Agronomie 22 (2002) 555–565
© INRA, EDP Sciences, 2002
DOI: 10.1051/agro:2002039

Original article

Reliability of the estimation of vegetation characteristics by inversion of three canopy reflectance models on airborne POLDER data

Cédric BACOUR[a]*, Stéphane JACQUEMOUD[a], Marc LEROY[b], Olivier HAUTECŒUR[b,c], Marie WEISS[c,d], Laurent PRÉVOT[d], Nadine BRUGUIER[d], Habiba CHAUKI[d]

[a] Laboratoire Environnement et Développement (LED), Université Paris 7, CP 7071, 2 place Jussieu, 75251 Paris Cedex 5, France
[b] Centre d'Étude Spatiale de la BIOsphère (CESBIO), 18 avenue Edouard Belin, BPI 2801, 31401 Toulouse Cedex 4, France
[c] NOVELTIS, Parc Technologique du canal, 2 avenue de l'Europe, 31520 Ramonville Saint-Agne, France
[d] Unité Climat, Sol et Environnement, Institut National de la Recherche Agronomique (INRA), site Agroparc, 84914 Avignon Cedex 9, France

(Received 18 December 2001; accepted 11 June 2002)

Abstract – The Bidirectional Reflectance Distribution Function (BRDF) of several plant canopies was extensively sampled by the POLDER airborne instrument in the Alpilles-ReSeDA campaign. The 16 flights carried out over the Alpilles test site from January to October 1997 cover all the plant growth stages. Estimation of biophysical variables was undertaken by inversion of three one-dimensional radiative transfer models, SAIL, KUUSK and IAPI, coupled with the PROSPECT leaf optical properties model, in order to fully utilize both the directional and the spectral information of the images. This study mainly focuses on the capability of model inversion to retrieve the leaf area index (*LAI*) of wheat, maize, sunflower and alfalfa crops, for which ground validation was available. In order to evaluate the quality of inversions and to map the *LAI* or the chlorophyll content C_{ab}, the associated estimation errors are determined for these two biophysical variables.

remote sensing / canopy reflectance model / inverse problem / estimation uncertainty

Résumé – Erreurs associées à la caractérisation des couverts végétaux par inversion de trois modèles de réflectance sur des données POLDER aéroporté. La Fonction de Distribution de Réflectance Bidirectionnelle (BRDF) de plusieurs couverts végétaux a été intensivement échantillonnée par l'instrument POLDER aéroporté lors de la campagne Alpilles-ReSeDA. Les 16 vols effectués au-dessus du site des Alpilles, couvrent la période de janvier à octobre 1997 et donc tous les stades de croissance des plantes. Les variables biophysiques ont été estimées par inversion de trois modèles de transfert radiatif unidimensionnels, SAIL, KUUSK, et IAPI, couplés au modèle de propriétés optiques des feuilles PROSPECT afin de tirer pleinement parti de l'information spectrale et directionnelle des images. Cette étude porte plus particulièrement sur la capacité des modèles à restituer l'indice de surface foliaire (*LAI*) dont la mesure au champ a été réalisée sur différentes parcelles de blé, maïs, tournesol et luzerne. Afin d'évaluer la qualité des inversions et de cartographier le *LAI* ou la concentration en chlorophylle C_{ab}, les erreurs d'estimation associées ont été déterminées pour ces deux variables biophysiques.

télédétection / modèle de réflectance des couverts végétaux / problème inverse / incertitude d'estimation

1. INTRODUCTION

The estimation of land surface properties with optical remote sensing data has long been influenced by the use of empirical or statistical methods, only based on *observations* of the spectral contrasts of reflectance. The reliability of these methods, although they bear upon most operational applications, is intrinsically limited by the fact that they poorly account for the anisotropic properties of these surfaces. In the mid-80s, the latter were observed to be crucial for diagnosing plant canopy functioning [16, 28]. Thanks to an enhanced *understanding* of the physical processes that

Communicated by Frédéric Baret (Avignon, France)

* Correspondence and reprints
cbacour@avignon.inra.fr

govern the interactions between light and the canopy elements, bidirectional canopy reflectance (CR) models emerged for inversion issues on multidirectional data in the early 90s [20, 37]. Model inversion, however, requires significant computational resources which are slow on large data sets. This problem results both from a complex description of the radiative field within the canopy, and from the inversion method itself. Besides the traditional iterative optimization approach, recent alternative inversion methods (mainly look-up tables [18, 30, 56, 58] and neural networks [6, 54]) permit inversions to overcome computer limitations. Nevertheless, they have been applied only to 1-D radiative transfer models so far, because of their fast execution speed and their restricted number of input variables, relative to full 3-D models. Moreover, the ill-posed nature of the inverse problem [11] remains an issue that equally affects all methods as it is due to (i) measurement errors, (ii) the inadequacy between the model and reality (i.e. between the variables of the model and the "real" state variables, and between the simulated and the measured reflectances). It translates into the non-unicity of the solution. In other words, different combinations of variables can produce similar reflectances. Finally, non-linear interactions between the state variables may also increase the instability of the solution [1]. The question of reliability is here considered for different 1-D canopy reflectance models and iterative optimization techniques.

This study was conduced as part of the European project ReSeDA [40]. The Alpilles test site, located south of Avignon (France), was widely monitored with the POLDER (POLarization and Directionality of the Earth's Reflectances) airborne sensor [13] to provide SVAT (Soil Vegetation Atmosphere Transfer) and canopy functioning models with the required vegetation and soil biophysical variables. POLDER was flown from January to October 1997, covering the whole vegetative cycle. It allows sampling of the Bidirectional Reflectance Factor (BRF) of anisotropic surfaces along the principal plane and around the hot spot direction [7, 9], which are relevant configurations for estimating canopy structural variables. The monitoring of vegetation with this instrument has been previously investigated with empirical or semi-empirical methods [33, 34, 47] as well as by inversion of CR models with neural networks [53, 57] and iterative methods [8].

This paper focuses on inversion of three canopy reflectance (CR) models with iterative inversion techniques. Their ability to retrieve the major crop biophysical variables is assessed on wheat, maize, sunflower and alfalfa, during the vegetative season. In particular, the crop estimates are compared together and with in situ measurements of the leaf area index (*LAI*). The data processing considers top of canopy (TOC) reflectances either at the field level or at the pixel level in order to study the spatial heterogeneities and to appraise scaling problems. We emphasize addressing the error determination of the estimated variables due to the inversion procedure. This issue, though crucial for characterizing the quality of remote sensing products used in assimilation processes, is the main innovation of this paper because it is often evaded in the literature.

2. MATERIALS AND METHODS

2.1. Models

To fully exploit the directional and spectral dimensions of POLDER data with radiative transfer models, three 1-D bidirectional canopy reflectance models, SAIL [49, 50], KUUSK [32] and IAPI [21], were coupled with the most recent version of the PROSPECT leaf optical properties model [26, 27] and renamed PROSAIL, PROKUUSK and PROSIAPI, respectively. SAIL, KUUSK and IAPI are derived from the radiative transfer equation with different formalisms. For instance, they differ in how canopy architecture is described. However, they require the same inputs: the leaf area index *LAI*, the mean leaf inclination angle θ_l, the hot spot parameter s_l, and a soil brightness parameter α_{soil} that controls the reflectance of a given soil. In PROKUUSK, the parameter representing the leaf distribution eccentricity *eln* is fixed at five so that the three models only depend on the mean leaf inclination angle [27]. A prior comparison has already demonstrated similar impacts of these biophysical variables on reflectance for spaceborne POLDER configurations [1], even though the processing might differ within the models. The main discrepancies were attributed to the leaf angle distribution – ellipsoidal in PROSAIL and PROSIAPI, and elliptical in PROKUUSK – that translated, above all, into different implementations of the *G* and phase functions. The description of the hot spot effect was also a discriminating factor, especially for high backward-view zenith angles [3] where it is weaker in PROSAIL and PROKUUSK [31] than in PROSIAPI [52].

PROSPECT requires the leaf structure parameter *N*, the chlorophyll *a*+*b* content C_{ab} ($\mu g \cdot cm^{-2}$), the equivalent water thickness C_w (cm or $g \cdot cm^{-2}$), and the dry matter content C_m ($g \cdot cm^{-2}$) to simulate leaf reflectance and transmittance spectra.

2.2. POLDER data

The calibration of POLDER is detailed in [35]. Here, we summarize the experiment. The database consists of superimposable reflectance images covering areas of 5 km × 5 km. Each one is an array of 250 by 250 pixels, corresponding to a 20 m grid resolution (Fig. 1a). Radiances were measured in four spectral bands centered on 443, 550, 670 and 865 nm (each 40 nm wide) and atmospherically corrected with SMAC (Simplified Method of Atmospheric Correction) [45] adapted from the 6S model [51]. However, the waveband at 443 nm is still contaminated by aerosols and was omitted from this study.

For each of the 16 Days Of Experiment (DOE), several flight sequences were conducted at about noon over the Alpilles test site (N43º47', E4º45'), at a standard altitude of 3000 m. Each flight is composed of four flight lines roughly parallel to the sun direction, plus one perpendicular. Using this scheme, POLDER allowed sampling of pixel radiances in many viewing geometries, especially around the principal plane where plant canopies display stronger anisotropy.

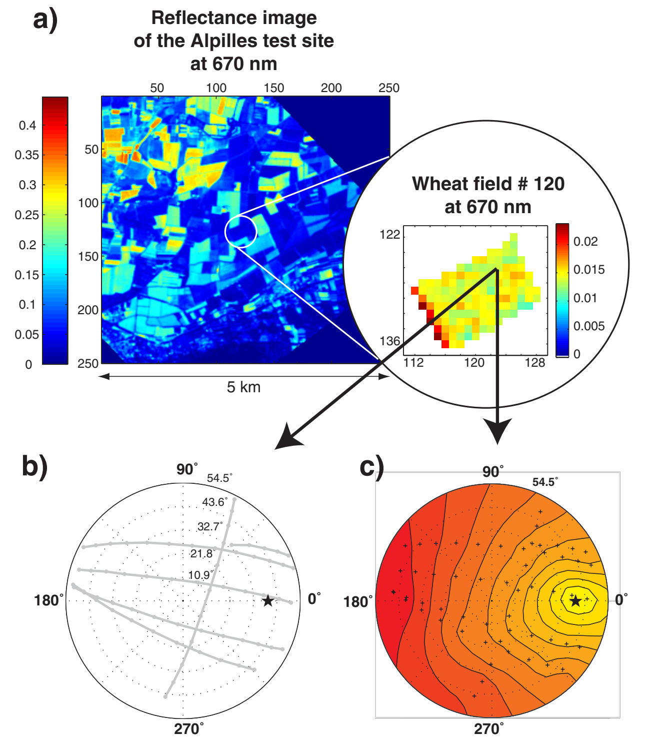

Figure 1. (a) Extraction of red reflectance of wheat field #120 from the airborne POLDER image of the Alpilles site acquired on 2 May 1997. (b) Directional sampling of the viewing geometry of the target (125,125), in polar coordinates, along six flightlines. (c) BRDF signature of the target obtained by ordinary kriging interpolation of the directional reflectance. The radius represents the view zenith angle (in degrees), and the polar angle the relative azimuth between sun and view directions. The star depicts the sun position.

Figure 1b shows the directional sampling over a wheat field along six flightlines. In this case, the interpolation (by ordinary kriging) of the reflectances at 670 nm produces a symmetrical BRDF on both sides of the principal plane (Fig. 1c). Such a symmetry is expected when leaves are randomly oriented in azimuth. The higher reflectances observed around the hot spot direction are also typical of non-turbid media like vegetation canopies. Because of geometrical calibration problems for highly oblique observations, only viewing angles $< 45^{\circ}$ were retained. Finally, georegistration of each field was refined using calibrated SPOT images.

2.3. In situ measurements

Field biomass and structure measurements were regularly performed on wheat (*Triticum aestivum*), maize (*Zea mays*), sunflower (*Helianthus annuus*) and alfalfa (*Medicago sativa*). The green leaf area index (*LAI*) was measured with a planimeter. Because *LAI* measurements and POLDER flights were not simultaneous, these data were interpolated with temporal functions adaptated from [5] and including a growth and senescence. Table I indicates the flight dates selected according to the crop; Table II gives the crop field numbers for which the biophysical variable estimations were performed.

2.4. Soil BRDF estimates

CR models require the optical properties of the underlying soil as an input. Since this information was not available in the Alpilles-ReSeDA database, the soil BRFs were estimated from POLDER observations and parameterized by the Modified Rahman Pinty Verstraete (MRPV) model [14, 44], chosen because of its ability to derive full BRDFs from a limited set of directional reflectance data [55]. Thus, they can be extrapolated to the POLDER observation geometries for the dates chosen for the analyses.

The MRPV parameters were estimated on early POLDER flights, assuming homogeneous bare soils. The dates chosen were based on plant germination: 01/12 for wheat, 01/30 for alfalfa, and 03/12 for maize and sunflower. Since the contribution of the soil to the canopy reflectance rapidly vanishes as vegetation expands, we can assume that their anisotropic

Table II. Field numbers used to estimate the vegetation biophysical variables for wheat, maize, sunflower and alfalfa. In italics are the plots measured with the planimeter; no in situ measurements were performed for plots in plain.

Crop	Fields #
Wheat	*101*, *120*, 124, 202, ***208***, ***210***, ***214***, 218, *300*, 310
Maize	***112***, 113, ***125***, 126, 311, 500, 504
Sunflower	***102***, 107, ***121***, 205, 217, 304, *501*, 503
Alfalfa	***203***

Table I. POLDER flight dates selected for estimating the biophysical variables of each crop. Days of experiment are given in mm/dd of year 1997.

	Days of Experiment													
Crops	02/27	03/12	03/26	04/10	04/16	05/02	05/22	06/09	06/24	07/08	07/29	09/04	09/18	10/24
Wheat		✓	✓	✓	✓	✓	✓	✓	✓					
Maize							✓	✓	✓	✓	✓	✓	✓	
Sunflower								✓	✓	✓	✓	✓	✓	✓
Alfalfa	✓	✓	✓	✓	✓			✓		✓	✓	✓	✓	

properties remain constant throughout the vegetative cycle. Nevertheless, variations in magnitude of the soil reflectance can be taken into account via the multiplicative parameter α_{soil} which is left free during the inversions.

2.5. Inversion technique

Without any a priori information on the variables to be retrieved, the inverse problem typically consists of determining the optimal set of variables Θ^* that minimizes a merit function χ^2 defined as the distance between the reflectances measured at the top of the canopy and those computed by the model. The choice of χ^2 for operational use in remote sensing is not straightforward, as underscored by the diversity of such functions [see 15, 18, 19, 38, 43]. Nevertheless, most result from the χ^2 expression in the L_2-norm, according to the inverse problem formulation of Tarantola [48].

The merit function in Nilson and Kuusk [38] implicitly takes into account the evolution of variance of the fit with the measurements, since it is directly proportional to the TOC reflectances $\tilde{\rho}(\Omega_j, \lambda_i)$. The latter act as a priori information related to the un-quantified errors of the model and the data. We therefore use the following merit function:

$$\chi^2 = \sum_{j=1}^{n_v} \sum_{i=1}^{3} w_j \cdot \frac{[\tilde{\rho}(\Omega_j, \lambda_i) - \hat{\rho}(\Theta|\Omega_j, \lambda_i)]^2}{\tilde{\rho}(\Omega_j, \lambda_i)} \quad (1)$$

which complies with a weighted least-square estimation to determine the set of variables Θ from measurements made in the three POLDER wavebands for n_v observation geometries Ω_j. The weighting factors w_j enhance observations in the principal plane where the reflectance is more sensitive to the variation dynamics of canopy biophysical variables [3, 41]. They are convenient insofar as the error of the routine used to conduct the optimizations, which informs on the quality of the minimum found for the merit function, puts better confidence in the results when using w_j. The latter are expressed as a function of the view zenith angle θ_v and the relative azimuth angle ϕ:

$$w_j = \frac{\cos(y)+1}{2} \quad \text{with} \quad y = \theta_v \times \sin(\phi) \quad (2)$$

such that $y \in [-1;1]$, and $y = 0$ in the principal plane.

The minimization algorithm is based on an iterative quasi-Newton method, which has already been documented in similar remote sensing problems [22, 24, 42, 46]. We chose the E04JAF routine – from the NAG (Numerical Algorithms Group) library because the derivatives of χ^2 with respect to the variables are not explicitely required. Furthermore, it allows for constraints on the variables to physically acceptable values. Iterative methods are suspected to be sensitive to the initial parameter guess and to local minima of the merit function; they can therefore lead to doubtful solutions. To reduce this problem, typical alternatives consist of generating random initial conditions [42] or restarting the inversion process using the estimated set of variables [43]. However, the cost in terms of computation time limits the processing of the POLDER data. The issue of solution reliability is nevertheless considered here with respect to the error estimation on the biophysical variables.

The quality of the estimation is usually appraised with regard to the Root Mean Square Error (RMSE) of the fit, even though it does not evaluate the reliability of the variables of interest. We propose an alternative criterion to assess it. For each variable, a confidence interval can be extracted from the covariance matrix of the estimates at the minimum of the merit function, χ^{2*} using the following approximation $\underline{\underline{V_\Theta}}$ [4, 39]:

$$\underline{\underline{V_\Theta}} = \frac{2}{m-n} \cdot \chi^{2*} \cdot \underline{\underline{N^{-1}}} \quad (3)$$

for m data and n estimated variables, $\underline{\underline{N^{-1}}}$ is the approximated value of the Hessian matrix at χ^{2*}. The above expression of the covariance matrix presupposes that the direct problem behaves quasi linearly in the neighborhood of the solution, which is a good assumption for plant canopy radiative transfer models [10] – and that the residues are small, which is verified when the minimum is indeed reached. $\underline{\underline{N^{-1}}}$ is computed with the E04XAF NAG routine. The diagonal of $\underline{\underline{V_\Theta}}$ contains the variances of the estimates. Strictly speaking, they are not variances according to a Gaussian distribution of errors one would expect, as the merit function is not the maximum likelihood function here. Rather, they should be interpreted, for each variable v_p, as a quantification of the stability of the minimum of χ_2 along the direction of v_p. The other elements of $\underline{\underline{V_\Theta}}$ are the correlations between the different estimated variables.

Among all of the variables, C_w and C_m have no, or very little, influence on the CR in the three selected POLDER wavebands (550, 670 and 865 nm). Moreover, a recent study has highlighted some difficulties in retrieving N [27]. Consequently, these three variables remained fixed during the inversions: $C_m = 0.01$ g·cm^{-2}, $C_w = 0.015$ cm and $N = 1.5$ which corresponds to average values in nature. Bacour et al. [1] showed that the reflectance was as sensitive to LAI as to θ_l, therefore the mean leaf inclination angle was left free. Thus, the vegetation variables estimated simultaneously were: LAI, C_{ab}, θ_l, s_l and α_{soil}. For each one, Table III provides the upper and lower bounds of their definition interval, as well as the initial guess starting the inversion procedure.

Inversions on POLDER BRDFs with PROSAIL, PROKUUSK and PROSIAPI were processed in two steps: (i) on the reflectances averaged over each field and (ii) on a per-pixel basis.

Table III. Constraints on the variables to be retrieved (lower and upper bounds) and initial guesses of the inverse process.

Variable	Range of variation	Initial guess
LAI	0.01–5	3
C_{ab} (µg·cm^{-2})	1–100	50
θ_l(°)	5–85	45
s_l	0.00001–1	0.5
α_{soil}	0.5–2	1

3. RESULTS

3.1. Quality of the fit

The ability of the three CR models to reconstruct the measured reflectances at the field level was evaluated. It was estimated by the RMSE of the fit, averaged over the flight days (Fig. 2a) and over the fields of each crop (Fig. 2b). One observes a consistent estimate of the BRF reconstruction for the three models, PROKUUSK globally producing slightly higher RMSEs. The same trend is obtained even when *eln*, one of the two parameters describing PROKUUSK's elliptical leaf angle distribution function, is left free during the inversions (results not shown).

Noticeable peculiarities underscore some inadequacies between the radiative transfer models and the data, probably because of particular crop histories or bad meteorological conditions. For instance, low vegetation covers on wheat fields #101 (strong heterogeneities due to growth problems) and #214 (late sowing of spring wheat) explain the high RMSE values in comparison with the other wheat fields. As clouds were present on most of the POLDER scenes acquired on 06/24, these data were omitted. Finally, there is no explanation to interpret the RMSE peak of DOE 07/29.

3.2. *LAI* estimates against in situ measurements

The models' consistency can also be appraised with regard to the *LAI* estimates compared with the interpolated measurements using the planimeter (Fig. 3). The results indicate concern for inversions conducted on reflectances at the field level (wheat, maize, sunflower and alfalfa of Tab. II).

The leaf area index estimates are consistent with planimeter values, especially the lowest ones. One notices an underestimation for values higher than 2.3 when reflectance becomes less sensitive to the dynamics of this variable [1, 17].

Simplifying assumptions sustaining CR models partly explain these divergences, as they affect the quality of the estimations (Tab. IV). In particular, row spacing effects and non-green foliar elements are ignored. The assumption of azimuthally uniform leaf orientations may be erroneous for heliotropic plant canopies (sunflower). PROSAIL generally

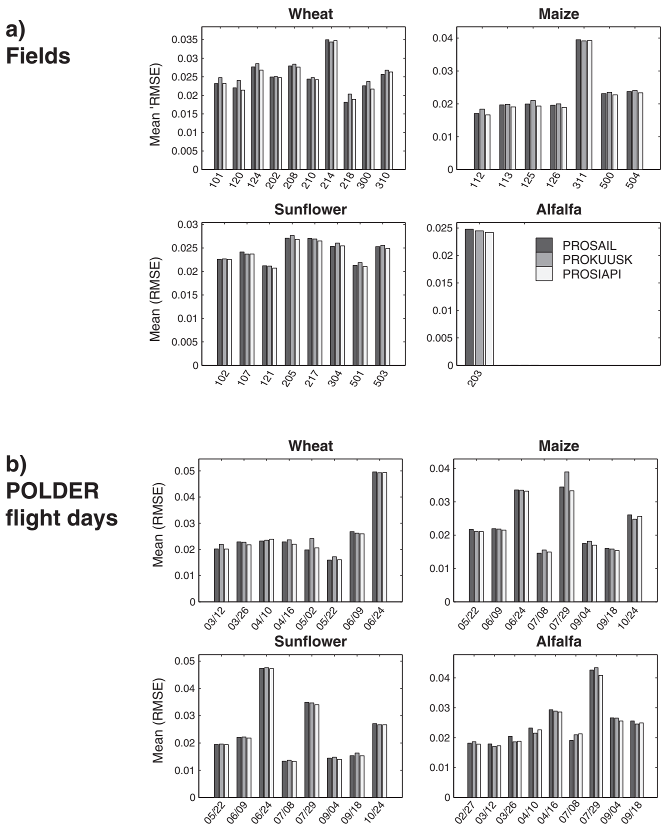

Figure 2. Root Mean Square Error of the fit between measured and reconstructed reflectances after inversion of PROSAIL, PROKUUSK and PROSIAPI, on wheat, maize, sunflower and alfalfa, with respect to (a) the field number, (b) the day of experiment.

provides the *LAI* estimates closest to the measurements, followed by PROSIAPI. Model inversions perform better on sunflower and wheat. Alfalfa is surprisingly the species that exhibits the strongest discrepancies between estimated and measured *LAI* values, whereas it confirms best the turbid medium assumption. This might be attributed to the difficulty of reliably measuring such small leaf surfaces with a high perimeter area, more than to a problem related to the inversion procedure as seen hereafter.

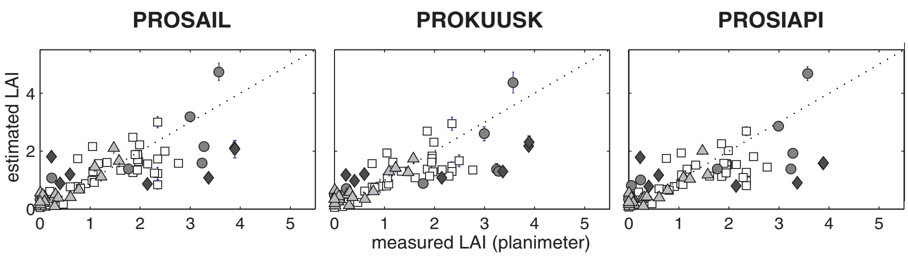

Figure 3. Comparison between *LAI* values measured with the planimeter and estimated by inversion of PROSAIL, PROKUUSK and PROSIAPI, on □ wheat, ● maize, △ sunflower and ♦ alfalfa. The error bars correspond to the standard deviations of the estimated *LAI* values computed from the approximation of the covariance matrix (Eq. (3)).

Table IV. RMSE between the *LAI* estimated with PROSAIL, PROKUUSK and PROSIAPI and the *LAI* measured with the planimeter, for wheat, maize, sunflower and alfalfa.

	Planimeter		
	PROSAIL	PROKUUSK	PROSIAPI
Wheat	0.48	0.50	0.53
Maize	0.88	1.14	0.99
Sunflower	0.27	0.27	0.26
Alfalfa	1.53	1.33	1.75

The quality of the radiometric data (georegistration and atmospheric correction) also conditions the results, as well as inaccurate planimeter measurements or wrong *LAI* interpolations for the POLDER flights. It is also likely that the in situ sampling strategy is inappropriate for describing global leaf area indices: the ground measurements are indeed very local, i.e. only partly representative of the field variability, whereas the inversions assume homogeneous crops.

In the following, these different hypotheses are examined with an analysis of the estimation error on field and pixel scales.

3.3. Interpretation of the estimates

3.3.1. Model intercomparison

The performances of the three CR models are compared for the five variables estimated on the whole fields (Tab. V and Fig. 4). There is a good consistency between PROSAIL, PROKUUSK and PROSIAPI for *LAI* and C_{ab}. This is not surprising insofar as these variables strongly affect the reflectance in the directional and spectral dimensions. The estimates of the soil brightness parameter are also consistent. One can notice that α_{soil} is usually > 1 for wheat. The radiometric measurements made on DOE 01/12 and used for the soil reflectance parameterization of wheat, correspond, in fact, to some dampness of the soils due to rainy conditions on prior days. High α_{soil} values therefore express the model capacity to take into account an increase in soil reflectance levels along with the development of the vegetation and the meteorological conditions that cause the soil moisture content to subside.

The discrepancies are more pronounced with regard to the other variables. For the mean leaf angle, they render different

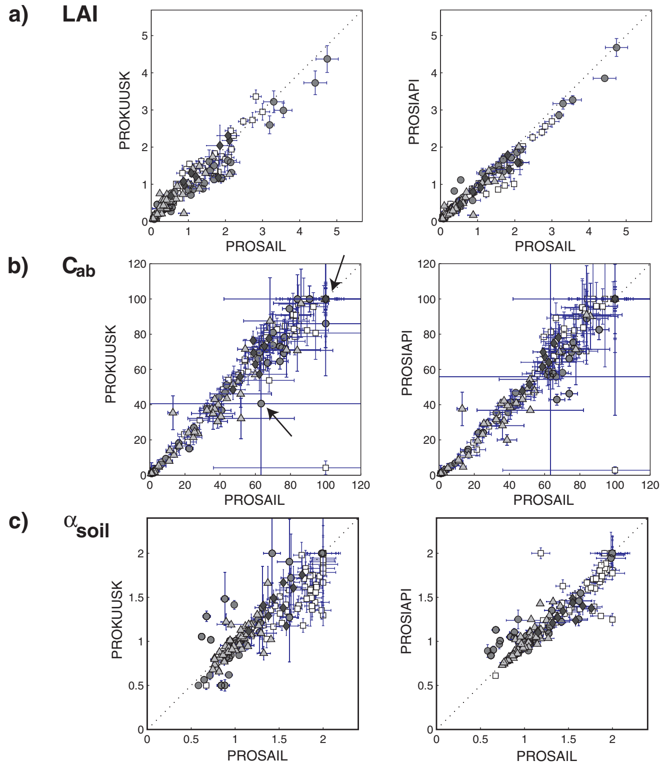

Figure 4. PROSAIL against PROKUUSK and PROSIAPI estimations of *LAI*, C_{ab}, and α_{soil}, on □ wheat, ● maize, △ sunflower and ◆ alfalfa. The error bars correspond to the standard deviations of the estimated values computed from the approximation of the covariance matrix (Eq. (3)).

descriptions of the canopy structure (in particular different leaf angle distribution functions between PROSAIL/PROSIAPI and PROKUUSK) and of multiple scattering. The retrieved hot spot parameter appears difficult to interpret physically according to Table V. The discrepancies between the models are partly due to different representations of the phenomenon but especially to the fact that its relative contribution to reflectance is lower than that of the other biophysical variables [3]; the lack of data around the hot spot region may also debase its estimation.

Examination of the standard deviation of the estimates allows detection of suspect results (shown by arrows in Fig. 4). Note that large estimation errors on C_{ab} do not necessarily result in high σ_{LAI} values.

Table V. Two by two RMSE comparison between the estimated variables by field with different canopy reflectance models.

	PROKUUSK					PROSIAPI				
	LAI	C_{ab}	θ_l	s_l	α_{soil}	*LAI*	C_{ab}	θ_l	s_l	α_{soil}
PROSAIL	0.27	9.78	31.66	0.42	0.21	0.21	9.43	19.53	0.49	0.16
PROKUUSK						0.26	8.10	32.50	0.49	0.21

Table VI. Estimation uncertainties of the biophysical variables following equation (4) averaged by field of each crop.

		Wheat	Maize	Sunflower	Alfalalfa
PROSAIL	LAI	7.8	8.4	14.3	11.5
	C_{ab}	12.6	13.9	23	12.5
	θ_l	9.8	11.7	19.3	10.6
	s_l	61.3	41.5	64.1	35.6
	α_{soil}	5.2	5.1	3.3	5.1
PROKUUSK	LAI	8.1	10	11.2	10.2
	C_{ab}	9.2	12	19.4	10.1
	θ_l	16.4	21.5	16.6	19.4
	s_l	40.6	39.9	46.2	29.1
	α_{soil}	8.6	14.8	4.1	9.1
PROSIAPI	LAI	6.9	7.1	10.2	6
	C_{ab}	12.3	15.3	20.5	9.1
	θ_l	10	10	12.9	9.2
	s_l	10.7	11.5	10.9	5.7
	α_{soil}	3.6	3.6	2	3

3.3.2. Uncertainties on the estimated variables

For the inversions on the field scale, we defined the estimation uncertainty of the variable v_p expressed as:

$$Er_{vp} = \frac{\sigma_{v_p}}{v_p} \times 100. \tag{4}$$

The small uncertainties (< 15%) for LAI, C_{ab} and θ_l (Tab. VI), show the robustness of the solution found by the inversion algorithms. Once again, they spotlight the significant impact of these variables on the reflectance. Model inadequacies for sunflower canopies (heliotropic behavior, the possible presence of flowers for some days of the experiment) may explain the less reliable estimations obtained for this species. For PROSIAPI, the estimation error of the hot spot parameter conforms with those of the other variables. On the other hand, this seems to be determined with poor accuracy for PROKUUSK and PROSAIL where s_l turns out to be a parameter allowing the control of reflectance levels during the inversion process, rather than a physically interpretable variable. As vegetation cover masks soil optical properties, the impact of the soil brightness parameter α_{soil} on the stability of χ^{2*} is weak as underlined by its low error estimations.

If one considers uncertainty as the only criterion, the most reliable estimations are found with PROSIAPI (the most complex model), in particular over alfalfa, the most "turbid" medium.

3.3.3. Interaction between the variables during the inversions

The correlation coefficient between the estimates of the two variables v_1 and v_2 gives an appraisal of the degree of interaction between the variables during the inversion process. It informs on the steadiness of the minimum of the merit function in the (v_1, v_2) space. Such a coefficient is determined from the off-diagonal elements of $\underline{\underline{V_\Theta}}$:

$$R_{v_1,v_2} = \frac{V_\Theta(v_1, v_2)}{\sigma_{v_1} \times \sigma_{v_2}}. \tag{5}$$

Table VII. Mean values of the correlation coefficients between the biophysical variables retrieved by inversion of the PROSAIL model over wheat fields.

	LAI	θ_l	s_l	α_{soil}
C_{ab}	0.07	0.07	0.19	0.06
LAI		0.53	0.26	0.17
θ_l			0.05	0.50
s_l				0

Table VII illustrates the mean values of correlation coefficients for PROSAIL inversions on wheat. The leading role of C_{ab} in the visible spectrum is recognized since correlations with the structural variables almost equal zero. Even though a significant interaction between LAI and C_{ab} has been reported in direct mode [1], the solution seems quite stable for small perturbations of C_{ab} and any of the other free variables around χ^{2*}. This is not the case for the leaf area index for which estimation stability is strongly correlated to the leaf angle ellipsoidal distribution parameter, as already observed for inversions conducted at nadir [56]. This may result from their contributions to canopy reflectance, having the same magnitudes and covering similar spectral and directional spaces [1, 3]. One also observes a strong correlation between the leaf angle and the soil brightness parameters. The lack of correlation between α_{soil} and s_l may be explained by the fact that the directional variation of the influence of these two variables is opposite, especially in the retro solar direction.

3.3.4. Impact of the spatial resolution

The issue of the spatial resolution addressed here is to determine how some field heterogeneities may worsen the estimation of the biophysical variables and explain part of the divergences mentioned above. This is illustrated with LAI and C_{ab}, two of the most informative biophysical variables for canopy physiological health. Inverting PROSAIL and PROKUUSK on POLDER data acquired with a 20 m spatial resolution is very informative about the aptitude of the models to represent the radiation regime within more heterogeneous plant canopies. PROSIAPI was discarded at this point because of the significant computer time requirements. Figure 5 shows a good correlation between the estimated variables on the field scale (LAI^f and C_{ab}^f) and the mean values of the estimates on the pixel scale (LAI^p and C_{ab}^p), the result being slightly better with PROSAIL. Changes in the observation scale have been shown to translate into altered estimates of plant canopy variables [36], since the aggregations of reflectance and the variables are linear with the

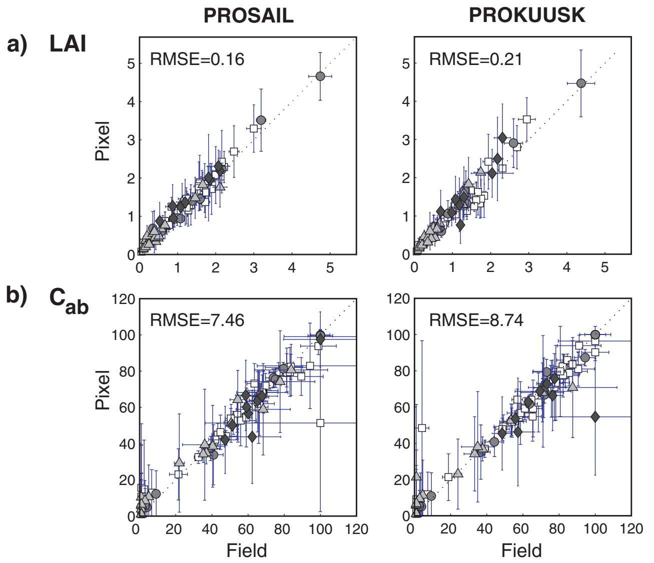

Figure 5. Comparison between field- and pixel-level estimations of (a) LAI and (b) C_{ab}, determined with PROSAIL and PROKUUSK, on □ wheat, ● maize, △ sunflower and ♦ alfalfa. The error bars on the x-axis correspond to the empirical error estimation of the corresponding variable (after Eq. (3)); on the y-axis, they correspond to the standard deviation of all the estimates for a given field ($\sigma(LAI^p)$ and $\sigma(C_{ab}^p)$).

spatial scaling whereas the variable effects are non-linear. Estimations conducted on a local area therefore produce larger values for the investigated variables than those measured on a larger scale: this trend is consistent with the results obtained for LAI and C_{ab}. It is slight, however, limiting the impact of such scale change. The standard deviation on all the estimates on the pixel scale are an appraisal of the level of heterogeneity within the fields. The increase of $\sigma(LAI^p)$ with the LAI depicts an increased spatial variability with plant development. The latter is explained by varying plant growth (this is especially the case for fields #101, 102, 107, 121, 208, 214, 217, 304 and 503) but also by approximate contour erosion: some edge pixels corresponding to morphologically different surfaces which may not have been discarded.

3.3.5. Mapping of the biophysical variables

The mapping of LAI and C_{ab} – and the corresponding estimation uncertainties – on wheat field #120 (Fig. 6) results from PROSAIL inversions on a pixel basis for the DOE 03/26, 02/05 and 09/06. It clearly shows field heterogeneity: the north-east part of the field exhibits earlier maturity as testified to by higher LAI values in March. In spite of it, the spatial variations in LAI and C_{ab} are relatively uniform, with only a few pixels exhibiting singular results and are consistent together.

For early dates, i.e., typically in March and May, the estimation uncertainties of the leaf area index and the chlorophyll content are generally below 15%. Conversely, they often exceed 40% during leaf senescence, for instance in June

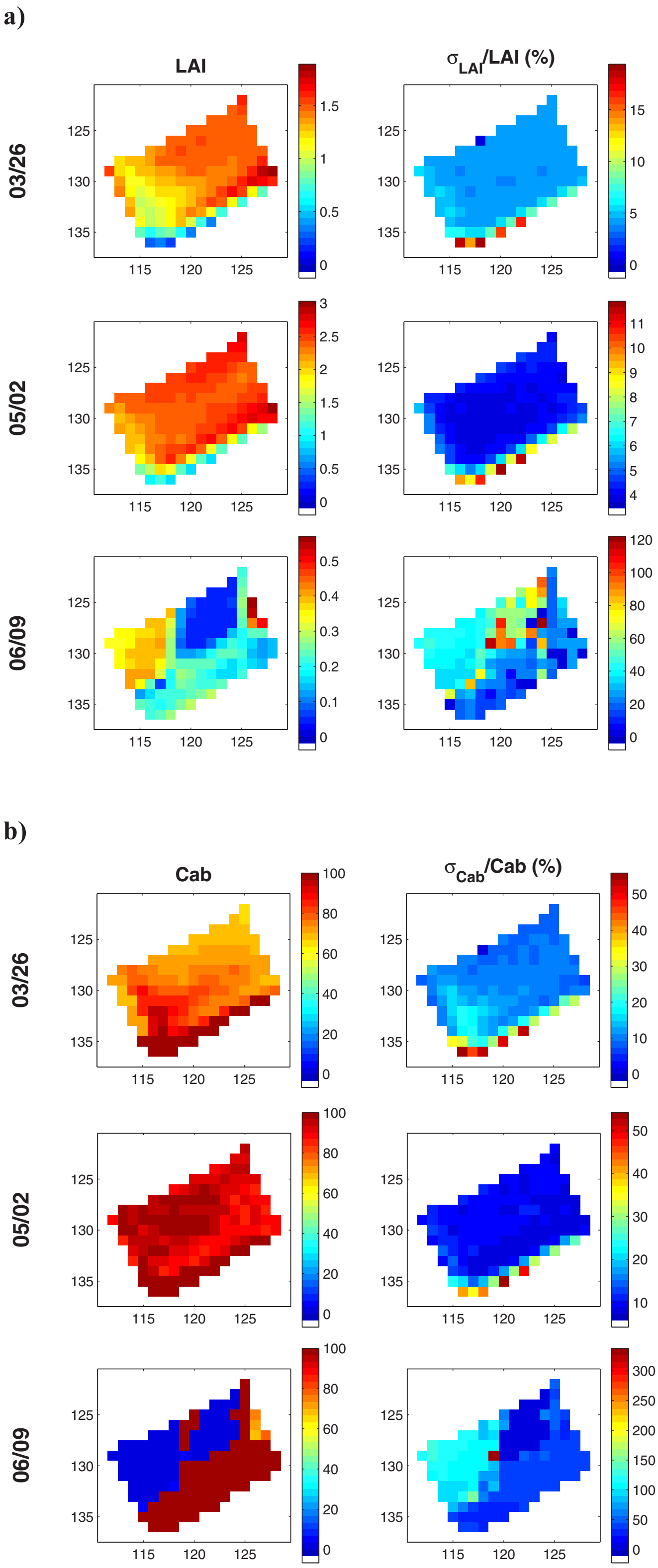

Figure 6. Mapping of (a) LAI and (b) C_{ab} estimated with PROSAIL, and the corresponding estimation uncertainties (after Eq. (4)), over wheat field #120 (03/26, 05/02 and 06/09).

when leaves are yellowing, bringing into focus the limits of the model and its inversion on such extreme cases. This translates into C_{ab} estimated values frozen at the upper and lower bounds of the definition interval. Similarly, the problematic determination of the contouring pixels shows itself at the bottom edge, where *LAI* estimates correspond to a sparse vegetation from March to June, that very likely coincides with the lane between fields #120, #134 (wheat) and #132 (tomato).

A correlation between these two variables is noteworthy: low *LAI* estimates correspond to high C_{ab} values and vice versa. It is rather tricky to decide whether this situation fits reality or whether it is an artifact resulting from a compensation effect between the variables. The latter is inherent of the radiative transfer in the canopy, since light absorption in the visible is similarly affected by an increase in the leaf chlorophyll content (considering a fixed *LAI*) and by an increase in the leaf surfaces (considering a fixed C_{ab}). The C_{ab}-*LAI* interaction probably expresses itself in inverse mode on the joint estimated values of the variables, even though it does not affect the stability of the minimum of the merit function found by the optimization algorithm (low $R_{LAI,Cab}$). Such compensations have been reported in the literature for leaf area index and other canopy variables [23]. Some authors consequently prefer to estimate the canopy contents rather than leaf contents [12, 25, 54], whatever the inversion method. These ambiguities might be bypassed by inverting the models on reflectances at chosen view and spectral configurations where the interactions between the canopy variables are minimum. This should be possible for *LAI* and C_{ab} because they impact canopy radiance in separate directions and wavelengths [2, 3]. Moreover, such optimal configurations should allow better fits between the model vs. reality and carry more information on the biophysical variables. Determination of these configurations is an issue [29] being addressed by space agencies (CNES, ESA, NASA) in order to improve the quality of remote sensing products and to define new instruments.

4. CONCLUSION

The Alpilles-ReSeDA campaign has produced a considerable amount of POLDER bidirectional and spectral reflectance data. Three CR models, PROSAIL, PROKUUSK and PROSIAPI were iteratively inverted to retrieve the biophysical properties of wheat, maize, sunflower and alfalfa crops during their vegetative growth. An inversion technique based on the quasi-Newton algorithm was used to simultaneously estimate the chlorophyll a+b content C_{ab}, the leaf area index *LAI*, the mean leaf inclination angle θ_l, the hot spot parameter s_l and a multiplicative soil parameter α_{soil}. The issue of the estimation reliability of these variables was addressed by determining the corresponding a posteriori uncertainty. The three models were shown (i) to reconstruct the BRDFs at any wavelength with similar accuracies and (ii) to accurately estimate the *LAI* compared to planimeter measurements. Inversions nevertheless tend to underestimate this variable after 2.3. The discrepancies between estimates and measurements mainly result from a weaker sensitivity of the reflectance to the *LAI* dynamics, but also from field heterogeneities that are poorly represented by the in situ measurements. The study reported difficulties interpreting some structural parameters such as θ_l and s_l, as underscored by the contradictory values estimated by the different models and by the strong estimation uncertainties. Therefore, these should be considered as control parameters that help to fit the reflectance measurements during the inversions. The interactions between the canopy variables also affected the estimation reliability, but we could not quantify their impact. On one hand, the minimum of the merit function appeared stable with respect to the joint estimation of C_{ab} and other variables (low correlation coefficients); but on the other hand, compensation effects between *LAI* and C_{ab} emerged from the spatial analyses of these variables on a pixel basis, even though the uncertainties were low. These results indicate that the ambiguities between variables are more intrinsic to the model structure than to the inversion. Finally, the special attention focused on determining the uncertainty of the estimates aimed to provide end-users with an objective quality criterion to evaluate remote sensing products.

Acknowledgments: This study was partly funded by the Programme National de Télédétection Spatiale (PNTS). The authors thank J. Iaquinta and A. Kuusk for providing the IAPI and KUUSK models, respectively and S.L. Ustin for her valuable help in improving the article.

REFERENCES

[1] Bacour C., Jacquemoud S., Tourbier Y., Dechambre M., Frangi J.-P., Design and analysis of numerical experiments to compare four canopy reflectance models, Remote Sens. Environ. 79 (2001) 72–83.

[2] Bacour C., Jacquemoud S., Vogt P., Hosgood B., Andreoli G., Frangi J.-P., Optimal sampling configurations for the estimation of canopy properties from BRDF data acquired with the EGO/JRC, in: Proc. 8th Int. Symp. Physical Measurements & Signatures in Remote Sensing, Aussois (France), Éditions du CNES, 8–12 January 2001, pp. 481–486.

[3] Bacour C., Contribution à la détermination des paramètres biophysiques des couverts végétaux par inversion de modèles de réflectance : analyses de sensibilité comparatives et configurations optimales, Ph.D. thesis, Université Paris 7–Denis Diderot, 2001, 210 p.

[4] Bard Y., Nonlinear parameter estimation, Academic Press, New York, 1974, 341 p.

[5] Baret F., Contribution au suivi radiométrique de cultures de céréales, Ph.D. thesis, Université Paris-Sud, 1986, 192 p.

[6] Baret F., Clevers J.G.P.W., Steven M.D., The robustness of canopy gap fraction estimates from red and near-infrared reflectances: a comparison of approaches, Remote Sens. Environ. 54 (1995) 141–151.

[7] Bicheron P., Leroy M., Hautecœur O., Bréon F.-M., Enhanced discrimination of boreal forest covers with directional reflectances from the airborne polarization and directionality of earth reflectances (POLDER) instrument, J. Geophys. Res.-Atmos. 102 (1997) 29517–29528.

[8] Bicheron P., Leroy M., A method of biophysical parameter retrieval at global scale by inversion of a vegetation reflectance model, Remote Sens. Environ. 67(1999) 251–266.

[9] Bréon F.-M., Vanderbilt V., Leroy M., Bicheron P., Walthall C.L., Kalshoven J.E., Evidence of hot spot directional signature from airborne POLDER measurements, IEEE Trans. Geosci. Remote Sens. 35 (1997) 479–484.

[10] Combal B., Contribution à l'analyse du problème inverse. Estimation des caractéristiques du couvert végétal à partir de mesures de télédétection, Ph.D. thesis, Université Blaise Pascal, Clermont-Ferrand, 1999, 177 p.

[11] Combal B., Baret F., Weiss M., Trubuil A., Macé D., Pragnère A., Myneni R.B., Knyazikhin Y., Wang L., Retrieval of canopy biophysical variables from bidirectional reflectance. Using prior information to solve the ill-posed inverse problem, Remote Sens. Environ. (2002), in press.

[12] Combal B., Baret F., Estimation of chlorophyll content from remote sensing observations in the solar domain, in: Proc. 8th Int. Symp. Physical Measurements & Signatures in Remote Sensing, Aussois (France), Éditions du CNES, 8–12 January 2001, pp. 461–471.

[13] Deuzé J.-L., Bréon F.-M., Roujean J.-L., Deschamps P.-Y., Devaux C., Herman M., Podaire A., Analysis of the POLDER (Polarization and Directionality of the Earth's Reflectances) airborne instrument observations over land surfaces, Remote Sens. Environ. 45 (1993) 137–154.

[14] Engelsen O., Pinty B., Verstraete M.M., Martonchik J.V., Parametric bidirectional reflectance factor models: evaluation, improvements and applications, report EUR16426EN, European Commission, Joint Research Centre, Space Applications Institute, Ispra, Italy, 1996, 120 p.

[15] Gao W., Lesht B.M., Model inversion of satellite-measured reflectances for obtaining surface biophysical and bidirectional reflectance characteristics of grassland, Remote Sens. Environ. 59 (1997) 461–471.

[16] Gemmel F., Testing the utility of multi-angle spectral data for reducing the effects of background spectral variations in forest reflectance model inversion, Remote Sens. Environ. 72 (2000) 46–63.

[17] Gobron N., Pinty B., Verstraete M.M., Govaerts Y., Theoretical limits to the estimation of the leaf area index on the basis of visible and near-infrared remote sensing data, IEEE Trans. Geosci. Remote Sens. 35 (1997) 1438–1445.

[18] Gobron N., Pinty B., Verstraete M.M., Martonchik J.V., Knyazikhin Y., Diner D.J., Potential of multiangular spectral measurements to characterize land surfaces: conceptual approach and exploratory application, J. Geophys. Res.-Atmos. 105 (2000) 17539–17549.

[19] Goel N., Thompson R.L., Inversion of vegetation canopy reflectance models for estimating agronomic variables. IV. Total inversion of the SAIL model, Remote Sens. Environ. 15 (1984) 237–253.

[20] Goel N., Inversion of canopy reflectance models for estimation of biophysical parameters from reflectance data, in: Asrar G. (Ed.), Theory and Applications of Optical Remote Sensing, Wiley Interscience, New York, 1989, pp. 205–250.

[21] Iaquinta J., Pinty B., Adaptation of a bidirectional reflectance model including the hot spot to an optically thin canopy, in: Proc. 6th Int. Symp. Physical Measurements and Signatures in Remote Sensing, Val d'Isère (France), Editions du CNES, 17–21 January 1994, pp. 683–690.

[22] Iaquinta J., Pinty B., Privette J.L., Inversion of a physically based bidirectional reflectance model of vegetation, IEEE Trans. Geosci. Remote Sens. 15 (1997) 687–698.

[23] Jacquemoud S., Inversion of the PROSPECT+SAIL canopy reflectance model from AVIRIS equivalent spectra: theoritical study, Remote Sens. Environ. 44 (1993) 281–292.

[24] Jacquemoud S., Flasse S., Verdebout J., Schmuck G., Comparison of several optimization methods to extract canopy biophysical parameters, in: Proc. 6th Int. Symp. Physical Measurements and Signatures in Remote Sensing, Val d'Isère (France), 17–21 January 1994, Éditions du CNES, 1994, pp. 291–298.

[25] Jacquemoud S., Baret F., Andrieu B., Danson F.M., Jaggard K., Extraction of vegetation biophysical parameters by inversion of the PROSPECT+SAIL models on sugar beet canopy reflectance data. Applications to TM and AVIRIS sensors, Remote Sens. Environ. 52 (1995) 163–172.

[26] Jacquemoud S., Ustin S.L., Verdebout J., Schmuck G., Andreoli G., Hosgood B., Estimating leaf biochemistry using the PROSPECT leaf optical properties model, Remote Sens. Environ. 56 (1996) 194–202.

[27] Jacquemoud S., Bacour C., Poilvé H., Frangi J.-P., Comparison of four radiative transfert models to simulate plant canopies reflectance – Direct and inverse mode, Remote Sens. Environ. 74 (2000) 471–481.

[28] Kimes D.S., Sellers P.J., Inferring hemispherical reflectance of the earth's surface for global energy budgets from remotely sensed nadir of directional radiance values, Remote Sens. Environ. 18 (1985) 205–223.

[29] Kimes D.S., Knyazikhin Y., Privette J.L., Abuelgasim A.A., Gao F., Inversion methods for physically-based models, Remote Sens. Rev. 18 (2000) 381–439.

[30] Knyazikhin Y., Martonchik J.V., Myneni R.B., Diner D.J., Running S.W., Synergistic algorithm for estimating vegetation canopy leaf area index and fraction of absorbed photosynthetically active radiation from MODIS and MISR data, J. Geophys. Res. 103 (1998) 32257–32276.

[31] Kuusk A., Scattering of direct solar radiation by the crown of a tree, Sov. J. Remote Sens. 7 (1985) 361–370.

[32] Kuusk A., A Markov chain model of canopy reflectance, Agric. For. Meteorol. 76 (1995) 221–236.

[33] Lacaze R., Roujean J.-L., Goutorbe J.-P., Spatial distribution of Sahelian land surface properties from airborne POLDER multiangular observations, J. Geophys. Res. 104 (1999) 12131–12146.

[34] Leroy M., Hautecœur O., Anisotropy-corrected vegetation indexes derived from POLDER/ADEOS, IEEE Trans. Geosci. Remote Sens. 37 (1999) 1698–1708.

[35] Leroy M., Hautecœur O., Gu X.F., Lelong C., Berthelot B., Hanocq J.-F., Balois J.-Y., The airborne POLDER data in the Alpilles/ReSeDA'97 campaign, in: Proc. XXV General Assembly of the European Geophysical Society (Nice), 25–29 Avril 2000, submitted.

[36] Liang S., Numerical experiments on the spatial scaling of land surface albedo and leaf area index, Remote Sens. Rev. 19 (2000) 225–242.

[37] Myneni R.B., Ross J., Photon-Vegetation interactions: applications in optical remote sensing and plant ecology, Springer-Verlag, New York, 1991, 565 p.

[38] Nilson T., Kuusk A., A reflectance model for the homogeneous plant canopy and its inversion, Remote Sens. Environ. 27 (1989) 157–167.

[39] Numerical Algorithm Group, Fortran library, Oxford, 1999.

[40] Prévot L., Baret F., Chanzy A., Olioso A., Wigneron J.-P., et al., Assimilation of multi-sensor and multi-temporal remote sensing data to monitor vegetation and soil: the Alpilles-ReSeDA project, in: Proc. 18th Int. Geosci. Remote Sens. Symp. IGARSS'98, Seattle (WA), USA, 1998, pp. 17–30.

[41] Privette J.L., Emery W.J., Schimel D.S., Inversion of a vegetation reflectance model with NOAA AVHRR data, Remote Sens. Environ. 58 (1996) 187–200.

[42] Privette J.L., Eck T.F., Deering D.W., Estimating spectral albedo and nadir reflectance through inversion of simple BRDF models with AVHRR/MODIS-like data, J. Geophys. Res.-Atmos. 102 (1997) 29529–29542.

[43] Qiu J., Gao W., Lesht B., Inverting optical reflectance to estimate surface properties of vegetation canopies, Int. J. Remote Sens. 19 (1998) 641–656.

[44] Rahman H., Pinty B., Verstraete M.M., Coupled Surface-Atmosphere Reflectance (CSAR) model. 2. Semi-empirical surface model usable with NOAA Advanced Very High Resolution Radiometer Data, J. Geophys. Res.-Atmos. 98 (1993) 20791–20801.

[45] Rahman H., Dedieu G., SMAC – A simplified method for the atmospheric correction of satellite measurements in the solar spectrum, Int. J. Remote Sens. 15 (1994) 123–143.

[46] Renders J.-M., Flasse S., Hybrid methods using genetic algorithms for global optimizaions, IEEE Trans. Syst. Man Cybern. 26 (1996) 243–258.

[47] Roujean J.-L., Tanré D., Bréon F.-M., Deuzé J.-L., Retrieval of land surface parameters from airborne POLDER bidirectional reflectance distribution function during HAPEX-Sahel, J. Geophys. Res.-Atmos. 102 (1997) 11201–11218.

[48] Tarantola A., Inverse problem theory. Methods for data fitting and model parameter estimation, Elsevier Science, 1987, 613 p.

[49] Verhoef W., Light scattering by leaf layers with application to canopy reflectance modeling: the SAIL model, Remote Sens. Environ. 16 (1984) 125–141.

[50] Verhoef W., Earth observation modeling based on layer scattering matrices, Remote Sens. Environ. 17 (1985) 165–178.

[51] Vermote E.F., Tanré D., Deuzé J.-L., Herman M., Morcrette J.-J., Second simulation of the satellite signal in the solar spectrum, 6S: an overview, IEEE Trans. Geosci. Remote Sens. 35 (1997) 675–686.

[52] Verstraete M.M., Pinty B., Dickinson R.E., A physical model of the bidirectional reflectance of vegetation canopies. 1: Theory, J. Geophys. Res.-Atmos. 95 (1990) 765–775.

[53] Weiss M., Développement d'un algorithme de suivi de la végétation à large échelle, Ph.D. thesis, Université Nice-Sophia Antipolis, 1998, 188 p.

[54] Weiss M., Baret F., Evaluation of canopy biophysical variable retrieval performances from the accumulation of large swath satellite data, Remote Sens. Environ. 70 (1999) 293–306.

[55] Weiss M., Baret F., Leroy M., Bégué A., Hautecœur O., Santer R., Hemispherical reflectance and albedo estimates from the accumulation of across-track sun-synchronous satellite data, J. Geophys. Res.-Atmos. 104 (1999) 22221–22232.

[56] Weiss M., Baret F., Myneni R.B., Pragnère A., Knyazikhin Y., Investigation of a model inversion technique to estimate canopy biophysical variables from spectral and directional reflectance data, Agronomie 20 (2000) 3–22.

[57] Weiss M., Baret F., Leroy M., Hautecœur O., Bacour C., Prévot L., Bruguier N., Validation of neural net techniques to estimate canopy biophysical variables from remote sensing data, Agronomie 22 (2002) 547–553.

[58] Zhang Y., Tian Y., Knyazikhin Y., Martonchik J.V., Diner D.J., Leroy M., Myneni R.B., Prototyping of MISR LAI and FPAR algorithm with POLDER data over Africa, IEEE Trans. Geosci. Remote Sens. 38 (2000) 2402–2418.

To access this journal online:
www.edpsciences.org