Model inversion procedure for retrieving wheat biophysical variables from hyperspectral measurements

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***Abstract*— The paper deals with the estimation of biophysical variables in the frame of a precision farming project. N-trials were performed on wheat crops for 2 years, providing a calibration and a validation dataset. Airborne radiometric measurements were acquired over the trials. Biophysisical variables were retrieved from inversion of the radiometric signal through radiative transfer models. To minimize the number of solutions and constrain the inversion, *a priori* knowledge about the parameters was introduced in the cost function. Using this technique, green leaf area index and leaf chlorophyll content were estimated with a 10% accuracy.**

***Keywords*- biophysical variables; hyperspectral reflectances**

I. INTRODUCTION

In the frame of a precision farming project [1], we attempt to assess the nitrogen status of a wheat crop. Remote sensing measurements can help with assessing the plant nitrogen status through indicators. The indicators are based on the retrieval of biophysical variables of the crop as green leaf area index (gLAI) and leaf chlorophyll content (Cab), which give access to the nitrogen status of the plant [2]. A method was developed to estimate gLAI and Cab by using the complementarity between hyperspectral remote sensing and radiative transfer modeling. The models and field experiment were described and the formulation of the merit function was discussed.

II. MATERIAL

A. Models

PROSPECT model [3] was used to describe the radiative transfer in the leaf. This model assumes that the leaf is built up with N elementary layers separated by air. Each layer is characterized by a refraction index (n) and an absorption coefficient $K(\lambda)$. The SAIL canopy reflectance model [4] was used to simulate crop bi-directional reflectances. SAIL is a physically based radiative transfer model that considers an homogeneous infinitely extended canopy with randomly distributed leaves. The hot-spot effect is taken into account according to [5]. The model computes spectral canopy reflectances depending on leaf spectral reflectance and transmittance as calculated by PROSPECT. In SAIL, the soil is characterized by a lambertian soil reflectance spectrum $\rho_{soil}(\lambda)$. The leaf distribution is assumed to be elliptical and characterized by a mean leaf angle ALA. The plant structure is also described by the green leaf area index and by the hot-spot parameter h. The external parameters are the solar ($_s$) and view ($_v$) zenith angles, the relative azimuth between view and sun (Δ), and the fraction of diffuse skylight in the incident flux (SKY (λ)). After coupling PROSPECT and SAIL, PROSAIL was obtained.

B. Field experiment

An experiment was conducted at Laon (France, latitude 49°38N, longitude 3°40E) on 2 winter wheat (*Triticum aestivum* L.) fields (F1 and F2), Shango variety [1]. Two field trials were conducted. Five nitrogen levels were used, from 0 to 300 kg $N.ha^{-1}$ on F1 trial and from 0 to 280 kgN.ha-1 on F2 trial. The N fertilizer was supplied at 5 dates for F1, 4 dates for F2, each of them differentiating a new treatment. The 2001-F2 data were the calibration dataset, whereas the 2000-F1 data was used for validation.

Biological measurements

Destructive samplings were performed on the nitrogen field trials as well as indirect measurements in 2000 and 2001 to estimate the green leaf area index and the leaf chlorophyll concentration of the wheat at different dates. Measurements of gLAI were performed using a LICOR® LAI-2000 and chlorophyll concentration was estimated with Hydro N-tester device. The relation between N-tester measures and Cab on one hand and between LAI-2000 measures and gLAI on the other hand were calibrated thanks to destructive measurements.

Radiometric measurements

Ground targets were characterized using 2 field radiometers either to estimate some PROSAIL inputs ($\rho_{soil}(\lambda)$ and SKY(λ)), to calibrate airborne sensor measurements or to validate the airborne sensor calibration. They consisted in bare soil surfaces, reference targets and N-test-sites. 4 and 3 airborne images were acquired over F1 and F2 during 2000 and 2001 wheat growing period, respectively, using an hyperspectral sensor. Images were acquired with a Compact Airborne Spectrographic Imager (CASI, ITRES, Canada) onboard an aircraft flying at a 1500m altitude and providing data in 32 spectral bands of 10nm width in the 350-1050nm range with a ground spatial resolution of 2m. Images were acquired in sunny sky conditions around 12:00 HTU.

III. Method

The set of PROSAIL input parameters are X_v={N, C_{bp}, C_w, C_{ab}, C_{dm}, ALA, gLAI, h, ρ_{soil}(), SKY(),$_s$, $_v$, Δ}. Some of those parameters can be set and do not require to be estimated through inversion. After calibration, the set of PROSAIL parameters to be adjusted was X_v={N, C_{bp}, C_w, C_{ab}, C_{dm}, ALA, gLAI, sb, h}.

Reference [6] has shown the importance of introducing a prior knowledge in the merit function to solve the ill-posed problem due to model and measurements uncertainties. It consists in adding a second term in the merit function, the first being commonly the rmse (root mean square error) between observed and modeled radiometric signal. The second term is the rmse on canopy parameters prior information (1).

$$C=\sum_{\lambda=1}^{n}\left(\frac{Y_\lambda^s-Y_\lambda^o}{\varepsilon_\lambda^y}\right)^2+\sum_{v=1}^{m}\left(\frac{X_v^s-X_v^p}{\varepsilon_v^x}\right)^2 \qquad (1)$$

where Y^s_λ is the simulated reflectance in wavelength λ, Y^o_λ is the observed reflectance in wavelength λ, ε^y_λ both account for measurements and model uncertainties, n is number of observations, i.e. of spectral bands. X^p_v is the prior value for v parameter and ε^x_v is the associated uncertainty on the parameter v, m is number of retrieved parameter.

By definition, prior information is information obtained independently of the results of measurements [7]. This information was found thanks to the calibration dataset (for C_w, C_{dm}, median of 2001 calibration measured values were used), from literature (N, ALA, h), or the radiometric measurements (sb, Cab and gLAI). We used the same set of X^p_v for the 4 dates except for gLAI and Cab, which showed strong time variability.

The quasi-Newton algorithm was used to solve the inverse problem. We tested the impact of : the second term of the merit function i.e. the prior information, the number n and the position of wavebands, the given prior information X^p_v , uncertainties on variables ε^x_v, impact of the first guess values X^{1st}_v.

For the different tests, the quality of the inversion was evaluated by computing the rmse and r² on the gLAI and Cab estimates versus 2000 indirect measurements (validation dataset). A reference configuration was defined by setting a default value of the mentioned variables (n=9, ε^x_v=50%, X^{1st}_v= X^p_v, ε^y_λ= Y^o_λ). The subscript *ref* corresponds to the results of inversion using the default values. The importance of each variables (n, ε^x_v, X^{1st}_v, ε^y_λ) is discussed through next section.

IV. Results

The inversion was performed for the reference configuration using eq. (1). The results of the inversion were evaluated in terms of investigated variables (gLAI, Cab) by comparing predicted variables with indirect measurements performed on the validation dataset. The following statistical parameters were obtained: $rmse^{ref}_{gLAI}$=0.449, $r^{2\,ref}_{gLAI}$=0.931, $rmse^{ref}_{Cab}$=0.141, $r^{2\,ref}_{Cab}$=0.601.

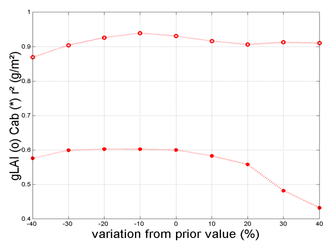
C. The a priori information

The inversion procedure was run by considering only the term on radiometric information in the merit function. The rmse on estimated gLAI was 2.2 ($rmse^{ref}_{gLAI}$=0.449) with a r² of 0.4 ($r^{2\,ref}_{gLAI}$=0.931), while it was 0.16 for Cab ($rmse^{ref}_{Cab}$=0.141) with a r² of 0.31 ($r^{2\,ref}_{Cab}$=0.601). This result confirmed the improvement obtained when taking into account some a priori information on the retrieved variables, especially for the gLAI. For Cab estimation, the results were not drastically improved; the radiometric signal alone provided a satisfactory estimation. However, if gLAI is not well estimated and if we consider that some compensations between variables are possible, it is important to obtain a good estimation of both variables.

The residual rmse on reflectances is obviously smaller (less than 1%) without prior knowledge, and 1.% to 2.4% with prior knowledge except for one case where the inversion result is a local minimum and the resulting reflectance spectrum does not fit well to the measured one.

D. Test on the number of wavebands

The maximum number of wavebands is 32. We took 1 of 2, 1of 3 etc up to 1 of 8 wavebands and run the inversion procedure. The best configuration was obtained for 8 wavebands. Rmse on Glai was about 0.6 for n=3 or n=32, as compared to 0.45 for 8 bands. Rmse on Cab was about 0.12 when increasing or decreasing n, as compared to 0.09 for n=8.



1 r² of estimated gLAI and Cab according to uncertainties on the a priori information.

E. Test on the impact of ε^x_v, X^p_v and X^{1st}_v

The optimization procedure was run for 7 levels of uncertainties (from 10 to 70 % of the prior values). Rmse on gLAI went up to 0.9 when increasing ε^x_v ($rmse^{ref}_{gLAI}$=0.449) and rmse on Cab went up to 0.16 ($rmse^{ref}_{Cab}$=0.141). We noticed that the correlation coefficient is always better for gLAI that for Cab. The best configuration was obtained for 40% uncertainty.

As for the test on uncertainties, the accuracy on the prior knowledge was found to be of first importance. A variation of more than 20% from the «actual» prior values decreases the estimation of 20% for gLAI and 30% for Cab. The correlation coefficient if always better for LAI than for Cab when modifying X^p_v from +/-40% of the actual values (Fig. 1).

The last test consisted in considering that X^p_v and X^{1st}_v were independent. X^{1st}_v was randomly chosen in the range between lower and upper boundaries. The difference between the estimated variables when using random X^{1st}_v and the reference estimated variable is negligible (less than 1%). The probability to fall in a local minimum when using prior information in the merit function is very small.

V. CONCLUSION

The results were drastically improved by introducing the *a priori* information in the merit function (gLAI and Cab root mean square error improvement equal 2 m²/m² and 10µg/cm² respectively). These results confirm the importance of introducing prior knowledge on the retrieved parameters as suggested by [6]. Results have shown that taking account the prior information prevent from falling in a local minimum. This prior information can be deduced from an independent dataset or from a crop model in particular for LAI prior value estimation.

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