use of high spectral resolution is the large redundancy of data amongst the many narrow,

Table 1. Main Information about the Experiments

<table>
<tr><th></th><th><i>Broom's Barn</i></th><th><i>Grignon</i></th></tr>
<tr><td>Position</td><td>52.16°N-0.34°E</td><td>48.51°N-1.58°E</td></tr>
<tr><td>Altitude</td><td>75 m above sea level</td><td>130 m above sea level</td></tr>
<tr><td>Date of measurements</td><td>5-6-19 July 1989</td><td>17-18 July 1990</td></tr>
<tr><td>Soil variation</td><td>Natural Soil</td><td>Natural soil</td></tr>
<tr><td></td><td>Peat</td><td>Black fabric</td></tr>
<tr><td></td><td>Sand</td><td>White fabric</td></tr>
<tr><td>Canopy variation</td><td colspan="2">Plant density
Chlorosis</td></tr>
<tr><td>Number of spectra</td><td>51</td><td>45</td></tr>
</table>

adjacent bands. This has been analyzed statistically by Price (1990; 1992), who concluded that a limited set of wavebands was enough to synthesize accurately all the spectral information. In this article, the problem has been addressed differently, by comparing the results of the inversion process performed using the full spectral information with that obtained from only the six Landsat TM broad bands.

CROP AND REFLECTANCE DATA

Measurements from two field experiments were used: Broom's Barn, England (52.16°N-0.34°E) in 1989 and Grignon, France (1°N-1.58°E) in 1990. Canopy reflectance spectra for sugar beet (*Beta vulgaris* L.) were acquired at nadir using the GER MK IV IRIS field spectroradiometer (FOV = 3° × 6.5°, 975 contiguous spectral wavebands from 350 nm to 2500 nm with a spectral resolution of 2 nm, 4 nm, and 5 nm, respectively, for the 400-1000 nm, 1000-1800 nm, and 1800-2500 nm domains). A minimum of three replicate spectra were required on each plot, providing a good spatial representation and some smoothing of the radiometric signal. Absolute reflectance was derived by comparison with the reflectance of reference panels whose directional and spectral properties had been characterized previously in the laboratory. Then, Gaussian filters of selected widths and positions were applied to coincide with the 224 AVIRIS wavebands (Vane et al., 1993). Due to the atmospheric water absorption bands, the regions that range from 1352 nm to 1451 nm and from 1757 nm to 1949 nm have been removed so that 188 wavebands were available in practice. Moreover, the signal measured by the Landsat Thematic Mapper (TM) was simulated by using the spectral response of its six filter functions (Markham and Barker, 1985).

In total, 96 plots were available, representing a wide range of LAI, leaf color, and soil background (Table 1). Differences in LAI were obtained by varying the sowing date and plant density. Chlorophyll concentration was manipulated by inducing chlorosis, either by infection with Beet Yellows Virus or by application of small doses of metsulphuron herbicide spray. Finally, soil reflectance was changed by placing artificial backgrounds (trays of peat or sand, white or black fabric) under the canopy. For each of the plots, the chlorophyll concentration ($10 < C_{ab} < 50\,\mu^{-2}$), water depth ($0.025 < C_w < 0.050$ cm), and leaf area index ($0 < \mathrm{LAI} < 5$) were measured by direct or indirect methods. Accurately determining the mean leaf inclination angle θ_l is tedious and only a few values were measured: Two methods were used. The first involved direct measurements with an electronic clinometer on plants in three plots in the Broom's Barn experiment (39.8°, 45.8°, and 55.7°) and four plots in the Grignon experiment (33.2°, 35.9°, 51.6°, and 52.0°). Because this method was so difficult and disturbed the foliage, a second method was developed; it was based on the analysis of the directional variation of gap fractions measured on hemispherical photographs (Baret et al., 1993). This showed that an ellipsoidal distribution with an average leaf inclination of 28.6° gave a good description of the gap frequency. The disagreement between the clinometer measurements and the average leaf inclination estimated from the photographs was attributed to the regularity of the canopy. The size and shape of the leaves and canopy height were also measured. Finally, meteorological conditions, including the fraction of diffuse radiation, were recorded throughout the experiment. Additional details of the experiments and the measurements are available from the authors.

MODELS AND INVERSION PROCEDURE

Accurate estimation of canopy biophysical variables from vegetation spectra assumes two conditions: an accurate model and an appropriate inversion procedure. These assumptions seem to be evident but the response is not trivial. Scores of canopy reflectance models have been proposed in the literature during the last 25 years, but none of them is universal; therefore, the first task was to select one suitable for this application. With regard to the inversion procedure, there are also several optimization methods where efficiency is rather dependent on the problem. In the following, we will try to justify our choice.

The Models

The basic model chosen was the PROSPECT + SAIL model described in details by Jacquemoud (1993). In the SAIL model, the canopy is considered as an horizontal, homogeneous, and infinitely extended vegetation layer made up of Lambertian scatterers (leaves) randomly distributed. The azimuth angle of the scatterers is assumed to be randomly distributed, while their zenith angle follows an ellipsoidal distribution characterized by a mean leaf inclination angle θ_l. Although it uses a simple description of canopy structure and a rough approximation of the radiative transfer equation, the SAIL model has already been tested with success on soybean (Goel and Thompson, 1984a,b) and maize (Major et al., 1992). However, the original SAIL model cannot reproduce properly the behavior of canopy reflectance, especially in the hot spot, the cone where the solar and viewing directions are close together. In this cone, reflectance is increased, and, to take account of this, the SAIL model was modified by Kuusk (1991a), introducing the hot-spot size parameter (s) defined as $s = L/H$, where L is the horizontal correlation length that depends on the mean size and shape of the leaves and H is the canopy height. The hot-spot size parameter is approximately 0.5 for sugarbeet crops (Looyen et al., 1991). Leaf reflectance and transmittance were derived from the PROSPECT model (Jacquemoud and Baret, 1990), which idealizes the leaf as a stack of N identical elementary layers defined by their refractive index and an absorption coefficient. For simplicity, only chlorophyll and water were explicitly taken into account, and they were assumed to be distributed homogeneously in the leaf.

The measurement configuration is defined by the zenith (θ_0) and azimuth (ρ_0) viewing angles, the solar zenith angle (θ_s), and the fraction of diffuse radiation. The latter can be replaced by the horizontal visibility (VIS), a single parameter which is not wavelength-dependent. VIS was inferred from a look-up table built using the 5S model (Tanré et al., 1990), where the entry was the fraction of diffuse radiation measured in a few wavebands during the experiments. In brief, the PROSPECT + SAIL model (Fig. 1) computes canopy reflectance spectra from the following parameters:

- Canopy biophysical parameters: chlorophyll $a+b$ concentration C_{ab} (μg cm^{-2}), water depth C_w (cm), leaf mesophyll structure N, leaf area index LAI, mean leaf inclination angle θ_l (°), and hot-spot size parameter s.
- Soil spectral reflectance $\rho_s(\lambda)$, which is assumed to be Lambertian.
- External parameters: zenith θ_0 (°) and azimuth ρ_0 (°) viewing angles, zenith solar angle θ_s (°), and horizontal visibility VIS.

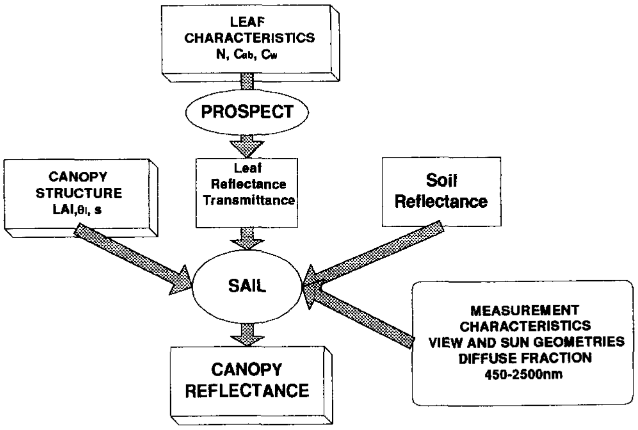


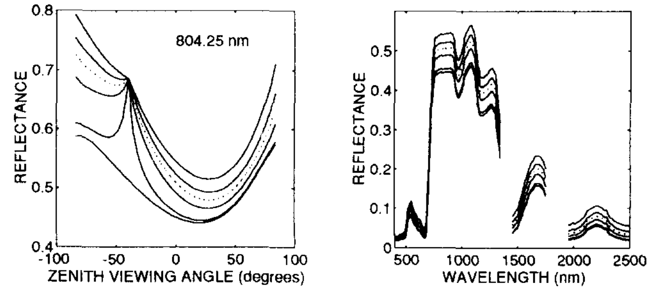
Figure 1. Schematic representation of the PROSPECT + SAIL canopy reflectance model.

The effects of C_{ab}, C_w, N, LAI, and θ_l on canopy spectral reflectance can be found in Jacquemoud (1993); additional simulations have been performed to test the influence of s on the directional and spectral reflectance. Figure 2a shows a pronounced effect on reflectance as a function of the zenith viewing angle in the principal plane. A variation of the hot-spot size parameter from 0 to 1 induces an increase of the width of the hot spot and also a general increase of the canopy reflectance. Figure 2b shows, for a fixed zenith viewing angle of 0°, the spectral effects of s: As observed with LAI and the mean leaf angle (Jacquemoud, 1993), the impact of s is particularly important in the near-infrared but also in the other optical domains. At this point, this model can be regarded as a compromise between the exact theory of radiative transfer, which may be too complicated for routine calculations or inverse problems, and simplified equations, which may be too unrealistic.

The Inversion Procedure

A model allows the simulation of a physical phenomenon by using mathematical equations, and it should be vali-

Figure 2. Variations of canopy reflectance simulated by the PROSPECT + SAIL model as a function of the hot-spot size parameter: $s=0$ (lower line), 0.05, 0.2, 0.33 (dotted line), 0.5, 1 (upper line): a) angle dependency at 804.25 nm; b) wavelength dependency at $\theta_s = 40°$ and $\theta_0 = 0°$. The mean set of parameters is: $N = 1.5$, $C_{ab} = 32$ μg cm^{-2}, $C_w = 0.0255$ cm, LAI = 3, $\theta_l = 58°$, and VIS = 40 km.



dated by comparing simulation outputs with experimental results. The principles of inversion of high spectral resolution data have been previously detailed by Jacquemoud (1993). In most cases, the complexity of canopy reflectance models prevents an analytical inversion so that numerical methods of optimization are required. As an illustration, consider the model M with p parameters, the vector X of explicative variables, and the vector Y of observed variables. We can relate X to Y trough the relation

$$Y = M(\Theta, X) + \varepsilon, \tag{1}$$

where Θ is the vector of the p unknown parameters. If n is the number of observations, the inversion procedure consists in determining Θ by minimizing the merit function $S(\Theta)$ defined by

$$S(\Theta) = \sum_{i=1}^{i=n} [Y_i - M(\Theta, X_i)]^2. \tag{2}$$

This equation is usually nonlinear and is solved by iteration. This may be difficult: Knowledge of the initial parameter set Θ_0 is often essential for the convergence speed of the solution and the validity of the convergence itself. Numerical instability phenomena may lead to local minima, which means that the uniqueness of the solution is never guaranteed. There are several classical optimization techniques such as the quasi-Newton algorithm (Gill and Murray, 1972), the Gauss-Marquardt algorithm (Marquardt, 1963), or the simplex method (Nelder and Mead, 1965). Recently, new methods based on genetic algorithms have been developed, which, in combination with classical algorithms, seem promising for inversion of remote sensing data (Renders et al., 1992). The choice of algorithm depends mainly on the model, the degree of linearity, and the number of input variables to be estimated. Jacquemoud et al. (1994) showed that the quasi-Newton algorithm gave accurate results in most cases and was computationally efficient; in this work it was used via the Numerical Algorithm Group's routine, E04JAF. This routine allows lower and upper limits to be placed on the independent variables to be estimated, and the code needs function evaluations only.

INVERSION ON CROP SPECTRA

The inversion of the PROSPECT + SAIL model consists of determining simultaneously some of all of the canopy biophysical parameters (C_{ab}, C_w, N, LAI, θ_l, and s) from radiometric measurements. The other parameters of the model—measurement configuration, irradiance conditions, and, above all, soil optical properties—are assigned their nominal values. Price (1990) showed that the reflectance spectra of many soils could be described with very few parameters. In the same way, Jacquemoud et al. (1992) modeled the soil bidirectional properties with a small set of parameters. However, because some of the soils used in this study were artificial, it was not possible to use those results easily. In consequence, in the inversion process the soil background reflectance was considered simply as known. This is a serious but unavoidable limitation for the moment. To avoid physically nonsensical values, the variables to be estimated were constrained within the following ranges which correspond to values observed in typical canopies: $1 < C_{ab} < 100$ μcm^{-2}, $0.001 < C_w < 0.1$ cm, $1 < N < 2.5$, $0.1 < \text{LAI} < 10$, $5° < \theta_l < 85°$, and $0 < s < 1$. For all inversion, the initial guess was [$C_{ab} = 32$ μg cm^{-2}, $C_w = 0.0255$ cm, $N = 1.5$, LAI $= 3$, $\theta_l = 45°$, and $s = 0.5$].

Total Inversion

Initially, an attempt was made to retrieve all six canopy biophysical parameters [C_{ab}, C_w, N, LAI, θ_l, s] from reflectances observed in the 188 AVIRIS bands. For 88 of the 96 plots the inversion process did converge: Only these results were used thereafter. In terms of reconstruction, the measured spectra were close to the spectra simulated using the PROSPECT + SAIL model with the six estimated variables. The root mean square error (rmse) between actual and simulated reflectances evaluated over all 88 plots and all the wavelengths was 0.0136. When presented as a function of wavelength, it was quite stable and small, always in the range 0.005 and 0.02 (Fig. 3a). The trends of the biases probably correspond to a residual of calibration problems (change in detectors, nonlinearity, etc). In summary, six variables were enough to reconstruct faithfully the canopy reflectance spectra measured in these experiments. The large variation in crop states (healthy / chlorotic, sparse / dense canopy) and soil types assures the validity of such an approach. This apart, it is important to be able to infer accurate and quantitative information about the vegetation. Careful analysis of the retrieved variables shows that the four canopy structure parameters [N, LAI, θ_l, s] are poorly estimated. In many cases, the fitted values are aberrant and remain at the lower (θ_l) or upper (N and s) limit imposed at the outset. Better results were obtained for the two parameters which describe leaf biochemical composition, C_{ab} and C_w (Fig. 4 and Table 2).

The same inversion was performed using only the six TM broad bands. From a mathematical point of view, when the number of unknowns is the same as the number of reflectances (six in this case), the problem is not, strictly speaking, an optimization problem; it is rather the search for the solution of six nonlinear simultaneous equations in six unknowns (Renders et al., 1992). However, results show that the "inversions" converted regularly for 88 plots out of 96. Spectra simulated with the PROSPECT + SAIL model using the retrieved values of the six biophysical variables showed good reconstruction performances with an overall rmse of 0.0212. The residuals had the same features of biases and rmse as the inversion using high spectral resolution data, but

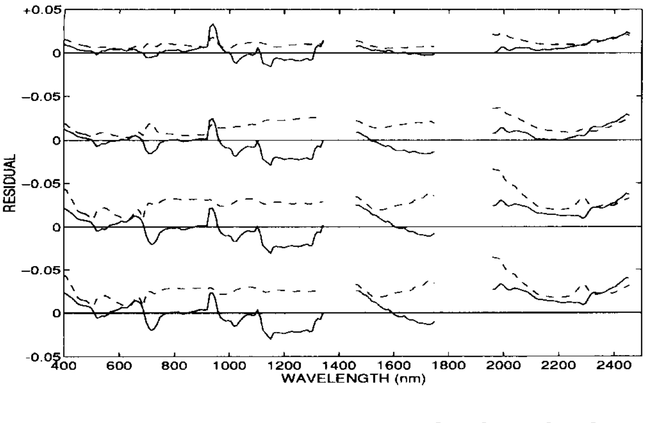
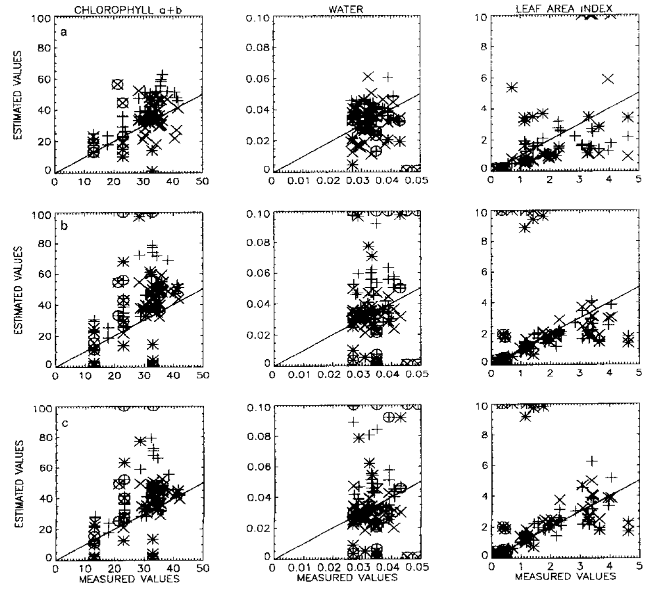


Figure 3. Comparison between measured and simulated spectra in the 188 AVIRIS bands with the PROSPECT + SAIL model using parameters retrieved from model inversion. For each case, the solid and broken lines represent, respectively, the biases $\Sigma(\rho-\rho^*)n$ and the rmse $[\Sigma(\rho-\rho^*)^2/n)^{1/2}$ (ρ and ρ^* are respectively the measured and estimated reflectances, n is the number of observations). From the top to the bottom, the spectra correspond to: a) fitting of [C_{ab}, C_w, N, LAI, θ_l, s] from the 188 AVIRIS bands; b) fitting of [C_{ab}, C_w, N, LAI, θ_l, s] from the six TM bands; c) fitting of [C_{ab}, C_w, LAI] from the 188 AVIRIS wavebands with fixed variables [$N=1.225$, $\theta_l=28.6°$, $s=0.33$]; d) fitting of [C_{ab}, C_w, LAI] from the 188 AVIRIS wavebands with fixed variables [$N=1.225$, $\theta_l=43.4°$, $s=0.33$] for the Broom's Barn experiment and [$N=1.225$, $\theta_l=35.3°$, $s=0.33$] for the Grignon experiment.

Figure 4. Comparison between measured canopy variables and values estimated through model inversion using the 188 AVIRIS bands: a) fitting of [C_{ab}, C_w, N, LAI, θ_l, s]; b) fitting of [C_{ab}, C_w, LAI] with fixed variables [$N=1.225$, $\theta_l=28.6°$, $s=0.33$]; c) fitting of [C_{ab}, C_w, LAI] with fixed variables [$N=1.225$, $\theta_l=43.4°$, $s=0.33$] for the Broom's Barn experiment and [$N=1.225$, $\theta_l=35.3°$, $s=0.33$] for the Grignon experiment. Plus signs, asterisks, and crosses, respectively, correspond to natural soils, white, and black backgrounds. Symbols for plots with LAI < 0.5 are inscribed in a circle.



in an enhanced manner (Fig. 3b). As expected, the four canopy structure variables were poorly estimated. Surprisingly, this was not the case for the two biochemical variables, which had rmse values similar to those calculated using high spectral resolution data (Table 2).

These results suggest unstable inversion processes for the structure variables. Otterman (1990) argued that, because two canopy parameters appear as products in the mathematical expression of the model, they are prevented from being inferred individually: Although structure variables do not appear as a simple product in the formulation of the SAIL model, they are grouped in expressions that define the bidirectional gap fractions observed in canopies. In the same way, Jacquemoud (1993) showed from numerical simulations that, when using only the spectral variation as the source of information, the variables LAI and θ_l were not independent during the inversion process. Additional constraints or information needed to be introduced to stabilize the inversion process. Initially, it may be possible to introduce complementary observations made from several viewing and sun configurations. This may also be achieved by assigning fixed values to some of the variables that do not change dramatically from one plot to another, and which have little influence on canopy reflectance. We chose this second option. The following section describes the performance of the inversion process at retrieving only a selection of the six canopy variables.

Partial Inversion

From simulation studies with the PROSPECT + SAIL model, the leaf structure parameter N, which roughly determines the balance between leaf reflectance and transmittance, has only limited influence on canopy reflectance (Jacquemoud, 1993) because a change in N induces only a small change to the single scattering albedo. In this experiment, N was estimated from inversion of the PROSPECT model using reflectance or transmittance spectra measurements from individual leaves. Results show that N varied from 1.00 to 1.38 with an average of 1.225. The LAI, θ_l, and s parameters are not totally independent so that individually they are not inferable unless the others are known: In this experiment, the greatest source of variation in canopy reflectance was created by differences in plant density, that is, mainly by LAI changes. Further, LAI is one of the most important variables for determining growth and yield. Therefore, standard values were imposed for the leaf orientation and hot-spot size parameter, leaving LAI to be estimated freely.

The hot-spot size parameter is the ratio between mean leaf size and canopy height: Throughout development, sugar beet canopy height is closely and positively correlated with mean leaf size. Consequently, s can be assumed to be constant. It was assigned its mean value, 0.33, which is in the same range as the value observed by Looyen et al. (1991) for sugar beet crops ($s=0.5$).

Table 2. Root Mean Square Errors (rmse) Observed on Five Canopy Biophysical Variables [LAI, C_{ab} (μg cm^{-2}), C_w (cm), LAI × C_{ab} (μg cm^{-2}), LAI × C_w (cm)] Retrieved from Inversion of the PROSPECT + SAIL Model on AVIRIS (188 Bands) and TM (Six Bands) Equivalent Reflectances[a]

		Size	*LAI*	C_{ab}	C_w	*LAI* × C_{ab}	*LAI* × C_w
Six variables free	188 bands	85(0)	2.29	10.9	0.0131	50.1	0.0327
[C_{ab}, C_w, N, LAI, θ_l, s]		78(1)	2.39	10.6	0.0107	52.3	0.0341
		82(2)	2.33	11.1	0.0133	50.9	0.0330
		75(3)	2.43	10.8	0.0109	53.2	0.0346
	6 bands	88(0)	2.74	10.8	0.0144	46.1	0.0390
		77(1)	2.92	10.4	0.0118	49.3	0.0417
		84(2)	2.75	11.0	0.0146	45.9	0.0382
		73(3)	2.94	10.6	0.0119	49.2	0.0410
Three variables free	188 bands	96(0)	2.61	19.7	0.0251	38.3	0.0510
[C_{ab}, C_w, LAI]		81(1)	2.64	16.2	0.0204	41.1	0.0551
Three variables fixed		82(2)	0.68	16.0	0.0231	23.4	0.0222
[$N = 1.225$, $\theta_l^* = 28.6°$, $s = 0.33$]		70(3)	0.72	12.2	0.0176	25.0	0.0236
	6 bands	96(0)	2.57	16.3	0.0178	33.1	0.0423
		78(1)	2.63	13.5	0.0140	35.8	0.0458
		82(2)	0.69	13.6	0.0166	21.0	0.0192
		70(3)	0.74	11.0	0.0124	22.5	0.0206
Three variables free	188 bands	96(0)	2.54	18.1	0.0234	39.9	0.0460
[C_{ab}, C_w, LAI]		81(1)	2.57	13.7	0.0181	42.3	0.0494
Three variables fixed		82(2)	0.75	15.4	0.0223	30.2	0.0233
[$N = 1.225$, θ_l^{**}, $s = 0.33$]		70(3)	0.81	10.4	0.0161	32.0	0.0247
	6 bands	96(0)	2.49	15.5	0.0173	32.7	0.0400
		81(1)	2.54	11.7	0.0138	35.1	0.0431
		82(2)	0.73	13.4	0.0166	22.8	0.0206
		70(3)	0.79	9.5	0.0128	24.4	0.0221

[a] The population size is presented for a selection of cases: (0) All plots with succesful inversion. (1) All plots with successful inversion and LAI > 0.5. (2) All plots with successful inversion but without a white background. (3) All plots with successful inversion, without a white background, and LAI > 0.5. $\theta_l^{**} = 43.4°$ and 38.8° for AVIRIS data and $\theta_l^{**} = 35.3°$ and 34.0° for TM data, respectively, for the Brooms Barn and Grignon experiments.

The leaf orientation parameter is difficult to determine accurately, and, as a result, we had to use an overall mean value. This conflicts with the knowledge that θ_l can cause large changes in canopy reflectance, particularly in the near-infrared. Two independent measurements of θ_l were available: a direct clinometer measurement and an estimate derived from analysis of hemispherical photographs. Another way to get information about θ_l is to invert the model with θ_l as the only unknown. This was done, and only a few of the 96 inversions did not converge: These corresponded to sparse canopies (LAI = 0.15). These failures were attributed to use of inappropriate soil optical properties or to aggregation problems not accounted for by the SAIL model hypotheses. The fit was not as good as in the case of total inversion but the mean rmse, respectively, 0.0288 for AVIRIS data and 0.0200 for TM data, were surprisingly low while measured (C_{ab}, C_w, LAI) and roughly estimated (N, s) canopy variables were used as input parameters. The averages of the fitted θ_l (43.4° for AVIRIS equivalent data and 38.8° for TM equivalent data in the Broom's Barn experiment, 35.3° and 34.0° in the Grignon experiment) were consistent with the clinometer results but quite different from those estimated by Baret et al. (1993) from hemispherical photography. This difference arose despite the SAIL and the Poisson models using the same assumptions about the randomness of the leaf position and the azimuth distribution. Tests were made on the two θ_l evaluations designated θ_l^* and θ_l^{**} for the hemispherical photography and model inversion estimates, respectively. Thus, in the inversion process one structure parameter (LAI) and the two biochemical parameters (C_{ab} and C_w) were kept free: The other three structure variables were assigned fixed values [$N = 1.225$, θ_l^*, $s = 0.33$] or [$N = 1.225$, θ_l^{**}, $s = 0.33$].

Inversions performed on high spectral resolution data ended regularly. By comparison with total inversion, the results obtained both with θ_l^* and θ_l^{**} showed a general increase in the root mean square error (rmse = 0.033) and the biases (Figs. 3c and 3d), particularly in the red edge and in the water absorption zone of the middle infrared. The LAI estimates were better: In detail, Table 2 shows that the main discrepancy occurred where the soil background was very bright (white fabric: $\rho_s \approx 0.8$). There are several explanations: First, multiple scattering in this particular situation was much too important to be well accounted for by the SAIL model, even when the soil background was known and fixed. Second, an error in soil reflectance induced large changes in canopy reflectance and, in consequence, in the retrieved values. For example, although the directional reflectance properties of the white fabric were quasi-Lambertian, errors due to the nonhorizontality of the fabric were still possible. Similarly, because the contrast between the background and leaf reflectances was at its greatest, any error in the structure variables (which

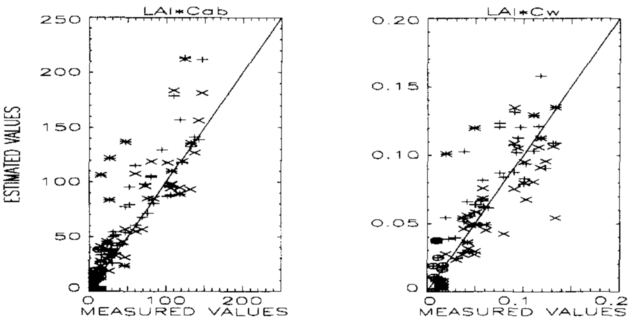


Figure 5. Comparison between measured canopy chlorophyll (LAI × C_{ab}) and water (LAI × C_w) contents and values estimated through model inversion using the 188 AVIRIS bands. The inversion was performed with [C_{ab}, C_w, LAI] to be retrieved and the fixed variables [$N = 1.225$, $\theta_l = 28.6°$, $s = 0.33$]. Plus signs, asterisks, and crosses respectively correspond to natural soils, white, and black backgrounds. Symbols for plots with LAI < 0.5 are inscribed in a circle.

were assumed) would cause a significant change in canopy reflectance and thus in the retrieved values. This problem should be most acute for small to medium LAIs; this was observed (Fig. 4). The estimation of chlorophyll $a+b$ concentration was less accurate than for the total inversion (Table 2). Ignoring the result from white backgrounds, there was an overestimation of C_{ab} that could compensate for the general underestimation of LAI. The same general pattern was observed for water depth (Fig. 4). The retrieval of more inaccurate information by the partial inversion process was related to its poorer ability to reconstruct reflectance spectra in the red edge and in the water absorption domains. Compensation between LAI and C_{ab} or C_w can be explained on the basis that, in the visible and the middle infrared regions, an increase in leaf chlorophyll or water contents, as well as an increase in LAI, induces a decrease in canopy reflectance. This is true for natural and bright soils; however, for black soils an increase in LAI would increase canopy reflectance. These compensation features stimulated an investigation of the performance of "synthetic" canopy variables, such as total canopy chlorophyll content or water content, defined as the product between LAI and C_{ab} or LAI and C_w. Using this configuration, total canopy chlorophyll or water contents was estimated with better accuracy than leaf chlorophyll, water content or even LAI alone; this is presented in Figure 5 for θ_l^*. However, the estimates of these variables over white backgrounds were still very poor (Table 2).

Inversions performed on simulated TM data showed similar results: White soils led to poor estimates of the canopy variables and for the same reasons. For the other backgrounds, on most plots LAI was underestimated; this was a compensation for an overestimation of C_{ab} or C_w. Table 2 shows that the estimates of the latter variables were even slightly better from the six TM broad bands than from the 188 AVIRIS narrow bands. This surprising result may be explained because much of the high spectral resolution data is redundant, particularly when no account is taken of small absorption features like those which may be induced in the middle infrared by lignin, nitrogen, cellulose, etc. In addition, the extra wavebands may add extra noise or bias which, through the inversion process, produces inaccurate values for the canopy biophysical variables.

DISCUSSION AND CONCLUSION

This study confirmed the theoretical work of Jacquemoud (1993) and showed that the inversion of a canopy reflectance model from a measured vegetation reflectance spectrum was possible. In most cases, the inversion process converged, and spectra simulated using the retrieved biophysical variables agreed well with measured spectra, having a rmse better than 0.02. Therefore, much of the high resolution spectral information was redundant. In this experiment, six parameters provided a faithful simulation of the 188 AVIRIS wavebands. However, our experimental conditions were specific and this obviously restricted the domain of validity of this result.

Although this work was not a real validation of the PROSPECT + SAIL model, that is, the total inversion was unsuccessful when using only a vegetation spectrum acquired at nadir, some of the canopy biophysical variables can be estimated under certain conditions. These can be summarized as follows: The structure parameters (leaf mesophyll structure, leaf area index, mean leaf inclination angle, and hot-spot size parameter) that describe the canopy architecture each affect the canopy spectral reflectance in such a way that several combinations of them may produce similar spectra. For this reason, they cannot be inferred simultaneously using only the spectral information, whereas, in theory, this should be possible with directional data; knowledge of one or two structure parameters may make this kind of inversion possible. Conversely, information about the plant's biochemical components—for the moment chlorophyll $a+b$ concentration and water depth but, in the near future, it may be possible to take into account other components such as lignin, cellulose, nitrogen, etc.—seem to be attainable by this method without an explicit description of canopy structure. The best results were obtained when the four structure variables were free in the inversion; this also gave the best agreement between the observed and the simulated spectra. This should give rise to further studies aimed at developing a clearer understanding of the process and to formulate an algorithm that synthesizes the effect of the structure allowing simple fits of the absorption features. When fixed values were assigned to some of the structure variables there was compensation between LAI and C_{ab} or C_w. The use of "synthetic" variables, such as the chlorophyll or water contents of the canopy, should minimize these problems.

Inversions performed using all the high spectral resolution information and those using only the six TM broad bands gave similar results for the retrieval of canopy structure or biochemical variables. This confirmed that much of the high spectral resolution data was redundant and encouraged the extension of such procedures to other sensors such as SPOT-HRV or NOAA-AVHRR by using more simplified models with only a few specific variables. The ability to obtain important canopy biophysical parameters, such as the chlorophyll concentration, the water depth, or the leaf area index, using operational broad band sensors should stimulate interesting agricultural and environmental studies. This is a new field in remote sensing which deserves to be pursued. The investigation of model inversion using both spectral and directional variations would also help a) in designing sensors which are better suited to monitor vegetation and b) in combining data from today's satellites. In that case, account will have to be taken of possible changes in soil background reflectance, which was assumed to be known in this study. This problem needs more studies on the modeling of soil optical properties. Similarly, we did not take into account possible variations of the atmospheric effects on reflectance: These variations are critical when using satellite data. Decoupling the vegetation signal from the soil and atmosphere signals will certainly require more than six bands if *a priori* information is not available.

Can inversion of the model produce valid results? First, inaccuracy of the model in representing the canopy spectral reflectance may cause errors in the estimation of the agronomic parameters. For example, although the SAIL model is known to work reasonably well on agricultural areas with homogeneous crops, in the early stages of growth the hypothesis that leaves are distributed at random is certainly not valid. Similarly, it would be inappropriate to invert the SAIL model on forested areas because these do not satisfy the hypotheses either. Second, radiometric data inevitably contain errors which affect the accuracy of the inversion. Renders et al. (1992) showed with simulation studies that the addition of noise to reflectance data moved the minimum of the merit function in the parameter space but did not increase the number of local minima. Thus noise linked to the instrument, the conditions of observation, or a bad atmospheric correction may mean that the inversion procedure does not converge to acceptable parameter values. Fortunately, signal-to-noise ratios determined on current field spectroradiometers or airborne imaging spectrometers are generally high enough for inversion to produce meaningful results. It is still not clear whether atmospheric corrections are accurate enough to allow successful inversion. Third, there is the question of precision of the measured variables; the measurement of the canopy biophysical characteristics will be prone to error. For example, the leaf chlorophyll concentration depends largely on the extraction method, and often the leaf samples are not properly representative of the canopy as a whole: Concentration deviations greater than 5 μg cm^{-2} can be obtained on the same sample. The type of solvent is also important. There are similar problems with the measurement of LAI and θ_l. For example, in the case of sugar beet, θ_l varies during the day as a function of weather conditions.

The speed of convergence can seriously limit the use of inversion of canopy reflectance models on high spectral resolution data. Although the computation time is only a few seconds on high-performance machines (NEC SX-3 of the Centro Svizzero di Calcolo Scientifico), it can take longer than is practical when less powerful computers and/or images with several hundred thousand pixels have to be used. The increasing capacity of computers for calculation allows one to imagine more and more complex models to solve more and more complex phenomena. However, faster computers will not necessarily solve the problem; the inversion theories themselves restrict the investigation of more complex models. Inversions need to be restricted to simple models with few parameters.

Finally, this study highlights two critical and complementary problems: The first relates to the difficulty of acquiring enough radiometric information about the target. Bidirectional data are usually gathered over several days, during which time the vegetation may have changed. Therefore, the use of this data requires knowledge about the development of the vegetation during this period. The second problem concerns the choice of approach to be used; these preliminary results suggest that inverting physical radiative transfer models may not provide accurate estimates of canopy biophysical parameters. A compromise has to be investigated between the realism of the model (this generally induces more complexity and more parameters) and its invertibility (this usually requires simplicity and very few variables). An alternative approach would necessitate some *a priori* knowledge about the target (e.g., the species and the type of soil), which could be used to constrain the inversion process.

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