Chapter 7
Estimating Canopy Characteristics from Remote Sensing Observations: Review of Methods and Associated Problems

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Abstract This article describes the methods and problems associated to the estimation of canopy characteristics from remote sensing observations. It is illustrated over the solar spectral domain, with emphasis on LAI estimation using currently available algorithms developed for moderate resolution sensors. The principles of algorithms are first presented, distinguishing between canopy biophysical and radiometric data driven approaches that may use either radiative transfer models or experimental observations. Advantages and drawback are discussed with due attention to the operational character of the algorithms. Then the under-determination and ill-posedness nature of the inverse problem is described and illustrated. Finally, ways to improve the retrieval performances are presented, including the use of prior information, the exploitation of spatial and temporal constraints, and the interest in using holistic approaches based on the coupling of radiative transfer processes at several scales or levels. A conclusion is eventually proposed, discussing the three main components of retrieval approaches: retrieval techniques, radiative transfer models, and the exploitation of observations and ancillary information.

7.1 Introduction

Many applications require an exhaustive description of the spatial domain of interest that may cover a large range of scales: from the very local one corresponding to precision agriculture where cultural practices are adapted to the within field variability, through environmental management generally approached at the landscape scale, up to biogeochemical cycling and vegetation dynamics investigated at national, continental and global scales. Most of these applications are using our knowledge on the

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S. Liang (ed.), *Advances in Land Remote Sensing*, 173–201.

main physical, chemical and biological processes involved such as energy balance, evapotranspiration, photosynthesis and respiration. This knowledge is encapsulated into a variety of surface process models. However, to account for the spatial heterogeneity observed at all scales, dedicated imaging systems are required to get a distributed description of surface characteristics within the domain of interest. By its capacity to cover exhaustively large space areas, remote sensing provides a very pertinent answer to those requirements. However, remote sensing observations sample the radiation field reflected or emitted by the surface, and thus do not provide directly the biophysical characteristics required by the models for describing some state variables of the surface. An intermediate step is therefore necessary to transform the remote sensing measurements into estimates of the surface biophysical characteristics.

Many methods have been proposed to retrieve surface characteristics from remote sensing observations. They span from simple empirical ones with calibration over experimental data sets, up to more complex ones based on the use of radiative transfer models. Radiative transfer models summarize our knowledge on the physical processes involved in the photon transport within vegetation canopies or atmosphere, and simulate the radiation field reflected or emitted by the surface for given observational configuration, once the vegetation and the background as well as possibly the atmosphere are specified. Retrieving canopy characteristics from the radiation field as sampled by the sensor aboard satellite needs to "invert" the radiative transfer model.

This article aims at presenting the state of the art in the estimation of surface characteristics from remote sensing observations. Although this is a very general problem in remote sensing, it will be illustrated by examples taken in the solar domain (400–2,500nm), with emphasis put on the current operational algorithms that are mainly used for medium resolution sensors such as MODIS, MERIS, AVHRR, VEGETATION, POLDER and SEAWIFS. Among the possible canopy characteristics accessible from remote sensing in the reflective solar domain, we will focus on leaf area index (LAI), defined as half the developed area of green elements per unit horizontal soil (Stenberg, 2006). As a matter of fact, LAI is one of the key canopy state biophysical variables required by many process models to describe energy and mass exchanges in the soil/plant/atmosphere system.

7.2 Principles of Biophysical Variable Retrieval Algorithms

Remote sensing data result from radiative transfer processes within canopies that depend on canopy variables, and observational configuration (wavelength, view and illumination directions). Canopy variables include the variables of interest for the applications such as *LAI*, and the other variables that are not of direct use for the applications but that influence the radiative transfer, such as soil background properties. The causal relationship between the variables of interest and remote sensing data corresponds to the forward (or direct) problem (Fig. 7.1). They could be

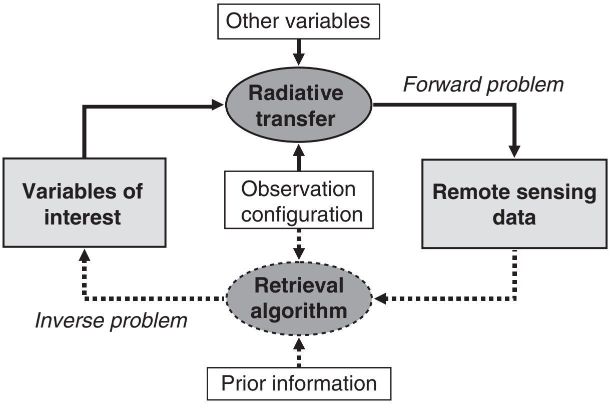

Fig. 7.1 Forward (solid lines) and inverse (dashed lines) problems in remote sensing

either described through empirical relationships calibrated over experiments or using radiative transfer models based on a more or less close approximation of the actual physical processes. Conversely, retrieving the variables of interest from remote sensing measurements corresponds to the inverse problem, i.e., developing algorithms to estimate the variables of interest from remote sensing data as observed in a given configuration. Prior information on the type of surface and on the distribution of the variables of interest can also be included in the retrieval process to improve the performances as we will see later.

A panoply of retrieval techniques currently used have been reviewed in the early 1990s by several authors (Asrar et al., 1989; Goel, 1989; Pinty and Verstraete, 1991) and more recently by Kimes et al. (2000) and Liang (2004). They can be split into two main approaches (Fig 7.2) depending if the emphasis is put on remote sensing data (radiometric data) or on the variables of interest to be estimated (canopy biophysical variables).

7.2.1 Canopy Biophysical Variables-driven Approach

The approach requires first to calibrate the inverse model: a parametric model representing the inverse model is adjusted over a learning data set (Fig. 7.2, left). It mainly consists in adjusting the parameters to fit a response surface between reflectance values and the corresponding canopy variables of interest (*LAI* in this example). Once calibrated, the parametric model is run to compute the variables of interest from the observed reflectance values. The learning data set can be generated either using simulations of radiative transfer models, or based on concurrent experimental measurements of the variables of interest and reflectance data.

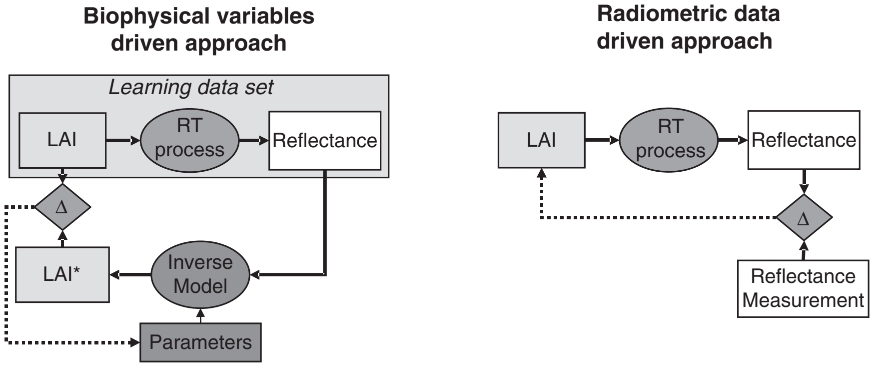

Fig. 7.2 The two main approaches used to estimate canopy characteristics from remote sensing data for LAI estimation. On the left side the approach focusing on the biophysical variables showing the calibration of the inverse model. Once the inverse model is calibrated it can be applied using the measured reflectance as input. On the right side, the approach focusing on radiometric data showing the solution search process leading to the estimated *LAI* value, *LAI**. "Δ" represents the cost function to be minimized over the biophysical variables (left) or over the radiometric data (right)

7.2.1.1 Calibration over Experimental Data Sets

This was the first approach historically used, the reflectance in few bands being generally combined into vegetation indices (*VI*) designed to minimise the influence of confounding factors such as soil reflectance and atmospheric effects (Baret and Guyot, 1991). The relationships between *VIs* and canopy variables are calibrated over experimental observations (Asrar et al., 1984; Huete, 1988; Wiegand et al., 1990; Wiegand et al., 1992; Richardson et al., 1992). Recently Chen et al. (2002) used simple *VIs* to derive *LAI* estimates from AVHRR and VEGETATION across Canada. This was extended at the global scale by Deng et al. (2006). In agreement with several observations, these authors found that the relationships vary from one cover type to another as illustrated by Fig. 7.3. The development of such empirical transfer functions is limited by the difficulty to get a training data base that represents the whole range of possible conditions encountered over the targeted surfaces, i.e., combinations of geometrical configurations, type of vegetation and states including variability in development stage and stress level, and type of background and state (roughness, moisture). Measurement errors associated both to the variables of interest and to radiometric data may also propagate into uncertainties and biases in the algorithm and should be explicitly accounted for Fernandes and Leblanc (2005) and Huang et al. (2006). Further, since ground measurements having a footprint ranging from few meters to few decametres, specific sampling designs should be developed to represent the sensor pixel. This task is obviously more difficult for medium and coarse resolution sensors as outlined by Morisette et al. (2006). Higher spatial resolution observations could be used to extend the local ground measurements to the actual pixel size of medium or coarse resolution sensors.

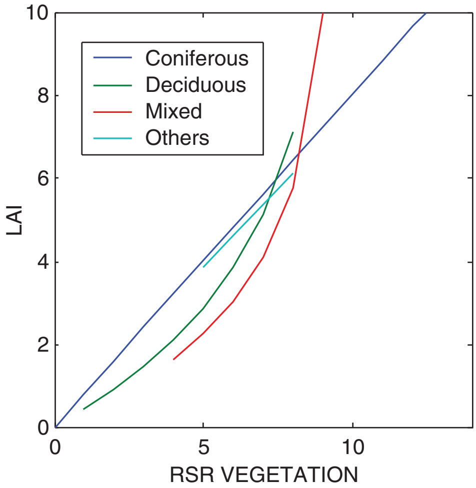

Fig. 7.3 Empirical relationships between *LAI* values as a function of the simple ratio vegetation index (*RSR*) computed for VEGETATION data for four types of canopies (After Chen et al., 2002)

7.2.1.2 Calibration over Radiative Transfer Model Simulations

To avoid limitations associated to the empirical nature of the training data base, radiative transfer models could be used alternatively to generate a training data base. Radiative transfer models can be used to create a data base covering a wide range of situations and configurations. Several authors have therefore proposed replacing actual observations by numerical experiments based on radiative transfer model simulations to calibrate empirical relationships (Sellers, 1985; Baret and Guyot, 1991; Rondeaux et al., 1996; Leprieur et al., 1994; Banari et al., 1996; Huete et al., 1997; Verstraete and Pinty, 1996). Based on these principles, operational algorithms developed for medium resolution sensors are currently used: MGVI for MERIS (Gobron et al., 2000) further extended to other sensors, MODIS back-up algorithm based on NDVI (Knyazikhin, 1999), POLDER algorithm based on DVI computed from bidirectional reflectance factor (BRF) measurements normalized to a standard geometrical configuration (Roujean and Lacaze, 2002). Nevertheless, although quite often effective, *VI*s are intrinsically limited by the empiricism of their design and the small number of bands concurrently used (generally 2–3). This might not be a major problem for *fAPAR* and *fCover* variables that are relatively simple to estimate, but would be more difficult for variables such as *LAI* or chlorophyll content (C_{ab}) showing higher level of non linearity with reflectance measurements (Weiss et al., 2000).

The efficient interpolation capacity of neural network (NNT) can be exploited to adjust surface responses (Leshno et al., 1993). Several authors have proposed such an approach since the beginning of the 1990s (Smith, 1992; Smith, 1993; Atkinson and Tatnall, 1997; Kimes et al., 1998; Abuelgasim et al., 1998; Gong et al., 1999;

Danson et al., 2003). Neural networks were compared with a specific implementation of multiple regression, the projection pursuit regression, and were concluded to achieve very similar performances (Fang and Liang, 2005). Baret et al. (1995) demonstrated that NNT used with individual bands were performing better than classical approaches based on vegetation indices especially when calibrated with radiative transfer model simulations rather than with experimental observations. Weiss et al. (2002a) validated such techniques over a range of crops for estimating the main canopy biophysical parameters *LAI* and *fCover* from airborne POLDER instrument. Recently, several authors developed operational products for medium resolution sensors, starting from top of canopy level: Lacaze (2005) for POLDER, Bacour et al. (2006) for MERIS, and Baret et al. (2007) for VEGETATION instruments. Baret et al. (2006b) proposed an operational algorithm from the MERIS top of atmosphere data by coupling an atmospheric radiative transfer model to the surface one, exploiting explicitly 13 over the 15 bands of MERIS.

Several ways may be used to build a data set for training empirical relationships depending on the performances targeted. Evaluation of the performances of an algorithm is generally achieved by computing the Root Mean Square Error (RMSE) value over a test data base made of representative cases. Best performances will therefore be obtained when the variables in the training data base are distributed similarly to those in the testing one, i.e., close to the actual distribution of the variables: the coefficients of the empirical transfer function will be optimized for these conditions, and uncertainties will be minimal for the most frequent cases. Although achieving poorer performances in term of RMSE, a more even distribution of the uncertainties may be alternatively obtained using uniform distributions of the variables. Note that, for a given number of cases simulated in the training data base, the density of cases that populate the space of canopy realization may rapidly decrease as a function of the number of required variables. Experimental plans may be used in this situation as proposed by Bacour et al. (2002b), in order to focus on the first order effects and interactions. Additionally, Baret et al. (2006b) proposed to steamline the data base in the reflectance space by retaining the cases that belong both to the simulated and actual remote sensing measurements spaces (Fig. 7.4). This allows discarding cases that were simulated but not actually observed. Conversely, it allows also identifying cases which are observed but not simulated. This is achieved by first compiling a large data base of reflectance measurements that should be representative of the possible situations available. Then the reflectance mismatch is

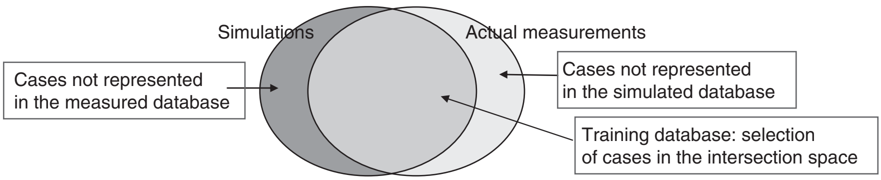

Fig. 7.4 Streamlining the simulated training data set by comparison to actual measurements. The intersection between the space of simulated radiometric data (in dark gray) with that of the actual measurements (in light gray) is used as the training data base

computed for each case in the simulated data base: it is the minimum RMSE value computed between the reflectance in the simulated data base and the ensemble of actual measurements. A threshold corresponding to the uncertainties in the radiometric measurements is then used to decide whether a simulated case is rejected from the training data base. Additional criterions could be used to streamline the training data base, based on the expected consistency between several products such as LAI and fAPAR as proposed by Bacour et al. (2006).

Although the use of radiative transfer models appears very appealing, this approach is however limited by several aspects. The first one is the capacity of the models to get a faithful description of the radiative transfer in canopies. Up to now, most radiative transfer models used are computer efficient ones allowing populating large training data base within few hours/days with a single regular computer. They generally correspond to simple description of canopy architecture which may not represent the actual one, particularly regarding the clumped nature of many vegetation types. This leads to model uncertainties that may dominate all other sources of uncertainties for some of the vegetation types. Recent advances in modeling more complex canopy architecture (e.g., Soler et al., 2001; Lewis et al., 2004) offer great potential for improvement. However, the second limitation will probably counterbalance these advancements: building a realistic training data set requires a fair description of the distribution and co-distribution of the corresponding architectural variables to define the actual space of canopy realization. For the simplest radiative transfer models (e.g., Verhoef, 1984; Kuusk, 1995; Gobron et al., 1997) at least three architectural variables are required (LAI, leaf angle distribution function and size of the leaves relative to canopy height), the distribution of which being very poorly known. This is even more difficult when using more complex and realistic architectural description that requires more variables.

Note that in these approaches based on radiative transfer model simulations, radiometric measurements uncertainties have to be added to the simulations when building up the training data base. This allows more robustness within the training process and thus improved retrieval performances. Accounting for these uncertainties is also critical when large differences exist among bands used or when these uncertainties are strongly correlated.

Canopy biophysical variables driven approaches present the advantage of being very flexible. For example, estimates of biophysical variables from one sensor could be used to constitute the training data base for another sensor. This could be applied over high spatial resolution products that are aggregated to coarser spatial resolution to generate an appropriate training data base. This could also apply to generate consistent products between sensors.

7.2.2 Radiometric Data-driven Approach

While the previous approach was focusing on minimizing the distance between the variables retrieved from the inverse model and those from the training data set, the alternative approach is based on finding the best match between the measured reflectance values and those either simulated by a radiative transfer model or stored within a database made of experimental observations. No proper calibration step is required in this approach. However, several ingredients of these techniques are difficult to evaluate (uncertainties, parameters of the search algorithm) and need generally some tuning over a "prototyping" data set. The performances of the approach will both depend on the minimization algorithm itself and on the level of ill-posedness of the inverse problem as a function of measurement configuration and model and measurement uncertainties. Several minimization techniques have been used: classical iterative optimization, simulated annealing (Bacour, 2001), genetic algorithms (Fang et al., 2003; Renders and Flasse, 1996), look up tables and Monte Carlo Markov Chains (Zhang et al., 2005). However, classical iterative optimization techniques (OPT) and look up tables (LUT) have been the most widely used and will be described with more details below.

7.2.2.1 Iterative Optimisation (OPT)

This classical technique consists in updating the values of the unknown input biophysical canopy radiative transfer model variables until the simulated reflectance closely fit the corresponding measurements (Goel and Deering, 1985; Kuusk, 1991a and 1991b; Goel, 1984a and b; Pinty et al., 1990; Jacquemoud et al., 1995; Privette et al., 1996; Bicheron and Leroy, 1999; Combal et al., 2000; Bacour et al., 2002a; Combal et al., 2002). A good review on optimization methods used in remote sensing for land applications can be found in Bacour (2001). The goodness of fit between measured and simulated reflectance spectra is quantified by a cost function (J) that may account explicitly for measurements and model uncertainties. The cost function may be theoretically derived from the maximum likelihood (Tarentola, 1987). When no prior information is available and when uncertainties associated to each configuration used are assumed independent and gaussian, J is assessed using norm L2, i.e., sum over the N observational configurations of the square of the difference between the measured reflectance values (R) and those simulated $(\hat{R})$, weighed by the variance (σ^2) associated to both reflectance measurements and model uncertainties:

$$J = \sum_{n=1}^{N} \frac{(R_n - \hat{R}_n)^2}{\sigma_n^2} \tag{7.1}$$

However, because of the difficulty to provide an estimate of σ^2, several approximations have been used as shown in Bacour (2001). It spans from the simple ones such as norm L1 to norm L2 with no weighing of the configurations, up to more complex based on some modeling of the variance term (Table 7.1).

The main limitation of OPT techniques is twofold. (1) Firstly, the algorithm might converge to a local minimum of the cost function that could be far away from the global one expected to correspond to the actual solution. This can be partly avoided by using a range of initial solutions, coupled with constraints on the range of variation of the variables to be estimated. The use of a priori information in the

Table 7.1 The cost functions (J) used in several studies dealing with radiative transfer model inversion for canopy biophysical variables retrieval. N is the number of configurations (bands and directions); $\hat{R}_n$ and R_n being respectively the simulated and measured reflectance values for configuration n. θ_v and ϕ are the zenith and relative azimuth view angles

Cost function	References
$J = \sum_{n=1}^{N} \frac{R_n - \hat{R}_n}{R_n}$	Gao and Lesht, 1997)
$J = \sum_{n=1}^{N} \left\| \frac{R_n - \hat{R}_n}{R_n} \right\|$	(Qiu et al., 1998)
$J = \sum_{n=1}^{N} \left(\frac{R_n - \hat{R}_n}{R_n + \hat{R}_n} \right)^2$	(Gobron et al., 1997)
$J = \sum_{n=1}^{N} (R_n - \hat{R}_n)^2$	(Goel and Thompson, 1984; Pinty et al., 1990; Privette et al., 1996; Braswell et al., 1996; Jacquemoud et al., 2000; Combal et al., 2002)
$J = \sum_{n=1}^{N} \left(\frac{R_n - \hat{R}_n}{R_n} \right)^2$	(Nilson and Kuusk, 1989; Kuusk, 1991a and b; Bicheron and Leroy, 1999; Weiss et al., 2000)
$J = \sum_{n=1}^{N} \omega_n \left(\frac{R_n - \hat{R}_n}{R_n} \right)^2 ;\ \omega_n = \frac{\cos(\theta_v \cdot \sin(\phi)) + 1}{2}$	(Bacour et al., 2002a)

cost function generally improves the convexity of the error surface, which is critical as we will see later (Combal et al., 2002). The descent algorithm may also limit the trapping in a local minimum by reducing the rate of descent. However, a compromise has to be chosen between rapid convergence achieved with large descent rate, and limiting the probability of falling in a local minimum achieved with a slow descent rate. Further, the optimization algorithm may sometimes lack of robustness due to numerical problems occurring generally with very small values of J. The criterion used to stop the iterations is in addition not always easy to adjust, requiring some preliminary tests (Bonnans et al., 2006). (2) Secondly, the OPT algorithm requires large computer resources because of its iterative nature. However, there are ways to speed up the process by limiting the number of model runs for each iteration using the adjoint model that provides an analytical expression of the gradient of the cost function (Lauvernet et al., 2007). Nevertheless, OPT techniques are still difficult to use routinely and exhaustively over large images, although image segmentation may help reducing significantly the number of pixels to process, the optimization process being restricted to a limited set of representative pixels. Note that these techniques allow getting some estimates of the uncertainties associated to the solution under some assumptions. However, the distribution of the solution will be here always unimodal, conversely to what could be achieved with the other radiometric driven approaches.

The main advantage of iterative optimization methods is their flexibility, allowing retrieving canopy characteristics from several observational configurations. It is even possible to invert radiative transfer models concurrently over several pixels. This opens great potentials for exploiting additional temporal or spatial constraints as we will see later.

7.2.2.2 Look Up Tables

This is conceptually the simplest technique, although its implementation is not trivial (Weiss et al., 2000). It is the basis of the MODIS and MISR LAI and fAPAR products (Knyazikhin et al., 1999). Firstly a large data base (the Look Up Table, LUT) is generated, consisting of sets of input variables of the canopy radiative transfer model used. Then, the corresponding reflectance values are simulated. The LUT can alternatively be based on experimental observations, although this requires a very good sampling of the space of canopy realization. Once the LUT has been generated, finding the solution for a given set of reflectance measurements consists in selecting the closest cases in the reflectance table according to a cost function, and then extracting the corresponding set of canopy biophysical variables. Note that the distribution of the solution could be obtained by accounting for the uncertainties associated to the reflectance values as discussed by Knyazikhin et al. (1998a and b).

This technique overcomes some of the limitations of iterative optimization techniques. As a matter of fact, the search for the solution is global here, leading to the true minimum if the space of canopy realisation is sufficiently well sampled. Note that for generating the LUT, the space of canopy realization has to be sampled to represent the surface response, i.e., with better sampling where the sensitivity of reflectance to canopy characteristics is the higher (Weiss et al., 2000; Combal et al., 2002). This is different from the sampling of the training data base required in canopy biophysical variables driven approaches.

The implementation of a LUT technique in algorithmic operational chains is very efficient because the radiative transfer model is run off-line. However, LUT techniques require a fixed number of inputs unless having very large tables that could be more difficult to manipulate. In addition, the way the solution is defined is not always based on solid theoretical background. The cases selected as possible solutions are either defined as a fraction of the initial population of cases (after tests and trials) such as in Weiss et al. (2000) or Combal et al. (2002). It can be also defined by a threshold corresponding to measurement and model uncertainties as in Knyazikhin et al. (1998a and b).

7.2.2.3 Bayesian Methods: Importance Sampling and MCMC

Alternative methods are available which are based on statistical backgrounds: Monte-Carlo Markov Chains (MCMC) and Importance Sampling (IS) (Makowski D., J. Hiller, et al., 2006). These two Bayesian methods approximate the posterior distribution, i.e., the distribution of the variables when the reflectance measurement is known. Although very little attention has been paid to these techniques at the exception of Zhang et al. (2005) who used with success the MCMC Metropolis-Hastings algorithm with MODIS data. However, Metropolis-Hastings algorithm is an iterative process that might not be well suited for operational applications at large scale, similarly to OPT methods. Conversely, IS methods that do not require multiple iterations might be efficient for this purpose and need to be properly evaluated for remote sensing applications.

7.3 The Under-determined and Ill-posed Nature of the Inverse Problem in Remote Sensing

7.3.1 Under-Determination of the Inverse Problem

Estimating biophysical variables from remote sensing measurements is often an under-determined problem: the number of unknowns is generally larger than the number of independent radiometric information remotely sampled by sensors. In the case of a simple canopy radiative transfer model such as SAIL (Verhoef, 2002), canopy reflectance at the top of canopy (ρ^{toc}) for a given illumination and view geometry $(\theta s,\ \theta v,\ \varphi)$ is simulated (Eq. (7.2)) using three variables describing canopy structure that do not depend on wavelength (*LAI*, average leaf angle (*ALA*) and hot spot parameter (*hot*) as modelled by Kuusk (1995)), and leaf reflectance (*refl*) and transmittance (*tran*) as well as soil reflectance (*Rs*) that obviously depend on wavelength (λ).

$$\rho^{\mathrm{toc}}(\lambda,\ \theta\mathrm{s},\ \theta\mathrm{v},\ \varphi)$$
$$= \mathrm{CAN}(LAI,\ ALA,\ hot,\ refl(\lambda),\ tran(\lambda),\ Rs(\lambda,\ \theta\mathrm{s},\ \theta\mathrm{v},\ \varphi),\ \theta\mathrm{s},\ \theta\mathrm{v},\ \varphi) \quad (7.2)$$

Several studies report that canopy (and soil) bidirectional reflectance distribution function (BRDF) could be decomposed using empirical or semi-empirical orthogonal functions with generally 2–4 kernels (Lucht, 1998; Bréon et al., 2002; Weiss et al., 2002). Therefore, 7–9 characteristics (3 canopy structure, 2 leaf properties [*refl, tran*] input variables and the 2–4 terms describing soil BRDF, $Rs(\lambda,\ \theta s,\ \theta v,\ \varphi)$ have to be estimated out of a maximum of 4 independent information derived from BRDF measurements in a single band. Retrieval of canopy characteristics from BRDF measurements in a single band is therefore not possible without introducing other information in the system, particularly when soil background plays a significant role, i.e., for low to medium *LAI* values.

Similar observations are made when considering the reflectance spectral variation: leaf spectral properties may be described by a dedicated model such as PROSPECT (Jacquemoud and Baret, 1990) requiring at least 5 input variables: mesophyll structure parameter (N), chlorophyll (C_{ab}), dry matter (C_{dm}), brown pigment (C_{bp}) and water (C_w) contents:

$$[refl(\lambda),\ tran(\lambda)] = \mathrm{LEAF}(N,\ C_{ab},\ C_{dm},\ C_{bp},\ C_w,\ \lambda) \quad (7.3)$$

Soil reflectance $Rs(\lambda,\ \theta s,\ \theta v,\ \varphi)$ may be described by a model such as that proposed by Jacquemoud et al. (1992) and derived from that of Hapke (1981). It requires a single scattering albedo $\omega(\lambda)$ that varies with wavelength and soil composition, between 1 to 4 phase function coefficients (α_i), and a roughness parameter (r). According to Price (1990), soil spectral variation, may be approximated as a linear combination of 2–10 end-members. This is assumed to apply similarly to the spectral variation of the single scattering albedo with weigh w_j and end members $\omega_j(\lambda)$:

$$\omega(\lambda) = \sum_j w_j \cdot \omega_j(\lambda) \tag{7.4}$$

The whole soil spectral and directional reflectance field could subsequently be simulated with at least five parameters:

$$Rs(\lambda,\ \theta s,\ \theta v,\ \varphi) = \mathrm{SOIL}([w_j],\ [\alpha_i],\ r,\ \lambda,\ \theta s,\ \theta v,\ \varphi) \tag{7.5}$$

Consequently, the whole spectral and directional top of canopy reflectance field could therefore be modelled by coupling together the soil, leaf and canopy reflectance models, which leads to at least 13 input variables. These 13 unknowns have to be estimated from the information content in remote sensing measurements. Most of currently available sensors for which operational biophysical products are available have a relatively small number of configurations: from two for AVHRR (red and near infrared bands), to 15 bands for MERIS (VIS and NIR) and MODIS (VIS, NIR, SWIR) with several bands dedicated to particular atmosphere, cloud, snow/ice, or ocean characteristics. In the case of multidirectional sensors, the number of configurations may be larger as in the case of MISR (36 configurations = 9 cameras ×4 bands), or POLDER (84 configurations = 14 directions ×6 bands). However, the actual dimensionality of remote sensing measurements is much smaller than the number of available configurations considering the relatively high level redundancy between bands (Price, 1994; Price, 1990; Liu et al., 2002; Green and Boardman, 2001) and directions (Zhang et al., 2002a and b; Weiss et al., 2002b). Although further investigation is required to better quantify the actual dimensionality of remote sensing observations, it is clear that retrieval of surface characteristics from reflectance measurements is an under-determined problem in many cases. Improving retrieval performances will require introducing ancillary information and constraints in the system.

7.3.2 Evidence of the Ill-posed Problem

A problem is well posed if and only if its solution exists, is unique, and depends continuously on the data (Garabedian, 1964). Several authors have reported that the inverse problem in remote sensing is ill-posed (Knyazikhin et al., 1999; Combal et al., 2001; Baret et al., 2000) because of its under-determination and uncertainties attached to models and measurements. In addition, models may incorporate sets of

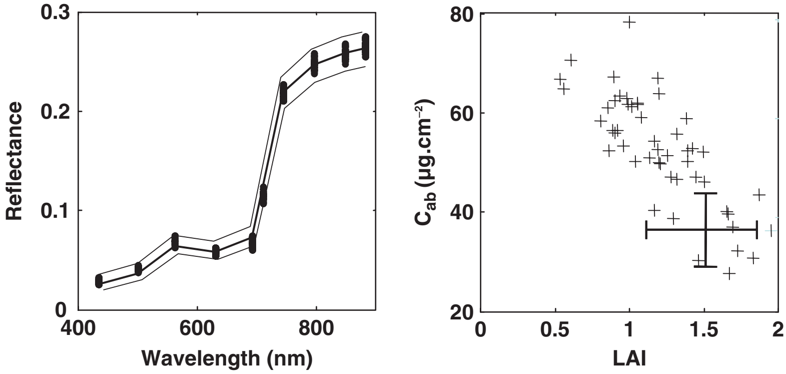

Fig. 7.5 Actual reflectance measurements (left plot, solid lines representing the mean and standard deviations) and the corresponding closer simulations achieved with a simple turbid medium radiative transfer model (the series of dots). On the right, the input LAI and Cab (the "+" symbols) variables used to simulate the reflectance spectra shown on the left plot. The actual LAI and Cab measurements are displayed with their associated confidence interval (bold line corresponding to 1 standard deviation). Data acquired over a sugar beet experiment conducted in 1990

variables that appear always in combinations such as products between variables. In these conditions, very similar reflectance spectra simulated by a radiative transfer model (Fig. 7.5, left) may correspond to a wide range of solutions (Fig. 7.5, right). In the case illustrated by Fig. 7.5, high correlation is found between *LAI* and those leaf chlorophyll content estimated values. This compensation between variables was sometimes termed "ambiguity" (Baret et al., 1999) or "equi-finality" (Shoshany, 1991; Teillet et al., 1997). This may also indicate that the product $LAI \cdot C_{ab}$ should be used in place of individual estimates of *LAI* and C_{ab}. Although not appearing formally in the radiative transfer model, this product is physically meaningful from the radiative transfer processes perspective and corresponds to the actual optical thickness of the medium (Weiss et al., 2000).

Measurement and model uncertainties may also induce instability in the solution of the inverse problem. This is particularly true for well developed canopies, where a small variation in the measured reflectance can translate into large variation of variables such as *LAI*, for which reflectance "saturates", i.e., is very little sensitive to *LAI* variation. A proper sensitivity analysis should help quantifying interactions between input variables. A complementary sensitivity analysis conducted over the cost function could also help evaluating the identifiability of the solution, i.e., if output variables could be accurately retrieved from a given set of observations (Salteli, 2004).

Regularization techniques are thus necessary to obtain a stable and reliable solution of the ill-posed inverse problem. This could be achieved both by using prior information on the distribution of the variables, and by exploiting some constraints on the variables. These two issues will be investigated separately in the following.

7.4 Improving the Retrieval Performances

7.4.1 Using Prior Information

If no remote sensing measurement is available, the best estimates of the variables would come from the prior information on their distribution (Fig. 7.6d), capitalizing, all the knowledge coming from bibliography, past experiments or experts. Conversely, when a radiative transfer model is available along with remote sensing measurements, the variables can be estimated by inverting the RT model without using any prior information. This will be illustrated using a simple example: estimating *LAI* from *NDVI* vegetation index. In this case the RT model consists in an analytical relationship as proposed by Baret and Guyot (1991):

$$NDVI = NDVI_{\infty} + (NDVI_s\text{-}NDVI_{\infty}) \cdot \mathrm{e}^{-K \cdot LAI} \tag{7.6}$$

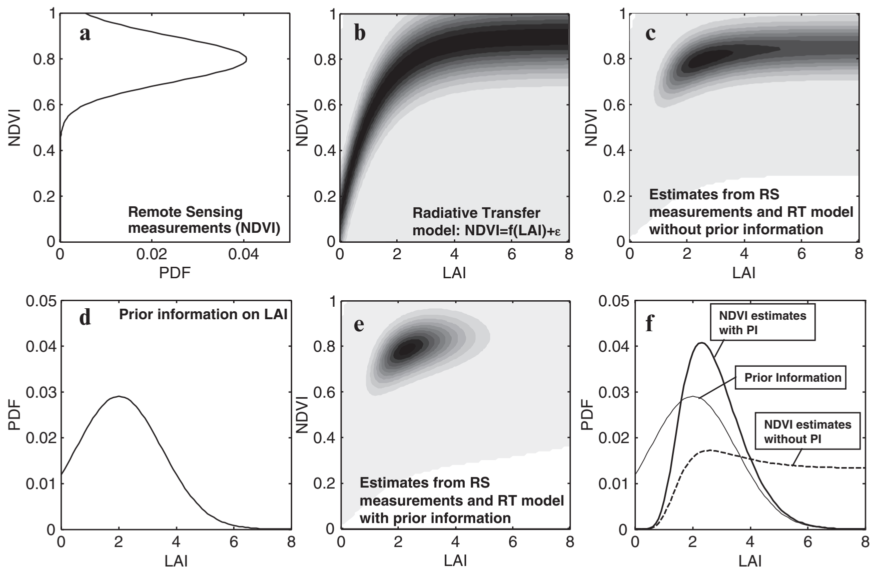

Fig. 7.6 Estimation of canopy variables by combining remote sensing measurements, radiative transfer model and prior information. All these pieces of information are represented by their probability distribution function (PDF): (**a**) PDF of remote sensing measurements in the simple case of *NDVI*; (**b**) PDF of RT model simulations $(NDVI = \mathrm{f}(LAI))$ accounting for model uncertainties; (**c**) PDF of LAI as retrieved from RT model and *NDVI* measurement and their associated uncertainties, without using prior information; (**d**) PDF of LAI used as prior information; (**e**) Computation of *LAI* PDF as estimated from *NDVI* measurements and RT model, using prior information on *LAI*; (**f**) PDF of the solution (posterior distribution) when using only prior information (idem as plot d), using RT model and *NDVI* measurements and their associated uncertainties only, and using all the information available (RT model and NDVI measurements and their associated uncertainties and prior information). The three contour plots (b, c, e) are coded from white to black for zero to max PDF values with the same gray scale. Very simple assumptions on uncertainties models and values are used here just for illustration

with $NDVI_s$ and $NDVI_\infty$ being respectively the bare soil and asymptotic values of *NDVI*, and K an extinction coefficient $(K = 0.8)$. However, uncertainties are associated both with remote sensing measurements (Fig. 7.6a $NDVI_r = \aleph(0.8, 0.1)$ where $\aleph(\mathrm{x},\ \sigma^2)$ means a Gaussian distribution with mean x and variance σ^2) and the RT model (Fig. 7.6b RT model represented by Eq. (7.2) with a Gaussian noise $\aleph(0, 0.1)$). Accounting for these uncertainties in the form of the corresponding probability distribution function (PDF) allows deriving the PDF of the estimated variable (Fig. 7.6c). The small sensitivity of *NDVI* to *LAI* as compared to measurement and model uncertainties induce a relatively broad PDF for the larger *LAI* values (Figs. 7.6c, f). This corresponds to an ill-posed problem, where a wide range of possible solutions match very similar measurements. The combination of RT model, remote sensing measurements and prior information on the variables (here $LAI = \aleph(2,\ 1.5)$ allows getting more reliable solutions accounting for all the sources of information available in an optimal way (Figs. 7.6e, f).

The example provided above for a measurement value of $NDVI = 0.8$ could be extended to the whole range of *NDVI* values. It shows that the mode of the distribution of the solution corresponding to the maximum likelihood (maximum of the PDF) strongly depends on the type of input information used (Fig. 7.7, left). When only prior information is used, the mode stays constant and obviously independent from measurements. When RT model and measurements are used with their uncertainties, the *LAI* mode is generally close to the values obtained without considering uncertainties, assuming perfect model and measurements. However, over the saturation domain corresponding to *NDVI* values higher than 0.85, accounting for the uncertainties provides lower modal values because of the non linearity of the

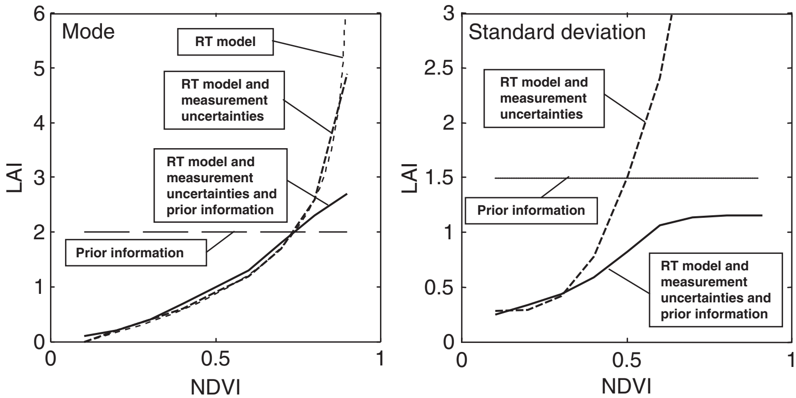

Fig. 7.7 Mode (plot on the left) of the distribution of the solution (*LAI*) of the inverse problem as a function of the measured value (*NDVI*). The mode corresponds to the maximum PDF value, i.e., the maximum likelihood. Four estimates are displayed: using only prior information; using RT model $(LAI = RT^{-1}\ (NDVI))$ assumed to be perfect with perfect measurements (no uncertainities accounted for); using RT model and measurements with their associated uncertainities; using RT model and measurements with their associated uncertainities and prior information. On the right, the standard deviation of the distribution of the solution is also displayed for the several cases. The case with perfect RT model and measurements is not displayed here because its standard deviation is null by definition

model. When prior information is used in addition to RT model and remote sensing measurements, differences of *LAI* mode are marginal over the domain where *NDVI* is sensitive enough to *LAI*. Conversely, over the saturation domain, *LAI* modal values are always lower (closer to prior information value) than those observed when not using prior information which would lead to a bias. However, the interest of using the prior information is clearly demonstrated when considering the standard deviation of the distribution of the solutions (Fig. 7.7, right).

Introducing prior information in the inversion process provides a very significant reduction of the variability of the posterior distribution. This is obviously more important for the larger *NDVI* values corresponding to the saturation domain: in this case, very large scattering of the retrieved *LAI* values is expected when no prior information is used. Although the maximum likelihood is often used as "the solution", the variability within the posterior distribution as represented by its standard deviation appears to be very informative and useful.

The theory behind this Bayesian approach has been extensively described by Tarantola (2005). When restricting the solution as that maximizing the likelihood, i.e., corresponding to the maximum of the PDF, a general formulation of the cost function may be derived under Gaussian distribution assumption:

$$J = \underbrace{(R-\hat{R})^t \cdot W^{-1} \cdot (R-\hat{R})}_{\text{Radiometric information}} + \underbrace{(\hat{V}-V_p)^t \cdot C^{-1} \cdot (\hat{V}-V_p)}_{\text{Prior information}} \tag{7.7}$$

where $\hat{V}$ is the vector of the input biophysical variables estimates, R corresponds to the vector of remote sensing measurements of dimension N (the number of bands and directions used), $\hat{R}$ is the vector of the simulated reflectance corresponding to the solution $\hat{V}$ (the vector of canopy biophysical variables) and V_p the vector of prior values of biophysical variables. Matrices W and C are the covariance matrices characterizing respectively the radiometric and model uncertainties, and that of the prior information. Note that the first part of this equation corresponds to the distance between the measured and the simulated radiometric data. It simplifies into Eq. (7.1) if the covariance terms of matrix W are assumed to be zero, i.e., measurement and model uncertainties are independent between configurations. The second part of Eq. (7.7) corresponds to the distance between the values of the estimated variables and those of the prior information. Very few studies are currently based on this formulation of the cost function where prior information is explicitly used (Combal et al., 2002).

Implementing the cost function as expressed by Eq. (7.7) requires some reasonable estimates of covariance matrices W and C as well as prior values V_p. The terms of W should reflect both measurement and model uncertainties. While some rough estimates of measurement uncertainties could be derived from the sensor specification, model uncertainties are far more difficult to estimate. Further, they may depend significantly on the type of situation considered, such as low or high vegetation amount. Even more difficult to estimate, are the covariance terms in W: measurement and model uncertainties may have important structure that translates into high covariance terms which are however very poorly known. When using simultaneously a large number of configurations as in the case of hyperspectral observations, these covariance terms will be very important to account for: they will allow weighing properly the several configurations used. The difficulty to estimate the covariance terms explains why a small number of configurations is often selected when a larger number is available as in the case of hyperspectral and/or directional observations.

Retrieval approaches should be used within well defined and if possible restricted domains. Larger domains will generally degrade retrieval performances since the prior information will be looser defined, similarly to the covariance matrices characterizing uncertainties. However, splitting the whole domain into a set of subdomains may introduce problems due to misclassification and attribution errors as observed by Lotsch et al. (2003), and artefacts at the limit between classes translating into more chaotic spatial or temporal variation of the solution.

The way prior information is introduced in the inversion process depends on the inversion technique used. The cost function represented by Eq. (7.7) is used within iterative optimization and LUTs. Bayesian methods include the a priori distribution through the use of the Bayes theorem to estimate the a posteriori distribution. For biophysical variables driven approaches the training data base should reflect the actual knowledge on the distribution of the variables. Note that the difficulty in defining explicitly the covariance terms in the uncertainties on remote sensing inputs (RT model and measurements) for the radiometric data driven approaches remains in the biophysical variables driven approaches for the generation of the training data base. However, implicit introduction of these terms may be achieved when using a training data base made from actual satellite measurements as suggested by Bacour et al. (2006).

7.4.2 Using Additional Constraints

7.4.2.1 Coupling Models

The radiative transfer in each element of the soil/leaf/canopy/atmosphere system is strongly coupled to the radiative transfer in the whole system. The simple example given previously to demonstrate the under-determined nature of the inverse problem in remote sensing shows that top of canopy reflectance could be written as:

$$\begin{aligned}\rho^{toc}(\lambda,\,\theta s,\,\theta v,\,\varphi) = \mathrm{CAN}(&LAI,\,ALA,\,hot,\,\mathrm{LEAF}(N,\,C_{ab},\,C_{dm},\,C_{bp},\,C_w),\\ &\mathrm{SOIL}([w_j],\,[\alpha_i],\,r,\,\lambda,\,\theta s,\,\theta v,\,\varphi),\,\theta s,\,\theta v,\,\varphi)\end{aligned} \tag{7.8}$$

The same applies when retrieving some characteristics of the system from top of atmosphere reflectance (ρ^{toa}) measurements as usually achieved by sensors aboard satellite:

$$\rho^{toa}(\lambda,\theta s,\theta v,\varphi) = \mathrm{ATM}(\rho^{toc}(\lambda,\theta s,\theta v,\varphi),\tau_{550},\ddot{A},P_{atm},C_{wv},C_{03},\lambda,\theta s,\theta v,\varphi) \tag{7.9}$$

where *ATM* represents an atmospheric RT model such as 6S (Vermote et al., 1997) or MODTRAN (Berk et al., 1998), τ_{550}, $\dot{A}$, being respectively the aerosol optical thickness at 550 nm and the Angström coefficient, P_{atm} is the atmospheric pressure, C_{wv} is the water vapor content and C_{03} the ozone content.

Retrieval of characteristics of some element of the system without solving (implicitly or explicitly) the whole system will therefore be sub-optimal as demonstrated below.

Let consider retrieving leaf biophysical properties $[N,\ C_{ab},\ C_{dm},\ C_{bp},\ C_w]$ from top of canopy remote sensing observations in B wavebands using a decoupled system and an iterative optimization technique. For sake of simplicity, soil reflectance will be assumed to be known. Estimates of leaf properties could be achieved in two steps. First, estimate the variables $[LAI,\ ALA,\ hot,\ refl(\lambda),\ tran(\lambda)]$ from the reflectance in each of the B bands. A cost function accounting for the reflectance in the B bands should be minimized with the constraint that *[LAI, ALA, hot]* does not vary with wavelength. The number of unknowns in the system will therefore be $(3+2\cdot B)$ corresponding to the 3 canopy structure variables and the 2 (reflectance and transmittance) leaf optical properties time the B bands. The second step of the process consists in estimating leaf biophysical properties $[N,\ C_{ab},\ C_{dm},\ C_{bp},\ C_w]$ from the retrieved leaf reflectance and transmittance in the B bands. The variables $[N,\ C_{ab},\ C_{dm},\ C_{bp},\ C_w]$ are tuned by minimizing a cost function accounting for leaf reflectance and transmittance in the B bands. Obviously, increasing the number of bands will not improve the underdetermined nature of the problem because the number of unknowns in the first step of the process will grow twice faster. In addition, since no biophysical constraints are set on the spectral variation of leaf optical properties, canopy structure variables derived from the first step may express larger and unrealistic range of variation. The proper way to solve this type of problem is to minimize a cost function accounting for canopy reflectance over the B wavebands based on the coupled leaf and canopy models. In this case, the number of unknowns will be eight (the three canopy structure variables and the five leaf characteristics) which is independent from the number of wavebands used. This allows limiting the under-determined nature of the problem by increasing the spectral sampling.

Most of the retrieval approaches from top of canopy radiometric observations are now using implicitly or explicitly coupled models as shown in Table 7.2. However, although offering great potentials as demonstrated recently (Baret, 2006b), the use of coupled atmosphere/surface models is still not very well developed because each sub-problem was handled by different communities.

7.4.2.2 Spatial Constraints

Up to now, most retrieval algorithms are applied to independent pixels, neglecting the possible spatial structure as observed on most images. However, some authors attempted to exploit these very obvious patterns at high spatial resolution. The "object retrieval" approach proposed by Atzberger (2004) is based on the use of covariance between variables as observed over a limited cluster of pixels representing the same

Table 7.2 Synthesis of the several algorithms currently used operationally to retrieve canopy biophysical variables. 1: (Lacaze, 2004); 2: (Knyazikhin et al., 1999); 3: (Gobron et al., 1999); 4: (Weiss et al., 2002; Baret et al., 2007); 5: (Chen et al., 2002; Deng et al., 2006); 6: (Bacour et al., 2006)

#	Algorithm	RT models				Inversion technique	uncertainties	prior information
		leaf	soil	Canopy	Atmosphere			
1	**POLDER** *LAI, fAPAR*	PROSPECT N, *Cab,* *(Cw,Cdm, Cs)*	PRICE 2 abundances	Kuusk LAI, ALA, hot	TOC	NNT	measurements	Some variables fixed Range of variation
2	**MODIS/MISR** *LAI, fAPAR*	prescribed for each biome	Hapke 3 typical + understorey	DISORD 6 biomes	TOC	LUT	measurements prescribed at 20%	specific values for 6 biomes
3	**MERIS**[(1)] **MGVI** *fAPAR*	PROSPECT N, *Cab,* *(Cw,Cdm, Cs)*	5 typical soil unique BRDF	Gobron LAI, ALA, hot	TOA (MODTRAN)	Parametric	not specified	Range of variation (uniform distribution)
4	**VEGETATION**[(2)] **CYCLOPES** *LAI, fAPAR, fCover*	PROSPECT N, *Cab,* *Cw,Cdm, Cbp*	brightness parameter &reference spectra	SAIL LAI, ALA, hot, vCover	TOC	NNT	model and measurements prescribed at 4% (relative)	approximation of actual distribution
5	**VEGETATION-Canada-Global** *LAI*	Empirical relations for specific biomes using TM sensor and the corresponding ground measurements over some sites Prescribed BRDF model			TOC	Parametric	not specified	Specific relations for each biome
6	**MERIS** *LAI, fAPAR, fCover, LAIxCab*	PROSPECT green/brown separated N, Cab, Cdm, Cw, Cbp	brightness parameter &reference spectra	SAIL, LAI, ALA, hot, vCover	2 versions: - TOC version - TOA version (SMAC)	NNT	model and measurements prescribed at 4% (relative)	approximation of actual distribution

class of object such as an agricultural field. Results show quite significant improvement of the retrieval performances for *LAI*, C_{ab} and C_w, presumably because of a better handling of the possible compensation between *LAI* and *ALA* in the retrieval process as suggested by Atzberger (2004) and outlined by Jacquemoud (1993).

Other approaches based on models with random effects (Faivre and Fischer, 1997) may be also very attractive, although rarely used within the land remote sensing community. They allow characterizing a population by their two first statistical moments (mean and variance). In the case of remote sensing applications, this could be applied over a cluster of P pixels belonging to the same class of surface as in the "object retrieval" approach of Atzberger (2004). The inversion process could be achieved by tuning both the mean and variance values of each input variable over the P pixels using iterative optimization techniques. The individual values of each pixel could be derived from the estimated mean and variance values of the variables and the departure between the actual radiometric measurements of the pixels and the mean values over the object. The under-determination of the problem could significantly decrease with this approach: the number of unknowns to estimate is independent on the number of pixels considered in the cluster and is just twice the number of variables to estimate (mean and variance).

Although quite promising, these methods need further evaluation, and probably adaptation before being accepted and used by the remote sensing community. Note that only statistical distributions are used for both methods presented, although additional geo-statistical constraints could be exploited particularly for the higher spatial resolutions, based on variograms (Garrigues et al., 2006).

7.4.2.3 Temporal Constraints

The dynamics of canopies results from elementary processes under the control of climate, soil and the genetic characteristics of the plants that incrementally change canopy structure and optical properties of the elements. Very brutal and chaotic time course are therefore not expected, at the exception of accidents such as fire, flooding, harvesting, or lodging. The smooth character of the dynamics of canopy variables may be exploited as additional constraint in the retrieval process. Kötz et al. (2005) proposed using a semi-empirical model of canopy structure dynamics to improve remote sensing estimates of *LAI* over maize crops. Results show a significant improvement of estimates, particularly for the larger *LAI* values where saturation of reflectance is known to be a problem. This approach requires a semi-empirical model of canopy structure dynamics (here *LAI*) describing the whole growth cycle with few parameters. In the case of the model used by Kötz et al. (2005) five parameters are needed. In this case, the under-determined nature of the inverse problem will decrease only if more than five dates of remote sensing observations are available and well distributed over the growth cycle. However, because the parameters of the model of *LAI* dynamics have some biological meaning, prior information on them could be accumulated and efficiently exploited.

More recently, Lauvernet et al. (2007) proposed a "multitemporal patch" inversion scheme to account for both spatial and temporal constraints. Reflectance data are here considered observed from top of atmosphere. Atmosphere/canopy/leaf/soil RT models are thus coupled to simulate top of atmosphere reflectance from the set of input variables as stated by Eqs. (7.8) and (7.9). Spatial and temporal constraints are based on the assumption that the atmosphere is considered stable over a limited area (typically few kilometres) but varies from date to date, and that surface characteristics vary only marginally over a limited temporal window (typically ± 7 days) but may strongly change from pixel to pixel. This has obviously important consequences on the under-determined nature of the inverse problem as demonstrated hereafter. The atmosphere characteristics $[P_{atm},\ C_{wv},\ C_{03}]$, except the aerosol ones $[\tau_{550},\ \ddot{A}]$, are assumed to be known from independent observations such as meteorological estimation or dedicated sensors or algorithms. The observational configuration $[\lambda,\ \theta s,\ \theta v,\ \varphi]$ is also known at the time of image acquisition. Soil reflectance was simply approximated as lambertian, with reflectance proportional to a reference soil spectra according to a brightness parameter *Bs* (Bacour et al., 2006). The brightness parameter is assumed to vary both from date to date and pixels to pixels, without any constraints. The forward model resulting from nesting the RT models presented previously could be written as a function of the ten unknowns $[N,\ C_{ab},\ C_{dm},\ C_{bp},\ C_w,\ LAI,\ ALA,\ hot,\ Bs,\ \tau_{550},\ \ddot{A}]$ with $\mathrm{n_A} = 2$ atmosphere variables, $\mathrm{n_C} = 8$ canopy and leaf variables and $n_s = 1$ soil variables. Let consider *d* dates of observation available over a limited temporal window during which the canopy variables are about constant, and a spatial window of *p* pixels for which the atmosphere is considered homogeneous. The number of unknowns, $N(p,d)$ in the case of concurrent inversion of an ensemble of *d* dates and *p* pixels using the spatial and temporal constraints described above is therefore:

$$N(p,d) = d \cdot n_A + p \cdot n_C + d \cdot p \cdot n_S \tag{7.10}$$

Inverting the nested radiative transfer models concurrently over an ensemble of d dates and p pixels will significantly reduce the total number of unknowns. $(N(p,d))$ as compared to p times d independent instantaneous pixel inversions $(p.d.N(1,1))$. Figure 7.8 shows that the number of unknowns to be estimated within the same inversion process for p pixels and d dates as compared to $p.d$ single pixel and single date inversions $(N(p,d)/(p.d.N(1,1)))$ decreases significantly up to about 10 pixels. However, the main advantage over "ensemble" inversion is reached when applying concurrently the inversion process to several dates. Using two dates and more than 10 pixels allows dividing by almost 2 the number of unknowns. Note that these results concern only the number of unknowns, and is therefore applicable to any observational configuration characterized by a set of bands and directions.

Results on the performances achieved demonstrate the interest of the approach for the estimation of most of the variables, particularly for the aerosol characteristics and for *LAI*, $LAI \times C_{ab}$ and *ALA* canopy characteristics. However, again, this new approach was only demonstrated over RT simulations, and its interest should be verified over experiments with actual remote sensing data and the corresponding ground truth.

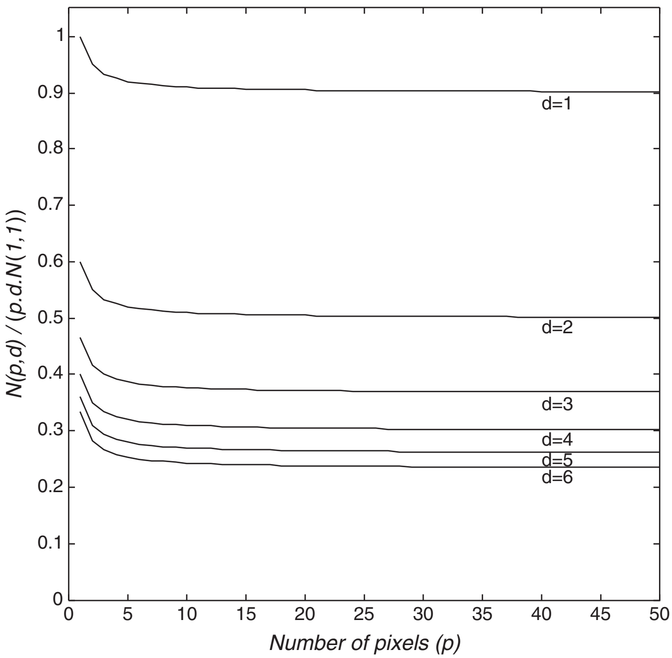

Fig. 7.8 Ratio, $N(p,d)/(p.d.N(1,1))$, between the number of unknowns when applying the inversion process concurrently to p pixels and d dates with that of single pixel and date inversion as a function of the number of dates and pixels considered

7.5 Conclusion

This overview of retrieval approaches is based on methods currently used, while alternative ways to solve the problem and hopefully improve the accuracy and robustness of estimates were briefly introduced. Several ingredients of the algorithms were identified apart from the retrieval techniques themselves: radiative transfer models, observations, additional information and constraints. We will briefly summarize the conclusions for each of these ingredients in the following.

7.5.1 Retrieval Techniques

The several techniques investigated have been classified as radiometric variables or biophysical variables driven approaches. However, both types of methods could be either derived from actual measurements or based on radiative transfer model simulations. The best approaches are obviously the ones that will be trained over data sets that are as close as possible to the evaluation data set. For this very reason, canopy biophysical variables trained over empirical data sets would be ideal. In addition, canopy biophysical variables driven approaches present the advantage of being very computer efficient once trained, allowing easy implementation within operational processing chains. However, because of the difficulty of getting a large enough training data set representing the actual distribution of cases (observational configuration, type of canopies and state, background properties, eventually atmosphere characteristics), training data base made of radiative transfer model simulations is preferred. These hybrid techniques as termed by Liang (2004) require however the radiative transfer models to be well adapted to the type of canopy they target, and their adequacy to be quantified to properly input model uncertainties. In addition, the structure of uncertainties on the radiometric variables and distribution and co-distribution of the input biophysical variables should be also known. An alternative approach currently not yet explored would consist in bridging the two retrieval approaches: actual sensor measurements are used to build the training data base allowing to keep all the structure of measurement uncertainties. This data base should be representative of the cases investigated, which might be possible by specific spatial and temporal sampling schemes as proposed by Baret et al. (2006a) in the case of global observations. The corresponding best estimates of canopy biophysical variables could be derived from inversion methods such as iterative optimization techniques for which all the information available should be exploited: fusion of all currently available sensors observations, prior information and spatial and temporal constraints.

As a matter of fact, most radiometric variables driven approaches are very flexible and could easily ingest data from several sensors, bands and directions, at the expense of computer requirements which make these methods more difficult for an operational use. Conversely, canopy biophysical driven approaches are not as flexible as radiometric driven approaches: they are generally tuned for a limited set of observational conditions: using other configurations would require a specific training or a dramatic enlargement of the training data base.

Retrieval methods will be more efficient when applied to a limited set of surface types as compared to a very generic (global) solution. Approaches based on a classification would thus allow closer adaptation to each class of both the radiative transfer model and prior information. However, attribution errors may significantly alter the performances. Using a continuous classification (Hansen et al., 2002; Hansen and DeFries, 2004; Schwartz and Zimmermann, 2005) will probably limit this source of uncertainties and avoid getting artefacts when two consecutive pixels will jump from one class to another.

Biophysical variables estimates are generally integrated within other process models such as hydrology or biogeochemical cycling along with other ground observations. Quantification of the associated uncertainties is therefore required to properly merge these several sources of information. Current available products did not provide quantitative evaluation of the confidence interval around the solution, but are limited to qualitative indices. Bayesian approaches provide a direct access to the distribution of the solution of the inverse problem and may be very useful for estimating the uncertainties. Current operational algorithms need further developments to fully satisfy this important user requirement.

7.5.2 Radiative Transfer Models

Performances of methods based on radiative transfer models are largely depending on the realism of the simulations. Radiative transfer models are based on a set of assumptions, particularly regarding the description of canopy architecture. A more realistic description of canopy architecture will require additional input variables and will be probably more demanding in computer resources. Knowledge of prior distribution and co-distribution of these additional canopy structure variables will constitute a limitation. Further, using such more realistic radiative transfer model requiring a larger number of unknowns will not necessarily improve the retrieval performances because the under-determination of the problem will be even more limiting. A compromise should therefore be found between the realism of the description of canopy structure, and its complexity.

Particular attention should be paid on the definition of the variables used in the radiative transfer model that should match the one required for the application. For example, the original *LAI* definition (Stenberg, 2006) may be altered depending on the way and scale at which leaf clumping is accounted for (Chen and Leblanc, 1997). Great caution should be also paid when comparing retrievals with ground measurements or inter-comparing several products.

As demonstrated here, holistic approaches based on the coupling of canopy, leaf and soil models are optimal for best performances. Eventually, coupled surface and atmosphere models would certainly help solving in an elegant way the retrieval of surface variables from top of the atmosphere observations.

7.5.3 Observations and Ancillary Information

The observational configuration is an important element that drives the accuracy of canopy biophysical variables estimation. It depends obviously on the variables targeted. For the time being, sufficient maturity is achieved for the estimation of LAI, fAPAR, the cover fraction, chlorophyll and water contents variables to implement operational algorithms for delivering the corresponding products to the user community. The interest of multidirectional and hyperspectral observations is still to be rigorously demonstrated for these variables by comparison over actual ground measurements.

Frequent observations are required to monitor the dynamics of the vegetation that conveys a large amount of information on the functioning of the surface. With the hopefully venue of systems capable of high revisit frequency with high spatial resolution, new retrieval methods should be developed to exploit the temporal and spatial dimensions in addition to the more classical spectral and in a lesser way directional ones. This would allow benefiting from the spatial and temporal constraints and consequently reduce the number of unknowns to be retrieved. Ultimately, this approach will converge towards direct assimilation of top of atmosphere radiances into surface process models. However, the research community is not mature enough on the coupling between radiative transfer models and canopy process models. Radiative transfer model inversion had still to mature and improve the accuracy of surface variables estimation before jumping towards radiance data assimilation.

Knowledge and management of uncertainties is one of the critical issues for the retrieval algorithms. If measurement uncertainties coming from the sensor are relatively well known, their structure (covariance between bands and directions for example) is poorly documented. This is even worse when considering model uncertainties that may change dramatically from place (and time) to place (and time) with presumably specific features (covariance between configurations).

The other critical issue is the lack of prior information on the distribution of most land surface attributes. However, this could be accumulated from the numerous experiments organized in support of satellite images. A mechanism should thus be developed to capitalize on the information gathered within the remote sensing research community as well as other communities working with ecosystems. Note that getting high spatial resolution data will considerably ease the characterization of prior distribution of the variables, provided that each pixel could be properly classified.

Any retrieval algorithm should be properly validated before delivering its products to the user community according to consensus protocols (Morisette et al., 2006). This process will not only provide a way to characterize the associated uncertainties, it will be also critical for improving the algorithms. A short feedback loop should therefore be set-up between algorithm prototyping and validation. When retrieval algorithms are based on radiative transfer modeling, this will implicitly merge observations and model to improve robustness and accuracy of the products at the expense of a decrease in the desired independency between the validation and calibration processes.

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