Use of coupled canopy structure dynamic and radiative transfer models to estimate biophysical canopy characteristics

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Abstract

Leaf area index (LAI) is a key variable for the understanding of several eco-physiological processes within a vegetation canopy. The LAI could thus provide vital information for the management of the environment and agricultural practices when estimated continuously over time and space thanks to remote sensing sensors.

This study proposed a method to estimate LAI spatial and temporal variation based on multi-temporal remote sensing observations processed using a simple semi-mechanistic canopy structure dynamic model (CSDM) coupled with a radiative transfer model (RTM). The CSDM described the temporal evolution of the LAI as function of the accumulated daily air temperature as measured from classical ground meteorological stations.

The retrieval performances were evaluated for two different data sets: first, a data set simulated by the RTM but taking into account realistic measurement conditions and uncertainties resulting from different error sources; second, an experimental data set acquired over maize crops the Blue Earth City area (USA) in 1998. Results showed that the proposed approach improved significantly the retrieval performances for LAI mainly by smoothing the residual errors associated to each individual observation. In addition it provides a way to describe in a continuous manner the LAI time course from a limited number of observations during the growth cycle.

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1. Introduction

Leaf area index (LAI) as defined by the single sided area of green leaves per unit of horizontal soil (Privette et al., 2001) is a key variable governing several processes such as photosynthesis, transpiration or rain interception. Estimates of LAI can be assimilated within vegetation process models to provide more accurate description of canopy functioning with emphasis on important environmental and economical outputs such as, carbon, water and nitrogen fluxes and stocks, canopy state and yield for crops (Chen et al., 2003; Matsushita & Tamura, 2002). Remote sensing allows for detailed and frequent observations of the vegetation to monitor the spatial and temporal variations of canopy characteristics. These remote sensing observations are expected to provide reliable and quantitative biophysical information, such as LAI, to be used in several applications including crop management at the local scale. In this context, remote sensing is foreseen to play a major role in precision farming, which consists in optimizing the cultural practices as a function of the spatial and temporal variability within fields (Colombo et al., 2003; Goel et al., 2003; Moran et al., 1997). It is therefore required to develop methods capable to accurately retrieve canopy biophysical variables such as LAI from the reflectance signal recorded by remote sensing platforms.
At the top of the canopy, the interaction of radiation within the vegetation depends on the contribution of several components such as leaves, stems, soil background as well as the illumination and view geometries. Canopy reflectance will thus depend on the optical properties of each canopy element, as well as on their number, area, orientation, and position in space (Goel & Thompson, 2000; Verhoef & Bunnik, 1981). The factors and processes controlling canopy reflectance are by far too numerous and too complex to be implicitly accounted for in a simple empirical equation. Conversely, radiative transfer models (RTM) provide an explicit connection between the canopy biophysical variables, the view and illumination geometry and the resulting canopy reflectance by exploiting our knowledge of the involved physical processes (Baret et al., 2000). The RTM have to be inverted to retrieve the biophysical variables from the measured canopy reflectance (Bacour et al., 2002; Kimes et al., 2000; Weiss et al., 2000). Radiative transfer models are mathematically invertible if the solution of the inverse problem to be solved exists, is unique, and depends continuously on the data (Knyazikhin et al., 1998). However measurement and model uncertainties are often leading to a large range of possible solutions, which prohibits the inversion to be properly solved (Combal et al., 2002). The measurement uncertainties are related to the errors associated to the sensor and the processing of the raw radiometric data including the radiometric calibration, atmospheric and geometric correction. Uncertainties are also partly due to inaccuracies associated to the characteristics of the observational configuration such as view and sun directions, slope and aspect of the observed surface and wavelength calibration. The model uncertainties result mainly from the assumptions on the canopy architecture and optical properties of the elements that are not fully verified when compared with those of actual canopies. Because of this ill-posed nature of the inverse problem in remote sensing, several combinations of canopy biophysical variables could lead to similar remote sensing signals as demonstrated by (Weiss et al., 2000). The regularization of such problems requires input of additional information to obtain more reliable and stable solutions (Combal et al., 2002, 2003). This could be achieved through a Bayesian approach (Malakoff, 1999) using prior information on the distribution of the biophysical variables.

Knowledge of the canopy structure dynamics is highly desirable as ancillary information to constrain the RTM inversion for the estimation of canopy characteristics. The dynamics of the canopy structure are strongly depending on crop growth processes, which result in a relatively smooth and typical temporal profile of LAI. Simple semi-mechanistic models have been proposed to describe the LAI time course (Baret, 1986; Werker & Jaggard, 1997). Such models could consequently be used to exploit the information on canopy structure dynamics and get more robust and reliable estimates of LAI. The use of a canopy structure dynamics model (CSDM) also allows to derive a continuous estimation of LAI which is required in some applications, particularly those based on the forcing of growth models (Delecolle et al., 1992; Moulin et al., 1998). The coupling of radiative transfer and canopy structure dynamics models offers consequently a great potential for the interpretation of remote sensing data since it integrates several sources of information (Baret et al., 2000):

- the knowledge of radiative transfer processes within RTM;
- the knowledge on some biological processes within CSDM;
- the temporal and spectral dimension of radiometric information; and
- ancillary information such as the climatic variables partly governing the CSDM including temperature, and the prior knowledge on the canopy type.

The objective of this study is to develop and evaluate a methodology that fully exploits the spectral and temporal information dimensions to estimate LAI from remote sensing data for agricultural applications. First the models used (RTM and CSDM) and their coupling scheme are presented. Then the proposed approach is evaluated based on a synthetic data set and actual measurements over maize canopies.

2. The models used

2.1. Canopy structure dynamics model

Among the canopy structure variables, LAI plays a particular role in remote sensing of vegetation since it is the main variable influencing canopy reflectance. The LAI temporal profile is governed by the net effect of growth and senescence, which are genetically programmed. However, the expression of this genetic potential is strongly influenced by environmental factors. The leaf area of an annual canopy typically shows first an exponential rise corresponding to dominant cell multiplication and elongation processes while the effects of competition for resources are limited. Then, this increasing absolute growth rate is rapidly modulated by senescence and competition for resources. LAI reaches thus a maximum when the production balances the senescence rate of leaf surface. Finally, LAI declines when senescence becomes the dominant process until all green leaves disappeared.

A simple semi-mechanistic model that describes LAI dynamics was proposed by (Baret, 1986):

\[
LAI = LAI_{Amp} \left[ \frac{1}{1 + e^{-b(T-T_s)}} - e^{-a(T-T_s)} \right]
\]

(1)

The independent variable \(T\) is defined as the accumulated daily mean air temperature above 8 °C starting from sowing.
This variable was chosen since both seedling emergence and leaf area expansion are temperature dependant (Hesketh & Warrington, 1989). The CSDM describes LAI in two parts, growth and senescence (Eq. (1)). The growth period is defined by a logistic equation with parameter \( b \) being the relative growth rate at the inflexion point \( T_I \). The senescence is determined by an exponential equation with parameter \( a \) being the relative growth rate and \( T_s \) the time expressed in temperature when leaves have all senesced. The parameter \( \text{LAI}_{\text{Amp}} \) describes the amplitude of maximal leaf area. The parameters \( b \), \( T_I \) describe the dynamics before the time of maximum LAI, while \( a \) and \( T_s \) focus on the period after the maximum LAI.

The distribution of the model parameters typical for the observed crop maize was derived from an extensive database acquired over 44 different sites spread over the world and spanning over different climatic and cultural practices conditions (Brisson et al., 2002; Duthil et al., 1999; Marloie et al., 2001).

### 2.2. Radiative transfer models

The turbid medium radiative transfer model, SAIL (Scattering from Arbitrarily Inclined Leaves (Verhoef, 1984, 1985), was used, since it describes the canopy structure in a fairly simple way while producing nevertheless realistic results as reported by several authors over different crops including maize (Andrieu et al., 1997; Goel & Thompson, 1984; Jacquemoud et al., 1995, 2000; Major et al., 1992).

The PROSPECT model (Fourty et al., 1996; Jacquemoud & Baret, 1990) was used to describe leaf optical properties. PROSPECT simulates leaf reflectance and transmittance spectra required by the SAIL model as a function of leaf biochemical contents and leaf structure.

The soil reflectance was assumed to keep the same spectral pattern and to exhibit predominantly variations in magnitude due to changes in soil moisture and roughness, which was described by a soil brightness factor \( s \). A reference soil reflectance spectrum taken over bare soil on the same fields was considered for the cases investigated. The soil was also assumed to be a Lambertian surface. This crude assumption was valid in our case, since observations were made in a single direction far from the hotspot configuration. Also the actual anisotropy would only act as a second order factor on the canopy reflectance computation.

### 3. The experiments

Two different data sets comprising top-of-canopy reflectance and the corresponding canopy variables were available to evaluate the retrieval performances of the developed approach. The first data set was acquired during an experimental campaign performed close to Blue Earth city (Minnesota, USA) in 1998 with the CASI hyperspectral sensor. A second data set was generated with the radiative transfer models described above to complement the evaluation allowing a more detailed analysis of the performances of the method by controlling the influence of uncertainties.

#### 3.1. Experimental data set

The Compact Airborne Spectro Imager (CASI) was flown in 1998 to monitor the reflectance of a 8.0 × 9.8 km area located in Minnesota (USA) close to Blue Earth City. Seven flights were performed to cover the growth cycle of the observed maize crops. The first flight corresponded to bare soil conditions. The radiance data acquired by CASI was resampled to an eleven bands configuration to improve

![Fig. 1. The experimental data set of Blue Earth City, 1998, left: Mean and standard deviation of the top-of-canopy reflectance (five overflight dates), right: LAI time courses measured over 27 elementary sampling units (* represents the observation dates, Tcum [°C]: accumulated daily mean air temperature above 8 °C).](image-url)
the radiometric performances and eliminate regions of strong atmospheric absorption while retaining most of the information. The spatial resolution was also degraded to 20 m in order to better match the foot print of the ground measurements and again, to improve the radiometric performances. The raw images acquired by the CASI sensor were calibrated, geolocated and corrected from the atmospheric effects to obtain top-of-canopy reflectance. Atmospheric corrections were achieved using the LOWTRAN radiative transfer model (Isaacs & Vogelmann, 1988) based on standard atmospheric characteristics. However, qualitative investigation on the quality of the calibration and atmospheric correction showed that the absolute accuracy of the top-of-canopy reflectance measurements was not optimal, although difficult to assess quantitatively because neither atmospheric characteristics, nor ground reflectance was measured concurrently to the flights. For these reasons, band 9 (807 nm) was discarded because of unexpected large variations.

Ground measurements of LAI were performed using the LAI-2000 instrument (LI-COR, 1992) over 27 elementary sampling units of approximately 20×20 m area distributed over five different fields. These measurements were repeated 5 times during the growing season within a 2 to 3 day shift as compared to the CASI flights 3–7. Only the remote sensing observations parallel to the field measurements were considered in the following of this study. For these observations, the local solar zenith angles varied within 30.6–46.7° and the solar azimuth angles within 98.6–155.2° (Fig. 1).

3.2. Generation of synthetic data set

The synthetic data set was generated by simulating top-of-canopy reflectance \( \rho(\lambda) \) observed from nadir in eleven bands, corresponding to the resampled CASI spectral configuration described in Table 1 (Fig. 2). The sun zenith angle \( \theta_s \) was set to 45°. For the sake of simplicity, the diffuse radiation was considered independent from the wavelength and set to 15%.

The input canopy variables of the SAIL+PROSPECT models were chosen for 44 different cases representing a wide range of variation of canopies and their structural development as described in the following. First, the LAI dynamics was simulated by the semi-mechanistic CSDM presented earlier based on the 44 sets of the 4 parameters that were derived from the adjustment over an independent data set of LAI ground measurements (Brisson et al., 2002; Duthil et al., 1999; Marloie et al., 2001). Eight dates of ‘observation’ equally distributed in time over the whole growth cycle were considered for the simulations. The temperature conditions of Blue Earth City in 1998 were used as driving input for the CSDM. This resulted in a total of 352 (44×8) instantaneous observations (Fig. 2). A Gaussian noise of 20% of the simulated LAI values was added to account for possible inadequacies due both to the RTM and CSDM models. Then, the remaining canopy characteristics variables were randomly drawn within uniform distribution chosen out of their respective range.
described in Table 2, independently for each date of observation and case considered.

Finally, radiometric noise was added to the simulated top-of-canopy reflectance to account for uncertainties resulting from the several error sources listed in the introduction. The relative instrumental noise was assumed to be 3% of the actual reflectance value. A relative error was chosen for the instrumental noise since it is generally proportional to the signal input (Nieke et al., 1999). The error related to the inaccuracy of the atmospheric correction was assumed to stem primarily from aerosol optical thickness uncertainties, and was therefore spectrally dependant. A 10% maximal error was assumed in the first band (444 nm). The error was propagated to the remaining wavelengths according to a $k/C_0^{1.3}$ law which is typical for continental aerosols (Richter & Schläpfer, 2002).

4. LAI estimation based on Look up tables

The estimation of LAI from RTM inversion was based on a LUT (Look Up Tables) approach. It is a conceptually very simple technique, that potentially overcomes limitations of iterative optimization algorithms associated to important computation time and the risk of converging to a local minimum that is not necessary close to the actual solution (Combal et al., 2002; Kimes et al., 2000). The LUT approach can be split in two parts: (i) the generation of the LUT itself, and (ii) the selection of the solutions corresponding to a given measurement. The constraints imposed by the temporal dimension provided by the canopy structural dynamic model will be introduced in the second part.

4.1. Generation of the LUT

The generation of a look up table consists first to sample the space of the $p$ input variables $V$ of the RTM ($\text{LUT}_V$). A total of 130,000 canopy realizations have been generated following a uniform distribution and specific ranges for the respective canopy variable (Table 2). Then, the RTM was used to simulate the corresponding reflectance table ($\text{LUT}_R$) with $m$ numbers of measurement configurations, corresponding to the bands and directions considered. The range of each variable was defined according to previous experiments performed over maize crops under a range of conditions (Baghdadi & Baret, 1998; Espana et al., 1998; Jacquemoud & Baret, 1990). Note that the generation of the $\text{LUT}_V$ allows already to define some prior information on the respective variable by restraining it to vary within a limited range.

The measurement configuration used represented the actual conditions of observations in the multispectral configuration of the CASI sensor (Table 1). The view zenith angle was set to nadir ($\theta_0=0^\circ$). Because the illumination geometry was varying from date to date, six LUTs were created, each corresponding to a specific date of observation and the associated sun zenith angle. The maximum range of sun zenith angle variation was in between $35^\circ$ and $60^\circ$. For the sake of simplicity, the fraction of diffuse irradiance was assumed to be 15% independent of the wavelength.

4.2. Selection of the solution

The selection of the solution within the LUT was achieved in two steps: the first one considered only the radiometric information. The second one used the CSDM fitted over the first estimates of LAI derived from the previous step to constrain the possible solutions. The later process could be iterated several times to reach convergence. The coupling of the RTM and CSDM models was based on the hypothesis that the remotely sensed observations of LAI (step 1) had to be consistent with the time profile of LAI generated by the CSDM. Consequently the remotely sensed LAI was recalibrated, when necessary, relative to the phenologically sound LAI provided by the CSDM (step 2). These two steps will be briefly described here after.

4.2.1. Step one: Exploiting the radiometric information

The LUT was sorted according to the cost function $\chi^2_{\text{rad}}$ corresponding to the simple squared-sum of differences between the measured reflectance $R$ and the simulated reflectance $R_{\text{LUT}}$ found in the $\text{LUT}_R$ (Eq. (2)).

$$\chi^2_{\text{rad}} = \sum_{i=1}^{m} \left( R_{i_{\text{LUT}}} - R_i \right)^2$$  

(2)
Note that no normalization between bands was applied because no precise information was available on the uncertainties associated to the measurements and above all on the radiative transfer model. Such a simple cost function has been used by several authors (Braswell et al., 1996; Combal et al., 2002; Goel & Thompson, 1984; Jacquemoud et al., 2000; Pinty et al., 1990; Privette et al., 1996). However, because of the composition of the bands available, an implicit weighing was achieved in the cost function; the six visible bands with lower reflectance values counterbalancing the three near infrared with the highest reflectance values. The possible solutions considered were those that were within 20% of the best radiometric match. This ensemble of possible radiometric solutions was noted \([S_{\text{rad}}]\). The 20% threshold was derived after test and error trials and is consistent with what Combal et al. (2002) proposed in an earlier study. The initial solution value, \(\text{LAI}_0\), was then set to the median value of the ensemble \([S_{\text{rad}}]\) of best radiometric cases.

### 4.2.2. Step two: Exploiting the prior information on canopy variables

The prior information was introduced here by refining the selection within the possible radiometric cases \([S_{\text{rad}}]\) according to the following cost function, \(\chi^2_{\text{var}}\):

\[
\chi^2_{\text{var}} = \sum_{i=1}^{n} \left( \frac{V_i - V_i^P}{\Delta_i^P} \right)^2
\]

where \(n\) was the number of canopy characteristics on which prior information was exploited, \(V_i^P\) was the most probable value of the canopy variable \(i\), and \(\Delta_i^P\) the corresponding confidence level. The LAI value of the case ensuring the minimum of \(\chi^2_{\text{var}}\) over \([S_{\text{rad}}]\) was selected as the solution, \(\text{LAI}_1\). Because the LUT already incorporated some prior information on the range of variation of all the canopy variables, only the LAI and soil brightness, \(s\), were considered in Eq. (3). For the soil brightness, no temporal constraint was used and \(V_i^P\) and \(\Delta_i^P\) were set respectively to 0.9 and 0.2. Conversely, temporal constraints were used for LAI to get the most probable value \(V_{\text{LAI}}^P\) at a given point in time. This was achieved by exploiting the CSDM adjusted over the set of first estimates \(\text{LAI}_0(t)\). The adjustment of the CSDM was performed using the simplex minimization algorithm (Nelder & Mead, 1965). The confidence value \(\Delta_{\text{LAI}}^P\) was assumed to be within 20% the most probable value. This value was in agreement with the magnitude of the standard deviation observed when estimating LAI from radiometric measurements without using much prior information (Combal et al., 2002). This second step was iterated a number of times up to the convergence. Experience showed that the convergence was quickly reached and only three iterations were used in the following part of the study. At last the CSDM adjusted over the most phenologically sound cases of \([S_{\text{rad}}]\) was used to produce the final results.

### 5. Evaluation of coupling strategy

Both the actual and the synthetic data sets were used to evaluate the performances of the proposed method. The emphasis of the evaluation was placed on the influence of exploiting the temporal dimension. For simplicity, the method was broken down to four successive stages to evaluate the impact of the different involved processing levels:

a) the inversion is initially solved exclusively based on radiometric information for each observation (Eq. (2)),

b) the radiometric estimated LAI values (\(\text{LAI}_0\)) are smoothed by the CSDM as a function of time,

c) the LAI derived from the previous stage is integrated in the inversion as prior information (Eqs. (2) and (3)),

d) the results are smoothed by a final run of the CSDM.

The retrieval performances associated to each of the four levels are presented in the subfigures A–D of Fig. 3 and 4. The simple root mean square error (RMSE) was calculated to quantify the agreement between the actual and the estimated LAI values. A linear regression was also used to quantify the possible biases of the estimates.

The results showed that in the case of the synthetic data set, the RMSE value on the estimated LAI was around 0.87 when no constraints on the LAI were imposed within the inversion and no temporal smoothing thanks to the CSDM was applied (level A, Fig. 3A). The disagreement increased with LAI as a consequence of the well known saturation problem, leading to a slight over-estimation (12%) when interpreting the linear best fit. These relatively good results were partly attributed to the prior information, which was implicitly introduced during the generation of the LUT. When the temporal dimension is exploited thanks to the CSDM providing prior information for the inversion and smoothing the final results, the agreement was significantly improved between the reference and estimated LAI values to a RMSE of 0.53 (level D, Fig. 3D). The slight overestimation bias vanished down to 3%. However, we should note that the main improvement on the retrieval performances was resulting from the temporal smoothing operated by the CSDM: when the first LAI estimates (Fig. 3A) were smoothed by the CSDM, the RMSE drastically decreased down to 0.51, and the bias went down to 2% (level B, Fig. 3B); whereas if the temporal information of the CSDM was only introduced as prior information in the inversion, the achieved performance was considerable lower (level C, Fig. 3C). The three iterations of the CSDM used for the convergence on the LAI prior information did not result in significant improvements on the LAI retrieval performances.

When applying the method to the actual measurements obtained during the Blue Earth City experiment, the retrieval performances relative to the synthetic data set
generally degraded in terms of the best linear fit (Fig. 4).
This could be attributed to the measurements uncertainties
of the CASI data that were possibly higher than anticipated
in the synthetic data set caused by its calibration and
atmospheric correction problems. Similarly to the synthetic
data set, an increase of the error in LAI retrieval was
observed for the higher LAI values. When information
based on the dynamics of LAI by means of the CSDM was
used, the performances of the retrieval improved signifi-
cantly from a RMSE of 0.79 (level A, Fig. 4A) to 0.72 (level
D, Fig. 4D), correcting especially the scattering of the larger
LAI values. Once again the prior information already
integrated within the LUT itself could explain the relative
good retrieval without constraints on the LAI. Larger
improvements in the retrieval performance would have
been expected when a more general LUT was applied.
Similarly to what was observed over the synthetic data
set, the effect of the temporal smoothing of LAI estimates
was the most important: after the first retrieval (level A,
Fig. 4A), the temporal smoothing by the CSDM decreased
the RMSE significantly down to 0.69 (level B, Fig. 4B).
After three iterative inversions integrating temporal prior
information on the LAI (Fig. 4C), the final temporal
smoothing thanks to the CSDM was still able to decrease
the RMSE significantly (level D, Fig. 4D). In all these
cases, it is more difficult to comment on the bias observed
because of the particular distribution of LAI values.

6. Conclusion

One of the main recent advances in the development of
techniques for biophysical variables estimation from remote
sensing data was to introduce prior information in the
system to get a more robust solution to this generally ill-
posed problem (Combal et al., 2003; Gemmell et al., 2002;
Song et al., 2002; Verhoef & Bach, 2003).

However, one of the major issues is to define this prior
information as accurately as possible. This is not trivial in
most situations, particularly when dealing with medium
resolution observations where the vegetation type is gen-
erally not very precisely known.

In the context of local agriculture applications such as
precision farming, there is already a very significant
quantity of information available through the knowledge
of the species and sometimes even cultivar and certain
-cultural practices. This knowledge was explicitly used in
this study when generating the LUT adapted to the observed
maize crops. However, we proposed in addition a method to
exploit the temporal dimension of the observations. This
was mainly based on the use of the phenological LAI dynamics through a simple semi-mechanistic model, here called CSDM.

Results showed significant improvements of the estimation performances for a synthetic and an experimental data set when the temporal information was exploited. A detailed inspection on the way the exploitation of the CSDM improved the retrieval performances showed that the gain due to a better definition of the prior information for LAI was limited. Conversely, most of the improvement was attributed to the smoothing process operated after RTM inversion. This adjustment of the CSDM allowed to reduce the saturation effect observed for the larger LAI values because part of the information on the periods of large LAI is conditioned by the information gathered during the periods before and after the LAI peak.

The whole growth cycle was considered in this study, which obviously corresponded to optimal conditions for implementing and applying this technique. However, it is possible to consider only part of the cycle, assuming some prior information on the distribution of the parameters of the CSDM is known. This will be very useful in the context of precision farming where the spatial distribution of canopy biophysical variables needs to be available at some critical stages, such as for nitrogen applications, already during the growth cycle, and not only at harvest.

The implementation of the proposed method requires measurements of the mean air temperature throughout the season to drive the LAI time course. It is probable that even a rough estimation of this variable through coarse temperature field recalculations by meteorological offices will not induce significant errors if local air temperature measurements are not available, although this has still to be proven. In addition, the method requires frequent remote sensing observations to better constrain the LAI dynamics.

Only the LAI dynamics was considered in this study. It would have been possible to include also additional constraints on other biophysical variables that may have a particular time course as a function of canopy phenology. This could be the case for the average leaf angle, the hotspot parameter and the leaf chlorophyll content used in the simple RTM applied here. However, the limits of this simple description of canopy architecture will be rapidly reached, without offering additional possibilities to get a more realistic description of the actual structure specificities. This calls for the development of dynamic canopy structure models as proposed by (España et al., 1999).

We should be aware that techniques based on the use of the dynamics of the canopy will rapidly converge towards the development of techniques based on the assimilation of remote sensing data within canopy process models (Guerif & Duke, 2000; Moulin et al., 1998; Verhoef & Bach, 2003;
Weiss et al., 2001). The effectiveness of such approaches will be reached only if relatively high frequency remote sensing observations at the pertinent spatial resolution will be available. This is currently available from the series of medium resolution sensors such as VEGETATION, POL- DER, MERIS, MODIS, SEAWIFS. The application of such techniques to these sensors requires specific CSDMs that have to be developed. However, the potential gain is very high, allowing to better filter problems related to poor cloud screening and atmospheric correction and even yield phenological information. Nevertheless, the spatial resolution makes the problem more complex to solve, mixing very different canopies. This calls for the development of specific space missions characterized by both high temporal and high spatial resolution.

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