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Inversion of the PROSPECT + SAIL Canopy Reflectance Model from AVIRIS Equivalent Spectra: Theoretical Study

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The potentials and limits of estimating canopy parameters are investigated using only a reflectance spectrum in the optical domain, and the PROSPECT + SAIL model. Simulations are performed on AVIRIS (Airborne Visible/Infrared Imaging Spectrometer) equivalent spectra, corrected for the atmospheric effects. It is established that this model is numerically invertible. The sensitivity analysis of reflectance spectral features to changes in the values of canopy parameters (leaf mesophyll structure N, chlorophyll a + b concentration C_{ab}, water depth C_w, leaf area index, LAI, and average leaf inclination angle θ_l) suggests that the accuracy of the inversion procedure needs some constraints. The C_{ab} and C_w parameters, which describe the leaf physiological status, can be generally retrieved with a reasonable accuracy; it is somewhat difficult to estimate the canopy geometrical parameters (LAI and θ_l) separately. Determining the fraction of absorbed photosynthetic active radiation (APAR) with parameters derived from the inversion procedure is discussed.

INTRODUCTION

High spectral resolution is a quite new domain in remote sensing. Until recent years, technological limitations have prevented us from measuring radiance of terrestrial targets with contiguous bands and a high spectral resolution. Now, field and airborne spectroradiometers, such as AVIRIS (Airborne Visible/Infrared Imaging Spectrometer) (Vane, 1987; Vane et al., 1993), are available and can provide reflectance spectra in the optical domain (from 400 nm to 2450 nm) with a resolution approaching 1 nm! This sensor images the Earth's surface in 224 spectral bands approximately 10 nm wide, with a 20 m × 20 m ground instantaneous field of view that is quite appropriate for agricultural areas. However, if measuring the spectral reflectance of a plant canopy is possible nowadays, methodologies that would allow analysis of vegetation spectra in order to identify the canopy characteristics are still poorly known. Two different approaches may be considered:

The semiempirical approach consists in using statistical techniques to obtain a correlation between the target and its spectral signature. A first method, called spectral mixture analysis, reduces the spectral information of a complex target into independent sources of variability, the endmembers. The latter can be chosen among a library of reference spectra acquired in the laboratory (leaves, mineral powders) or in the field on well-known surfaces (vegetation types, rocks) (Adams et al., 1986). If several experimental spectra are available, the endmembers can be directly identi-

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fied by applying principal component analysis (Huete, 1986) or are selected from the image itself (Adams et al., 1991; Ustin et al., 1992). Then, the spectral analysis amounts to determining the best combining of these spectra for each target or pixel. However, such a method, when used for extracting compositional information from multispectral data, can only provide qualitative information about vegetation. Moreover, it assumes that processes involved are additive, but there are many situations where linear mixing rules are known not to apply (Adams et al., 1991; Huete, 1986).

In order to extract quantitative information about a canopy, spectral indices have been built and related to some biophysical characteristics of the canopy. This is the case for vegetation indices commonly used in remote sensing (e.g., Baret and Guyot, 1991; Richardson and Everitt, 1992). But high spectral resolution also induced the development of specific tools based on shape analyses of reflectance spectra: The red-edge, a region of the spectrum where the reflectance greatly increases from the red (650 nm) to the near infrared (800 nm), has given rise to a lot of literature (e.g., Miller et al., 1990a; Demetriades-Shah et al., 1990; Baret et al., 1992). As for vegetation indices, relationships have been established between the leaf or canopy variables and the position of the inflexion point λ_i, which characterizes this transition. For instance, Miller et al. (1990b) recently attempted to extract canopy chlorophyll content from AVIRIS data, by translating leaf-level relationships to canopy scale. In fact, as discussed by Baret et al. (1992), canopy geometry may greatly affect leaf-level conclusions making this method rather approximative. For that very reason, there are some limits to the use of semiempirical relationships. The second approach is related to the development of nonlinear optimization techniques.

The inversion of physical models consists, first, in describing the interactions between the sunlight and the canopy (leaf + soil) through an analytical reflectance model. Goel (1987) made an excellent review of canopy reflectance models published in the literature: geometrical models, turbid-medium models, hybrid models, and computer simulation models. Once this model has been validated on experimental data sets, the inversion procedure is possible, that is, the estimation of the canopy biophysical variables from reflectance measurements. Two methods of inversion can be distinguished:

1. A first method using directional data allows estimation of physical variables describing the canopy architecture. Goel and Thompson (1984a, b) have shown that the LAI and, with less precision, the average leaf angle θ_l, can be retrieved by inversion of the SAIL model (Verhoef, 1984; 1985). Pinty et al. (1990) and Kuusk (1991) have also estimated the leaf optical properties as well as the spatial distribution of scatterers in the canopy by inverting analytical models of directional reflectance. These procedures are generally performed for a given wavelength, the choice of which largely conditions the results.
2. A second method using spectral data acquired for example at nadir would permit extraction of canopy spectral information, but also, under certain conditions, the variables describing its structure. Until now, the number of wavebands available on satellite sensors was smaller than the number of canopy parameters that determine the reflectance: inversion using nadir reflectances in several wavelength bands was therefore inaccurate (Goel, 1989). The development of imaging spectroscopy offers the prospect of using such a method. In this way, by curve fitting methods to AVIRIS data, Gao and Goetz (1990) retrieved the equivalent liquid water thickness of vegetation.

This study is an attempt to use high spectral resolution for estimating the biophysical parameters of a plant canopy by model inversion. Due to the complexity of the absorption and scattering processes, the atmospheric transfer that perturbs the useful signal is, for the moment, ignored. Modeling vegetation spectral radiance at ground level requires:

1. a leaf optical properties model
2. a soil optical properties model
3. a plant canopy reflectance model

After a presentation of the canopy reflectance model (PROSPECT + SAIL) including a sensitivity analysis, we discuss problems connected with its invertibility and the ability to provide valuable information on vegetation. The last section deals with the possibility of determining APAR (absorbed photosynthetically active radiation) from high spectral resolution data. Computations are performed on synthetic spectra that simulate the AVIRIS bands, keeping operational use into perspective.

MODELING CANOPY SPECTRAL REFLECTANCE

The PROSPECT + SAIL Model

According to Goel and Thompson (1984), two conditions are necessary for estimating canopy variables from spectral signatures of vegetation: an accurate model and the choice of an appropriate inversion procedure. At the moment, several canopy reflectance models are available: Some of them simulate the anisotropy of canopy reflectance, particularly the hot spot effect, with greater accuracy; other ones are better suited either for sparse or dense canopies (for review, see Goel, 1987). In order to model the spectral reflectance of a plant canopy measured at nadir (vertical viewing), we have chosen the one-layer SAIL (Scattering from Arbitrarily Inclined Leaves) model (Verhoef, 1984; 1985): This radiative transfer model represents the canopy structure in a simple way and requires only a few parameters, which makes the inversion procedure easier. Moreover, it produces near-realistic results of plant canopy bidirectional reflectance properties. The key assumptions of the SAIL model are an homogeneous semiinfinite medium, lambertian reflecting leaves, leaf optical properties identical for the bottom and top surfaces, and leaf azimuth distributed at random. The parameters occuring in this model are the leaf reflectance (ρ_l) and transmittance (τ_l), leaf area index (LAI = one-sided area of all leaves above a unit area of ground), average leaf inclination angle (θ_l, ellipsoidal distribution function), soil reflectance (ρ_s), and the fraction of diffused incident solar radiation (*skyl*). Among these parameters, four (ρ_l, τ_l, ρ_s, and *skyl*) are wavelength-dependent. This means that the knowledge of each of these spectral properties is necessary to simulate the spectral reflectance of a plant canopy, which considerably increases the number of parameters and the dimension of the inversion problem. The first task is thus to simplify the model parameterization: Although the fraction of diffused radiation *skyl* depends on the wavelength and atmospheric conditions, it will be assumed constant. In any case, as illustrated by Clevers and Verhoef (1991), the influence of *skyl* on simulated reflectances is only minor, so that it should not affect the simulation results.

Modeling soil optical properties is more complex: Jacquemoud et al. (1992) have proposed a model, SOILSPECT, which simulates the spectral and directional reflectance of bare soils as a function of six parameters, five of which depend mainly on surface conditions (soil roughness parameter h and phase function parameters b, c, b', and c'), and one of which varies spectrally [single scattering albedo $\omega_s(\lambda)$]. The ω_s parameter, which represents the intrinsic optical properties of soil materials (minerals, organic matter or water content), varies from one soil to another; consequently, its spectral variation cannot be reduced to few parameters. In this article, we will then assume that the soil optical properties are known: We have chosen an organic dominated soil (peat) studied by Jacquemoud et al. (1992) (Fig. 1).

The leaf optical properties are generally described by the directional-hemispherical reflectance and transmittance measured in the laboratory using a spectrophotometer. For a near-normal incidence angle, the leaf surface is assumed to be approximately lambertian. A radiative transfer model, PROSPECT, has been developed (Jacquemoud and Baret, 1990); it simulates the leaf optical properties, from the visible (400 nm) to the middle infrared (2500 nm), as a function of only three variables: a parameter which accounts for the internal structure of the leaf mesophyll (N), a chlorophyll $a+b$ concentration expressed in μg cm^{-2} (C_{ab}), and a water depth expressed in cm (C_w). N, C_{ab}, and C_w are independent of the selected wavelength. In the abstract, N relates to the cellular arrangement within the leaf: N ranging between 1 and 1.5 corresponds to monocotyledons with compact mesophyll; dicotyledons characterized by a spongy parenchyma with air cavities have N values between 1.5 and 2.5. Finally, N values greater than 2.5 represent senescent leaves with a disorganized internal structure. The spectral variations of ρ_l or τ_l are determined by the refractive index of plant materials [$n(\lambda)$] and the specific absorption coefficients of chlorophylls [$k_{ab}(\lambda)$] and water [$k_w(\lambda)$], which do not depend on the leaf type (Jacquemoud and Baret, 1990).

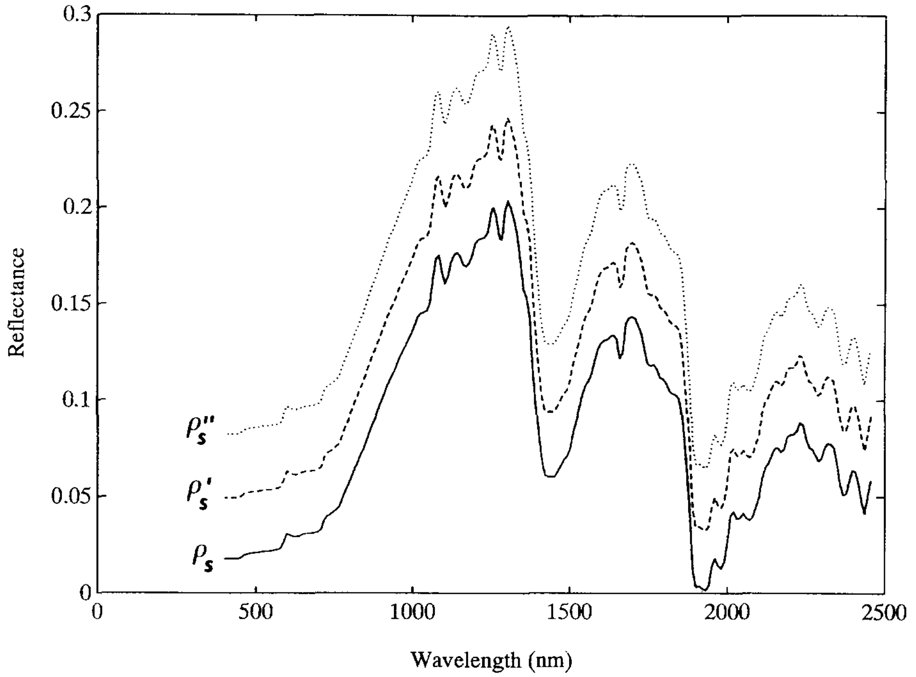

Figure 1. Soil spectral reflectances used for the simulations. ρ_s is computed using the SOILSPECT model and to the single scattering albedo ω_s of a peat soil (Jacquemoud et al., 1992). ρ_s' and ρ_s'' respectively correspond to $\omega_s + 0.075$ and $\omega_s + 0.15$.

PROSPECT is, for the moment, a simplified approach of the light regime within plant leaves: It does not include the effects of other constituents such as lignin, cellulose, starch, nitrogen, and amino acids, which may be of great interest for ecological studies.

In conclusion, the canopy spectral reflectance $\mathscr{R}(\lambda)$, as calculated by the PROSPECT + SAIL model, depends on the following parameters:

- Biophysical parameters: the quantities C_{ab}, C_w, N, LAI, and θ_l already defined.
- Soil spectral reflectance, $\rho_s(\lambda)$, which will be assumed known.
- External parameters: zenith ($\theta_0 = 0°$) and azimuth ($\varphi_0 = 0°$) viewing angles, zenith illumination angle ($\theta_s = 40°$) and fraction of diffuse incident radiation (*skyl* = 0.2 corresponds to a visibility of 50 km). These values will not change during the sensitivity analysis.

In comparison with previous works, the improvement of this model is that leaf and thus canopy optical properties are now described in terms of biological characteristics (chlorophyll and water content). Thus, in principle, physiological processes of the plant canopy, such as photosynthesis or water stress status, can be directly related to remote sensing data: This is essential to understand ecosystems processes. Before focusing on inversion problems, a sensitivity analysis using a wide range of input parameters should provide useful information about what can reasonably be done and to what accuracy levels.

Sensitivity Analysis

In order to quantify the relative influence of each of the canopy parameters, let us define the following data set representative of a real sugar beet canopy (*Beta vulgaris* L) studied at Brooms Barn Experimental Station (Malthus et al., 1989): $N = 1.5$, $C_{ab} = 32$ μg cm^{-2}, $C_w = 0.0255$ cm, LAI = 3, and $\theta_l = 45°$. As discussed previously, soil spectral reflectance is known and presented in Figure 1. Although the canopy biophysical variables are not totally independent, that is, a change in leaf water content may induce a change in chlorophyll concentration and leaf internal structure, as well as a change in the average leaf angle, let each of them vary separately for the sensitivity analysis.

Figure 2a illustrates the variations of the canopy spectral reflectance $\mathscr{R}(\lambda)$ as a function of the leaf structure parameter N. As noticed by Clevers and Verhoef (1991), the influence of a varying N is not extremely large, which, at first sight, may seem surprising. Table 1 can help us to better understand the phenomena involved here: the leaf optical properties (reflectance ρ_l and transmit-

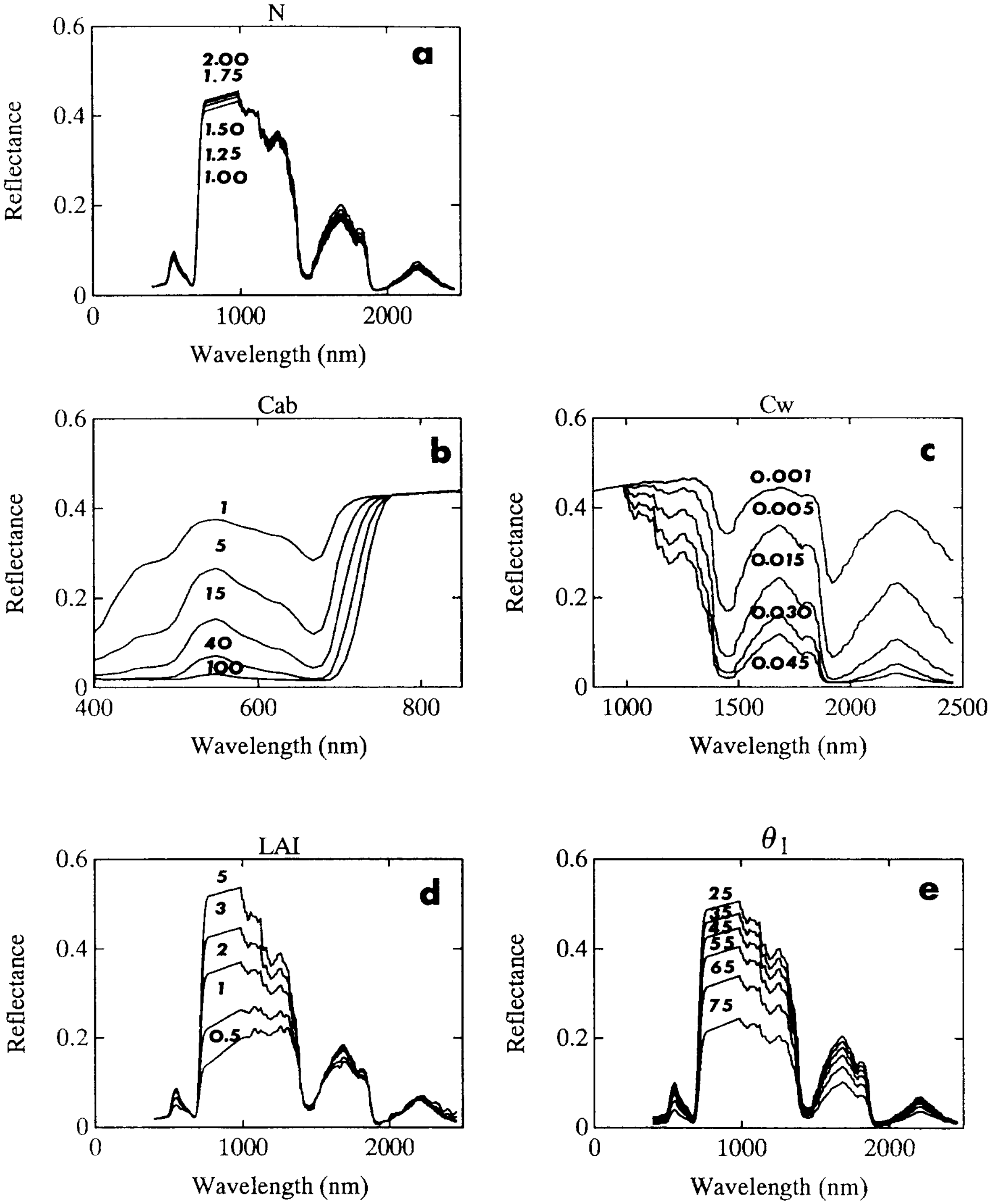

Figure 2. Variations of canopy reflectance spectra as a function of: a) leaf mesophyll structure N; b) chlorophyll $a+b$ concentration C_{ab} (μg cm^{-2}); c) water depth C_w (cm); d) leaf area index LAI; e) average leaf inclination angle θ_l. The mean set of parameters is: $N=1.5$, $C_{ab}=32$ μg cm^{-2}, $C_w=0.0255$ cm, LAI $=3$, $\theta_l=58°$, $\theta_s=40°$, $\theta_0=0°$, $\varphi_0=0°$, and $skyl=0.2$.

tance τ_l) are simulated by the PROSPECT model in the near-infrared region (804 nm) for different N values. For N ranging between 1 (monocotyledons) and 2 (dicotyledons), ρ_l increases by 0.162 and τ_l decreases by 0.191. These variations are important enough to permit identification of two different leaf species from laboratory spectrophotometric measurements. However, still at leaf

Table 1. Effects of the Leaf Mesophyll Structure Parameter N on Leaf Reflectance ρ_l, Transmittance τ_l, and Absorptance $1-(\rho_l+\tau_l)$ (PROSPECT model)[a]

N	1.0	1.25	1.5	1.75	2.0	δ
ρ_l	0.3683	0.4213	0.4646	0.5003	0.5302	0.1619
τ_l	0.6008	0.5401	0.4895	0.4464	0.4093	-0.1914
$1-(\rho_l+\tau_l)$	0.0309	0.0386	0.0459	0.0533	0.0605	0.0296
$\mathscr{R}$	0.4138	0.4249	0.4317	0.4355	0.4374	0.0236

[a] Idem for canopy reflectance $\mathscr{R}$ (SAIL model). Simulations are performed at 804 nm. δ represents the differences between $N=2$ and $N=1$.

level, the absorptance defined as $1-(\rho_l+\tau_l)$ only increases by 0.03: Remembering now that the single scattering albedo ω_l single leaves depends on the sum $\rho_l+\tau_l$, and that the SAIL model, as well as many other canopy reflectance models, is a function of ω_l, the results of Figure 2a are plausible. The effect of a varying leaf reflectance is partly compensated by the varying leaf transmittance. That agrees with Clevers and Verhoef (1991) work and suggests that crop type recognition through the N parameter is not possible at canopy scale.

As expected, chlorophyll $a+b$ absorbs light in the visible (Fig. 2b), water in the middle infrared (Fig. 2c). The absorbtion domains of these two foliar constituents are completely separated by the near infrared plateau. The sensitivity of canopy reflectance to C_{ab} or C_w is the same as that observed at leaf scale (Jacquemoud and Baret, 1990): We distinguish domains of strong absorption (450 nm, 672 nm for chlorophylls, 1160 nm, 1450 nm, 1950 nm, and 2500 nm for water), which are very sensitive to low concentrations, and domains of low absorption (548 nm for chlorophylls, 1684 nm and 2211 nm for water), which are more sensitive to high concentrations. For real concentrations observed in nature ($C_{ab}<100\ \mu g\ cm^{-2}$ and $C_w<0.05$ cm), simulation studies show that changes in reflectance are important enough to be sensed remotely, and, consequently, the variability of plant canopies is potentially attainable.

Leaf area index and average leaf angle determine the reflectance levels mainly in the near infrared, but also in the other optical domains (Fig. 2d and 2e). One can notice that increasing the LAI resembles decreasing θ_l; in other words, the reflectance spectrum of a sparse planophile canopy is very similar to the one of a dense erectophile canopy. Nevertheless, these phenomena are not totally symmetrical: There are some spectral regions (around 548 nm, 1684 nm, and 2211 nm), where the reflectance rapidly reaches a limit with the LAI, which is not the case with θ_l.

In conclusion, we observe that the sensitivity of the canopy reflectance to each of these biophysical parameters varies both with the wavelength and the values of other parameters. Simulations show that, except for the leaf mesophyll structure N, reflectance spectra are sensitive to the variability of the other canopy parameters. If these variations are sufficiently independent, it should be possible to invert the model and estimate a set of optimal parameters.

INVERSION OF THE PROSPECT + SAIL MODEL

The inversion of the PROSPECT + SAIL model consists in determining the set of parameters $P=(N, C_{ab}, C_w, \mathrm{LAI}, \theta_l)$, which minimizes Δ^2 over the whole spectrum:

$$\Delta^2=\sum_{i=1}^{i=224}[\mathscr{R}_{\mathrm{mes}}(\lambda_i),-\mathscr{R}_{\mathrm{mod}}(\lambda_i,P)]^2, \qquad (1)$$

where $\mathscr{R}_{\mathrm{mes}}(\lambda)$ is the measured and $\mathscr{R}_{\mathrm{mod}}(\lambda,P)$ the modeled spectral reflectance of the canopy. In Eq. (1), the summation is over the 224 AVIRIS equivalent bands (10 nm resolution). Although the success or failure of the inversion procedure may be sensor-dependent, results should not be really different with another high spectral resolution instrument, as long as it covers the whole optical domain. The routine HAUS59, which minimizes a function using the Marquardt (1963) algorithm, optimum interpolation between the Taylor series method and the gradient method, was chosen for this purpose (Roux and Tomassone, 1973). This routine is robust, that is, the minimization process generally does not lead to local minima (Goel, 1989), and, at the end of the computation, it provides valuable statistical information such as the correlation matrix of the fitted parameters and a 95% confidence interval for each of them. The root mean square of the fit (rms), defined as $\sqrt{\Delta^2 / n_f}$, where n_f is the number of degrees of freedom, gives an indication of the quality of the optimization. One can immediately notice that 224 wavebands are probably not necessary to estimate five parameters. Price (1991) worked on AVIRIS data sets and showed that most of the radiometric signal (soil + vegetation) was accounted for by 5–10 spectral intervals. However, he admits that the reduction of the number of spectral wavebands is a sensitive problem which has not yet found a solution. From a theoretical point of view, five independent wavebands should be enough to retrieve the five parameters of the PROSPECT + SAIL model, but, for the above-mentioned reason, we retain the entire spectral domain in this study.

Inversion from Synthetic Spectra

Is the PROSPECT + SAIL model numerically invertible? To answer this question, canopy reflectance spectra have been simulated, taking for each parameter its maximum, minimum and average values (Table 2): this data set corresponds to $3^5 = 243$ different spectra. The performance of the inversion procedure is first tested on the synthetic spectra, with an initial guess $N = 1.5$, $C_{ab} = 32$ μg cm^{-2}, $C_w = 0.0255$ cm, LAI = 3, and $\theta_l = 45°$. For each spectrum, the inversion procedure converges on the "true values" of the canopy parameters, suggesting that the PROSPECT + SAIL model used in spectral mode is *numerically invertible.* Thus, in theory, we can determine all of the canopy parameters from only a reflectance spectrum acquired at nadir.

Table 2. Canopy Parameters Used to Simulate the Synthetic Spectra[a]

	N	C_{ab} (μg cm^{-2})	C_w(cm)	LAI	θ_l
Minimum	1.0	2	0.0010	1	25°
Average	1.5	32	0.0255	3	45°
Maximum	2.0	62	0.05	5	65°

[a] The average set is the initial guess for the inversion. $\theta_s = 40°$, $\theta_0 = 0°$, $\psi_0 = 0°$, and $skyl = 0.2$. The soil spectrum is presented in Figure 1.

In order to test the sensitivity of the parameters obtained by inversion, we may perform the following computations: 1) Consider the initial guess above described and simulate the corresponding reflectance spectrum; 2) invert the model on this spectrum, assuming that one of the five parameters is kept fixed, for example, LAI, at a value close to its initial value (LAI $\pm$ δLAI). The modifications in estimation of the other parameters induced by a 15% or 30% LAI change are presented in Table 3 of LAIs of 0.25, 0.5, 1, 2, 3, and 6: Chlorophyll $a + b$ concentration and water depth are relatively stable around their mean values. On the other hand, decreasing LAI is equivalent to increasing the leaf structure parameter N and decreasing the average leaf angle

Table 3. Inversion of Synthetic Spectra Defined by $N = 1.5$, $C_{ab} = 32$ μg cm^{-2}, $C_w = 0.0255$ cm, LAI = 0.25, 0.5, 1, 2, 3, 6, and $\theta_l = 45°$[a]

N	C_{ab}	C_w	LAI	θ_l	rms	APAR
			LAI = 6			
2.02	34.74	0.0269	4.2	25.49	2.1×10^{-4}	0.925
1.75	33.13	0.0260	5.1	35.87	5.0×10^{-5}	0.932
1.25	31.51	0.0255	6.9	52.92	5.3×10^{-5}	0.931
1.02	31.83	0.0262	7.8	59.40	2.8×10^{-4}	0.922
			LAI = 3			
1.92	34.37	0.0270	2.10	27.03	2.0×10^{-4}	0.788
1.70	32.93	0.0260	2.55	36.98	4.4×10^{-5}	0.817
1.29	31.77	0.0256	3.45	51.19	3.5×10^{-5}	0.848
1.04	33.26	0.0271	3.90	55.83	1.2×10^{-4}	0.853
			LAI = 2			
1.86	33.81	0.0272	1.40	28.21	2.5×10^{-4}	0.652
1.68	32.68	0.0261	1.70	37.67	5.2×10^{-5}	0.692
1.32	31.95	0.0255	2.30	50.45	3.8×10^{-5}	0.744
1.08	33.45	0.0268	2.60	54.20	1.2×10^{-4}	0.758
			LAI = 1			
1.78	32.79	0.0279	0.70	29.61	3.4×10^{-4}	0.411
1.64	32.22	0.0264	0.85	38.49	7.5×10^{-5}	0.451
1.34	32.40	0.0253	1.15	49.49	5.7×10^{-5}	0.515
1.09	34.87	0.0267	1.30	51.59	1.9×10^{-4}	0.538
			LAI = 0.5			
1.68	32.34	0.0289	0.35	29.79	2.6×10^{-4}	0.232
1.59	32.08	0.0269	0.425	38.59	5.9×10^{-5}	0.260
1.39	32.36	0.0247	0.575	49.34	5.0×10^{-5}	0.311
1.21	33.92	0.0248	0.65	51.65	1.8×10^{-4}	0.332
			LAI = 0.25			
1.58	32.46	0.0299	0.175	29.05	1.1×10^{-4}	0.123
1.53	32.27	0.0274	0.2125	38.14	2.7×10^{-5}	0.140
1.46	31.80	0.0239	0.2875	49.94	2.5×10^{-5}	0.172
1.41	31.85	0.0228	0.325	53.38	9.6×10^{-5}	0.188

[a] In each case, LAI is kept fixed to a value near those mentioned above. The last column presents the corresponding APAR values.

θ_l. For each LAI level, the rms values are very low (10^{-4}–10^{-5}), pointing out that the corresponding spectra are very close one from each other. In particular, the deviations from the mean spectrum (Fig. 3) show that the curves cannot be visually separated. In a second step, we have inverted the model on these spectra, all of the parameters being free: We recover the initial sets of parameters, in accordance with previous results. In conclusion, these tests show that, from a mathematical point of view, there is a one-to-one relationship between the set of parameters and the set of spectra, assuming that everything is independent. However, as pointed out in the sensitivity analysis, several different sets of parameters can correspond to almost similar spectra; this suggests future difficulties when studying noisy or real spectra.

Noisy Data

Real data are generally noisy. In what extent is the accuracy of the inversion procedure affected by noise? To determine this, a random noise component (gaussian distribution $\mathcal{N}$ of zero mean and known variance σ) was added to each reflectance value of the synthetic spectrum in order to simulate the noise due to the instrument. Let $\mathcal{R}$ be the simulated reflectance and $\mathcal{R}^*$ the noisy reflectance:

$$\mathcal{R}^* = \mathcal{R}(1 + \mathcal{N}(0,1)\sigma). \tag{2}$$

We first create two basic data sets: X for which $N = 1.2$, $C_{ab} = 20\ \mu g\ cm^{-2}$, $C_w = 0.005$ cm, LAI = 0.5, and $\theta_l = 30°$, and Y for which $N = 1.7$, $C_{ab} = 40\ \mu g\ cm^{-2}$, $C_w = 0.03$ cm, LAI = 3.5, and $\theta_l = 60°$. The inversion procedure is performed on both spectra which have been preliminarily modified by random errors. Results in Table 4 show that a satisfactory minimum can be estimated whatever the error amplitude $\sigma = 0.01$ or $\sigma = 0.05$. These values correspond respectively to signal-to-noise ratios (SNR) of 100 and 20. By comparison, the in-flight AVIRIS SNR determined during the 1991 calibration experiment is much higher than 100 (Green et al., 1992) outside the atmospheric absorption bands. Standard deviations and confidence limits (linear hypothesis, 95%) are reasonable, when compared with the corresponding average values. In order to quantify the fitting sensitivity as a function of the parameters values, consider now the 243 synthetic spectra previously defined, add the same noise, and invert the model. Table 5 shows that, with a relative noise level of 0.05, the inversion procedure provides some fitted parameters very close to the initial parameters. As mentioned by Goel and Thompson (1984a,b), the sensitivities for all the variables seem higher for a planophile canopy ($\theta_l = 25°$) than for an erectophile canopy ($\theta_l = 65°$), probably because the sensitivity of the reflectance is higher for an erectophile canopy (Fig. 2e).

Influence of Soil Background

The soil background is known to disturb the relationships between the canopy reflectance and

Figure 3. Deviation between the spectrum calculated with the set of parameters (N, C_{ab}, C_w, LAI, θ_l) = (1.5, 32, 0.0255, 3, 45) and spectra calculated with the other sets on Table 3 corresponding to LAI variation: (O) for LAI = 2.10, (+) for LAI = 2.55, (●) for LAI = 3.45, and (x) for LAI = 3.90.

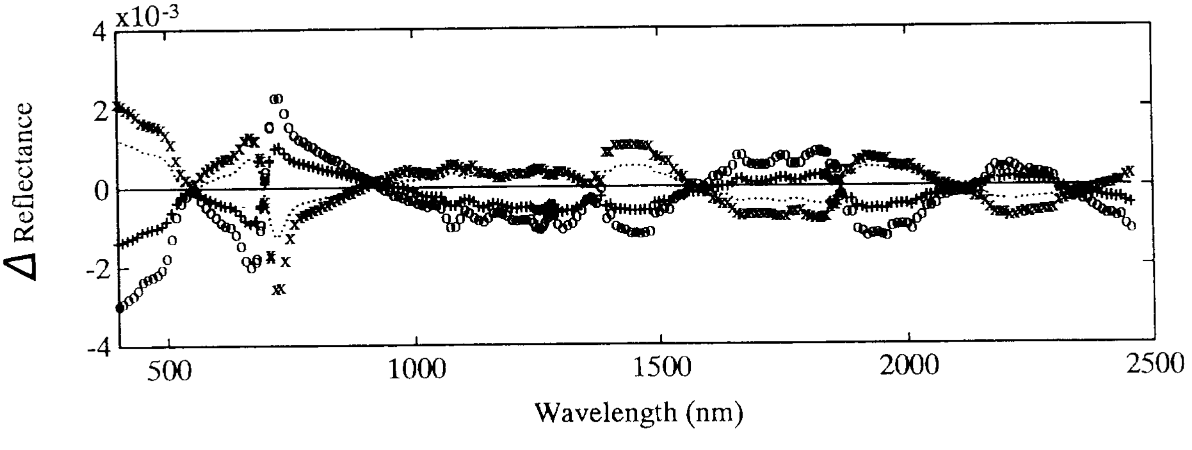

Table 4. Inversion on 100 Noisy Spectra for Parameter Sets X and Y[a]

		N	C_{ab}	C_w	LAI	θ_l
Set X		*1.2*	*20*	*0.005*	*0.5*	*30*
$\sigma = 0.01$	Mean	1.2104	19.959	0.0050	0.4998	29.999
	Std	0.0927	0.8063	0.0002	0.0178	3.2823
	ε	0.1823	1.6472	0.0003	0.0276	5.8223
$\sigma = 0.05$	Mean	1.3238	19.5304	0.0049	0.5233	10.969
	Std	0.3799	2.9639	0.0005	0.0825	13.418
	ε	0.9522	7.2326	0.0013	0.1387	29.069
Set Y		*1.7*	*40*	*0.030*	*3.5*	*60*
$\sigma = 0.01$	Mean	1.6934	39.929	0.0300	3.5188	60.111
	Std	0.0503	0.6444	0.0004	0.9061	0.7448
	ε	0.1457	1.4072	0.0009	0.3012	2.3957
$\sigma = 0.05$	Mean	1.6923	41.415	0.0309	3.5268	59.613
	Std	0.3088	5.1228	0.0039	0.5193	4.3726
	ε	0.7289	9.1806	0.0063	1.4540	12.166

[a] If $\overline{p_i}$ is the mean retrieved value of the parameter i, the 95% confidence interval is given by: $\overline{p_i} - \varepsilon < \overline{p_i} < \overline{p_i} + \varepsilon$.

vegetation indices (Baret and Guyot, 1991; Clevers and Verhoef, 1991). For the moment, we have assumed a known soil. It should be interesting to test the influence of soil reflectance on the accuracy of the canopy parameters retrieved by inversion. Suppose we translate the original soil reflectance spectrum (peat) by adding 0.075 and 0.15 to the single scattering albedo $\omega_s(\lambda)$: $\omega_s'(\lambda) = \omega_s(\lambda) + 0.075$ and $\omega_s''(\lambda) = \omega_s(\lambda) + 0.15$. Such a variation may be attributed to a change of soil moisture content (Jacquemoud et al., 1992). The corresponding reflectance spectra (ρ_s, ρ_s', and ρ_s'') are presented in Figure 1. The test consists in computing eight synthetic canopy reflectance spectra with the original soil, and the following data set: $N = 1.5$, $C_{ab} = 32\ \mu g\ cm^{-2}$, $C_w = 0.005$ cm, $\theta_l = 30°$, and LAI = 0.25,0.5,1,2,3,4,5,6. Then, for each LAI value, we invert the PROSPECT + SAIL model with the overestimated soil reflectances ρ_s' or ρ_s''. As expected, results of Table 6 show that largest estimation errors on LAI and θ_l are obtained for low LAI values (LAI < 2), when vegetation does not completely cover soil background. For LAIs higher than 2, sensitivity to background reflectance is minimal. The estimation of chlorophyll concentration and water depth is good until LAI decreases to 1. In this study, the uncertainties

Table 5. Inversion on Noisy Spectra Calculated with Parameters of Table 2[a]

N		*1*	*1.5*	*2*
$\sigma = 0.01$	Mean	0.9947	1.4711	1.9707
	Std	0.0994	0.1337	0.1227
$\sigma = 0.05$	Mean	1.0694	1.5109	2.0153
	Std	0.2985	0.3534	0.3721
C_{ab}		*2*	*32*	*62*
$\sigma = 0.01$	Mean	1.9546	31.646	61.043
	Std	0.0409	0.8010	1.3690
$\sigma = 0.05$	Mean	1.8179	30.628	58.257
	Std	0.1730	2.8771	5.3929
C_w		*0.001*	*0.0255*	*0.05*
$\sigma = 0.01$	Mean	0.0010	0.0251	0.0490
	Std	0.0000	0.0003	0.0008
$\sigma = 0.05$	Mean	0.0011	0.0237	0.0467
	Std	0.0001	0.0013	0.0024
LAI		*1*	*3*	*5*
$\sigma = 0.01$	Mean	1.0110	3.1661	5.3995
	Std	0.0196	0.2188	0.3810
$\sigma = 0.05$	Mean	1.0670	3.8569	5.9333
	Std	0.1122	1.1208	0.9662
θ_l		*25*	*45*	*65*
$\sigma = 0.01$	Mean	28.823	47.292	65.747
	Std	4.3275	2.6717	1.1100
$\sigma = 0.05$	Mean	36.592	51.472	67.285
	Std	11.636	6.9258	3.4788

[a] The number of successful cases is 230 for $\sigma = 0.01$ and 203 for $\sigma = 0.05$.

Table 6. Inversion of Synthetic Spectra with Soil Reflectance ρ_s, ρ_s', and ρ_s'' presented in Figure 1[a]

	N	C_{ab}	C_w	LAI	θ_l	rms	$APAR$
ρ_s	1.5	32	0.0255	6	45	0	0.934
ρ_s'	1.50	31.83	0.0254	5.99	45.55	1.8×10^{-6}	0.933
ρ_s''	1.49	31.57	0.0253	6.02	46.37	1.2×10^{-5}	0.933
ρ_s	1.5	32	0.0255	5	45	0	0.920
ρ_s'	1.49	31.67	0.0253	5.04	46.21	5.0×10^{-6}	0.920
ρ_s''	1.47	31.17	0.0251	5.13	47.90	3.1×10^{-5}	0.920
ρ_s	1.5	32	0.0255	4	45	0	0.893
ρ_s'	1.47	32.38	0.0252	4.13	47.67	1.3×10^{-5}	0.893
ρ_s''	1.42	30.50	0.0247	4.33	50.96	7.9×10^{-5}	0.896
ρ_s	1.5	32	0.0255	3	45	0	0.836
ρ_s'	1.39	31.03	0.0251	3.30	50.85	3.3×10^{-5}	0.845
ρ_s''	1.29	29.81	0.0246	3.67	56.35	1.9×10^{-4}	0.854
ρ_s	1.5	32	0.0255	2	45	0	0.721
ρ_s'	1.17	32.04	0.0261	2.57	56.27	6.3×10^{-5}	0.759
ρ_s''	1.01	31.65	0.0265	3.05	62.90	4.1×10^{-4}	0.764
ρ_s	1.5	32	0.0255	1	45	0	0.486
ρ_s'	0.89	39.45	0.0305	1.64	61.48	4.5×10^{-4}	0.573
ρ_s''	1.03	30.91	0.0238	2.33	72.00	1.9×10^{-3}	0.651
ρ_s	1.5	32	0.0255	0.5	45	0	0.286
ρ_s'	1.02	43.02	0.0273	1.20	70.39	2.4×10^{-3}	0.466
ρ_s''	1.20	31.58	0.0176	2.03	79.75	5.3×10^{-3}	0.603
ρ_s	1.5	32	0.0255	0.25	45	0	0.156
ρ_s'	1.16	57.48	0.0226	1.01	78.17	4.9×10^{-3}	0.424
ρ_s''	1.26	48.58	0.0139	1.81	85.64	9.5×10^{-3}	0.590

[a] Single scattering albedos are respectively w_s, $w_s + 0.075$, and $w_s + 0.15$. The last column presents the corresponding APAR values.

on soil optical properties were very strong: In consequence, these results encourage us to test this new approach for estimating canopy biophysical parameters from high spectral resolution data.

DISCUSSION-CONCLUSION

From theoretical results obtained with synthetic spectra, it is difficult to be sure that numerical inversion of radiative transfer models is realistically applicable to spectral measurements acquired with field spectroradiometers or airborne sensors such as AVIRIS. However, one can try to separate what is feasible from what is not. First, it has been shown that the PROSPECT + SAIL model is numerically invertible. This means that, in theory, one can estimate the biophysical variables of a plant canopy from one reflectance spectrum acquired at nadir. Unfortunately, reality is not so simple: Radiometric measurements always contain errors; moreover, the SAIL model, like most canopy reflectance models, is a simplified description of the structure of the canopy and of the transport of photons inside the vegetation. For example, as explained by Pinty et al. (1990), a sparse vegetation with small LAI values is not well accounted for by the model. All of these reasons may complicate the inversion procedure and its interpretation.

Estimating canopy parameters which describe the vegetation architecture, that is, LAI and θ_l, is more complex. As seen in Figures 2d and 2e, these two parameters are not totally independent; moreover, the correlation coefficient provided by the inversion routine is close to 1, suggesting that the model needs to be parameterized in another way. In practice, it means that separating LAI and θ_l would be problematic, unless we can introduce constraints such as the knowledge of one parameter. The leaf structure parameter N, which only slightly influences canopy reflectance, can be fixed at the mean value 1.5. As for leaf chlorophyll concentration or water content, simulations show that they can be reasonably estimated whatever the canopy structure. The absolute determination of canopy biochemical properties—chlorophyll and water but also carotenoids, starch, lignin, nitrogen, etc., which are not yet included into the PROSPECT model—is a challenge for this decade: Mapping the spatial heterogeneity of ecosystems, observing biochemical variations which occur within these ecosystems, may henceforth be possible with instruments like AVIRIS.

Spectrum reconstruction from fitted values N, C_{ab}, C_w, LAI, and θ_l is a direct application of model inversion to high spectral resolution data. First, within the limits of the hypotheses presented in this article, it should allow synthesis of a complete canopy reflectance spectrum into only five parameters, thus considerably reducing the dimension of problems which require spectral data. Under some constraints, one can hope to retrieve canopy parameters which have a physical meaning; considering again the forward problem, the PROSPECT + SAIL model can be used to compute the daily fraction of absorbed photosynthetically active radiation (APAR) as a function of latitude (45°) and season (1 July). APAR is a useful parameter related to photosynthetic activity of vegetation. As discussed earlier, without any constraints, only the chlorophyll concentration or water content may be estimated with an acceptable accuracy: Leaf and canopy structure parameters are undermined even if the spectrum reconstruction is good! It is now appropriate to ask the following question: Is there a one-to-one relationship between APAR and a given reflectance spectrum? Can different sets of parameters (N, C_{ab}, LAI, θ_l), which produce the same or almost the same reflectance spectra, have the same APAR value? Computations of the daily fraction of APAR have been performed with input parameters defined in Tables 3 and 6. Table 3 shows that the absolute error in APAR estimation does not exceed 0.12, which is generally better than estimations derived from the normalized difference vegetation index (NDVI) or other visible / near infrared combinations. The precision is good for high LAI values corresponding to a dense canopy, or for low values when soil background effects are not negligible. Table 6 confirms these results. The hypothesis of a known soil is realistic in field experiments, but it rarely happens with airborne data. It will be necessary, in future works, to take into account parameters characterizing soil optical properties when inverting the reflectance model. Atmospheric parameters may also be integrated into the inversion procedure. In that case, 5 or 10 wavebands are probably not enough to describe the entire variability of the signal measured by a spaceborne sensor: This justifies the use of high spectral resolution data.

Until now, the extraction of canopy properties has been investigated only by inversion of physical models for bidirectional reflectance. Such an approach, which has been validated at a local scale, generally provides accurate informations on canopy morphology, since sufficient directions of observation are available (from 25 to 50 different combinations). At a larger scale, in spite of the development of airborne experimental instruments such as ASAS (Advanced Solid-State Array; Irons et al., 1991) or POLDER (Polarization and Directionality of the Earth's Reflectances; Deschamps, 1989), there is no way to acquire so many bidirectional reflectances. Our method which needs only a reflectance spectrum acquired at nadir, is quite different. The AVIRIS sensor should make it immediately operational, assuming good instrument calibration and accurate atmospheric corrections. At the beginning, we have discussed two inversion methods for remote sensing data: A third way may consist of combining directional and spectral measurements in order to access all of the plant canopy information. Future sensors such as HIRIS (High Resolution Imaging Spectrometer; Goetz and Herring, 1989), MODIS (Moderate Resolution Imaging Spectrometer; Salomonson et al., 1989), or MISR (Multiangle Imaging Spectroradiometer, Diner et al., 1989) proposed for EOS (Earth Observing System) should offer new possibilities for acquiring such data.

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