A comparative approach for the retrieval of leaf area index from Earth observation data

FRANCESCO VUOLO[1], **GUIDO D'URSO**[1] **& LUIGI DINI**[2]

1 *Dept Agricultural Engineering and Agronomy, University of Naples "Federico II", via Università, 100, 80055 Portici (NA), Italy*
durso@unina.it

2 *ASI, Centro di Geodesia Spaziale, Unità Applicativa Osservazione della Terra, c.p. 11–75100 Matera Italy*

Abstract The use of Earth Observation data to retrieve biophysical parameters of the land surface such as Leaf Area Index has proven to be useful in many operational tools to repetitively gather information at spatial and temporal resolutions suitable for agricultural applications. The main objective of this work is to exploit the rich information content of CHRIS/PROBA data, in both directional and spectral domains, to estimate *LAI*. Inversion of a canopy reflectance model was performed and results compared, in terms of accuracy and operational practicability, to a more empirical approach. Results show that the directional information content improves *LAI* estimation for two out of three of the analysed crops. For the best case (corn), a RMSE of 0.4 was achieved by using 5 angles and 62 spectral bands with an improvement of almost 65% relative to 1 angle and 17 bands. Finally, the accuracy of the *LAI* estimates for the two approaches was demonstrated to be comparable.

Key words CHRIS/PROBA; *LAI* retrieval; model inversion; multi-angular imagery; SPARC; vegetation index

INTRODUCTION

Water managers and irrigation engineers need to have accurate and precise estimates of evapotranspiration (ET) to make decisions on water allocation and to design irrigation infrastructures. Currently, the most used approach for estimating ET is the so-called "Kc ETo" methodology suggested by the Food and Agriculture Organization (FAO) (Jensen, 1990; FAO, 1998). In order to apply this methodology operationally it is necessary to have accurate measurements of weather parameters (wind speed, air temperature, humidity, solar radiation) as well as accurate estimates of vegetation characteristics such as canopy surface albedo, crop height and Leaf Area Index (*LAI*). Earth observation data are definitely a cost-effective source of information to retrieve vegetation parameters required for Kc calculation over both spatial and time scales.

Two main approaches were used to estimate *LAI* from reflective optical measurements (Verstraete *et al*., 1996): (1) based on empirical–statistical relationships between *LAI* and vegetation indices; and (2) on the inversion of canopy reflectance models (CRM)

Most vegetation indices combine information in two spectral broad bands: in the red (R) and near-infrared (NIR) wavelength region. Despite the large effort in improving the performance of such empirical formulas, they still present limitations since they are site and sensor specific, and they require a reliable ground reference data set for calibration and saturate quickly, becoming insensitive to variations of *LAI* at high

LAI-values (Curran, 1994; Gobron *et al*., 1997). Moreover, vegetation indices do not take into account that the canopy reflectance depends on the canopy geometry (leaf angle distribution, leaf distribution, row orientation, and spacing), leaf and soil optical properties, sun position and view observation (Huete, 1987; Bacour *et al*., 2002).

Alternative approaches based on the inversion of canopy reflectance models (review in RAMI, Pinty *et al*., 2000) represent a challenging opportunity for the estimation of *LAI* from remotely sensed data with high dimensionality, both in the spectral and the directional domains. On the one hand, they better characterize the anisotropy of the surface reflectivity and exploit the full spectrum obtained by multi-angular and hyper-spectral sensors. On the other, the parameter retrieval performance depends on both the inversion algorithms (Kimes *et al*., 2000) and the model accuracy.

Furthermore, the inversion of CRM is by nature an ill-posed problem, since different model parameter combinations may produce almost identical spectra (D'Urso *et al*., 2004a). Different methodologies can be found in literature for the regularization of this problem (review in CROMA, 2000; Atzberger, 2002, 2004; Combal *et al*., 2002). The main objective of the paper is to exploit the rich information content of CHRIS/PROBA data, both in the directional and spectral domains, to estimate *LAI*. For this purpose, inversion of a CRM was performed and results compared in terms of accuracy and operational practicability, to a more empirical approach.

SATELLITE AND GROUND DATA

The data used in this study were acquired in the context of the first ESA Spectra Barrax Campaign (SPARC) (Moreno *et al*., 2004). Satellite and ground measurements were collected over Barrax (N30°3′, W2°6′), an agriculture test area situated within La Mancha region in the south of Spain, from 12 to 14 July 2003. The area has been a favourite location for agricultural research for many years due to its flat topography (elevation differences ranging only 2 m) and to the presence of large and uniform vegetation fields (e.g. alfalfa, corn, sugar beet, onions, garlic, potatoes), with *LAI* ranging from 0.5 to 6.5. For this study, 32 samples of alfalfa (9), corn (15) and potato (8) were considered. During the campaign a large amount of ground measurements of *LAI*, leaf chlorophyll, water and dry matter content were carried out, together with other complementary data. A total of five hyper-spectral and multi-angular CHRIS/PROBA images were acquired for this period as well.

Satellite data

For this study, we worked on a set of five hyper-spectral consecutive CHRIS/PROBA images collected on 14 July 2003 at 11:30 h GMT, at five different view angles, during a single orbital pass. These images ("A1", "A2", "A3", "A4", "A5") were acquired in Mode-1 with a spectral resolution of 62 bands over the visible/NIR bands from 400 to 1050 nm, with a spectral sampling interval ranging between 1.25 (at 400 nm) and 11 nm (at 1000 nm) in a spatial resolution of 34 m (see satellite handbook for more details). The acquisition geometry for the images is shown in Table 1.

Table 1 CHRIS/PROBA acquisition geometry.

Geometry	Satellite acquisitions				
	A1	A2	A3	A4	A5
VZA	57.2	42.4	27.6	42.5	57.4
VAA	353.7	339.4	285.2	231.2	216.9
SZA	19.8				
SAA	148.3				

VZA and VAA: View Zenith and Azimuth Angles; SZA and SAA: Sun Zenith and Azimuth Angles.

The image closer to nadir, "A3", was acquired with a view zenith angle of 27.6°. Radiometric calibration, atmospheric and geometric correction of CHRIS imagery was performed by the Department of Thermodynamics, University of Valencia. Since important calibration problems were reported in several CHRIS channels, a dedicated atmospheric correction algorithm was applied along with radiometric calibration, without the need for any ancillary data (Guanter *et al*., 2005).

Ground measurements

During the SPARC campaign, a large amount of ground measurements of *LAI*, leaf chlorophyll, water and dry matter content ground measurements were collected in the Barrax study area (Fernández *et al*., 2005)

Field non-destructive measurements of *LAI* and Mean Tilt Angle (MTA) were made by means of the digital analyzer LI-COR *LAI*-2000 (LI-COR, 1992); the manufacturer's recommendations were followed in deciding sampling strategy. In order to reduce the effect of multiple scattering on *LAI*-2000 measurements, the instrument was only operated near dawn and dusk (06:30–09:30 h; 18:30–20:30 h) and under diffuse radiation conditions, using one sensor for both above and below canopy measurements. *LAI* values are the result of averaging 24 individual measurements taken randomly within an area of approximately 15 × 15 m^2 (Elementary Sampling Unit, ESU). In order to prevent interference caused by the operator's presence and the illumination condition, the sensor field of view was limited with a 180° view-cap. Both measurements were azimuthally oriented opposite to the sun azimuth angle.

Measurements of dry matter and water content were also carried out on three samples per ESU. Each sample was weighed within a few hours and digital photographs of the leaves were taken over graph paper for the calculation of the leaf area. Samples were dried at 70ºC, until constant weight was reached, and then reweighed. The leaf chlorophyll content was measured with the CCM-200 Chlorophyll Content Meter (Gandia *et al*., 2005).

METHODOLOGY

For the purpose of this study, two well known reflectance models were used: the PROSPECT model (Jacquemoud *et al*., 1990) for the simulation of the leaf reflectance and transmittance, and the one-dimensional canopy reflectance model SAILH

(Verhoef, 1984, 1998), adapted to take hotspot effects and multiple scattering in the canopy into account (Kuusk, 1991). The combination of these two algorithms, indicated here as the PSH model, was selected on the basis of results from the RAMI experiment (Pinty *et al*., 2000) and tested in forward mode. Comparison between model output and CHRIS data showed satisfactory results (D'Urso *et al*., 2004a,b).

To understand the contribution of directional information in *LAI* estimation, the PSH model was inverted by using one, three and five view angles. In order to reduce redundancy in the spectral domain, the experiment was initially performed with the full set of 62 CHRIS bands. The procedure was repeated with 17 bands (according to the results of previous literature (Thenkabail *et al*., 2004), and finally with 4 bands, similar to Landsat-TM spectral configuration.

To compare the physical approach based on the PSH model with an empirical method using vegetation indices, the relationship between the Weighted Differences Vegetation Index and *LAI* (CLAIR model, Clevers, 1989) was tested. The view-angle closest to nadir ("A3") in the red (24) and infrared (42) bands was considered. The CLAIR model was calibrated by using ad-hoc ground-measured *LAI* values taken at the time of a CHRIS/PROBA overpass. For each of the experiments, the *LAI* accuracy is evaluated in terms of root mean square error ($RMSE_{LAI}$) and relative percentage error (RPE_{LAI}).

The PROSPECT and SAILH Models

The SAILH model (Verhoef, 1984, 1998) assumes the canopy as a horizontal, homogenous and infinitely extended vegetation layer (turbid medium), made up of Lambertian scatterers (leaves) randomly distributed within the canopy. The radiative transfer equation is solved by the four-stream approximation method: ascending and descending fluxes of direct and diffuse radiation are considered.

The SAILH model requires few parameters such as single leaf hemispherical reflectance and transmittance (ρ, τ), leaf area index (*LAI*), average leaf angle (ALA), geometric parameters (the solar zenith, the view zenith angles and the azimuth angle between sun and observer, hotspot parameter (hot), introduced by Kuusk (1991), the fraction of diffuse radiation (E_{sky}) and soil hemispherical reflectance (α_{soil}). A reflectance factor (α_{soil}) was introduced to scale the mean measured soil spectrum accounting for variances in soil brightness.

The PROSPECT model (Jacquemoud *et al*., 1990) provides the leaf hemispherical reflectance and transmittance to the SAILH model as a function of the leaf structural parameter (*N*), the leaf chlorophyll a + b concentration (Chl_{a+b}), the equivalent water thickness (C_w) and the dry matter content (C_m).

The CLAIR Model

The CLAIR model (Clevers, 1989) is based on the logarithmic relation between *LAI* and the *WDVI*. It assumes that all parameters are constant, except *LAI* and soil brightness:

$$LAI = -\frac{1}{\alpha^*}\ln\left(1 - \frac{WDVI}{WDVI_\infty}\right) \tag{1}$$

where α^* is an extinction coefficient, expressing the increase of LAI for a unitary of $WDVI$. It has to be estimated from simultaneous measurements of LAI and $WDVI$. $WDVI_\infty$ expresses the asymptotical value of $WDVI$ for $LAI \rightarrow \infty$.

$$WDVI = \rho_{42} - \rho_{24}\frac{\rho_{s42}}{\rho_{s24}} \tag{2}$$

where ρ_{42} and ρ_{24} indicate the reflectance of the observed canopy in red and infrared bands respectively, while ρ_{s42} and ρ_{s24} are the corresponding values for bare soil conditions. The ratio ρ_{s42}/ρ_{s24} can be taken as constant, in analogy with the "soil line concept" (Baret *et al*., 1993).

Model inversion, parameterization and set-up

A traditional optimization Marquardt-Levenberg (M-L) algorithm (Levenberg, 1944; Marquardt, 1963) was implemented in order to retrieve LAI by inverting the PSH model. The solution is achieved by iteratively running the PSH model in direct mode and comparing the model output with the acquired CHRIS spectra until an optimal parameter set is found. To this end, a cost function depending on simulated and observed reflectance data was defined as follows:

$$C = \sum_{i=1}^{nb}\sum_{j=1}^{nd}(\rho_{i,j,obs} - \rho_{i,j,\mathrm{mod}})^2 \tag{3}$$

In the objective function (3) nb is the number of spectral bands, nd is the numbers of view directions and ρ_{mod} expresses the modelled reflectance for the sun-sensor geometry corresponding to the observed reflectance ρ_{obs}.

The inversion of CRM models is by nature an ill-posed problem since different model parameter combinations may produce almost identical spectra (Combal *et al*., 2002). Baret *et al*. (Baret & Guyot, 1991; Atzberger, 2002, 2004), for instance, have demonstrated that the spectral reflectance of sparse canopy with mostly horizontal leaf orientation is similar to a dense canopy with mostly vertical leaf orientation. Simultaneous directional observations, which better characterize the anisotropy of the vegetation, should contribute to decouple the counterbalancing effect between LAI and ALA on spectral signal. In this sense, multi-directional information should smooth the ill-posed problem. Thus, the only regularization taken into account in this study was a physical coherent bound on the parameter values.

To start off the inversion process the M-L algorithm needs an initial set of parameter values as well as their lower and upper bounds (summarized in Table 2).

The N and HOT parameters values bounds were left as broad as possible since no field measurements is possible to perform due to their uncertain physical nature. Chl_{a+b} is allowed to vary between 30 and 70, C_w between 0.015 and 0.1 and C_m between

Table 2 Input parameters, units, initial values and bounds.

Parameters	Units	Initial values	Lower bounds	Upper bounds
N	–	1.3	1.3	2.0
Chl_{a+b}	μg cm^{-2}	30.0	30.0	70.0
C_w	g cm^{-2}	0.015	0.015	0.100
C_m	g cm^{-2}	0.001	0.001	0.010
LAI	m^2 m^{-2}	0.1	0.1	6.5
HOT	–	0.0	0.0	1.0
ALA	deg.	30	30	80
α_{soil}	–	0.80	0.80	1.20

0.001 and 0.01. The parameter settings take into account field and intra-fields variability from *in situ* measurements, and were then conservatively broadened.

The input soil reflectance is calculated by averaging spectral samples of soils measured by means of a field spectrometer during the campaign. A wavelength-independent scaling factor, α_{soil}, was left free to vary in a range of ±20% from the mean. The E_{sky} parameter (diffuse irradiance) was fixed to 0.16 independent of the wavelength considering local irradiance measurements. The parameters to be retrieved by model inversion, *LAI* and *ALA*, were allowed to vary in the range 0.1–6.5 and 30°–80° (starting point 0.1 and 30°), respectively.

RESULTS AND DISCUSSION

LAI root mean square error ($RMSE_{LAI}$) and relative percentage error (RPE_{LAI}) trend is reported in Tables 3, 4 and 5 for alfalfa, corn and potato, respectively.

Going from left to right, in each table the $RMSE_{LAI}$ and RPE_{LAI} values were shown corresponding to one angle (“A3”), three angles (“A1”,“A3”, “A5”) and five angles (“A1”,“A2”, “A3”, “A4” and “A5”). From up to down the values corresponding to 4 (LANDSAT-TM configuration), 17 (441, 542, 563, 583, 605, 664, 674, 694, 706, 718, 731, 745, 758, 773, 780, 831 and 889 nm) and 62 (full CHRIS data set) spectral bands are shown.

Table 3 *LAI* root mean square error ($RMSE_{LAI}$) and relative percentage error (RPE_{LAI}) trend.

Alfalfa		1	3	5	View angles
Spectral Bands	4	0.71	0.49	0.44	
	17	0.82	0.61	0.49	
	62	0.76	0.59	0.41	
					$RMSE_{LAI}$
		1	3	5	View angles
Spectral Bands	4	24.5%	23.1%	18.5%	
	17	25.6%	25.7%	21.1%	
	62	24.4%	25.3%	18.8%	
					RPE_{LAI}

Table 4 *LAI* root mean square error ($RMSE_{LAI}$) and relative percentage error (RPE_{LAI}) trend.

Corn		1	3	5	View angles
Spectral Bands	4	1.42	1.31	1.25	
	17	1.57	0.54	0.58	
	62	0.76	0.59	0.41	
					$RMSE_{LAI}$
		1	3	5	View angles
Spectral Bands	4	38.4%	32.9%	30.6%	
	17	41.1%	14.1%	14.0%	
	62	31.4%	13.1%	12.9%	
					RPE_{LAI}

Table 5 *LAI* root mean square error ($RMSE_{LAI}$) and relative percentage error (RPE_{LAI}) trend.

Potato		1	3	5	View angles
Spectral Bands	4	3.21	3.18	3.14	
	17	3.45	3.29	3.10	
	62	3.46	3.37	2.98	
					$RMSE_{LAI}$
		1	3	5	View angles
Spectral Bands	4	59.8%	59.3%	58.3%	
	17	64.3%	61.5%	57.5%	
	62	64.5%	62.9%	55.3%	
					RPE_{LAI}

In the alfalfa case and even more of the corn, the *LAI* estimation accuracy improves for each fixed spectral configuration when we add directional information. The inclusion of additional spectral bands does not improve *LAI* estimation accuracy for alfalfa. However, for corn, we do observe a significant increase in estimation accuracy going from 4 to 17 spectral bands, although the increase is less evident going from 17 to 62 spectral bands. Considering these results, the contribution of directional information seems to be more marked for the estimation performance of *LAI* than the spectral dimensionality.

Concerning the *LAI* accuracy analysis for potato crops, the results indicate the impossibility to achieve reasonable values by using model inversion. Looking at field book notes and photos, reasons may be related to the agronomic practices of growing potato: during the satellite overpass the potato field revealed deep grooves, partly filled with water. Further investigations are required. Perhaps additional restrictions on the soil reflectance should be considered in the model inversion parameterization.

For the CLAIR model approach, calibration and validation of equation (1) was performed by using two independent data sets of *LAI* measurements collected during the campaign. The value of soil-line slope coefficient was calculated resulting in a value of 1.10 (ρ_{s42}/ρ_{s24}), with $\alpha^* = 0.4$ and $WDVI_\infty = 64$. $RMSE_{LAI}$ and RPE_{LAI} are reported for each crop in Table 6.

Table 6 *LAI* estimation accuracy by using CLAIR model.

Crop	$RMSE_{LAI}$	RPE_{LAI}
Alfalfa	0.68	35.3%
Corn	0.45	9.0%
Potato	0.67	12.1%

Comparison of the two approaches for alfalfa, using similar spectral and directional information, the $RMSE_{LAI}$ values are relatively similar: 0.68 (CLAIR, 1 angle, 2 bands) and 0.71 (PSH, 1 angle, 4 bands). With the best angular and spectral sampling (5 and 62, respectively), the physical approach improves the accuracy slightly less than 25%. As for corn, with similar information contents, the CLAIR model performs better than the PSH inversion: 0.45 (CLAIR, 1 angle, 2 bands) and 1.42 (PSH, 1 angle, 4 bands). Only by using 5 angles and 62 bands, does model inversion provide comparable results to the empirical approach. For potato, in all cases the vegetation index approach performs better than the inversion of the PSH model.

CONCLUSIONS

The CHRIS/PROBA mission and the ESA SPARC campaign have given us the unique opportunity to exploit the high spatial and spectral multi-angular imagery. This data set has been used to assess the importance of the directional information on the *LAI* estimation accuracy. Moreover, a comparison analysis between an empirical *vs* a physical approach has been carried out. Results show that the directional information content improves *LAI* estimation for two out of three of analysed crops. In the best case (corn) it achieved a *LAI* RMSE of 0.41 by using 5 angles and 62 spectral bands with an improvement of almost 65% respect to 1 angle and 17 bands.

It also seems that the directional is predominant on the spectral information, suggesting in the future the design of space-borne instruments with better capabilities to sample the surface reflectance anisotropy.

From an operational point of view, results obtained by inverting PSH model and exploiting the full CHRIS data are better or comparable to the ones from the empirical approach. The inversion process results are highly demanding in terms of computational time and parameterization complexity; however, it does not require any field measurements to be calibrated, unlike the empirical approaches.

REFERENCES

Atzberger, C. (2002) Object-based retrieval of structural and biochemical canopy characteristics using SAIL+PROSPECT canopy reflectance model: A numerical experiment. In: *Recent Advances in Quantitative Remote Sensing* (ed. by J. Sobrino), 129–138. Publications de la Universitat de València, Spain.

Atzberger, C. (2004) Object-based retrieval of biophysical canopy variables using neural nets and radiative transfer models. *Remote Sens. Environ.* **93**, 53–67.

Bacour, C., Jacquemoud, S., Leroy, M., Hautecoeur, O., Weiss, M., Prévot, L., Brugueir, N. & Chauki, H. (2002) Reliability of the estimation of vegetation characteristics by inversion of three canopy reflectance models on airborne POLDER data. *Agronomie* **22**, 555–565.

Baret, F. & Guyot, G. (1991) Potentials and limits of vegetation indices for *LAI* and APAR assessment. *Remote Sens. Environ.* **35**, 161–173.

Baret, F., Jacquemoud, S. & Hanocq, J. F. (1993) About the soil line concept in remote sensing. *Adv. Space Res.* **13**(5), 281–284.

Clevers, J. G. P. W. (1989) The application of a weighted infrared-red vegetation index for estimating leaf area index by correcting for soil moisture. *Remote Sens. Environ.* **29**, 25–37.

Combal, B., Baret, F., Weiss, M., Trubuil, A., Macé, D. & Pragnère, A. (2002) Retrieval of canopy biophysical variables from bidirectional reflectance using prior information to solve the ill-posed inverse problem. *Remote Sens. Environ.* **84**, 1– 15.

Curran, P. J. (1994) Imaging spectrometry. *Progr. Phys. Geogr.* **18**(2), 247–266.

CROMA (2000) Crop reflectance operational models for agriculture. Description of work. Energy, Environment and Sustainable Development work programme, EF5/PhD/0035.00

D'Urso, G., Dini, L.,Vuolo, F. & Guanter, L. (2004a) Preliminary Analysis and Modelling of BRDF on CHRIS/PROBA Data from SPARC 2003. *Rivista Italiana di Telerilevamento* **2**, 1015–1020.

D'Urso, G., Dini, L., Vuolo, F., Alonso, L. & Guanter, L. (2004b) Retrieval of Leaf area index by inverting hyper-spectral, multi-angular CHRIS/PROBA Data from SPARC 2003. In: *Proc. 2nd CHRIS/Proba Workshop ESA/ESRIN* (Frascati, Italy).

FAO (1998) Crop evapotraspiration. Guidelines for computing crop water requirements. *Irrigation and Drainage, Paper* 56.

Fernández G., Moreno, J. , Gandía, S., Martínez, B., Vuolo F. & Morales F. (2005) Statistical variability of field measurements of biophysical parameters in SPARC-2003 and SPARC-2004 data campaigns. In: *Proc. SPARC final Workshop WPP-250*.

Gandia, S., Fernández, G. & Moreno, J. (2005) Chlorophyll content measurements in the SPARC campaigns. In: *Proc. SPARC final Workshop WPP-250*.

Gobron, N., Pinty, B. & Verstraete, M. M. (1997) 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**(6), 1438–1445.

Guanter, L., Alonso, L. & Moreno, J. (2005) A method for the surface reflectance retrieval from PROBA/CHRIS data over land: application to ESA SPARC campaigns. *IEEE Trans. Geosci. Remote Sens.* **43**(12), 2908–2917.

Huete, A. R. (1987) Soil and sun angle interactions on partial canopy spectra. *Int. J. Remote Sens.* **8**, 1307–1317.

Jacquemoud, S. & Baret, F. (1990) PROSPECT: A model of leaf optical properties spectra. *Remote Sens. Environ.* **34**, 75–91.

Jensen, M. E., Burman, M. E. & Allen, R. G. (1990) *Evapotranspiration and Irrigation Water Requirements*. ASCE Manual.

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

Kuusk, A. (1991) The hot spot effect in plant canopy reflectance. In: *Photon–Vegetation Interactions* (ed. by R. B. Myneni & J. Ross), 139–159. Springer-Verlag, London UK

Levenberg, K. (1944) A method for the solution of certain problems in least squares. *Quart. Appl. Math.* **2**, 164–168.

LI-COR (1992) *LAI*-2000 plant canopy analyzer instruction manual. LI-COR, Lincoln, Nebraska, USA.

Marquardt, D. (1963) An algorithm for least-squares estimation of nonlinear parameters. *SIAM J. Appl. Math.* **11**, 431–441.

Moreno J. (2004) The SPECTRA Barrax Campaign (SPARC): an overview and first results from CHRIS data. In: *Proc. the 2nd CHRIS/Proba Workshop*.

Pinty, B., Gobron, N., Widlowski, J.-L., Gerstl, S. A. W., Verstraete, M. M., Antunes, M., Bacour, C., Gascon, F., Gastellu, J.-P., Goel, N., Jacquemoud, S., North, P., Qin, W. & Thompson, R. (2000) The RAdiation transfer Model Intercomparison (RAMI) exercise. *J. Geophys. Res.* IWMMM-2.

Thenkabail, P. S., Enclona, E. A., Ashton, M. S., Van Der Meer, B. (2004) Accuracy assessments of hyperspectral waveband performance for vegetation analysis applications. *Remote Sens. Environ.* **91**, 354–376.

Verhoef, W. (1984) Light scattering by leaf layers with application to canopy reflectance modelling: The SAIL model, *Remote Sens. Environ.* **16**, 125–141.

Verhoef, W. (1998) Theory of radiative transfer models applied in optical remote sensing of vegetation canopies. PhD Thesis, National Aerospace Laboratory, Amsterdam, The Netherlands.

Verstraete, M. M., Pinty, B. & Myneni, R. B. (1996) Potential and limitations of information extraction on the terrestrial biosphere from satellite remote sensing. *Remote Sens. Environ.* **58**, 201–214.