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Comparison of Four Radiative Transfer Models to Simulate Plant Canopies Reflectance: Direct and Inverse Mode

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*Four one-dimensional radiative transfer models are compared in direct and inverse modes. These models are combinations of the PROSPECT leaf optical properties model and the SAIL (Scattering by Arbitrarily Inclined Leaves), IAPI, KUUSK, and NADI (New Advanced Discrete Model) canopy reflectance models. To evaluate their ability to estimate canopy biophysical parameters, inversions were first performed on synthetic reflectance spectra (10 wavelengths in the visible and near-infrared). The simulated spectral and directional reflectances showed good agreement among the four models. A 1997 airborne experiment in the United States was used to test their performance on real data. This experiment gathered a unique data set composed primarily of 200 reflectance spectra acquired over corn (*Zea mays L.*) and soybean (*Glycine max*) fields, and the corresponding ground truth (chlorophyll a+b content and leaf area index). Only the first three models, which ran fast enough to allow the processing of a large data set, were actually inverted by iterative optimization techniques. Inversions were conducted in successive stages where the number of retrieved parameters was reduced. No significant difference can be observed between the three models. Globally, the leaf mesophyll structure parameter and leaf dry matter content couldn't be estimated. The chlorophyll content, the leaf area index, and the mean leaf inclination angle yielded better results, although the latter wasn't validated due to missing ground data. Assuming that model inversion by iterative optimization techniques is a promising method to extract information on plant canopies, the SAIL and KUUSK models, which perform well in terms of accuracy and running time, proved to be good candidates for remote sensing application in ecology or agriculture (precision farming).* ©Elsevier Science Inc., 2000

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INTRODUCTION

The estimation of terrestrial surface properties from optical remote sensing data has been the subject of many studies ever since satellites have permitted the measurement of reflectances over the Earth. Nonetheless, following the properties of the vegetation from space has been limited by a lack of repeat data acquisitions occurring close together in time, as well as by the limited number of spectral wavebands and viewing directions of the sensors. The evolution of technology (improvement of spatial and spectral resolution and increase in signal-to-noise ratio), the decreasing cost of the sensors, and a better understanding of the interaction between radiation and plant canopies have opened up new prospects. Until now, the complexity of the physics of interaction of light with matter (absorption, refraction, scattering) has promoted the development and the intensive use of empirical or semiempirical methods to relate simple vegetation indices to biophysical characteristics of plant canopies such as the leaf area index (LAI) or the fraction of photosynthetically active radiation (fPAR). Classically, these indices are combinations of reflectances measured over several broad bands. Most of them are scarcely based on physics, which limits their robustness and their use over targets that have not been calibrated. Moreover, they are not specific to the characteristic of interest. New methods to extract information from remote sensing data, such as multispectral analysis, lookup tables, or neural networks, have been successfully tested for some time. Among these approaches, model inversion by iterative

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optimization techniques has arisen as a promising method (Myneni and Ross, 1991; Verstraete et al., 1996) and has extended to extracting the physical and biological properties of various media, such as the atmosphere, a bare soil, or a plant canopy, in parallel to the development of analytical models of optical properties of these media.

When the first inversions were performed in the field of remote sensing data interpretation 15 years ago, little came of this technique for operational studies. Until now, they have been mostly considered as a way to validate radiative transfer models, in general by using the same limited field data sets used in the forward modeling direction. With few exceptions (Privette et al., 1996a; Gao and Lesht, 1997; Qiu et al., 1998; Bicheron and Leroy, 1999), they have never emerged as an alternative way to extract information about plant canopies from reflectances. The complexity of the method, as well as prohibitive calculation times in the past, are without doubt the two main reasons for that failure. A successful inversion is the conjunction of three factors: a good model, an appropriate inversion procedure, and a set of calibrated reflectances. Only the first factor will be detailed in this paper.

Remote sensing, as in many scientific disciplines, uses modeling that consists of an abstract and simplified version of reality. What is a good model? From our perspective, the choice of the model is governed by a few rules: With many parameters, it is clear that one can always construct a mathematical model describing any situation, but this is obviously not the real problem. The challenge, rather, consists in constructing a model that does not rely excessively on untestable mathematical hypotheses (i.e., that has a physical meaning). Thus, there is a conflict between the strict adhesion to empirical data, commonly called the fit, and the number of input parameters used by a model: a lot of parameters may provide a good fit but also imply a complicated model. For the purposes of classical inversion (i.e., iterative optimization techniques), the best model is a compromise between a few parameters and a good fit (Thom, 1983). That statement directly excludes ray tracing or three-dimensional radiative transfer models that require a detailed description of the canopy architecture and, in consequence, powerful computers and long calculation times to simulate reflectances. As the merit function may be called hundreds of times, detailed models will imply a very slow inversion. They are consequently better suited to neural networks or lookup tables. Although the running time of a model on a given computer depends on many factors, it is unfortunately never discussed in publications. This element, however, is critical for successful applications. Another condition that governed the choice of a particular model is that its input parameters represent quantities measurable in the field and interpretable in terms of plant biophysical characteristics. This criterion excludes some parametric models that are nevertheless used for other purposes. Although they only apply to limited homogeneous canopies (a definition that is scale-dependent), one-dimensional radiative transfer models are best suited to iterative optimization techniques. The early innovators in this domain include: Goel and Thompson (1984), Goel (1989) pioneered, followed by Otterman (1987, 1990), Pinty et al. (1990, 1991, 1996), Kuusk (1991, 1995a), Deering et al. (1992), Privette et al. (1994, 1996a, 1996b), and Bicheron and Leroy (1999). These recent works mainly concern the retrieval of canopy architecture (LAI, leaf angle distribution) by using bidirectional reflectances. In the mid-1980s, hyperspectral instruments in their turn led to works on the modeling of high spectral resolution and on the inversion of analytical models to extract information not only about vegetation biochemistry (Gao and Goetz, 1995), but also about the amount of vegetation (Jacquemoud et al., 1995; Asner et al., 1998). Recently, projects like the EOS platform have reenergized the notion of synergy between spectral and bidirectional data. Inverting models on these data should lead to better characterization of terrestrial surfaces in the future. However, considering that there are already many impressive codes at leaf and canopy levels, the development of new models has been stated to be of secondary importance with regard to the practical use of existing ones (Wickland and Smith, 1995).

This creates a question: Which model is the best suited for a given application? Although the models used by the authors quoted above meet the requirements for a good inversion, no one can answer this question. In this paper, we compare the performance of four one-dimensional radiative transfer models of plant canopies reflectance, first in direct mode and then by inverting them on the same data set. A strict comparison of their performance must imply that these models accept the same input parameters. For instance, a study contrasting a one-dimensional to a three-dimensional radiative transfer model would be meaningless since these models are built on different hypotheses and they don't do the same job. The first part of this paper is a short description of the four models that are structured as a combination of a leaf optical properties model and four bidirectional canopy reflectance models. Their behavior in the direct mode is analyzed before introducing the inverse problem with a theoretical study and a validation over corn and soybean fields.

THE MODELS

The schema that consists of running together a canopy reflectance model and a leaf optical properties model is now widespread in the literature (Jacquemoud et al., 1994, 1995; Kuusk, 1995b; Bicheron and Leroy, 1999; Pragnère et al., 1999). At scales of both the leaf and the canopy, the models have been adapted to provide the best tool for comparison.

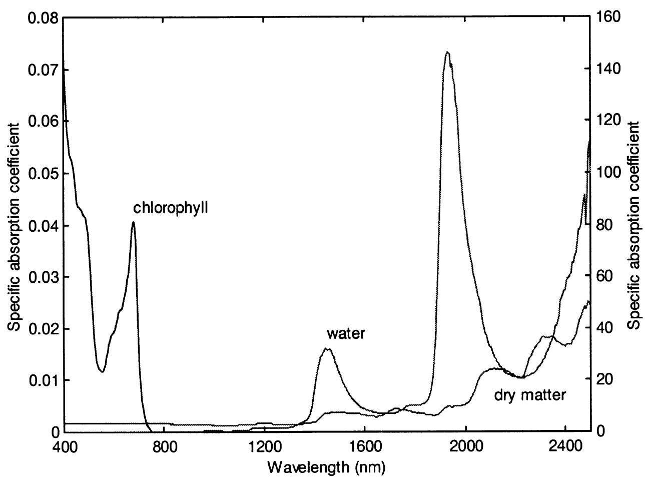


Figure 1. Specific absorption coefficient of (left scale) chlorophyll a+b (cm^2 μg^{-1}) and (right scale) water (cm^2 g^{-1}) and dry matter (cm^2 g^{-1}).

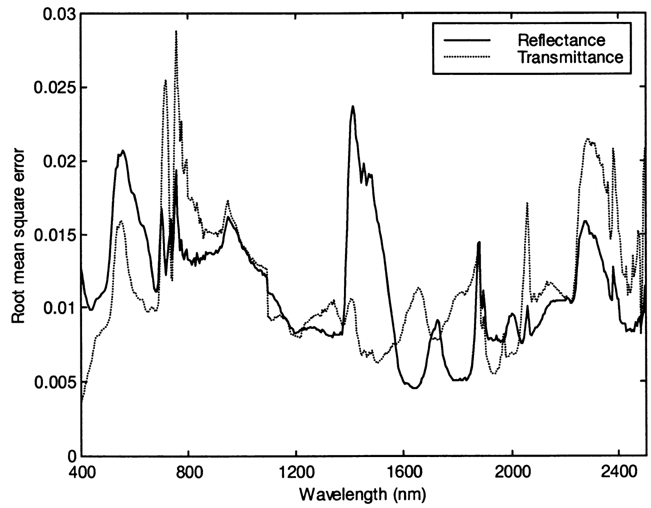


Figure 2. Root mean square errors between the measured and simulated reflectance and transmittance data.

At Leaf Level

The last version of the PROSPECT model (Jacquemoud et al., 1996) including the leaf biochemistry has been simplified by Baret and Fourty (1997), who considered the dry matter content C_m as a whole instead of individually treating the protein, cellulose, lignin, and so on. C_m expressed in g cm^{-2} is equivalent to the specific leaf area (SLA), which is essential in plant growth studies and which is a major input parameter of ecosystem functioning models. In short, PROSPECT requires the leaf structure parameter N, the chlorophyll a+b content C_{ab} (μg cm^{-2}), the equivalent water thickness C_w (g cm^{-2}), and the dry matter content (g cm^{-2}) to simulate leaf reflectance and transmittance spectra in the optical domain. Since Baret and Fourty (1997) have restricted their study to the middle infrared, we decided to validate PROSPECT on the whole optical domain in the same way as Jacquemoud et al. (1996). Figure 1 presents the specific absorption coefficient of chlorophyll, water, and dry matter as a function of the wavelength. The action spectrum of chlorophyll species ranges from 400 nm to 700 nm, while water and dry matter present absorption features only after 950 nm. There is nearly constant absorption of radiation across the visible spectrum by dry matter, however, as confirmed experimentally by albino leaves. The inversion of PROSPECT on 63 reflectance and transmittance spectra of the LOPEX93 data set (Hosgood et al., 1995) shows that the chlorophyll, water, and dry matter can be retrieved with an R^2 of 0.67, 0.95, and 0.65, respectively, which is a satisfactory result for fresh leaves. In terms of reflectance and transmittance reconstruction, the results also show a very good agreement between the 63 measured and simulated spectra (Fig. 2), with a root mean square error less than 0.02 (0.014 on average for reflectance and 0.017 on average for transmittance).

At Canopy Level

Leaves are the main surfaces of green plant canopies. It's no wonder that leaf optical properties are the major input parameters common to all canopy reflectance models. The choice of a model is driven by a variety of factors detailed earlier. One-dimensional radiative transfer models proved to meet these requirements. An excellent review of photon transport in leaf canopies can be found in Myneni and Ross (1991). These models apply to homogeneous absorbing and diffusing media, and they proceed from the same transfer equation. They differ from one another in the way this equation is solved. For instance, different approximations may be used to calculate the hot spot effect or the multiple scattering in the canopy. One of the most popular models is the SAIL model (Verhoef, 1984, 1985), which was adapted in the early 1990s by A. Kuusk (personal communication) to take into account the hot spot effect. This success is attached to a simple and fast code that accurately calculates the reflectance of homogeneous crops. Since then, many other outstanding codes have been proposed in the literature, but they have been rarely compared to each other in terms of accuracy, speed, or invertibility. For that reason, in addition to the SAIL model, we have chosen the IAPI model developed by Iaquinta and Pinty (1994), the KUUSK model based on a Markov chain approach (Kuusk, 1995b) to describe the architecture, and the NADI semidiscrete model recently published by Gobron et al. (1997). We have no intention here of detailing these four models. Only improvements in the original versions will be described; otherwise the reader is referred to the above-mentioned publications. In spite of their similarities, these models were not immediately comparable. For instance, three different leaf angle distribution (LAD) functions were used: continuous ellipsoi-

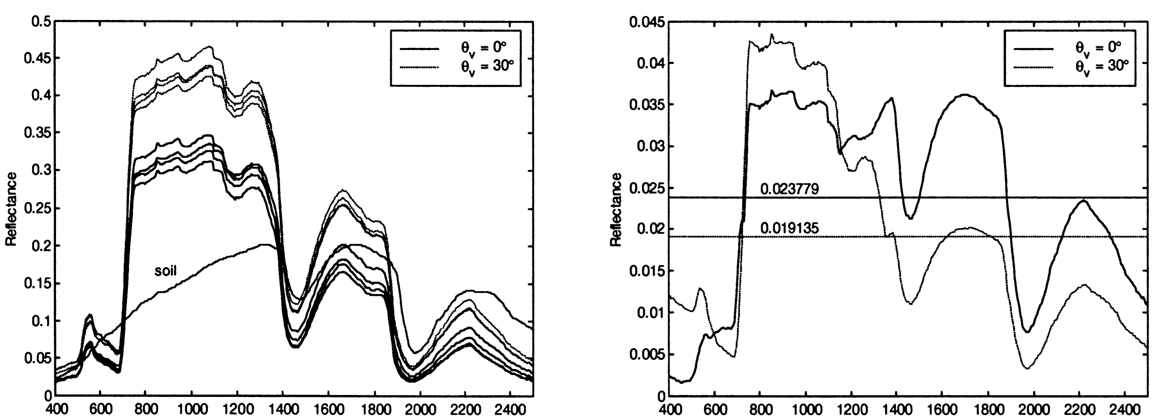
Table 1. An Example of PROSAIL Input and Output Files

input.m			*output.m*					
Parameters=[			30.0	60.0	30.0	.0	30.00	60.0
4	0	% isat	.0	.0	.0	.0	180.0	180.0
30.0	0	% Theta_s, Phi_s	500.00	.0377	.0424	.0293	.0237	.0222
57.0	0	% Theta_1	595.00	.0778	.0846	.0591	.0501	.0535
2.0	0	% LAI	677.50	.0466	.0636	.0421	.0335	.0295
1.5	0	% N	800.00	.4061	.3953	.3029	.2803	.3228
35.0	0	% Cab	1707.50	.1981	.2340	.1667	.1459	.1567
0.0150	0	% Cw	2187.50	.0676	.0978	.0647	.0545	.0558
0.0100	0	% Cm						
0.250	0	% Sl						
50.0	0	% vis						
5	0	% na						
60.0	0.0	% Theta_v(j), Phi_v(j)						
30.0	0.0							
0.0	0.0							
30.0	180.0							
60.0	180.0							
];								

Simulations have been performed for the six TM wavebands (isat=4) and five viewing angles (na=5) distributed around the nadir. The six wavelengths in the first column of output.m correspond to the maximum sensitivity of each filter function of the TM instrument.

dal (SAIL) or elliptical (KUUSK) inclination angle distributions, and the six discrete Bunnik functions (IAPI and NADI) that are supposed to cover a large range of leaf inclinations. A discrete function is obviously not adapted to inversions unless the canopy architecture is known *a priori*. After comparing all the leaf angle distributions proposed until today (i.e., polynomial, trigonometric, beta, ellipsoidal, and elliptical), we fixed our choice on the ellipsoidal one (Campbell, 1990). It is only characterized by a mean leaf inclination angle θ_l since the leaf azimuth angle is assumed to be randomly distributed. The corresponding change was made for SAIL, IAPI, and NADI but not for KUUSK, whose LAD can be matched to the ellipsoidal one by fixing the *eln* parameter, which determines the ellipse eccentricity. Another example is given by the hot spot parameter S_l, defined as the ratio between the radius of a single leaf and the canopy height in SAIL, KUUSK, and NADI, but as the average radius of the sun flecks in IAPI. Gobron et al. (1997) showed that the latter definition could be related to the first one so that all four models now use the first definition of S_l to take into account the hot spot effect. Other minor parameters, such as the Markov parameter in KUUSK and the horizontal visibility in SAIL, have been fixed to make the best comparison between the four models. Finally, they have been coupled to the PROSPECT model and, for this paper, renamed PROSAIL, PROSIAPI, PROKUUSK, and PRONADI.

Figure 3. Canopy spectral reflectance simulated by PROSAIL, PROSIAPI, PROKUUSK, and PRONADI at nadir (θ_v=0°) and in the hot spot direction (θ_v=30°). The shape of a standard soil reflectance spectrum is added. The differences between the maximum and minimum reflectance are drawn on the right with the average over the wavelengths.



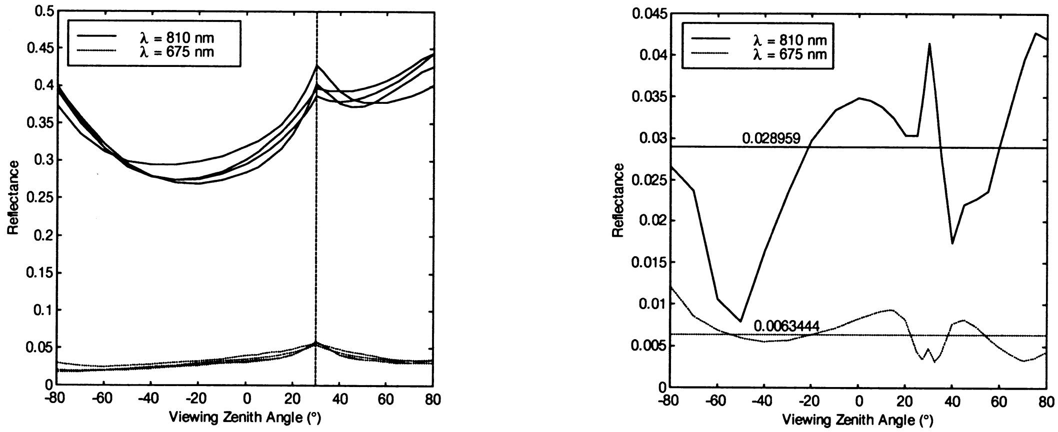


Figure 4. Directional reflectance simulated by PROSAIL, PROSIAPI, PROKUUSK, and PRONADI, at 675 nm and 810 nm. The differences between the maximum and minimum reflectance are drawn on the right with the average over the directions.

Typical PROSAIL input and output files can be seen in Table 1. For a given parameter set, both spectral and directional reflectances are calculated after choosing the type of sensor (isat) and the number of viewing angles (na). Besides the most common space-borne sensors (HRV, TM, AVHRR, AVIRIS, etc.) available, any new one can easily be introduced in the codes as long as the spectral response of the filter functions is known. Assuming a sun zenith angle of 30°, the reflectance of a standard plant canopy (N=1.5, C_{ab}=35 μg cm^{-2}, C_w=0.015 g cm^{-2}, C_m=0.01 g cm^{-2}, LAI=2, spherical leaf angle distribution or $\theta_l \approx 57°$, S_l=0.25) has been calculated from 400 nm to 2500 nm (in 5-nm steps) and from θ_v=0° to θ_v=89°, in the backward and forward directions (in 1° steps). The Lambertian soil reflectance can be seen in Figure 3. The latter shows quite a good superposition of the four reflectance curves simulated at nadir (θ_v=0°) and in the hot spot direction (θ_v=30°), considering the various mathematical formalisms of these models. The differences are generally maximum in the near-infrared, which is not surprising since these models are distinguishable from each other by the way that multiple scattering is accounted for. In the visible, the strong absorption of radiation by chlorophylls smoothes the divergences. The differences also depend on the viewing direction, but surprisingly not consistently as a function of the wavelength. The canopy reflectance simulated at 675 nm and 810 nm as a function of the viewing zenith angle also shows a good agreement both in the forward and backward directions (Fig. 4). As seen earlier, the discrepancy is maximum in the near-infrared and varies as a function of the viewing zenith angle. These results, however, don't allow us to draw any conclusion from the accuracy of one model with regard to the others. A validation of the four models (*i.e.*, inversions performed on the same data set) should enlighten us on this question.

VALIDATION

Verstraete et al. (1996) gave an excellent review of the philosophy of inversion. However, other than the theory, there are several ways to invert a model according to the code itself, the nature and the number of the radiometric data available (spectral or directional reflectances), and the optimization algorithm. We will restrict the scope of this study to reflectances acquired at nadir in 10 wavebands nearly regularly spaced out in the visible/near-infrared domain from 430 nm to 880 nm. The latter were resampled from the 48 Compact Airborne Spectrographic Imager (CASI) spectral bands to study crop development. Then inversions consist in minimizing the merit function χ^2, shown in Eq. (1) as:

$$\chi^2 = \sum_{\lambda=1}^{10} [\rho_{\mathrm{meas}}(\lambda) - \rho_{\mathrm{mod}}(\lambda,\Theta)]^2 \tag{1}$$

where Θ is the vector of parameters to retrieve. Among the parameters used in direct mode, some of them like C_w have no influence on the reflectance in the visible/near-infrared; other ones like S_l have discriminable effects only around the hot spot direction. It may be difficult or impossible to retrieve their value. Consequently, we shall maintain them as a constant. The E04JAF routine from the Numerical Algorithms Group (NAG) library, which is based on a Quasi-Newton algorithm and only requires function evaluations, was chosen to minimize χ^2. This algorithm is now well known and commonly used in remote sensing, so we won't describe it further. The initial parameter guess has been fixed to N=1.5, C_{ab}=50 μg cm^{-2}, C_m=0.015 g cm^{-2}, LAI=3, and θ_l=45°. To avoid function evaluations at nonsensical points, the parameters were bounded by the applicability of the models ($1<N<2.5$, $1<C_{ab}<100$ μg cm^{-2}, $0.05<\mathrm{LAI}<10$, and $5°<\theta_l<85°$). The E04JAF routine provides an error flag, ifail, indicating whether the condi-

Table 2. Inversions on Simulated Reflectances

Inverted by	Simulated by PROSAIL	PROSIAPI	PROKUUSK	PRONADI
PROSAIL				
N	**1.51**	1.59	1.40	1.39
C_{ab}	**35.0**	39.6	29.3	36.1
C_m	**0.0100**	0.0104	0.0048	0.0116
LAI	**2.01**	2.32	2.10	2.26
θ_l	**57.2**	56.8	62.2	59.1
RMSE	**0.0000**	0.0003	0.0028	0.0005
CNTR	**585**	350*	521	557
cpu time	**11″**	6″	9″	10″
PROSIAPI				
N	1.35	**1.51**	1.30	1.37
C_{ab}	30.3	**35.1**	20.4	32.8
C_m	0.0098	**0.0101**	0.0043	0.0123
LAI	1.73	**2.00**	2.32	1.97
θ_l	57.0	**57.0**	72.7	59.4
RMSE	0.0003	**0.0000**	0.0018	0.0009
CNTR	570	**451**	951*	888
cpu time	2′52″	**2′16″**	5′04″	4′27″
PROKUUSK				
N	1.00	1.00	**1.56**	1.00
C_{ab}	33.1	36.2	**35.8**	36.0
C_m	0.0118	0.0114	**0.0103**	0.0148
LAI	1.66	1.92	**1.99**	1.83
θ_l	23.1	22.8	**54.3**	25.2
RMSE	0.0016	0.0017	**0.0001**	0.0020
CNTR	1373*	484	**585***	301
cpu time	19″	7″	**8″**	4″
PRONADI				
N	1.43	1.48	1.42	**1.33**
C_{ab}	34.3	34.4	32.8	**36.9**
C_m	0.0160	0.0070	0.0154	**0.0154**
LAI	2.03	2.09	2.01	**1.94**
θ_l	47.2	55.6	47.6	**48.3**
RMSE	0.0025	0.0009	0.0052	**0.0017**
CNTR	684	676	395	**500**
cpu time	2h50′28″	2h51′36″	1h38′31″	**2h04′43″**

The RMSE and the ratio of the cpu time to the number of calls of the merit function (CNTR) give an idea of the performance of inversions. C_{ab} is expressed in μg cm^{-2}, C_m in g cm^{-2}, and θ_l in degrees. Stars indicate cases for which the algorithm didn't converge after 400×5=2000 function evaluations and for which the initial parameter set was reinitialized; cpu=central processing unit. Calculations were performed on a CRAY J90 (1600 Mflops).

tions for a minimum are satisfied or not: the degree of confidence in the result decreases as ifail increases. The mean number of calls of the merit function χ^2 (CNTR) is informative about the convergence speed, but as the running time of the models might be variable, the central processing unit (cpu) time necessary to achieve the inversions on a given machine was also considered. Finally, the root mean square error (RMSE) of the fit defined as $\sqrt{\chi^2/n}$ tells us how well the calculated canopy reflectances (using the model and the fitted parameters) match the measured ones. Before comparing the four models on a large field data set, the inversions were performed on synthetic data.

Synthetic Data

Let us consider the standard canopy shown in Table 1. Canopy reflectance spectra have been calculated by each model in the 10 wavebands described previously under fixed conditions (sun zenith angle of 30°, standard Lambertian soil of Fig. 3, and θ_v=0°). Testing the inversion procedure on a synthetic data set generated by the model itself gives an idea of the invertibility of the model. While this step is not a proof, it is a prerequisite before going further. The diagonal of Table 2 (in bold) shows the excellent behavior of the four models in self-inversion mode. We subsequently found interesting results when we inverted each model on reflectance spectra generated by the other three models. Such a study is an original way to evaluate the robustness of the inversion procedure when radiometric data are biased due to an approximate calibration. This sometimes happens during airborne campaigns (for instance, due to a lack of atmospheric measurements over the study site). Then, a systematic over- or underestimation of the reflectance

Table 3. Results of the 200 Inversions Performed by PROSAIL, PROSIAPI, and PROKUUSK

#	*Model*	θ_l	*cpu Time*	*CNTR*	*RMSE*	ΔC_{ab}	*n_Cab*	*ΔLAI*	*n_LAI*
5	PROSAIL	70.3°/55.6°	9′30″	376	0.0052/0.0083	34.5/13.5	165	1.36/1.91	152
	PROSIAPI	66.6°/51.4°	12h23′18″	570	0.0005/0.0009	30.2/13.1	165	1.52/2.07	162
	PROKUUSK	54.4°/44.0°	4′57″	349	0.0081/0.0076	23.3/22.0	115	1.15/1.13	155
4	PROSAIL	66.5°/55.9°	5′44″	264	0.0061/0.0087	26.1/13.8	145	1.41/2.00	169
	PROSIAPI	64.2°/51.0°	7h38′10″	401	0.0055/0.0087	28.2/14.4	148	1.49/1.91	168
	PROKUUSK	54.9°/49.7°	2′43″	236	0.0129/0.0080	24.6/18.0	105	1.11/1.56	167
3	PROSAIL	60.7°/54.0°	3′19″	153	0.0073/0.0084	22.7/17.1	152	1.40/1.35	166
	PROSIAPI	56.7°/47.8°	5h47′40″	301	0.0071/0.0085	25.0/15.4	172	1.62/1.66	178
	PROKUUSK	59.1°/51.7°	1′50″	154	0.0140/0.0083	21.0/22.2	127	1.28/1.21	173
2	PROSAIL	x	1′02″	53	0.0130/0.0109	19.4/19.0	131	1.11/1.63	175
	PROSIAPI	x	1h06′48″	68	0.0148/0.0111	16.3/20.9	126	1.24/1.45	175
	PROKUUSK	x	38″	53	0.0150/0.0103	18.2/18.6	128	1.20/1.76	174

When two values are given, the first corresponds to corn fields and the second to soybean fields. The first column is the number of free parameters. The cpu time is the total time necessary to invert a model on 200 reflectance sets. CNTR is the mean number of calls of the merit function. ΔC_{ab} is expressed in μg cm^{-2}. Among the 200 plots, only 190 values of C_{ab} and 180 values of LAI were available: n_Cab and n_LAI are the number of data points used to calculate ΔC_{ab} and ΔLAI, which exclude the cases considered as failures by E04JAF. Calculations were performed on a IBM RS/6000 (480 Mflops).

may occur. The cross-inversions show some peculiar behaviors like the difficulty of PRONADI and PROKUUSK to retrieve the right mean leaf inclination angle. Calculations performed with directional data provide much better results (unpublished results), which tends to prove that these two models get things confused between θ_l and some other parameters when only spectral reflectances are available. C_{ab} and LAI are globally well estimated over the 10 spectral wavebands. For inversions with a given model, CNTR varies by twice as much depending on which model is used to compute the reflectance. But the most significant result is the markedly different cpu time of the inversions with the four different models and for the same number of calls of the merit function.

Field Data

A field experiment was organized in 1997 in Minnesota on behalf of Matra Marconi Space. The main goal was to compare crop parameters estimated with remote sensing techniques to the ground truth. About 20 soybean (*Glycine max*) and 20 corn (*Zea mays* L.) parcels were overflown by CASI on five different dates covering the growing season, giving rise to an impressive data set, with 200 spectra available together with some canopy biophysical characteristics like the green LAI or C_{ab}. LAI and C_{ab} have been measured *in situ* respectively with the LAI-2000 plant canopy analyzer and the Minolta SPAD-502 chlorophyll meter. We were informed afterward that some calibration problems might affect the chlorophyll content measurements of corn leaves because the use of the SPAD-502 is based on a very strict procedure that hadn't been totally applied. The reflectance spectra measured both over bare soils and crops have been calibrated (geometric, radiometric, and atmospheric corrections) to obtain top-of-canopy reflectances and were resampled to fit the 10 wavebands defined earlier. The inversions were conducted as previously (*i.e.*, with the same minimization algorithm and initial parameters), except that only PROSAIL, PROSIAPI, and PROKUUSK were considered. The reason for excluding PRONADI at this stage in the study is due to the slowness of this code. It doesn't presume upon the accuracy of the model and its use with other inversion techniques, but it makes traditional inversions by iterative methods impossible. The soil reflectance has been measured separately on each plot before the growing season. It is assumed to be known and to be Lambertian. The three models have been compared in inverse mode in terms of computation time, RMSE, and accuracy defined as the mean distance from the measured values of LAI and C_{ab} to the global minimum. The calculation of the accuracies of ΔC_{ab} and ΔLAI excludes the cases that among the 200 inversions performed on canopy reflectances were considered as failures (with regard to the E04JAF's flag). In the first run, we allow five free parameters, and then reduce this number in subsequent runs to see to what extent additional constraints improve the inversions. Table 3 summarizes all these results.

Step 1: Assume that N, C_{ab}, C_m, LAI, and θ_l are estimated at once. For corn, the leaf structure parameter N is stuck to the upper bound (PROSAIL and PROSIAPI) or to the lower one (PROKUUSK), while no real trend can be detected for soybean. The retrieved values of the dry matter content C_m also cannot be interpreted. Since the ground truth is not available for the leaf inclination angle θ_l, the averages of the estimated values of this parameter have been calculated for each crop, excluding the lower (5°) and upper (85°) bounds. The values of Table 3 seem to overestimate the ones expected for these plants. However, the results are coherent since corn (erectophile distribution) has more vertical leaves than soybean (spherical

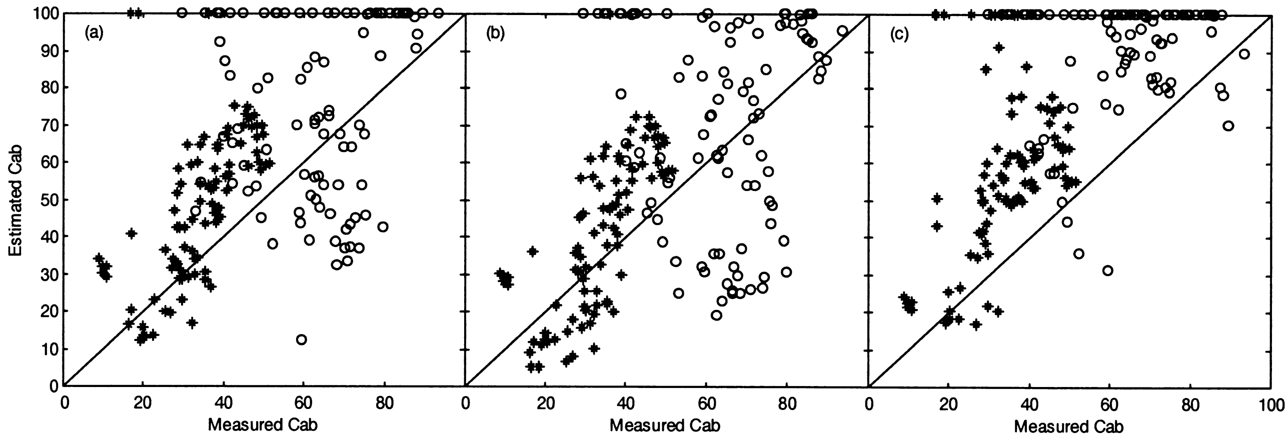


Figure 5. Comparison between measured leaf chlorophyll content C_{ab} (in μg cm^{-2}) and values estimated through (a) PROSAIL, (b) PROSIAPI, and (c) PROKUUSK inversion using 10 wavelengths in the visible and near-infrared. Circles stand for corn and stars for soybean. LAI and θ_l are the two other free parameters.

distribution). The comparison between estimated and measured C_{ab} shows a much larger discrepancy for corn than for soybean, probably due to the above-mentioned calibration problems. The LAI is retrieved with good accuracy. PROSIAPI is extremely slow as compared to the other two models, but it provides the best reflectance reconstructions.

Step 2: To refine the inversions, some constraints were introduced by fixing C_m. For instance, in natural conditions, the dry matter content C_m varies from 0.0019 g cm^{-2} to 0.0135 g cm^{-2} (Hosgood et al., 1995) with an average of 0.045 g cm^{-2}. Since there was no significant difference between the monocotyledons (i.e., corn) and the dicotyledons (i.e., soybean), C_m was set to the above average value. The behavior of N is still confused; the leaf inclination provides the same results as in Step 1; and no significant improvement was observed for the estimation of C_{ab} and LAI (Table 3).

Step 3: In this step we fixed the leaf structure parameter N. The leaf optical properties of corn and soybean are quite distinct in the near-infrared where scattering predominates. On average, N=1.4 for corn and N=1.7 for soybean. These values issue from inversions performed with PROSPECT on leaf spectra. Then PROSAIL, PROSIAPI, and PROKUUSK have been inverted on three parameters: C_{ab}, LAI, and θ_l. The mean leaf inclination angles are surprisingly similar for the three models. LAI is better retrieved than before, while C_{ab} estimates seem to deteriorate for soybean *in situ* measurements of which are reliable. Figures 5 and 6 give a clearer idea of the behavior of these last two parameters. The marks at the top of the figures mean that the upper bound has been reached during the inversion: The statistics of Table 3 consequently don't include these values. Although C_{ab} for soybean doesn't follow the one-to-one line, one can see a good relationship between the measured and retrieved values (R=0.76, 0.75, and 0.71, respectively, for PROSAIL, PROSIAPI, and PROKUUSK), which overestimates high concentrations and underestimates low concentrations.

Step 4: The last series of inversions is the most restrictive since only C_{ab} and LAI are kept free. The mean leaf inclination angle is fixed to values determined in the previous step (Table 3). In many cases, the E04JAF error flag expressed doubt about the solution, probably because of the lack of degrees of freedom during the inversion procedure. This is corroborated by a higher RMSE.

DISCUSSION AND CONCLUSION

The comparison of four radiative transfer models in direct mode and three of them in inverse mode is instructive. When a new model appears "on the market," it is generally validated on a unique and restricted data set that cannot stand for a categorical proof. Moreover, the difficulties that necessarily occur during the inversions are generally avoided, and the computer powers or the calculation times required to invert the model are barely described. Our goal here was not to validate the models (it has already been done by their authors) but to evalu-

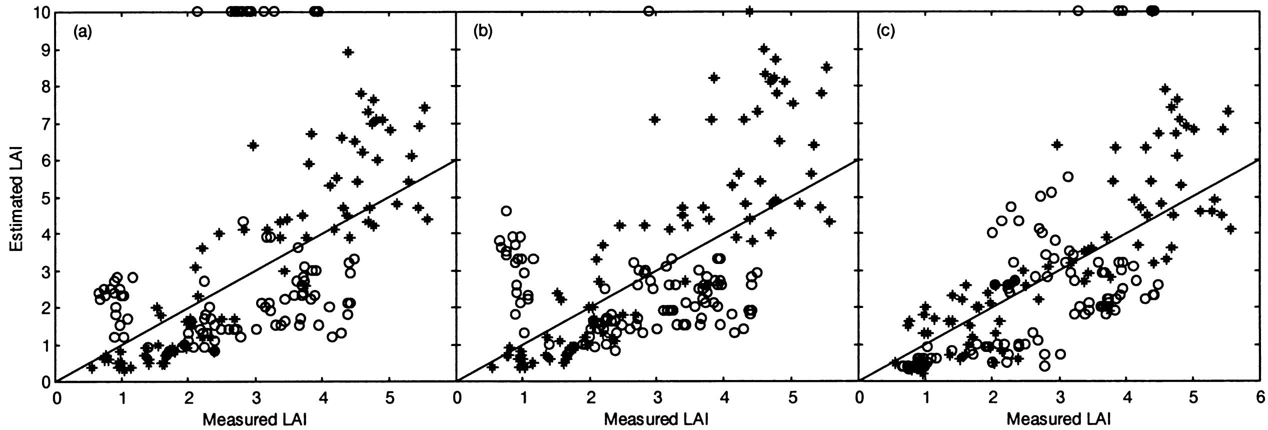


Figure 6. Comparison between measured leaf area index LAI and values estimated through (a) PROSAIL, (b) PROSIAPI, and (c) PROKUUSK inversion using 10 wavelengths in the visible and near-infrared. Circles stand for corn and stars for soybean. C_{ab} and θ_l are the two other free parameters.

ate their performance with the focus on applying them operationally in remote sensing studies. This means that objective criteria suitable for comparison can be defined; it also means that we are able to hierarchize them. For instance, is a fast, moderately accurate model better than a slow, highly accurate one? The answer is conditional and not easy to evaluate. As a preliminary, we stated that a good model was a compromise between a few parameters and a good fit for traditional inversion purposes. It is also a compromise between a fast running time and good accuracy.

Therefore, a model inversion that lasted several minutes to several hours was not satisfying, regardless of whatever accurate results it produced. For that very reason, PRONADI was discarded for our inversions on field data. An approach using neural networks or lookup tables, for instance, might produce a different conclusion. If the running time prevails over the accuracy, then PROKUUSK<PROSAIL<PROSIAPI<PRONADI. If the accuracy on C_{ab} is considered the preeminent factor, then PROSAIL<PROSIAPI<PROKUUSK; if it is the accuracy on LAI, then PROKUUSK<PROSAIL<PROSIAPI (Table 3). The differences, however, are less noticeable than those for running times. Without digressing into all the details, it was a surprise to see a certain coherence between the four models in direct mode, and between PROSAIL, PROSIAPI, and PROKUUSK, in inverse mode. It is consequently virtually certain that any other model named PRO-X that was also based on the radiative transfer equation would lead to similar conclusions.

Besides the choice of a good model, an appropriate inversion procedure and a set of calibrated reflectances were the other two conditions identified for a successful inversion in the introduction. The choice of an optimization algorithm is a complex question that has not been studied much (Jacquemoud et al., 1994; Renders and Flasse, 1996). Operational prospects will require that inversion procedures be speeded up before they become widely used. Moreover, although inversion applies in theory to each pixel independently, a new methodology should also be developed to improve its efficiency when hundreds or thousands of pixels are analyzed. Finally, the last factor is the quality of the data (*i.e.*, the measured reflectances that are the fixed part of the merit function) and the biophysical parameters (leaf biochemicals and canopy architecture) that will allow the validation of the model. Many studies obviously consider that these two conditions are satisfied, although in reality, they are only approximated due to calibration and measurement errors. The problems associated with the use of the Minolta SPAD-502 chlorophyll-meter encountered in this study is a good example. Anyway, although these questions are essential whenever remote sensing data are processed, they were beyond the scope of this paper, and we have not developed them. These remain as interesting problems to dwell on in future studies nevertheless.

Is inversion by iterative optimization techniques a method with a future? Do the accuracies obtained with these methods satisfy ecologists and agronomists for their application models? These questions are still points at issue since there is a lack of studies in the literature concerning chlorophyll and LAI estimation by model inversion. Recent works in precision farming, however, suggest that such methods may provide better estimations than the NDVI, a classical vegetation index, when the NDVI is directly calibrated with field data (H. Poilvé, unpublished data). If confirmed, these results are very promising and encourage the development of new inversion algorithms as was recently recommended by the NASA "Ecological Processes and Modeling" program (Privette et al., 1997).

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