ASSESSMENT OF LAI RETRIEVAL ACCURACY BY INVERTING A RT MODEL AND A SIMPLE EMPIRICAL MODEL WITH MULTIANGULAR AND HYPERSPECTRAL CHRIS/PROBA DATA FROM SPARC

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Abstract

The objective of this study was to investigate an innovative approach for the estimation of Leaf Area Index (LAI) from EO data. To this aim multiangular CHRIS/PROBA data, from SPARC 2003 and 2004, were used in the inversion of PROSPECT-SAILH models using a numerical optimization technique based on Marquardt-Levenberg algorithm. The optimal spectral sampling to estimate LAI was investigated using a sensitivity analysis. From the same data set, the reflectance in the red and near-infrared bands, from the closer to nadir image, was considered in order to estimate the LAI using an empirical approach based on the CLAIR model. The LAI obtained from the empirical approach was finally employed as prior information in the physical based model. LAI values retrieved with the combined approaches were realistically estimated with a good accuracy (RMSE is 0.51 m^2m^{-2}).

1. INTRODUCTION

Biosphere is one of the main components of the Earth's system since it regulates exchanges of energy and mass fluxes at the soil, vegetation and atmosphere level. Global Circulation Models (GCMs), carbon cycle models and water models all use, as input, vegetation biophysical and biochemical parameters for describing those fluxes [1] [2]. Same parameters play also a critical role, on a much smaller scale, in precision farming and water management to describe the state of plants development and water needs.

Hydrological models for the simulation of water flows in the soil-crop system need the characterisation of the canopy, based on variables such as Leaf Area Index (LAI), surface albedo, and crop height. For example, evapotranspiration fluxes for crops can be estimated, for given climatic conditions, knowing the cited canopy variables accordingly to the FAO methodology [3] [4].

New generation of satellite remote sensing sensors like CHRIS (Compact High Resolution Imaging Spectrometer) on PROBA platform [5] have hyperspectral and multi-angular capabilities, which allow for a complete exploitation of the spectral and directional information of the canopy radiometric measurements. From these data canopy variables can be estimated with a higher level of accuracy than usual methods and with little need for calibration of empirical functions [6] [7]. To this end complex reflectance models have been investigated in the recent past in order to describe the radiative fluxes from soil trough canopy and atmosphere up to the sensor [8]. Most of them are suitable to be used in inverse mode for physically-based estimation of canopy parameters from hyperspectral and multiangular observations.

In this study, the well known PROSPECT and SAILH models have been set in inverse mode with multiangular and hyperspectral CHRIS/PROBA data collected over Barrax, a test area in the south of Spain. Data collected during the SPARC in July 2003 and 2004 included extensive collection of canopy biophysical parameters. The main goal of the study will thus be to assess the accuracy of LAI retrieval achieved with a model inversion techniques based on Marquardt-Levenberg optimisation algorithm using a prior information obtained from an uncalibrated empirical LAI-Vegetation Index (LAI-VI) relationship (CLAIR model).

2. MATHERIALS AND METHODS

The SPARC campaign was carried out in 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 and from 14 to 16 July 2004.

The area has been analysed for agricultural research for many years thanks to its flat topography (differences in elevation range up to 2 m only). The land cover is dominated by large, uniform stands of alfalfa, corn, sugar beet, onions, garlic and potatoes. Around 35% of the area is irrigated while the remaining 65% is dry land.

Hyperspectral, multiangular images were acquired by CHRIS/PROBA on 12 and 14 July 2003 with overpass times 11:07 and 11:32 (UT) (minimum satellite zenith angle 19,4° and 27,6°) respectively and on 16 July 2004 (minimum satellite zenith angle 8,4°) with overpass times 11:24 (UT). Five images with different view angles Tab. 1 (along-track zenith angles) and 62 spectral bands (from 410 nm to 1050 nm) per angle were acquired for each pass. The covered image area is 14 km x 14 km (748 X 748 pixels) with a spatial resolution of 36 m (acquired in Mode 1).

	Minimum satellite zenith angle				
12/07/2003	56,0	38,8	19,4	39,2	56,2
14/07/2003	57,3	42,4	27,6	42,5	57,4
16/07/2004	55,2	36,6	8,4	36,6	55,2

Tab. 1. CHRIS/PROBA acquisition during SPARC

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2.1. Ground measurements

Field non-destructive measurements of LAI and Mean Tilt Angle (MTA) were made by means of the digital analyser Li-cor LAI-2000 [9]; the manufacturer's recommendations were followed in deciding a measurement plan. For reducing the effect of multiple scattering on LAI-2000 measurements, the instrument was only operated near dusk and dawn (6:30-9:30 am; 6:30-8:30 pm) under diffuse radiation conditions using one sensor for both above and below canopy measurements. 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.

LAI measurements were taken with the instrument held a few centimeters above the soil within the days of image data acquisition. One measurement of ambient light was made with the sensor extended upward and over the top of the canopy at arm's length. Eight below-canopy readings were then made. This pattern was repeated three times per spot, and the resulting twenty-four samples comprise one full set of measurements in each Elementary Sampling Unit (ESU). Finally, the centre of each ESU was geolocated by using GPS. This protocol yield a low Standard Error of measurement to assure 90% to 95% confidence interval.

Leaf chlorophyll content, dry matter and water content were also measured. They were analysed and delivered from a team of the University of Valencia.

Measurements of LAI and leaf chlorophyll content were carried out again in the laboratory from destructive samples in order to validate those taken in situ by a chlorophyll content meter (CCM-200; Opti-Sciences, Inc.) showing a good correlation between the two data sets [10].

3. LAI RETRIEVAL

Two different approaches have been selected in the retrieval of the LAI. First, a semi-empirical relationship between the Weighted Differences Vegetation Index WDVI and LAI [11] has been calibrated and tested with the available spectral information from the closer to nadir images. The second method used is based on the inversion of the PROSPECT [12] and SAILH [13] [14] models (PHS). The models have been tested in forward mode and the results were compared to CHRIS data in a previews work [15] [16].

3.1. Spectral Vegetation Index (VI)

Several optical indices have been reported in literature and have been proven to be well correlated with LAI [17] [18] [19]. The WDVI, a simpler index related to orthogonal-based VIs, was chosen since it has been used for many years in our laboratories and so well know.

For estimation of LAI was chosen the simplified model CLAIR based on the WDVI. We assume that all parameter except LAI and soil brightness are constant. An advantage of a simple semi-empirical model is that its inversion is very easy. A disadvantage is that it has to be re-calibrated for each new crop type and for each measurement condition. When changes in LAI are accompanied by systematic changes in other parameters like leaf slope and leaf colour, the near-exponential reletinship between WDVI and LAI does not longer hold, so the model is not applicable[11].

3.2. Radiative transfer models

In order to simulate the top of the canopy reflectance we have chosen the PROSPECT model for the simulation of the leaf optical properties coupled to the one-dimensional canopy reflectance model SAILH adapted to take into account the hotspot effect or the multiple scattering in the canopy [20].

Two fundamental criteria have led us to choose PSH model: i) simplicity, i.e. the possibility to have a rather good representation of the radiative transfer of the canopy using a relatively small amount of input parameters as well as limited computational requirements, and ii) reliability since the SAILH model has been successfully tested for a large set of crops, among which corn [21] and sugar beet [22] which were present in our study-area.

The SAILH model assumes the canopy made of a uniform infinitely extended turbid medium, with infinitely small Lambertian scatterers 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. A major limitation of SAILH model is that it badly takes into account vegetation architecture. It results that simulated reflectance of structured system as corn or of sugerbeet that has narrow leaves could be erroneous. The PROSPECT model assumes a uniform distribution of water and pigments throughout the leaves, and constant leaf surface roughness. The models require few canopy parameters: ro, tau (respectively single leaf hemispherical reflectance and transmittance provided by PROSPECT model as a function of the leaf structural parameter N, the leaf chlorophyll a+b concentration Ca+b, the equivalent water thickness Cw and the dry matter content Cm), LAI (leaf area index), LIDF (leaf inclination distribution function), geometry condition of observation (solar zenith and azimuth angles, view azimuth angle), the soil hemispherical reflectance and HOT (hotspot kuusk parameter). The hotspot parameter for circular leaves is roughly computed as the ratio between the average size of the leaf to the height of the canopy (0.01: small leaves, tall canopies; 0.5: large leaves, short canopies).

3.2.1. Inversion procedure: Marquardt-Levemberg algorithm

In order to retrieve the LAI by inverting the PSH, the independent Parameter Estimation program PEST [23] is used. It runs the PSH model, compares the model results with the observed (measured) values and adjusts selected parameters using Marquardt-Levenberg optimisation algorithm, until an optimal parameter set is found. This optimal parameter set is defined as that for which the sum of squared deviations between model-generated observations and experimental observations is reduced to a minimum; the smaller is this number (referred to as the "objective function") the greater is the consistency between model and observations and the greater is our confidence that the parameter set determined on the basis of these observations is the correct one. Expressing this mathematically, we wish to minimise Φ, where Φ is defined by the equation:

$$\Phi = \sum_{i=1}^{m} (\omega_i r_i)^2 \qquad (1)$$

where r_i (the i'th residual) expresses the difference between the model outcome and the measured top of the canopy reflectance for the i'th observation and ω_i expresses the observation weight. This process requires that an initial set of parameters have to be supplied to start off the optimisation process.

3.2.2. The use of prior information and the initial parameter set in the parameter estimation process

A global minimum in the objective function may be difficult to find in nonlinear problems as the inversion of the PSH model. For some models the task is made no easier by the fact that the objective function may even possess local minima. Hence it is necessary to supply an initial parameter set that is considered to be a good approximation to the true parameter set. A suitable choice for the initial parameter set can also reduce the number of iterations necessary to minimise the objective function. Moreover, the inclusion of prior information into the objective function can change its structure in parameter space, often making the global minimum easier to find (depending on what weights are applied to the articles of prior information). In fact, the aim of the estimation process is to lower the objective function to its minimum possible value (global minimum). If there is no prior information, the parameter estimation process is more likely to be trapped in local minimum. The process of iterative convergence towards the objective function minimum is represented diagrammatically for a two-parameter problem (LAI and HOT spot parameter) in Fig.1.

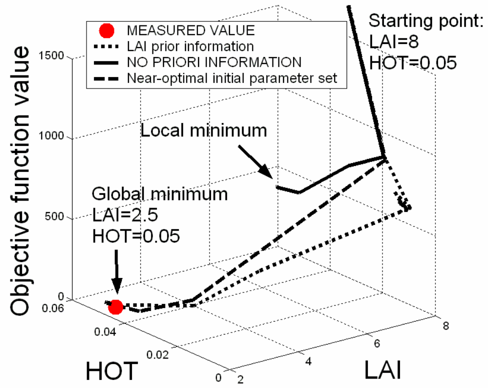

Fig. 1. Robustness of the inversion procedure of PROSPECT SAILH models applied to synthetic data

To enhance optimisation efficiency and to avoid minimisation algorithm to be trapped in local minima of the objective function it has been employed a strategy that combine BRDF model inversion and semi-empirical LAI-VI approach used as a source of prior information.

The trick in implementing this strategy has been the selection of a weight to assign to the prior information. The weight applied to this prediction should be such that the contribution to the final objective function by the residual associated with the single observation group (reflectance in one angle) is of the same order as the contribution to the objective function by the prior information. If this is the case, then the model will not be producing an estimation which is exactly equal to the user-supplied priori information. Because of this, the estimation may have to be supplied as a little "worse than worst" or "better than best".

Fig. 2 shows the iterative improvement of initial LAI and HOT spot parameter toward the objective function minimum for the inversion of PSH model fed by CHRIS/PROBA data (310 observations: 5 angle and 62 spectral bands) for an alfalfa stand with a LAI value of 1.32. The initial value of the other parameters is showed in table 2. The weight of each observation is set to 1. The weight of the prior information (LAI=2.0 from WDVI) is set to 0.1. The lowest objective function value and the highest correlation coefficient were achieved using the strategy that use prior information and initial parameters set to lower bounds.

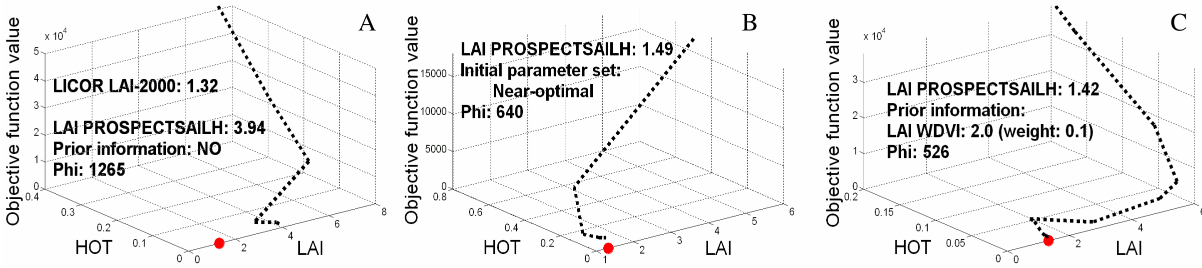

Fig. 2. Inversion procedure: (A) No Prior Information, (B) Near-optimal initial set of parameters (except for LAI), from references (C) Prior Information on LAI. The dot represents the LAI value (1.32) for an alfalfa canopy measured during SPARC2003

	A		B		C	
Parameter	Initial value	Lower-Upper bounds	Initial value	Lower-Upper bounds	Initial value	Lower-Upper bounds
N	1	1-3	1,8	fixed	1	1-3
C_{a+b} (µg/cm^2)	10	10-110	55	10-110	10	10-110
C_w (g/cm^2)	0,022	0,01-0,03	0,022	fixed	0,022	0,01-0,03
C_m (g/cm^2)	0,001	0,001-0,02	0,007	fixed	0,001	0,001-0,02
LAI (m^2/m^2)	6	0,3-8	6	0,3-8	6	0,3-8
HOT	0,5	0,001-0,5	0,5	0,001-0,5	0,5	0,001-0,5
Esky (%)	0,16	fixed	0,16	fixed	0,16	Fixed
Average leaf inclination	45°	free	45°	fixed	45°	Free
Objective function value	0,12*10^4		0,064*10^4		**0,052*10^4**	
Correlation Coeff.	0,9945		0,9971		**0,9976**	
Iteration number/ Total model calls	8/107		7/49		12/156	
Time (sec.)	15,5		7,6		22,5	

Tab. 2. Model parameter set and optimization results

3.2.3. Optimal spectral sampling

As known, there is a high correlation between bands in hyperspectral data, especially between adjacent bands [24]. The number of spectral bands is not simply equal to the number of information dimension because of the existence of band correlation and data redundancy. Therefore, two different approaches based on references information and on a sensitivity analysis have been employed to evaluate the optimal spectral sampling for leaf area index retrieval. First, the optimal spectral sampling to estimate LAI was chosen according to data quality, atmospheric correction and literature. Guanter reports that real CRHIS/PROBA data present important calibration problems, especially around 0.5 and 0.85 nm [25]. Even bands in the extremes of the spectral range showed some discrepancies in atmospheric correction. To estimate LAI some wavelengths were selected in visible (516, 536, 558, 579, 680 and 685 nm), in the red edge (702, 747 and 769 nm) and in the infrared (776, 814, 883 and 932 nm) [26]. So, a set of 14 wavelengths was selected for each view direction. In a second step, in order to evaluate more accurately the optimal spectral sampling for CHRIS/PROBA data, the composite sensitivity of each observation was computed. This is the magnitude of the j^{th} row of the Jacobian matrix multiplied by the weight associated with the observation, this magnitude is then divided by the number of adjustable parameters (LAI, Ca+b and HOT). It is thus a measure of the sensitivity of the observation j to all parameters involved in the parameter estimation process. Thus, it may be possible to characterize the observations made at nearly the same wavelength with the same information content and to omit one or more of these observations from the parameter estimation process in order to reduce the redundant information.

For this aim, the reflectance of an alfalfa canopy of LAI 1.32 from CHRIS reflectance acquired during SPARC2003 was evaluated and the sensitivity for each observation was calculated in each view angle. Seven wavebands were considered in the visible (447, 548, 568, 587, 611, 669 and 680 nm), six wavebands in the red edge (697, 709, 721, 734, 748 and 762 nm) and four in the infrared (776, 783, 839 and 893 nm).

4. RESULTS AND DISCUSSION

4.1. LAI from spectral vegetation index

In order to estimate LAI applying the model CLAIR (Eq. 2) it is necessary to identify the soil-line slope, to calculate the WVDI and to estimate the empirical parameters $WDVI_\infty$ and α using ground measurements. For the closer to nadir images, different bare soil surface were identified and their corresponding reflectance values in bands 24 (663 nm) and 46 (831 nm) were plotted. Linear regression techniques were applied to determine the slope of the so called soil line that varies from 0.9 (12/07) to 1.1 (12/07). The $WDVI_\infty$ values, that is the asymptotical value of WDVI for $LAI \rightarrow \infty$, ranges from 64 (14/07) to 68 (12/07).

The value of α was estimated by using 9 and 15 field measurements for the images of the 12th and 14th of July, respectively. The value of α was determined for each field measurement by inversion of the expression:

$$LAI = -\frac{1}{\alpha}\ln\left(1 - \frac{WDVI}{WDVI_\infty}\right) \qquad (2)$$

The value of α was in the range [0.19; 0.72]. The final value was taken in correspondence of the minimum error between observed and estimated LAI. It resulted 0.47 for the 12th and 0.40 for the 14th of July, leading to an average error of 16% and 25% in the estimation of LAI, respectively. The empirical relationship has been validated by using 40 independent field measurements. The correlation between measured and predicted LAI, evaluated in terms of root mean square error, is shown in Fig. 3. The RMSE ranges from 0.46 m^2m^{-2} (12/07) and to 0.59 m^2m^{-2}(14/07) calculated for all the crops in the study area.

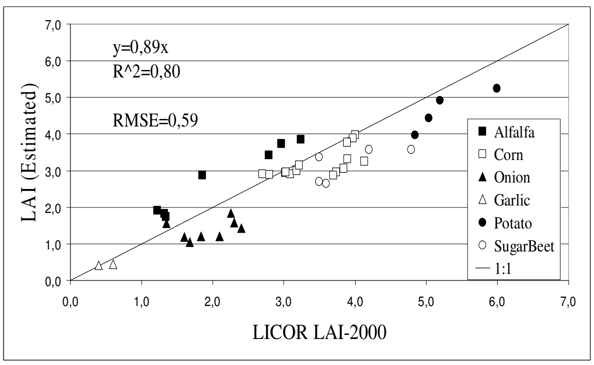

Fig. 3 Measured (LICOR LAI-2000) vs estimated (model CLAIR) LAI for closer to nadir view from the 14th of July (SPARC 2003)

4.2. Optimal spectral sampling

Starting from the optimal parameter set that provides the best estimation performances the optimal spectral bands were selected from all angular data using the sensitivity information of each observation.

In order to evaluate the inversion performances using the selected bands from the references and from the sensitivity analysis we set up the initial parameter value as in Tab. 1 (case C) and tried to estimate the LAI. Results showed that only a limited number of bands were required for biophysical variable estimation and that when the number of bands used increases, the extra bands added only some noise.

	14 bands from references			*17 bands from sensitivity analysis*		
Parameter	Estimated	Lower limit	Upper limit	Estimated	Lower limit	Upper limit
N	**1,06**	0,51	1,61	**1,00**	0,58	1,48
Ca+b (mgcm-2)	**40,80**	30,80	50,87	**31,03**	25,95	36,10
Cw (gcm-2)	**0,022**	fixed		**0,022**	fixed	
Cm (gcm-2)	**0,004**	0,001	0,006	**0,003**	0,001	0,005
LAI (m2m-2)	**1,21**	1,08	1,35	**1,30**	1,17	1,43
HOT	**0,001**	0	0,001	**0,001**	0	0,006
Esky (%)	**0,16**	fixed		**0,16**	fixed	
LIDF	**45°**			**45°**		
Objective function value	87,39			94,89		
Correlation Coeff.	0,9982			0,9981		
Iteration number	18			26		
Total model calls	262			375		
Time (sec.)	35,47			60,72		

Tab. 3. Estimation parameter for the two spectral sampling configuration and optimization results. The measured LAI is 1.32.

The optimal spectral sampling for LAI estimation from CHRIS/PROBA data and the optimization results are presented in Fig.4 and Fig.5. Therefore, according to optimization results in terms of objective function value, correlation coefficient and inversion time, the optimal spectral sampling we decided to keep the optimal spectral bands from references. Thus, considering the whole CHRIS spectral bands and the optimal spectral sampling, a full set of five angular data was employed for the canopy biophysical variables estimation. First, the angular images have been co-registered, all bands stacked in one image and, for the available LAI measurement, have been extracted the reflectance value. The inversion results are presented in next session. Moreover, it was demonstrated from this step that when it is not possible to perform a sensitivity analysis for each data set or a statistical band selection it is still possible to estimate LAI just adding a prior information as showed in Fig.2 and Tab. 1 (case C) in which the parameter LAI was estimated for an alfalfa stand with a good accuracy (measured: 1.32; estimated: 1.42) using all the spectral information.

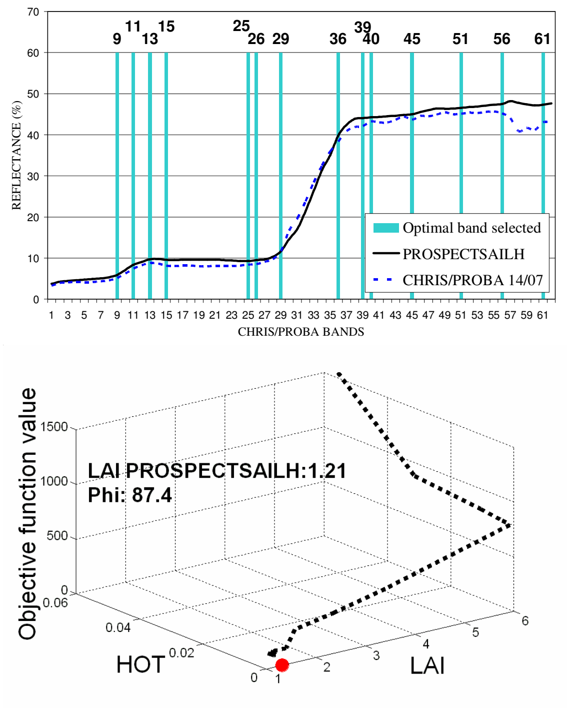

Fig. 4. Optimal spectral sampling for CHRIS/PROBA data from 14/07 (closer to nadir view) vs. PROSPECT-SAILH optimized response and results using selected bans from references

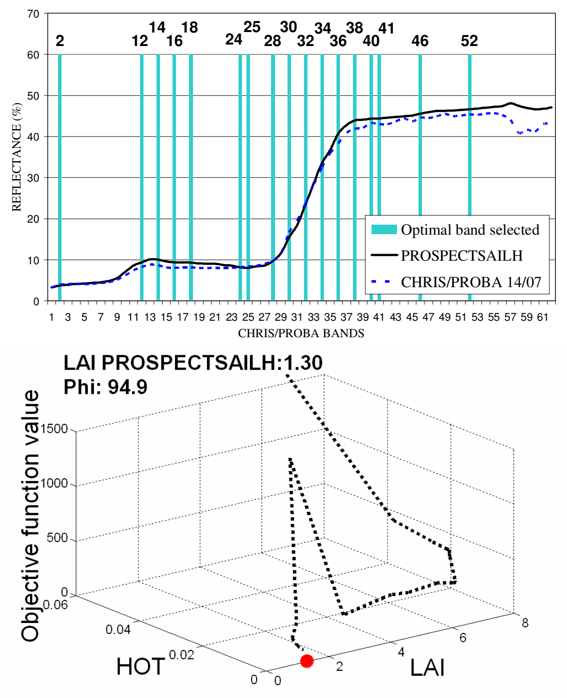

Fig. 5. Optimal spectral sampling for CHRIS data from 14/07 image (closer to nadir view) vs. PROSPECT-SAILH optimized response and results using selected bands from sensitivity analysis.

4.3. LAI from radiative transfer modelling

The first step was to invert the PSH model using CHRIS data from SPARC2003 and SPARC2004 on different development stages of alfalfa canopies.

To this aim, 12 in situ measurements (from 1.2 to 4.8 m^2m^{-2}) were selected and the corresponding reflectance values were extracted manually from the angular images as a mean value on a grid of 3x3 pixel. The initial parameter set in the LAI estimation process was set as in Tab. 1 Case C. The spectral bands were selected from references and the weight of the prior information from semi–empirical LAI map was set to 0.1 (the observation value was 1). Fig. 6 shows the results. The accuracy in terms of RMSE is 0.5 m^2m^{-2} and the average inversion time is 35 sec per pixel using a personal computer based on 2 CPU of 2.6 GHz and 1GB of RAM.

The correlation coefficient (mean value 0.99) between modelled and observed reflectance values shows a good accuracy in the simulation of the bidirectional reflectance.

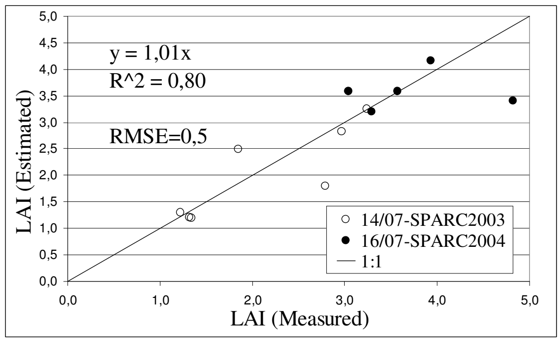

Fig. 6. Measured vs estimated LAI for different alfalfa canopies (12 samples) from SPARC2003 and SPARC2004 CHRIS data.

The mean values of the other estimated parameters involved in the inversion process are: N: 2.24; Ca+b: 29.4; Cw: 0.02; Cm:0.001; HOT:0.01 and LIDF: 45°.

The inversion process was performed again using as initial parameter set the mean values of the parameter obtained from the previous optimization. Any further improvement was not possible to achieve and the RMSE achieved with this strategy is 0.56 m^2m^{-2}.

In order to evaluate the error that can be produced in the estimation of LAI inverting the PSH model by using a prior information based on uncalibrated LAI-VI relationship, a noise was added to the prior information. Considering an error of +/- 20% on LAI-VI the RMSE achieved on the new outcomes was 0.59/0.53 m^2m^{-2} while for an uncalibrated LAI-VI relationship the RMSE would be 1.00 m^2m^{-2}.

The model inversion technique was thus applied to a wide range of crops (Corn, Potato, Sugarbeet, Onion and Garlic) with different geometrical structure and biophysical proprieties. First, the inversion was carried out using all the spectral information. The RMSE, evaluated on 40 in situ LAI measurements, increases drastically to 1.1 m^2m^{-2}. Employing the optimal spectral sampling and a near-optimal initial parameter set for each crop type (as show in Tab. 4) the RMSE results in 0.96 m^2m^{-2}. LAI is constantly underestimated. This trend let us suppose that the 1-D radiative transfer approach used in this work model is inadequate for this aim.

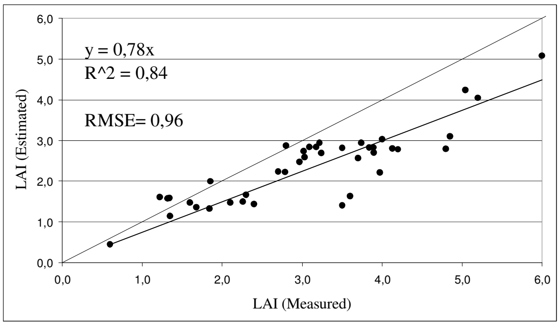

Fig. 7. Measured vs. estimated LAI for Barrax site during SPARC2003.

	Potato		Corn		Other crops	
Parameter	Initial value	Lower-Upper bounds	Initial value	Lower-Upper bounds	Initial value	Lower-Upper bounds
N	1,3	1,3-1,6	1,5	1-3	1,5	1-3
Ca+b (mgcm-2)	37	30-60	60	20-100	50	20-100
Cw (gcm-2)	0,022	0,01-0,03	0,022	0,01-0,03	0,022	0,01-0,03
Cm (gcm-2)	0,004	0,001-0,02	0,006	0,001-0,02	0,007	0,001-0,02
LAI (m2m-2)	4	0,3-8	2	0,3-8	2	0,3-8
HOT	0,05	fixed	0,25	fixed	0,25	0,01-0,5
Esky (%)	0,16	fixed	0,16	fixed	0,16	0,09-0,2
LIDF	45°		51,7°		45°	

Tab. 4. Initial parameter set provided for the inversion of CHRIS/PROBA images

Finally, the model inversion technique was adapted for an operational application implemented in Matlab software. This procedure was directly applied to CHRIS images. In order to reduce the registration error and the high computational requirements the data were degraded to a spatial resolution of 50 m. A land use map provided the model inversion with the initial parameter set needed and a NDVI map lets start the optimization process for NDVI value greater of 0.2. Fig. 8 shows a LAI map derived from CHRIS data inverting the PSH model by using a technique based on the optimization of the Marquardt-Levemberg algorithm and prior information obtained from a generalized empirical approach.

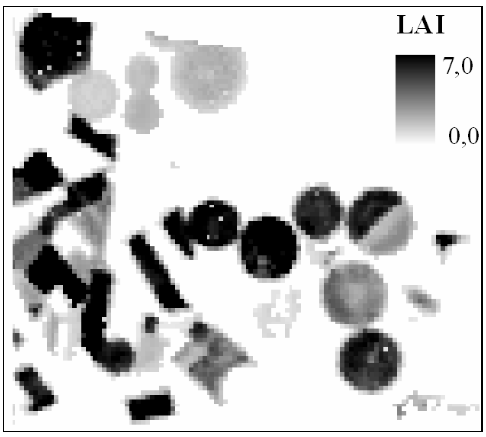

Fig. 8. LAI map derived inverting PROSPECT-SAILH models by using angular CHRIS data of 14th July 2003.

5. CONCLUSIONS

The data presented here provide good evidence that multi-angular and hyper-spectral remote sensing approaches may have real potential for estimating LAI and other biophysical parameters of agriculture crops as alfalfa (RMSE 0.5 m^2m^{-2}). In spite of the limitations of the radiative transfer model assumptions the PROSPECT SAILH produced satisfactory results for a wide range of crops (RMSE 0.96 m^2m^{-2}).

The incorporation of a prior information based on estimation of LAI from WDVI improves inversion results and compensates for initial assumptions of PROSPECT and SAILH models.

In the present work it has been confirmed as in previous studies that the reduction of spectral redundancy improve results of inversion. The CHRIS/PROBA mode 3 configuration may appear optimal in heterogeneous landscapes. Nevertheless, we should note that the sensitivity analysis was limited to the particular conditions of an alfalfa stand. Therefore, more accurate investigation has to be carried out on the hyperspectral and multiangular content of CHRIS imagery.

6. REFERENCES

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