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A review on reflective remote sensing and data assimilation techniques for enhanced agroecosystem modeling

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Abstract

During the last 50 years, the management of agroecosystems has been undergoing major changes to meet the growing demand for food, timber, fibre and fuel. As a result of this intensified use, the ecological status of many agroecosystems has been severely deteriorated. Modeling the behavior of agroecosystems is, therefore, of great help since it allows the definition of management strategies that maximize (crop) production while minimizing the environmental impacts. Remote sensing can support such modeling by offering information on the spatial and temporal variation of important canopy state variables which would be very difficult to obtain otherwise.

In this paper, we present an overview of different methods that can be used to derive biophysical and biochemical canopy state variables from optical remote sensing data in the VNIR-SWIR regions. The overview is based on an extensive literature review where both statistical–empirical and physically based methods are discussed. Subsequently, the prevailing techniques of assimilating remote sensing data into agroecosystem models are outlined. The increasing complexity of data assimilation methods and of models describing agroecosystem functioning has significantly increased computational demands. For this reason, we include a short section on the potential of parallel processing to deal with the complex and computationally intensive algorithms described in the preceding sections.

The studied literature reveals that many valuable techniques have been developed both for the retrieval of canopy state variables from reflective remote sensing data as for assimilating the retrieved variables in agroecosystem models. However, for agroecosystem modeling and remote sensing data assimilation to be commonly employed on a global operational basis, emphasis will have to be put on bridging the mismatch between data availability and accuracy on one hand, and model and user requirements on the other. This could be achieved by integrating imagery with different spatial, temporal, spectral, and angular resolutions, and the fusion of optical data with data of different origin, such as LIDAR and radar/microwave.

Keywords: Data assimilation; Agroecosystem modeling; Vegetation indices; Canopy reflectance modeling; Biophysical variables; Biochemical variables; Parallel processing

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1. Introduction

More than one fourth of the global land surface area is covered by agroecosystems (Coleman and Hendrix, 1988). Nevertheless, the definition of an agroecosystem is context-specific, and in many cases somewhat arbitrary. Generally, it can be defined as a human-induced ecosystem oriented towards the production of food and/or other valuable goods such as timber, fibre or fuel (Elliott and Cole, 1989; Wood et al., 2000). Wood et al. (2000) defined agroecosystems in a more quantitative way, being areas in which at least 30% of the land surface is dedicated to croplands or intensively managed pastures. The geographic extent can vary from a single field to communities and watersheds composed of many farms or even beyond that to large eco-regions (Peden, 1998).

The increasing demand for agricultural products during the last 50 years, along with the search for higher profitability, have resulted in major changes in the traditional (local) management of agroecosystems (Tilman, 1999). These changes mainly consist of intensifying the use of agrochemicals and agricultural machinery, expanding irrigated areas, and incorporating new crop varieties. Changes in management strategies have been adopted in many parts of the world and, as a consequence, in most of these regions food production has expanded faster than human population. The African continent is the only exception to this trend (Easterbrook, 1997).

Although the new management strategies have substantially contributed to increased human well-being and supported the economic development of many regions all over the world, they also play a significant role in the degradation of our environment (Gardner, 2005). Salinization and erosion of agricultural soils, pollution and overexploitation of fresh water, loss of biological diversity and increasing resistance of weeds and pests are some of the environmental problems that can be imputed to inaccurate agroecosytem management (Tilman, 1999). These environmental problems are hampering further increases in crop yields for both developed and developing countries (Pinstrup-Andersen et al., 1999) and unless addressed, they may jeopardize the development possibilities of future generations (Millennium Ecosystem Assessment, 2005).

Thorough knowledge of the processes responsible for agroecosystem degradation could help to reverse the negative trend and to develop new management strategies that are able to deal with the inherent complexity of agroecosystems in such a way that outputs are maximised while environmental impacts are minimised. In this context, models that adequately describe the response of agroecosystems to changes in management strategies and/or in climatological and environmental conditions are an indispensable tool.

1.1. Agroecosystem modeling

The science of agroecosystem modeling was initiated in the late 1960's, when computational power was no longer a restriction (Passioura, 1996). Since that time, many agroecosystem models have been developed for numerous vegetation types, for different scales, and with a wide variety of applications (Table 1).

Current agroecosystem models, also known as Soil–Vegetation–Atmosphere (SVAT) models, not only incorporate biological and physiological knowledge of plants, but also model the interactions between plants and their environment. In SVAT models, vegetation state variables, such as developmental phase, organ dry mass, and leaf area index (LAI) are linked to driving variables like weather conditions, nutrient availability and management variables. Output of the models usually is final yield or accumulated biomass (Delécolle et al., 1992). Fig. 1 illustrates how SVAT models use computational iterations that represent the time step of the model. At each iteration, vegetation state variables are updated based on the input driving variables and the values of the state variables at the previous time step (Delécolle et al., 1992).

The need to account for the intrinsic spatial variation present in agroecosystems (for example, in soil properties, management practises, or climatic conditions) has lead to the concept of spatialising SVAT

Table 1
Potentials of agroecosystem models (adapted from Boote et al., 1996)

Primary model use	Main possibilities/applications
Research tool	Synthesize research understanding Integrate knowledge across disciplines Document experiment Assist in genetic improvement Yield analysis, relevant factors
Crop system management	Assist in cultural management Assist in water and fertilizer management In-season decision aid for farmers Precision farming
Policy analysis	Assist in best management practices to reduce fertilizer and pesticide leaching and soil erosion Yield forecasting Evaluate climate change effects

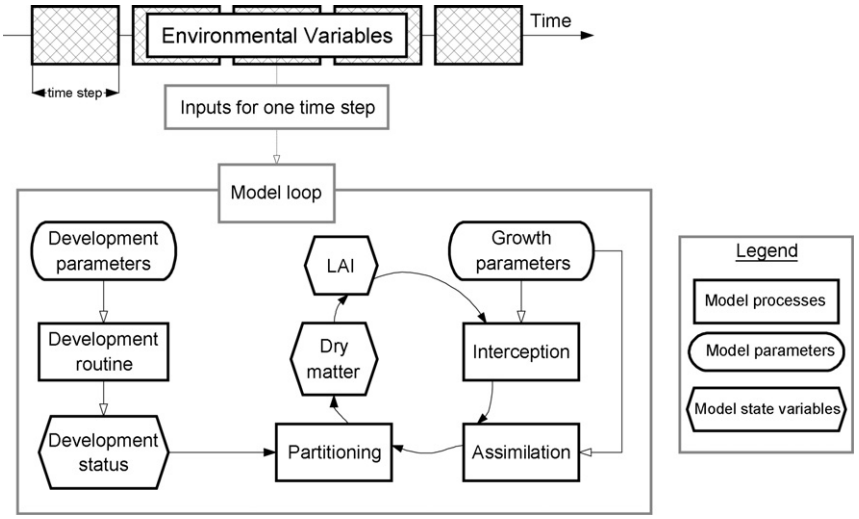

Fig. 1. Simplified scheme of an agrosystem (adapted from Delécolle et al., 1992).

models (Faivre et al., 2004). Spatialised SVAT models require such a large amount of input that it is virtually impossible to gather all of them with a sufficient degree of confidence (Wallach et al., 2001). Here we face two options: either the model is run with default values for many of the variables (disregarding spatial heterogeneity and introducing uncertainties) or we make use of remote sensing (RS) data, which can provide information on meteorologic, vegetation, and soil conditions over large areas.

1.2. Integrating remote sensing in agroecosystem modeling

The parallel development of agroecosystem models and remote sensing techniques led to an early fusion of these fields and to the development of synergic applications. The first civil satellite for earth observation, LANDSAT-1, was launched in 1972 and showed that RS is an excellent tool to monitor the bio-geophysical processes that take place on our planet from global to regional scales (Goward and Williams, 1997). Only a few years later the North-American Large Area Crop Inventory Experiment (LACIE) and AgRISTARS programs proved that RS data could successfully assist in crop identification, estimation of some important crop canopy properties, and even help to forecast crop production (Moran et al., 1997).

Since these early days many scientists have retrieved canopy state variables over large areas using available sensors (see Table 2 for some examples). Leaf area index (LAI), fractional cover (fCOVER), the fraction of

Table 2
Canopy state and driving variables retrieved from remote sensing data and used in agroecosystem modeling studies

Biophysical parameter	Main indicator	Application	State (S) or driving (D)
Fraction of absorbed photosynthetically absorbed radiation (fAPAR)	Photosynthesis	Clevers (1997); Gobron et al. (2000)	S
Leaf Area Index (LAI)	Plant functioning	Bouman (1995); Doraiswamy et al. (2004); Mo et al. (2005); Moulin et al. (2003)	S
Fractional cover (fCOVER)	Plant development	Bouman (1995)	S
Chlorophyll and other pigments	Nitrogen stress/photosynthesis	Haboudane et al. (2002); Zhao et al. (2004)	S
Mineral content (K, P, Ca, Mg)	Crop quality	Mutanga et al. (2004)	S
Plant water content	Drought stress	Moran et al. (1994)	S
Above ground biomass/net primary production	Carbon storage; crop yield	Tucker et al. (1983)	S/D
Evapotranspiration	Drought stress	Bastiaanssen and Ali (2003); Hurtado et al. (1994)	D
Vegetation height	Plant development	Richardson et al. (1982)	S

photosynthetically active radiation absorbed by the canopy (fAPAR), and plant chlorophyll concentration are among the most important canopy state variables and therefore frequently assimilated in agroecosystem models. LAI represents the leaf surface actually available for the exchange of energy and mass between the canopy and the atmosphere and is a key variable when modeling surface evaportransation and biomass production as well as yield and yield loss (Broge and Mortensen, 2002). fCOVER corresponds to the gap fraction in the nadir direction. It is used for decoupling vegetation and soil effects for several processes, including evapo-transpiration (Baret et al., 2005). fAPAR is another critical state variable in crop functioning models and is directly related to LAI, leaf chlorophyll content and leaf angle distribution. fAPAR is often used by simple primary productivity models to derive the biomass accumulated during a given period (Baret et al., 2005). Finally, plant chlorophyll content is the most important biochemical compound in agroecosystem models as it is an indicator of photosynthetic potential (Baret and Fourty, 1997). It is closely related to nitrogen concentration in green vegetation and is therefore a sensitive indicator of crop response to nitrogen deficiency (Baret and Fourty, 1997).

Remote sensing can also be used to derive crop phenological information (Karnieli, 2003; Xin et al., 2002). Knowledge of plant phenology is essential for most agroecosystem models since it governs the partitioning of assimilates. Therefore, a precise knowledge of the phenological status of the plants will greatly improve the results obtained by agroecosystem models (Delécolle et al., 1992).

1.3. Organization of the paper

This paper is organised as follows. Section 2 gives an overview of the different methods that can be used to retrieve canopy state variables from reflective remote sensing observations (∼400–2500 nm).[1] Section 3 presents the prevailing techniques for assimilating remotely sensed data into agroecosystem models and discusses their merits and limitations. The concept of parallel and distributed processing and its role in agroecosystem modeling are discussed in Section 4. Finally, section 5 summarizes the main conclusions of this paper and presents an outlook on the future of integrating remote sensing observations in agroecosystem modeling.

[1] Notice that other remote sensing systems such as thermal infrared or microwave sensors also provide important information on agroecosystem functioning (e.g. canopy temperature, canopy height, biomass, soil/canopy moisture content). However, treating all the remote sensing systems is beyond the scope of this paper.

2. Retrieving canopy state variables from reflective remote sensing data

2.1. Canopy reflectance characterization

In the wavelength range between 400 and 2500 nm, the radiance incident on a vegetation canopy is influenced by three principal factors: (i) the optical properties of the vegetation elements themselves, (ii) the arrangement of these elements in the vegetation canopy, and (iii) the optical properties of the soil underneath the canopy. Apart from these canopy intrinsic components, the radiance measured at the sensor is also highly dependent on the constellation of viewing and illumination angles as well as on the atmospheric conditions (Cierniewski and Verbrugghe, 1997; Roujean and Bréon, 1995). The contribution of each component is discussed in the following paragraphs.

The atmosphere affects the quantity of solar radiance incident on the canopy and, after being reflected, reaching the earth observation sensor (Richter and Schläpfer, 2002). It is also responsible for the anisotropy of the radiation reaching the canopy (Berk et al., 2005; Verhoef, 1984). The radiance flux can reach the canopy either directly, without any intervention of the atmosphere, or indirectly, by atmospheric scattering. This indirect or diffuse flux is wavelength dependent and is more significant at low solar elevation angles and for high atmospheric turbidities (Berk et al., 1998, 2005; Verhoef, 1984).

The spectral properties of vegetation elements such as leaves, stems, and fruits, can be considered the major determinant of canopy reflectance and influence the shape of the overall spectrum (Jacquemoud and Baret, 1990). Solar radiation is either absorbed by chemical constituents, or scattered by the structural elements such as cell walls (Jacquemoud and Baret, 1990). Scattering, including both reflection and transmission, can be either specular or diffuse, is non-Lambertian, and depends on wavelength and angle of incidence (Bousquet et al., 2005; Jacquemoud and Ustin, 2001). Main absorbers in vegetation elements are chlorophyll and other pigments in the visible domain, and water and various carbon based chemicals such as protein and cellulose in the near- and shortwave infrared (Fourty and Baret, 1997).

Canopy architecture mainly accounts for the magnitude and the directional variation in the reflected

signal. Several factors play a role in this respect: the distribution of vegetated and non-vegetated areas, the uniformity of this distribution, the LAI of the canopy and the leaf angle distribution (Kuusk, 1995b; Verhoef, 1984). The latter parameter, which can be computed from the leaf inclination and leaf azimuth, determines the occurrence and magnitude of the hot spot effect (Camacho-de Coca et al., 2004).

Soil reflectance is highly non-Lambertian (Cierniewski and Verbrugghe, 1997) and depends on soil composition (e.g. organic matter content, mineralogy), surface roughness, and soil water content (Baumgardner et al., 1985). The influence of the soil background over the total signal recorded by the sensor is wavelength dependent and largest in the near infrared region (Atzberger et al., 2003). Nevertheless, this influence can be neglected for canopies with LAI greater than three (Atzberger et al., 2003).

Various algorithms have been developed to retrieve biophysical and biochemical variables from reflective remote sensing data. These can be roughly subdivided in two categories: (i) statistically/empirically based methods that seek a statistical relationship between the spectral signature and the measured biophysical or biochemical properties of the canopy (Section 2.2) and (ii) physical methods that are based on the principles of radiation propagation within a canopy (Section 2.3). Hybrid approaches, a combination of both methods, use physical models to establish statistical relationships between the spectral signal and the biophysical parameters of interest.

2.2. Statistical approaches

Statistical approaches search for a consistent relationship between the spectral signature of an object, in general the leaf or canopy reflectance, and the biophysical or biochemical variable of interest (Fig. 2). To establish such relationships, spectral, biophysical, and biochemical measurements have to be taken under varying field or laboratory conditions and for different plant species and phenological development stages. The accuracy of the measurements and the range of conditions considered for the development of a relationship determine to a large extent the validity and portability of the relationships (Sims and Gamon, 2002). The traditional way of linking spectral information to the variable of interest is by simple or multiple regression techniques (Clevers, 1989; Jacquemoud et al., 1995b). Recently, more sophisticated statistical approaches, such as partial least square regression and artificial neural networks, have been introduced (Atzberger, 2004; Huang et al., 2004). The different techniques for linking spectral information to the canopy variable(s) of interest will be dicussed in Section 2.2.3.

Spectral information (reflectance, absorptance, and transmittance) is rarely directly used to construct the response function to biophysical and biochemical

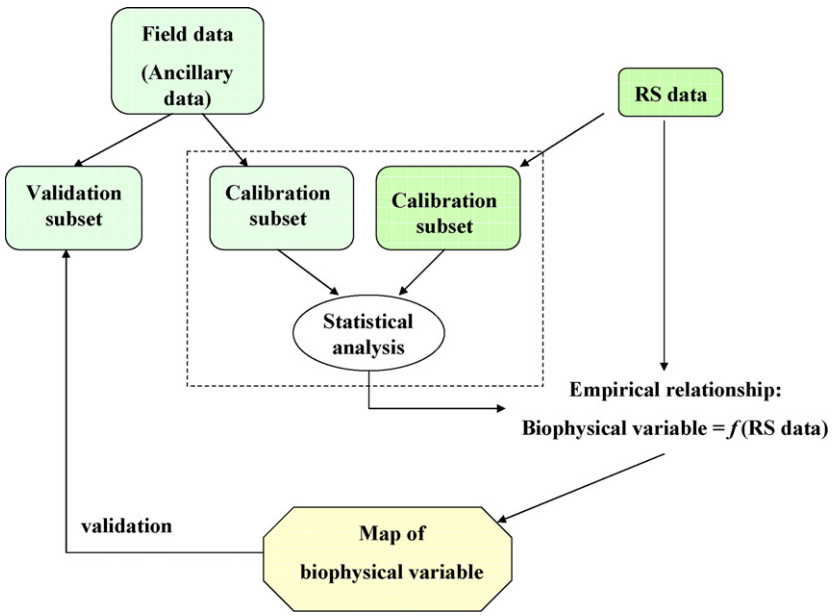

Fig. 2. Concept of the statistical approach.

Table 3
Classification of spectral vegetation indices used in this study

Broadband VIs	
	Ratio
	Orthogonal
	Hybrid
VIs based on discrete narrow bands	
	Ratio
	Red edge and shape
	Spectral continuum

variables. Many data manipulations have been proposed to enhance subtle spectral features and to reduce undesired effects caused by variations in soil reflectance, sun and view geometry, atmospheric composition, and other leaf or canopy properties. Standard manipulations, often used in imaging spectroscopy, involve normalization (Chappelle et al., 1992), logarithmic transformation (Jacquemoud et al., 1995b; Yoder and Pettigrew-Crosby, 1995), continuum removal (Kokaly and Clark, 1999; Mutanga et al., 2004), and the calculation of first or second derivatives (Huang et al., 2004).

However, the most widespread method used to reduce background effects and enhance spectral features is to express spectral reflectance in a combination of a limited number of (transformed) spectral bands, to create what is known as a vegetation index (VI). Most VIs concentrate on the red-edge region, which is the region between 680 and 800 nm that is characterized by a sharp decrease of chlorophyll absorption from maximum absorption around 680 nm to almost zero absorption at 800 nm. This makes this wavelength range very well suited to study vegetation characteristics (Baret et al., 1992).

VIs can be subdivided into two main categories (Table 3): (i) VIs designed for broadband multispectral sensors (Section 2.2.1), and (ii) hyperspectral VIs based on discrete narrow bands (Section 2.2.2).

2.2.1. Broadband vegetation indices

The group of classical broadband VIs can be roughly subdivided into *ratio* and *orthogonal* indices (Broge and Mortensen, 2002). The *ratio* indices are calculated independently of soil reflectance properties, while *orthogonal* indices refer to a baseline specific to the local soil background. *Hybrid* indices can be considered as a combination of ratio and orthogonal indices.

2.2.1.1. Ratio vegetation indices. The original ratio VIs are based on the reflectance in the red and near infrared (NIR) part of the spectrum. Their ratio line (also called LAI-isoline) joins the origin in the Red–NIR space. Best known ratios in this category are the ratio vegetation index (Pearson and Miller, 1972) and the normalized difference vegetation index (NDVI; Rouse et al., 1973). The latter is probably the most extensively used VI overall.

2.2.1.2. Orthogonal and hybrid vegetation indices. Orthogonal indices were introduced in an attempt to reduce (soil) background effects. For orthogonal vegetation indices the LAI-isolines in the Red–NIR do not converge in the origin but remain parallel to the principal axis of soil spectral variation (Richardson and Wiegand, 1977). This soil line is expressed by the intercept and slope as determined by linear regression of the local soil reflectance in the Red–NIR feature space. The simple difference between NIR and red reflectance (Jordan, 1969) was the first index of this category. Other orthogonal VIs are the Perpendicular Vegetation Index (Richardson and Wiegand, 1977) and the Weighted Difference Vegetation Index (Clevers, 1989).

The soil-adjusted vegetation index, SAVI, (Huete, 1988), containing elements of both ratio based and orthogonal VIs, was developed to minimize the influences of the soil background on the NDVI values. The SAVI index has been modified several times to optimize the removal of soil background influences (Baret et al., 1989b; Qi et al., 1994; Rondeaux et al., 1996). For a good overview of all the modified SAVI indices see, Broge and Leblanc (2000).

2.2.2. Indices based on discrete narrow bands

With the recent development of imaging spectrometers, new indices have been explored using the information contained in narrow absorption features. In this way it is possible to improve estimations of leaf constituents like chlorophyll and water (Haboudane et al., 2004) or even to explore biochemicals with more subtle spectral absorption features such as protein, lignin and phosphorus (Fourty et al., 1996; Mutanga et al., 2004). Apart from new ratios based on a few discrete bands, novel approaches based on spectral shape and the depth of spectral absorption features have been developed. Although the majority of these new techniques were originally developed for identifying leaf constituents, many of them have been successfully applied in estimating other biophysical variables such as LAI (Broge and Leblanc, 2000; Haboudane et al., 2004).

2.2.2.1. Narrow band ratios. New narrow band ratios have mainly been used for the retrieval of water and chlorophyll concentration. Absorption due to leaf water takes place at wavelengths greater than 1000 nm. This is

why ratio indices attempting to explain water content always use one or more bands in this domain (Penuelas et al., 1997; Zarco-Tejada and Ustin, 2001).

Most hyperspectral ratios used for estimating leaf chlorophyll content make use of the three discrete bands describing the typical reflectance pattern of green vegetation: the reflectance peak in the green and NIR and the region of maximum absorption in the red. Kim et al. (1994) found the ratio of 550 and 700 nm reflectance to be constant at the leaf level regardless of chlorophyll concentration. Based on this relationship they defined their Chlorophyll Absorption Ratio Index (CARI). Different alterations to CARI were proposed to make the original index more sensitive to chlorophyll changes (Daughtry et al., 2000; Haboudane et al., 2002).

A quite different concept was proposed by Broge and Leblanc (2000). Their Triangular Vegetation Index (TVI) is expressed as the area of the triangle defined by the green peak, the near-infrared shoulder, and the minimum reflectance in the red region. The general idea behind TVI is based on the fact that the total area of the triangle will increase as a result of chlorophyll absorption (decrease of red reflectance) and leaf tissue abundance (increase of near-infrared reflectance; Broge and Leblanc, 2000).

2.2.2.2. Indices based on the spectral shape and the red edge. The use of first or second order derivatives of the reflectance versus wavelength provides a way to minimise the effect of soil and atmosphere (Baret et al., 1992). Most studies focussing on the shape of the spectrum concentrate on the position of the red-edge inflection point (REIP), defined as the wavelength around 720 nm at which the slope of the spectral reflectance curve reaches its maximum value. A shift of the REIP towards shorter wavelengths (blue-shift) is associated with a decrease in green vegetation, while a shift towards longer wavelengths (red-shift) is associated with an increase in green vegetation density (Baret et al., 1992). Various techniques have been developed for parameterizing the shape of the red-edge and determining the position of the REIP, including inverted Gaussian models (Miller et al., 1990), fitted high-order polynomials, linear interpolation (Clevers et al., 2002; Guyot et al., 1988) and Langrangian interpolation (Dawson and Curran, 1998).

A different approach in using spectral derivatives was proposed by Elvidge and Chen (1995), who calculated the first and second derivatives of the spectral reflectance data and integrated the absolute derivative values over the spectral region between 626 and 795 nm.

2.2.2.3. Indices based on spectral continuum measures. Imaging spectroscopy enables the calculation of a spectral continuum for which the analysis is based on the depth and area of the troughs spanned by this continuum. This approach was first developed by geologists looking for spectral fingerprints of minerals, but can be used for any material exhibiting discrete absorption features, such as chlorophylls in green vegetation (Broge and Leblanc, 2000). Similar to the TVI, but using all the hyperspectral bands between the green and NIR reflectance maximum, Broge and Leblanc (2000) developed the chlorophyll absorption continuum index (CACI) and a continuum removed version of this index (CRCAI). They also studied the possibilities of using the maximum depth of the continuum-removed chlorophyll absorption trough (Continuum Removed Chlorophyll Well Depth; CRCWD) for the estimation of chlorophyll content and LAI. Last mentioned are very similar to the approaches suggested by Kokaly and Clark (1999) and Mutanga et al. (2004).

2.2.3. Linking spectral information to the measured biophysical and biochemical variables

2.2.3.1. Single regression. Spectral information, usually expressed in the form of a VI, is normally linked to the biophysical variable of interest by a single regression function. In its simplest form, the regression function is expressed by a linear equation:

$$V = aR + b + \varepsilon$$

where V is the (dependent) variable of interest, R the spectral information (explanatory variable), a and b are the coefficients of the regression and ε the error term which condenses the unpredicted or unexplained variation of V. Although many scientists have tried to transform their VIs in such a way that a linear relationship can be established between VI and the variable of interest, an exponential function still appears to be the best approximation (Fig. 3). This owes to the fact that VIs reach a saturation level at higher canopy densities (Baret and Guyot, 1991; Hansen and Schjoerring, 2003).

2.2.3.2. Stepwise multiple linear regression. Linear regression can be extended to functions containing two or more independent variables (spectral information) that explain the biophysical or biochemical variable of interest. This approach is known as multiple linear regression. Often a stepwise approach is used for the selection of the relevant spectral bands for the multiple regression function (Fourty and Baret, 1997;

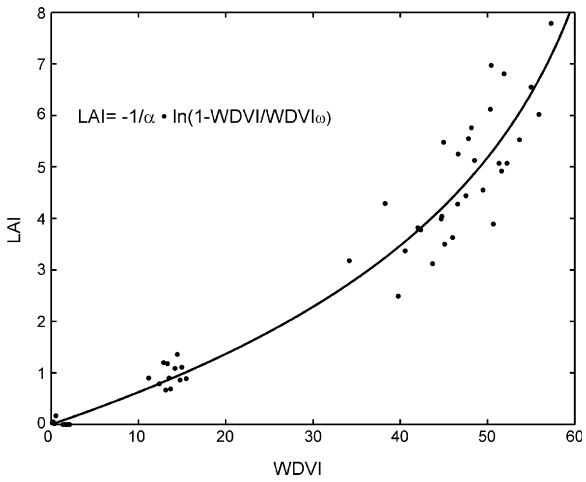

Fig. 3. Exponential empirical relationship between WDVI and LAI (adapted from Clevers, 1989).

Jacquemoud et al., 1995b; Yoder and Pettigrew-Crosby, 1995). This stepwise multiple linear regression (SMLR) procedure starts with the selection of the band that explains most variation in the dependent variable. In each successive step the spectral band is added that in conjunction with the band(s) selected in the previous step(s) provides the best prediction of the biophysical variable. The procedure is repeated until a satisfactory regression is achieved or stepping is no longer possible given the stepping criteria (Jacquemoud et al., 1995b; Yoder and Pettigrew-Crosby, 1995). SMLR is frequently used for exploiting hyperspectral data spaces and allows one to identify the wavelengths or spectral bands that are most and least sensitive to particular biochemicals. These bands in turn can be used for designing new vegetation indices (Section 2.2.2; Mutanga et al., 2004; Penuelas et al., 1997).

SMLR has often been critized for suffering from the potential of overfitting, and leading to a selection of bands that fails to correspond to known absorption features (Curran, 1989; Grossman et al., 1996). Moreover, in SMLR the wavebands are assumed to be independent, which often, especially in imaging spectroscopy, is not the case (Yoder and Pettigrew-Crosby, 1995).

2.2.3.3. Partial least squares regression. Partial least squares regression (PLS) is a multivariate extension of the multiple regression model. PLS is less restrictive than other multiple regression models, which allows it to be used in situations where there are fewer observations than predictor variables (Huang et al., 2004). It works in a manner similar to principal components analysis: the multidimensional feature space is (linearly) transformed in a way that the information that correlates with the variable of interest is combined into a few factors constituting the prediction function. Background effects and random noise are explained by less important factors (Bolster et al., 1996). It deals efficiently with data sets where there are many highly correlated bands and avoids the potential overfitting problem typically associated with stepwise regression analysis (Huang et al., 2004). Several studies report that PLS performs better in comparison to traditional regression techniques (Hansen and Schjoerring, 2003; Huang et al., 2004).

2.2.3.4. Artificial neural networks. The regression techniques discussed in the previous paragraphs all assume a linear relationship between the biophysical variable and the measured spectral signature. This is often not the case (Huang et al., 2004). Recently, Artificial Neural Network (ANN) modelling has found its way into remote sensing (Atzberger, 2004; Combal et al., 2002; Huang et al., 2004). It is a sophisticated technique capable of modeling extremely complex non-linear functions. ANNs can be considered as an interpolation technique that establishes a response surface (M) between the reflectance values R (inputs) and the variables of interest V (outputs), i.e.:

$$V = M(R) + \varepsilon$$

where ε accounts for the model error. Calibration is performed on a learning data set. In the training stage inputs (spectral information) can be linked to a few selected output variables, therefore optimizing the network for the variables of interest (Combal et al., 2002). This is because a non-parametric statistical model can non-linearly project data so that some factors are enhanced while others are suppressed. ANNs are frequently used for inverting canopy reflectance models (Section 2.3.3), although encouraging results have also been obtained for measured variables (Huang et al., 2004).

2.2.4. Comparison, merits, and complications

Statistical approaches search for consistent relationships between the spectral information of an object and one or more of their biophysical or biochemical components. This usually entails two important steps: (i) a transformation of the spectral information so that sensitivity of the spectral signal for the variable of interest is optimized while background effects are minimized and (ii) a statistical function expressing the relationship between the (manipulated) spectral signal and the biophysical or biochemical variable. A few

Table 4
Examples of using statistical–empirical approaches for the estimation of canopy state variables

Vegetation index	Parameter	Vegetation type	Regional/global	Source
CRDR (Mutanga et al., 2004)	Nitrogen	Range land	Regional	Mutanga et al. (2004)
EVI (Huete et al., 1994)	LAI	Various	Global	Huete et al. (2002)
MGVI (Gobron et al., 2000)	fPAR	Green vegetation	Global	Gobron et al. (2000)
Multiple linear regression green, red, NIR + NDVI	LAI, shoot and leaf dry and fresh weight, plant height	Rice	Regional	Yang et al. (2004)
NDVI (Rouse et al., 1973)	Yield	Soybean	Regional	Liu and Kogan (2002)
PVI (Richardson and Wiegand, 1977)	fAPAR	Corn	Regional	Wiegand et al. (1991)
RVI (Pearson and Miller, 1972)	LAI	Maize	Regional	Gardner and Blad (1986)
MTCI (Dash and Curran, 2004)	Chlorophyll	Various	Global	Dash and Curran (2004)
TSAVI (Baret et al., 1989a,b)	Green Crop Area Index	Wheat	Regional	Broge and Mortensen (2002)
WDVI (Clevers, 1989)	fAPAR, LAI, Biomass	Rice	Regional	Casanova et al. (1998)

examples of studies successfully applying such a statistical approach at different spatial scales are listed in Table 4.

Until recently spectral transformations mainly focussed on the construction of VIs. Although many VIs have been presented in previous sections, they only make up a fraction of the total amount of indices that have been developed in past few decades. They all have been developed for particular purposes and under different circumstances. Therefore, it is difficult to declare which VI is the best. An index that works well for retrieving leaf water content with a spectrometer under laboratory conditions does not necessarily lead to satisfying results when it is applied to multispectral data from a satellite platform. The performance of the different indices and selected "optimal" wavebands depends on vegetation and land cover type, the variables to be retrieved, sun/view geometry, and so on. For a systematic comparison of the performance of part of the VIs we refer to other studies (Broge and Leblanc, 2000; Broge and Mortensen, 2002; Haboudane et al., 2004; Huete et al., 1997; Jordan, 1969; Zarco-Tejada et al., 2004). However, even these extensive studies only refer to a limited data set and to few specific vegetation types. Nevertheless, we summarize the most important findings of these comparison studies in the next paragraphs.

The classical broadband vegetation indices all use a spectral band in the red and one in the NIR. As both red and NIR reflectance saturate when LAI increases, the VIs become insensitive for very dense canopies (Haboudane et al., 2004; Knyazikhin et al., 1999). The main problem in using the red and NIR bands lies in the fact that the LAI-isolines do not join the origin of the Red–NIR feature space nor evolve parallel to the soil line (Fig. 4). Their position and slope in the Red–NIR feature space depends on the vegetation density, leaf angle, and leaf optical properties (Atzberger, 2004). The same dependence on canopy composition accounts for other band combinations which makes it nearly impossible to find a consistent relationship between a VI of this type and the biophysical or biochemical variable under consideration. However, some indices appear to perform better than others.

Regarding the stability of the indices in relation to canopy architecture, illumination geometry, soil background reflectance, and atmospheric conditions (Broge and Mortensen, 2002; Haboudane et al., 2004) found that soil-adjusted VIs and derivative indices perform better than classical ratio indices such as NDVI. This

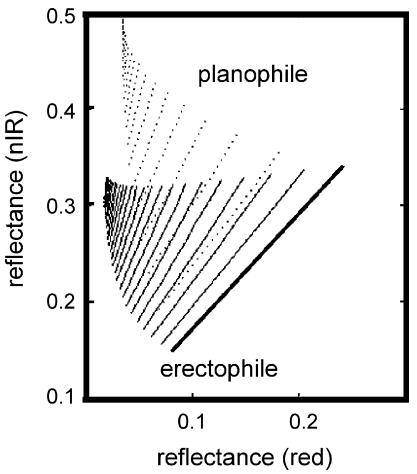

Fig. 4. Simulated LAI-isolines in Red–NIR feature space for planophile (average leaf angle (ALA) = 30°) and erectophile canopies (ALA = 70°). LAI values range from 0 (bare soil; bold line) to 5 by increments of 0.2. LAI-isolines were simulated using the SAILH + PROSPECT canopy reflectance model (from Atzberger, 2004).

makes them more suitable for studies in areas with low or high vegetation cover (Haboudane et al., 2004; Huete et al., 1997). As soil-adjusted vegetation indices are more sensitive to NIR reflectance than classical ratio indices, they are more useful for estimating structural canopy parameters such as LAI, biomass and leaf morphology (Huete et al., 1997). On the contrary, the classical ratio indices, being more sensitive to red reflectance, are more suitable for studying biophysical parameters related to absorbed photosynthetically active radiation such as fAPAR and fraction of green cover, especially in areas with intermediate LAI (Huete et al., 1997). At the same time, their higher sensitivity to red reflectance makes them susceptible to soil background variations.

Various studies have shown that the use of narrow spectral bands in indices originally designed for broad band sensors do not always improve parameter predictions and in some cases even lead to poorer results (Broge and Leblanc, 2000; Broge and Mortensen, 2002; Elvidge and Chen, 1995). On the contrary, narrow band spectral indices originally designed for the retrieval of leaf biochemicals in canopies mostly seem to perform better than classical broadband indices (Haboudane et al., 2004; Zarco-Tejada et al., 2005). Several studies underscore the importance of bandwidth and the position of the center wavelength on the performance of the VI (Fourty and Baret, 1997; Hansen and Schjoerring, 2003; Zhao et al., 2005).

An important issue in using spectral VIs for the estimation of biophysical parameters is the necessity of a good validated relationship between VI and the variables(s) of interest. This implies a costly and time intensive measurement program if relationships want to be valid for a wide range of species, canopy conditions, and view/sun constellations. For this reason there has been a growing use of canopy reflectance models (Section 2.3). With these models a wide range of canopy realizations can be simulated and based on these simulations new indices and relationships can be created and tested for their consistency and sensitivity (Ceccato et al., 2001; Haboudane et al., 2004; Zarco-Tejada et al., 2005; Zarco-Tejada and Ustin, 2001). Equations developed in this way are sometimes refered to as predictive equations (Gastellu-Etchegorry and Bruniquel-Pinel, 2001).

Novel statistical approaches such as PLS regression and ANNs are promising alternatives to classical regression techniques in linking spectral information to dependent canopy variables. They appear to deal better with the non-linear and multivariate character of canopy reflectance and are able to use the information contained in the complete spectral signal (Hansen and Schjoerring, 2003; Huang et al., 2004).

Although in this chapter the different data transformation and statistical techniques have been described separately, several cases are known where various techniques are combined (Chappelle et al., 1992; Gastellu-Etchegorry and Bruniquel-Pinel, 2001; Hansen and Schjoerring, 2003; Huang et al., 2004). Partly due to the phenomenon that almost for every new situation (e.g. changing soil background or canopy type), and for every biophysical parameter, a new relationship has to be fitted, increasing interest is observed in the use of physical models for the retrieval of biophysical and biochemical parameters.

2.3. Physical approach

The physical approach consists of inverting a canopy reflectance model for the estimation of leaf and canopy properties. Canopy reflectance models simulate the interactions between solar radiation and the elements constituting the canopy using physical laws. Before discussing the inversion of canopy reflectance for the estimation of biophysical parameters, a more detailed look at the functioning of these models is indispensable.

The most established way of modeling reflectance in canopies is to combine a leaf optical model with a canopy reflectance and a soil reflectance model and calculate the top-of-canopy reflectance. For applications in remote sensing this calculated reflectance should be in agreement with measured reflectance data corrected for atmospheric influences. A different approach consists of computing the radiance as it would have been measured by the sensor and therefore encompasses a model for the calculation of radiance propagation in the atmosphere (e.g. Verhoef and Bach, 2003b). In the following sections we will confine our discussion to reflectance at canopy level, and therefore do not consider any atmospheric model. Soil reflectance is an important element in modeling canopy reflectance, being the lower boundary condition and having its own spectral properties (e.g. absorption features and directional reflectance properties). Knowing soil reflectance is fundamental if sparse or low vegetated canopies are to be simulated. This model input is typically measured in the field, taken from the image itself, or can be simulated using soil reflectance models (Hapke, 1981; Jacquemoud et al., 1992). Variations in soil reflectance representing differences in soil moisture content, surface roughness, soil organic matter, and inorganic carbon content are often

Table 5
Examples of various approaches used to model leaf and canopy reflectance

Medium	Type	Leaf model	Canopy model
Homogeneous	1D radiative transfer	(Fukshansky et al., 1991)	SAIL (Verhoef, 1984), KUUSK (Kuusk, 1995a)
	Plate model	PROSPECT (Jacquemoud and Baret, 1990)	–
Heterogeneous	3D radiative transfer	–	DISORD (Myneni et al., 1992)
	Geometric	–	Chen and Leblanc (1997)
	Hybrid	–	DART (Gastellu-Etchegorry et al., 1996), GeoSAIL (Huemmrich, 2001), TRIM (Goel and Grier, 1988) INFORM (Schlerf and Atzberger, 2006)
	Ray tracing	RAYTRAN (Govaerts et al., 1996)	RAYTRAN (Govaerts and Verstraete, 1998), SPRINT (Goel and Thompson, 2000)
	Radiosity	ABM (Baranoski and Rokne, 1997)	PARCINOPY (Chelle and Andrieu, 1998)
	Stochastic	SLOP (Maier et al., 1999)	SMRT (Shabanov et al., 2000)

parameterized using simple empirical formulae and scaling factors (Atzberger, 2004; Atzberger et al., 2003; Baret et al., 2005). Soil reflectance models are beyond the scope of this paper so they will not be discussed in further detail here.

2.3.1. Leaf optical models

Our understanding of leaf microstructures and the distribution of biochemical components in leaves is still very limited. The same is true for the anisotropic scattering of leaves (Jacquemoud and Ustin, 2001). Nevertheless, various approaches have been proposed, successfully describing leaf scattering and absorption in a more or less simplified way (Table 5).

N-flux models (Fukshansky et al., 1991; Richter and Fukshansky, 1996) are based on the Kubelka–Munk theory and consider the leaf as being a slab of diffusing and absorbing material. The advantage of this approximation is its simplicity. However, it is very difficult to link the overall absorption coefficient of the leaf with the specific absorption coefficients and the concentrations of the plant chemicals. A retrieval of concentrations of biochemicals by model inversion is therefore rather complex, if not even impossible (Fukshansky et al., 1991).

In plate models the leaf is considered a pile of N plates separated by $N-1$ air spaces, where N does not have to be a discrete value. The structure parameter N is comparable to the scattering parameter in the Kubelka–Munk theory. It is an uncomplicated model which assumes Lambertian scattering and absorption elements (biochemicals) distributed homogeneously throughout the leaf. This assumption makes it suitable for the retrieval of leaf biochemicals by model inversion. However, biochemicals with only relatively small absorption features cannot be retrieved accurately (Fourty et al., 1996). The best-known model in this category is the PROSPECT model developed by Jacquemoud and Baret (1990).

Ray tracing models (Govaerts et al., 1996), based on Monte Carlo simulations, are the only type of models that accounts for the complexity of internal leaf structure and are therefore the most realistic. A ray-tracing model simulates the propagation of photons within a leaf foliage. This potency is at the same time its weakness: it requires a very detailed description of individual cells, their optical constants and their arrangement within the foliage. This complex description of light propagation makes the model computationally very intensive and model inversions numerically difficult to implement.

Radiosity models describe the total amount of energy leaving a surface per unit time per unit area (Liang, 2004). The leaf is divided in discrete reflecting and transmitting elements with distinct shapes, positions and orientations. The major advantage of this method is that once a solution has been found for radiative transport, leaf and canopy reflectance can be simulated at any view angle for any wavelength. The major limitation of the method is the initial computational load in forming the view factor matrix and solving for radiative transport. The Algorithmic BDF Model of Baranoski and Rokne (1997) is the best-known leaf radiosity model.

Stochastic models are based on Markov chains where transition probabilities from one radiation state to another, for instance from reflected to absorbed, are described. Unfortunately these models are more computation-intensive than plate and *N*-flux models and are not suited for direct inversions. An example of such a model is SLOP (Maier et al., 1999).

2.3.2. Canopy reflectance models

The traditional canopy reflectance models, which are based on the radiative transfer approach, assume that the canopy is a turbid medium where the canopy elements (leaves) are treated as small, randomly distributed absorbing and scattering elements with no physical size. A one-dimensional approximation (Verhoef, 1984) assumes the canopy to be horizontally homogeneous and infinite but vertically variable and finite. These assumptions, together with the fact that leaf area is explicitly taken into account, make this type of model well suited for describing radiance propagation in denser canopies where the single vegetation elements are smaller than the canopy height, which is the case for most agricultural crops. Most models of this type are based on the Kubelka–Munk theory and consider four different radiative fluxes describing both specular and diffuse downwelling and outgoing radiation. A hotspot function describes reflectance in the principal plane. Various models of this type have seen the light of day during the last two decades (e.g. Kuusk, 1995a; Verhoef, 1984).

For situations in which the assumption of a horizontally homogeneous and infinite canopy does not apply (e.g. heterogeneous canopies like row crops and orchards with isolated tree crowns), different approaches based on the principle of radiative transfer have been proposed. Geometrical models have been formulated to describe radiation propagation in sparse canopies where multiple scattering can be ignored and mutual shading is negligible due to low zenith angles (Chen and Leblanc, 1997). In this approach the canopy is described as a ground surface with opaque geometrical objects with known spatial distribution and optical properties. Often geometrical and turbid medium approaches have been combined to form so-called hybrid models, in which the canopy is made up of translucent geometrical objects (plants) to which the turbid medium radiative transfer equation is applied. Therefore, this type of model is especially suited for representing forests or sparse canopies. The Three Dimensional Radiation Interaction Model (TRIM; Goel and Grier, 1988), GeoSAIL (Huemmrich, 2001), the Discrete Anisotropic Radiative Transfer (DART) model (Gastellu-Etchegorry et al., 1996), and the INvertible FOrest Reflectance Model (INFORM) by Schlerf and Atzberger (2006) are examples of such 3D hybrid radiative transfer models. Various other approaches based on radiative transfer have been suggested to account for both vertical and horizontal heterogeneities (Kuusk, 1995b; Myneni et al., 1992; Shabanov et al., 2000; Table 5).

Monte Carlo ray tracing models (Goel and Thompson, 2000; Govaerts and Verstraete, 1998) and radiosity models (Borel et al., 1991; Chelle and Andrieu, 1998; Gerstl and Borel, 1992) give a more realistic representation of the radiation transfer in the canopy and offer the possibility to study the statistical nature of a radiation behavior. Unfortunately, this type of model is very computationally intensive. A comparison between radiosity modeling and radiative transfer modeling in canopies can be found in Table 6.

For a detailed overview of the various leaf and canopy reflectance models that have been described in this section, and the equations used to simulate radiation propagation, we refer to the original publications and to Liang (2004). A vast intercomparison of the performance of various existing canopy reflectance models is given in Pinty et al. (2004).

2.3.3. Inversion of canopy reflectance models

Inverting a canopy reflectance model consists in finding the set of input parameters that leads to the best match between the bi-directional reflectance factor (BRF) simulated with a canopy reflectance model and the reflectance measured by the sensor (Combal et al., 2002). Considering that the BRF of any canopy is a function f of the canopy variables V and the measurement geometry C, the reflectance R can be written as follows:

$$R = f(V, C) + \varepsilon$$

where ε represents the error, both for measurement (sensor noise, data pre-processing, etc.) and model uncertainties (model simplifications, assumptions, etc.). The inverse problem consists, therefore, in estimating the set of variables V that leads to the observed spectrum R. Different methods have been developed to solve this problem.

Table 6
Differences between radiative transfer and radiosity approach (after Gerstl and Borel, 1992)

Radiative transfer	Radiosity
Volume scattering	Surface reflection and transmission
Continuous medium	Discrete and oriented surfaces
Averaged scattering phase function	Explicit scattering characteristics
No physically based spatial correlations of leaves	Spatial correlations retained
No holes or clumps in canopy	Holes and clumps describable
Multiple scattering	Multiple scattering
Integrodifferential equation	System of coupled linear equations

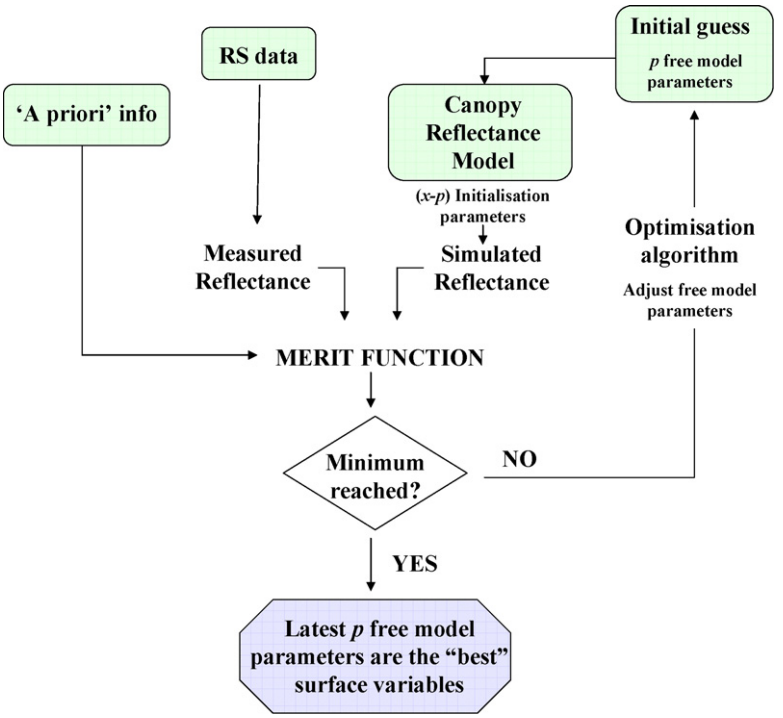

Fig. 5. Conceptualization of the iterative optimization technique.

2.3.3.1. Iterative optimization. The iterative optimization technique searches for the best fit between the simulated and the measured reflectance by iteratively running the canopy reflectance model with different sets of input variables (Fig. 5). The minimization of a merit function that traditionally accounts for differences between the simulated and the measured reflectance is used as a stopping criterium for this optimialization problem. A wide range of mathematical and statistical approaches is used for finding the minimum, such as Quasi-Newton algorithms (Bacour et al., 2002b), genetic algorithms (de Wit, 1999), and Markov Chain Monte Carlo approaches (Zhang et al., 2005). This method presents three main drawbacks: (i) it requires an initial guess of the solution. The correctness of this initial guess can be critical to get a successful inversion. If an inadequate inversion algorithm is used the solution may get trapped in a local minima (Qiu et al., 1998). (ii) The accuracy of the solution depends on the merit function. Several merit funcitons are available in literature ranging from ones that exploit only radiometric information to others that use ''a priori'' information on the biophysical and biochemical parameters (see below). (iii) The approach is computationally too intensive to be suited for operational use or for the inversion of complex three dimensional canopy reflectance models (Liang, 2004). Despite these drawbacks, various authors have succesfully applied this technique for various vegetation types (Bacour et al., 2002b; de Wit, 1999; Fang et al., 2003; Jacquemoud et al., 1995a; Qiu et al., 1998).

2.3.3.2. Lookup table approach. In the lookup table (LUT) approach, the canopy reflectance model is used in a direct way to simulate a large number of possible spectra, depending on different combinations of input parameter values. In a next step, a merit function searches in the LUT for the spectrum that has the highest similarity to the measured one. The set of variables used to simulate this spectrum is the final solution of the inversion. The LUT based inversion offers the possibility to use a set of LUT spectra close to the absolute minimum for the calculation of the solution. This allows one to derive a variable distribution indicating the ''confidence level'' around the final estimate (Koetz et al., 2004). The LUT approach has the advantage that it is considerably faster than the iterative optimization technique, although time can significantly increase if large lookup tables, representing many possible parameter combinations, are used. The technique can also deal with more complex canopy reflectance models, such as ray tracing models, since the model is used only in the direct mode.

A major drawback of this method is that a certain LUT is designed for a specific sun and view geometry. However, Gastellu-Etchegorry et al. (2003) and Dorigo et al. (2005) found ways to overcome this problem without significant loss in prediction accuracy. A point of concern which may strongly influence the final result of the inversion is the composition of the LUT. A poor choice of the distribution of the different variables (e.g. uniform or gaussian) or the step size between successive values of the variables in the LUT may lead to an over- or under-representation of certain variable ranges and thus to a non-representative result (Combal et al., 2002). The composition of the LUT is especially critical for models having many input arguments. For these models, the size of the LUT dramatically expands if input parameters are sampled at small intervals (Combal et al., 2002; Weiss et al., 2000). LUT inversion is being effectively applied for the retrieval of LAI and fAPAR on a global scale from MISR/MODIS data (Knyazikhin et al., 1999).

2.3.3.3. Artificial neural networks. Inversion based on an artificial neural network (ANN) can be seen as the most prominent member of a collection of hybrid approaches that combine physical and statistical models (Liang, 2004). Like in the LUT approach, a canopy reflectance model is used in the direct mode to build a large synthetic data set that represents a wide variety of canopy realizations. While the LUT approach searches for the simulated spectrum closest to the measured one, the ANN minimizes the distance between canopy variables. ANNs are fast after the training stage and according to Combal et al. (2002), less sensitive to model uncertainties than the iterative optimization and LUT approach. ANNs can effectively adapt for multi-spectral and multi-angular data (Liang, 2004), making it an adequate technique for estimating variables from sensors with large swath angles. Baret et al. (2005) found satisfying results estimating LAI, fCover, and fAPAR for the globally operating medium resolution MERIS sensor (Fig. 6). As the canopy reflectance model is used only in the direct way, ANNs are suited for inverting more complex models such as 3D or ray tracing models.

2.3.3.4. The ill-posed problem and its solutions. A major drawback of the inversion of physically based canopy reflectance models is that the inversion does not

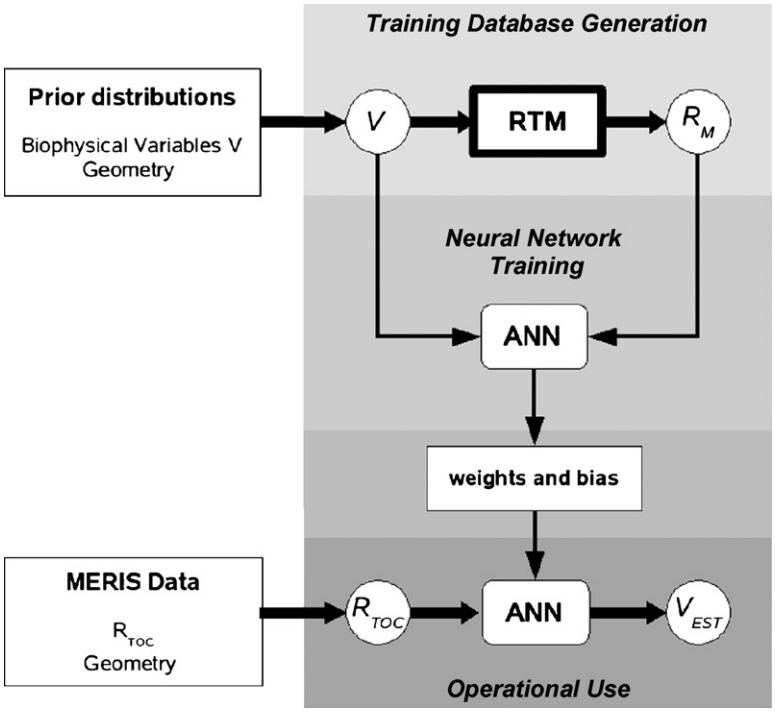

Fig. 6. Flow chart showing how products for MERIS are generated by an Artificial Neural Network (ANN). The ANN is characterized by its structure and its coefficients (corresponding to the synaptic weights and bias); R_M corresponds to the canopy reflectance simulated with a Radiative Transfer Model (RTM). R_{TOC} corresponds to the MERIS Top Of Canopy reflectance used in the operational mode and V corresponds to the biophysical variable in the training data base and is estimated (V_{EST}) by running the ANN over the simulated MERIS TOC reflectance and geometry (adapted from Baret et al., 2005).

fulfil the Hadamard's postulates of well-posedness (Combal et al., 2002). Hadamard stated that a problem is well posed if and only if its solution exists, this solution is unique, and depends continuously on the data. The inversion of canopy reflectance models is ill-posed for two reasons: The solution is not necessarily unique because of compensation between several variables that could affect canopy reflectance in the same way (Combal et al., 2002; Fourty and Baret, 1997). For example, for the combined leaf and canopy reflectance model PROSPECT (Jacquemoud and Baret, 1990) and Scattering by Arbitrarily Inclined Leaves (SAIL; Verhoef, 1984) the spectral reflectance of a sparse canopy (low LAI) with planophile leaf orientation is quite similar to one of a dense, erectophile canopy (Baret and Guyot, 1991; Jacquemoud et al., 1995a). On the other hand, measurement and model uncertainties and simplifications may induce large variations in the solution of the inverse problem (Combal et al., 2002). The problem of ill-posedness augments with an increasing number of input variables that are left free during inversion (Combal et al., 2002).

There are several possibilities for addressing the drawback of the ill-posed problem. The most common way to reduce the number of possible solutions is the incorporation of a priori information (Combal et al., 2002). Several sources of prior information exist, for example, ancillary data measured on the site or products provided by another sensor such as a land cover classification (Knyazikhin et al., 1999). Also knowledge of the dynamic evolution of the biophysical variables over time (Koetz et al., 2005) and knowledge about the typical distribution of the input variables in a particular development stage can help to reduce the number of possible solutions. For iterative optimization approaches, prior information can be introduced during inversion by defining upper and lower values between which the final result has to lie. For the LUT and ANN approaches prior knowledge on variables can be introduced while defining the step size and distributions of the values that are used in the forward calculation of canopy realizations.

Other ways to circumvent the ill-posed problem is the combination of single variables into synthetic variables such as the canopy level content of absorbing materials, which is the product between the content of material per unit leaf area and the leaf area index. Satisfying results with this approach have been achieved by several authors using PROSPECT and SAIL models (Combal et al., 2002; Fourty and Baret, 1997; Jacquemoud et al., 1995a).

Enclosure of neighbourhood information by a moving window or an object-based approach (Atzberger, 2004) is another alternative to reduce the ill-posed inverse problem. In this approach, the shape and orientation of the spectral cluster to which a pixel belongs is taken into account, when inverting the canopy reflectance model. The inversion of the model at view and spectral configurations where the interactions between the canopy variables are minimal are also a good alternative. However, in an operational environment the user will normally not have this choice, although recently there has been an expansion of sensors providing multi-angular imagery designed to reduce the uncertainties associated with the inversion of traditional (nadir) images (Bacour et al., 2002a; CHRIS/PROBA[2]; POLDER[3]).

2.4. Statistical versus physical approach

In this section many approaches have been presented for the retrieval of biophysical parameters from reflective remote sensing data. The question rises: which one to use? No clear answer can be given to this question because each approach has its own advantages and disadvantages and all approaches have yielded good results for various studies. In the following paragraphs we will summarize the benefits and drawbacks of the various approaches (Table 7).

2.4.1. Robustness/stability

One of the major drawbacks often ascribed to statistical approaches, is that they are generally restricted to the conditions that prevailed during the experiment, being (i) factors intrinsic to the vegetation canopy itself (e.g. phenological stage, canopy geometry) and (ii) external factors (local soil properties, atmospheric conditions, sun and view geometry). However, numerous data transformations, such as spectral indices, have been proposed to minimize these effects. It is crucial to evaluate the robustness of the relationships by testing their predictive performances over independent data sets, such as other crops and fields or even at the same field but under different viewing conditions or during another phenological stage. Recently, canopy reflectance modelling has proved its ability in establishing and validating

[2] CHRIS/Proba data exploitation website: http://www.rsacl.co.uk/chris/; visited January 2006.

[3] POLarization and Directionality of the Earth's Reflectances: http://smsc.cnes.fr/POLDER/; visited January 2006.

Table 7
Comparison of physical and statistical approaches

Statistical	Physical
Many field or laboratory measurements required for establishment of statistical relationship	Field or laboratory measurements only used for validation
Spectral data usually transformed	Original spectra used for inversion
Function usually based on a limited number of spectral bands	Inversion usually based on complete spectral information
Statistical function accounts for one variable at the time	Various parameters estimated at the same time
Not possible to incorporate information of other variables	Possibility to incorporate prior information on distribution of different variables
Computationally not very demanding	Computationally very intensive
Atmosphere, view, and sun geometry are not directly accounted for	Influences of atmosphere, view and sun geometry are directly incorporated
Statistical approaches normally based on nadir measurements	Possibility to use multiangular information
Little knowledge of user required	Knowledge of user required for the choice of appropriate canopy reflectance model, inversion technique, and distribution of variables

statistical approaches since it enables one to test their performance over thousands of canopy realizations for which the input biophysical and biochemical variables and sun/view geometry are known (Gastellu-Etchegorry and Bruniquel-Pinel, 2001; Haboudane et al., 2004, 2002; Zarco-Tejada et al., 2005; Zarco-Tejada and Ustin, 2001). On the other hand, the intrinsic capability of canopy reflectance models to describe cause–effect relationships makes it possible to optimize variable retrieval based on canopy reflectance model inversion. This can be done by customizing the model to the canopy condition and the view/sun geometry at the time of data recording.

The robustness of biophysical parameter retrieval using canopy reflectance models is mainly governed by the selection of an appropiate model for the canopy under consideration. Additionally, retrieval accuracy strongly depends on the choice of an appropriate inversion procedure, an accurate parameterization of canopy realizations, and the availability and use of prior knowledge (Combal et al., 2002; Liang, 2004). Although a few studies exist on evaluating the retrieval performances of different inversion techniques using simulations (e.g. Combal et al., 2002), a comprehensive study using real earth observation data has not yet been produced.

2.4.2. Model sensitivity

In statistical approaches based on VIs, the statistical relationship between VI and biophysical parameter accounts only for one parameter at a time. Therefore, for each biophysical variable of interest a new relationship needs to be developed. Additionally, no VI is sensitive only to the desired variable and totally insensitive to all other vegetation parameters and non-vegetative elements (Baret et al., 1992; Govaerts et al., 1999). Inverting a canopy reflectance model usually returns more than one useful biophysical variable, depending on the number of variables that are left free during the inversion.

2.4.3. Data exploration

Statistical approaches based on VIs often use only two or three spectral wavebands. On the contrary, parameter retrieval based on PLS regression models, artificial neural networks, or canopy reflectance modelling can exploit the complete spectral data space provided by the sensor. In the latter case it is important to choose an appropriate inversion algorithm and/or merit function since overrepresentation of bands in spectral ranges with high absolute reflectance may favour the retrieval of only those canopy variables that affect these wavelengths (Weiss et al., 2000).

2.4.4. Practical considerations

A big advantage of statistical approaches is that they are simple and computationally undemanding. This is certainly not the case for most canopy reflectance models which describe complex physical processes. Also inversion algorithms themselves can be computationally very extensive, e.g. numerical optimization techniques and inversions based on large lookup tables (Liang, 2004). This calculation speed may become a limiting factor for operational environments where large quantities of data have to be processed on a daily basis.

Moreover, complex radiative transfer models require more knowledge from the user concerning the specification of inputs, the construction of the merit

function, the use of prior information, and so on. In contrast, statistical approaches implicitly assume that only the variable of interest varies while all other variables are constant.

A more practical complication that limits the use of certain indices based on discrete narrow bands, lies in the fact that red-edge characterization can be achieved only when an observational system is used that measures reflectance at narrow spectral bands around 10 nm width. Nevertheless, ever more attention is paid to the development of operational satellite imaging spectrometers (CHRIS/PROBA; MERIS; EnMAP (Müller et al., 2004)).

From above it may become clear that both statistical and physical approaches have their limitations. These mainly result from the fact that canopy reflectance measured by a sensor is the result of complicated non-linear interaction between the various scattering and absorbing leaf, canopy, soil, and atmospheric elements.

3. Using RS-derived biophysical variables in agroecosystem models

Agroecosystem models are widely used to decribe the impact of climatic conditions and management strategies at field scale, and can be applied in a distributed mode at regional scale. The major problem with models may be an oversimplified description of the natural system, inaccurate parameterization and uncertainty, and hence a low prediction performance. These problems are particularly evident at regional scales where model input parameters have to be gathered from scattered point locations such as weather stations (de Wit et al., 2005). Boundary conditions (soil, management) are often poorly known and model parameters have to be estimated from limited experimental data. Then there is the contribution of remote sensing which offers the spatial observation of biophysical/biochemical variables. Therefore the combined use of RS-derived biophysical/biochemical state variables and agroecosystem models is expected to improve their predictive performance, especially at regional scale (Launay and Guérif, 2005).

3.1. Remote sensing data assimilation strategies

The general objective of data assimilation is to characterize the state of an agroecosystem by combining information from various sources such as mathematical models and observations in space and time of the variables of interest. Within a data assimilation framework it is necessary to distinguish (1) driving variables, which force the system, (2) state variables, which provide a complete description of system behaviour, (3) model parameters, which characterise the relationships between driving variables and state variables, and (4) output variables, which are observable functions of the state variables (Delécolle et al., 1992).

Various methods have been developed to integrate remotely sensed observations in agroecosystem models. In general, three different strategies can be applied which have been described in various papers (Bach and Mauser, 2003; Delécolle et al., 1992; Houser et al., 1998; Makowski et al., 2003; Moulin et al., 1998; Olioso et al., 1999; Paniconi et al., 2003):

- Calibration: With the '*calibration*' method, model parameters or initial states are adjusted to obtain an optimal agreement between the simulated and the observed state variables, which characterise the system behaviour (Fig. 7a). The sensitive and uncertain model parameters are calibrated either manually or automatically by running the model with various combinations of parameter values within realistic ranges. Examples of this type are given by Maas (1988) and Bouman (1995).
- Forcing: The '*forcing*' method replaces a state variable in the model using the observed data (Fig. 7b). The direct use of observed data to prescribe a state variable requires the availability of observations at each model time step, which is daily or weekly in case of most of the agroecosystem models. In reality, remotely sensed observations are available at time of satellite passage only, generally less frequent than the model step. To derive the state variable at model time step, different interpolation techniques, such as linear interpolation, fast Fourier transformations (Roerink et al., 2000) and wavelet approaches, are used to fill the gaps between two observations.
- Updating: The '*updating*' method consists of the continuously updating of model state variables, whenever an observation is available (Fig. 7c). This method is based on the assumption that a better-simulated state variable at day t will also improve the accuracy of the simulated state variable at succeeding days. The updating strategy is more generally referred to as 'sequential data assimilation' and several algorithms have been developed for assimilating observations into models (McLaughlin, 2002).

In recent years 'updating' has received increased attention for agro-ecologic and hydrologic modeling due to its versatility in combining models and

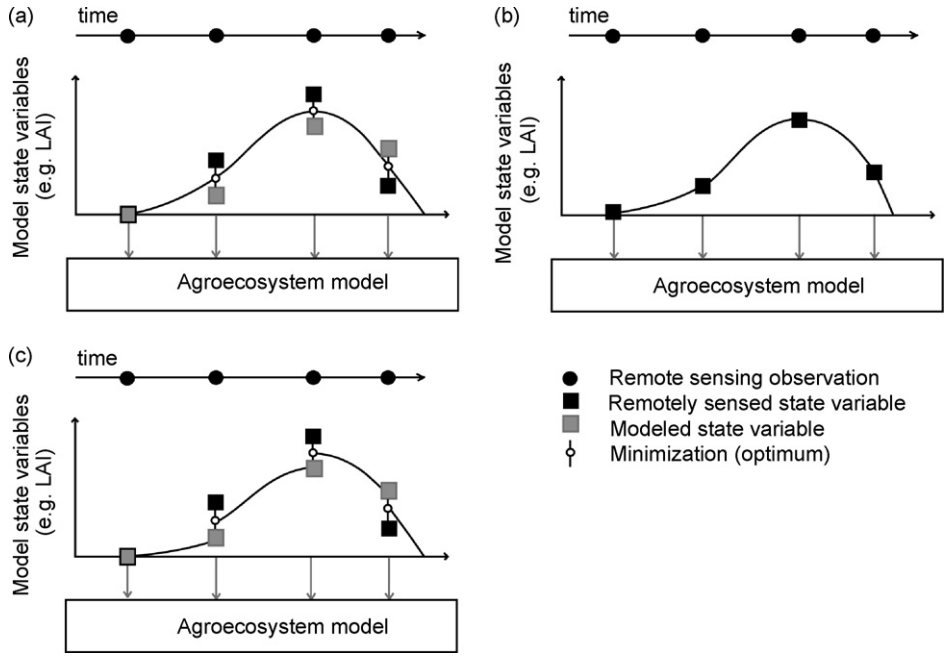

Fig. 7. Schematic representation of different methods for the assimilation of remotely sensed model state variables in agoecosystem models: (a) 'calibration', (b) 'forcing', and (c) 'updating' (adapted from Delécolle et al., 1992).

observations. The paradigm that underlies the data assimilation approach can be formulated as: ''what to trust, the model or the observation?'' At some point during the model run a decision will have to be taken on how to combine the model state variable and the observed state variable. Several algorithms have been developed that try to quantify the relative weight that should be assigned to the model state and the observed state. Examples of these are the Newtonian nudging algorithm (Paniconi et al., 2003) which defines a priori function for the relative weight of observed and modeled state variables and various types of Kalman filters (Aubert et al., 2003; Crow and Wood, 2003; Pastres et al., 2003; Pellenq and Boulet, 2004). Several problems have been identified with applying basic Kalman filters (Kalman, 1960) in agroecological and hydrological models (McLaughlin, 2002):

- The (extended) Kalman filtering techniques are unable to cope with the high dimensionality, the non-linearity and the threshold functions that are often contained in these models.
- The structure of many agro-ecological models does not lend itself very well to be formulated into a state-space formulation.
- The formulation of the uncertainty in the model itself due to parameter, structural and input uncertainty is often difficult.

To overcome these problems the ensemble Kalman filter (EnKF) has been developed (Evensen, 1994). The EnKF approach is based on the notion of representing the statistical properties of the model state by a representative ensemble of models. As a result, there is no need to explicitly propagate the model uncertainty because the uncertainty is preserved in the ensemble. Several studies have successfully demonstrated the usefulness of the ensemble Kalman filter for data assimilation (Crow and Wood, 2003; Reichle et al., 2002).

3.2. Merits and demerits of data assimilation strategies

In representing the natural system, agroecosystem models conceptualise and aggregate the relatively complex processes and their heterogeneity through relatively simple mathematical equations, and therefore contain a certain extent of modeling error. The assimilation of observed (remotely sensed) state variables is expected to improve the model predictions. However, the observed state variables generally derived through remote sensing at regional scale also might contain some observation errors (Bastiaanssen, 1998). In case of the '*forcing*' method, the model forgets its own information, and follows the observed state variable, including the observation errors. The observa-

tion error in the remotely sensed state variables, therefore, would be propagated into the model if the assimilation is achieved through the '*forcing*' method. The '*calibration*' and '*updating*' methods have more flexibility in the assimilation of remotely sensed state variables and their associated errors into the model. As the physical description of underlying process is an acceptable representation of the natural system, the '*calibration*' method is expected to give more representative input parameters and improve model's predictions (Nouvellon et al., 2001). This only applies if there are sufficient observations, and the observation error is small. A major drawback of the '*calibration*' method is large amount of computation time, because of the optimization procedure, required to assimilate the remotely sensed state variables. Nouvellon et al. (2001) suggested testing more robust and low time-consuming procedures, for example, those based on extended and non-linear Kalman-filtering.

Adopting the '*updating*' method, which requires only one run of the model, would significantly reduce the computation time as compared to the '*calibration*' method. However, this approach has the drawback that some measure of uncertainty in the model state variables must be propagated through the system which could become computationally expensive if the model is complex or the model spatial domain is large. Moreover, for the updating methods it is necessary to adjust model state variables during the model run, which often intervenes deeply in the model structure and processing loops. (Walker et al., 2001) compared the direct insertion 'forcing' and Kalman '*updating*' techniques using a synthetic case, and concluded that the Kalman filter is superior to direct insertion. However, there are potential problems in using the Kalman filter such as the necessity for repeat coverage frequency.

3.3. Spatial restrictions

It has been widely demonstrated that remote sensing observations of biophysical variables can be successfully used to calibrate parameters and initialise variables such as sowing date and initial leaf area index in agroecosystem models (Guerif and Duke, 2000; Maas, 1988) or can be used to adjust or replace a state variable, notably LAI and fAPAR, in agroecosystem models (Bach and Mauser, 2003; Boegh et al., 2004; Bouman, 1995; Launay and Guérif, 2005; Moulin et al., 1995). The majority of these studies have been carried out at local to sub-regional scale where the models can still be applied at the level of individual land cover units (fields) and relatively high resolution satellite data (SPOT, Landsat TM) can be applied that match the scale of the land cover units. At these scales the number and timing of satellite images becomes a critical factor (Delécolle et al., 1992; Launay and Guérif, 2005).

Relatively few studies have tried to scale up the use of remote sensing in agroecosystem models to regional or continental scales. Most notably are the results of (Bastiaanssen and Ali, 2003) who applied a light use efficiency driven approach by evapotranspiration estimates derived from NOAA-AVHRR to estimate yields of wheat, rice, cotton and sugarcane over the Indus basin in Pakistan. Similary, Mo et al., 2005) used AVHRR-derived LAI to drive a crop model over the North China Plain in order to predict yield of winter-wheat and grain maize.

Although the above-mentioned applications successfully demonstrated the assimilation of remote sensing derived biophysical variables in agroecosystem models at regional scales, their application was feasible because the land cover units (the crop areas) in those specific regions are so homogeneous that retrieval of crop specific biophysical variables was possible at the 1-km scale of AVHRR. Both studies acknowledge that the results deteriorate in areas where the land cover is fragmented and many crop types are grown within one AVHRR pixel. As such, the application of agroecosystem modeling using remote sensing derived biophysical variables is hampered in many parts of the world by the coarse resolution of current satellite sensors relative to the scale of the landscape units on which the agroecosystem model should operate (Delécolle et al., 1992).

Medium resolution type of satellites (MERIS, MODIS) offer a spatial resolution of 250–300 m which is much better suited for agroecosystem modeling, while still providing daily global coverage. In combination with a crop-specific rapid land cover assessment this type of data could be used to regionalise agroecosystem models. Results presented by Doraiswamy et al. (2004) demonstrate that MODIS-derived LAI at 250 m resolution in combination with a crop specific land cover map can be successfully assimilated into crop models in order to predict crop yield. For areas with complex landscapes where even medium resolution satellite data is inappropriate, the application of data from constellations of satellite such as the Disaster Monitoring Constellation holds promise[4] because a constellation of satellites can provide near-daily global coverage with high spatial resolution.

[4] http://www.dmcii.com/.

4. Computational considerations in agroecosystem modeling and data assimilation

As predicted by Moore's law (Moore, 1965), single processor computational performance has doubled roughly every 18 months over the last 30 years. With this continuous increase in commodity processing capability, the scale and complexity of problems that can be feasibly modeled on an average computer has also improved. As noted in Section 1, this has had the effect of continuously adding more capability and complexity to current state of the art agroecosystem models as a prelude to the next cycle in computational improvement. This in turn implies that state of the art models will typically be slightly beyond the computing capability of the current commodity computing power thereby leading to the need for parallel or distributed processing which allow multiple compute nodes to cooperate on a common problem. Additionally, unless fundamental computing models are changed from the current von Neumann-based (Burks et al., 1946) computing systems to computing systems based on, e.g. non-deterministic logic made possible by quantum physical properties (Deutsch, 1985), performance limits for single CPUs will eventually be reached due to inherent physical constraints such as the size of atoms and the speed of light.

So while many well-established agroecosystem can still be run feasibly by single commodity computing systems, practitioners and developers of state of the art models need to be familiar with issues introduced by the use of parallel and distributed computing systems. Two fundamental concepts to be understood are the typical ways multiple compute nodes are made to cooperate and the ways problems must typically be partitioned for implementation on such systems.

4.1. Distributed and parallel computing models

Due to the previously mentioned commoditization and continuous improvement of CPU's, general purpose parallel computing has converged roughly toward two models known informally as the cluster model and the grid model (Fig. 8). Previously, dedicated super-

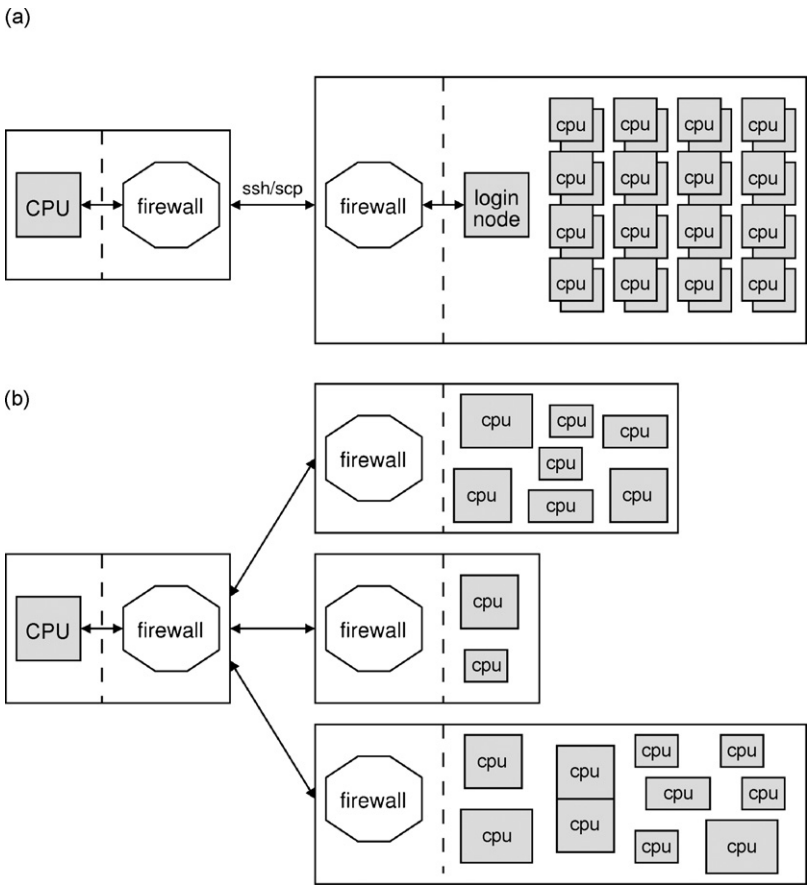

Fig. 8. Cluster (a) vs. grid (b) model of parallel/distributed processing.

computing systems provided another option but the CPU components of such hardware could not keep up with the rate of improvement provided by the commodity market pushing this niche into near extinction.

The cluster model employs relatively high-speed internetwork connections between compute nodes. which implies (1) that the compute nodes are physically near each other, i.e. in the same building and (2) that the number of compute nodes are limited. Clusters are often homogeneous meaning that each compute node has the same CPU speed, amount of RAM and binary executable format. They are also usually dedicated to exclusively solving parallel problems—that implies batch mode processing where parallel jobs are queued and each job runs to completion before the next one is allowed to run. However, heterogeneous (e.g. composed of different CPU speeds, memory sizes and/or binary formats) and non-dedicated clusters (e.g. simultaneously serving as desktop workstations) are not uncommon. The standard method for implementing a program for a cluster is to use the Message Passing Interface (MPI) library of routines, available with C or Fortran interfaces, for internode communication and synchronization.

The grid model implies only that some network connection exists between a compute node and some other node. Compared to clusters, internetwork connections are usually either high latency or low bandwidth (or both) implying that it is not suitable for situations where sub problems are highly interdependent. An advantage for the grid model is that there is no technical limit to the number of compute nodes that can participate toward the common problem.

4.2. Problem decomposition

Perhaps the most important concept to understand in employing parallel or distributed computing for use in agroecosystem modeling is that of problem decomposition—or how problems can be reformulated in terms of sets of smaller problems. For example, an iterative time series agroecosystem model might be able to be split into subproblems along the temporal dimension, or along the spatial dimension, or per variable—depending on which aspects of the model require the most computation and/or how independent these component dimensions can be made from each other.

An example concrete strategy for partitioning subproblems involves using modulo math on some property of the input data that is assumed to be uniformly distributed (e.g. using the last digit of a feature's latitude and longitude could partition a large group of features into $10 \times 10 = 100$ categories). When no such property is available, it may be useful to introduce one that covers the range of the parameter space solely for the purpose of partitioning, e.g. the parameter X is in general unknown but typically assumed to be one of N discrete choices, and the simulation is run over all N cases. When subproblems seem to be hopelessly interdependent, it might be helpful to partition jobs by simulation process (e.g. pre-growth, germination, tillering, flowering, ripening, etc.) rather than by the data, although this form of partitioning is much less likely to produce equal-sized (i.e. efficient) partitions. Another general strategy for partitioning highly interdependent sub problems involves duplicating only the overlap that is necessary to make sub-jobs independent, e.g. by duplicating immediately neighboring cells. This is clearly non-optimal yet allows for useful parallelization if the topology of the cells overcomes the lack of efficiency resulting from duplicated effort.

Knowing that the grid model of distributed computing has no technical bound to the number of compute nodes that can participate in the solution, it seems clear that one should attempt to decompose problems into those suitable for grids rather than clusters. This class of problems is often referred to as ''embarrassingly parallel''—each sub-problem is completely independent from the others and in particular no internode communication is needed during computation of the result. These kinds of problems can be solved using any parallel computing model, e.g. cluster or grid. However there are many problems that cannot be decomposed in this way and internode communication is required during computation that may need to be low latency (e.g. quick but possibly short messages) or high bandwidth (e.g. large volumes of data but possibly slow to start and stop).

4.3. Examples

One example of an application whose implementation evolved from an independent to an interdependent model is described in Keppenne and Rienecker (2002), where an ocean circulation problem initially based on a univariate optimal interpolation (UOI) model was employed. Good scalability on parallel systems was possible via independent sub problem decomposition due to the assumption of a steady state error covariance model. However, a higher quality model was desired which lead first to an improved parallel multivariate OI (MvOI) system (Borovikov and Rienecker, 2002) but

eventually to a completely dynamic model by employing a parallel multivariate ensemble Kalman filter (MvENKF). The improved dynamic model came at the cost of highly interdependent sub problems that removed the possibility of implementation on a typical loosely coupled grid.

An example of an application that evolved the other direction involves the reduction of airborne hyperspectral imaging data sets using the MODTRAN radiative transfer code. The atmospheric modeling that is performed by MODTRAN contains many interdependencies requiring the cluster model to speed up any particular execution (Wang et al., 2002). However, as single run times have decreased due to Moore's law (Moore, 1965), it has become feasible and interesting to perform several, possibly thousands, of single MODTRAN runs in order to support applications as varied as image-based sensor characterization (Gao et al., 2004) or general purpose atmospheric correction (Richter and Schläpfer, 2002). Since each single run is independent, a grid model can be used to scale up to the number of runs that are desired (Brazile et al., 2004).

An example application that makes extreme use of the independent grid model is the climateprediction.net project which uses the boinc (Anderson, 2004) grid environment to perform individual simulations using idle processing capacity on personal computers volunteered by members of the general public (Stainforth et al., 2005). This resulted in the ability to make 2578 simulations (corresponding to >100,000 simulated years) to explore combinations of climate perturbations in six parameters according to various rising levels of greenhouse gases.

Additional example agroecosystem applications which have achieved improvements in accuracy or scale due to exploitation of parallelism include forest growth model prediction quality using a tightly coupled implementation of a neural network on a CM-2 supercomputer (Guan et al., 1997); a modest improvement in computation efficiency for the temporal scaling of a vegetation ecosystem model using a small cluster (Cornwell et al., 2001); and spatial, temporal and compositional scaling in air pollution models implemented on various supercomputers and clusters (Dimov et al., 2004). The latter example additionally points out the importance of dynamic sizing of the sub-problem during parallel decomposition depending on the computation power of individual compute nodes in the cluster. This, along with the MODTRAN example underscores the importance of acknowledging Moore's law during any parallel implementation for applications that are expected to be useful over a span of years.

4.4. Trends and outlook

There will continue to be niche applications deemed important enough by governments to support a small number of very large supercomputers such as America's BlueGene/L for nuclear stockpile stewardship (BlueGene/L[5]) and Japan's Earth Simulator for ''holistic simulation of the earth'' (Earth Simulator[6]). However, more typical large problems are increasingly likely to be served mainly by commodity component based computer clusters in industrial and academic research institutions or grids of more loosely coupled standard workstations (Top 500 Supercomputer sites[7]).

Researchers often have varying degrees of freedom during the design and development of agroecosystem models. From an implementation point of view, it would be desirable to engineer models that are on the edge of feasibility and that not only can be decomposed into relatively independent sub problems, but where the computation of individual subproblems can be sized up by an order of magnitude. This amortizes the cost of the implementation of the model and helps ensure that it is useful over a span of years rather than months. Creativity is needed to see how this can be done, whether is it by increasingly finer grain coverage of a wide parameter space (Brazile et al., 2004), increasingly longer sequential time-step sequences in individual simulations of varying parameters (Stainforth et al., 2005), or functional rather than temporal or spatial parallelism (Cornwell et al., 2001). There will always be the need for iterative models where subsequent steps rely on previous results, but if the degrees of freedom in the model design allow it, choosing independent sub-problems that can be scaled up will improve the model's longevity.

5. Conclusions and outlook

In this paper, we presented an overview of the role that reflective remote sensing (~400–2500 nm) can play in increasing the performance of agroecosystem modeling. The added value mainly consists in providing canopy state variables at a spatial coverage and at spatial and temporal resolutions that would be impossible to achieve via ground observations or field

[5] http://www.llnl.gov/asci/platforms/bluegenel/; visited May 2005.
[6] http://www.es.jamstec.go.jp/esc/eng/ESC/index.html; visited May 2005.
[7] Top 500 Supercomputer sites—Architecture Trends: http://www.top500.org/lists/2005/06/overtime.php?c=1; visited May 2005.

campaigns. The most promising approach for improving agroecosystem management strategies is not the mere provision of canopy state variables but on the possibility of assimilating this information into agroecosystem models. However, remote sensing based data assimilation is still subject to a few drawbacks.

First of all, canopy reflectance is governed by the interaction of a large number of canopy elements and external factors. This leads to difficulties in retrieving state variables since often absorption features cannot be ascribed to single variables. Moreover, different combinations of canopy, leaf, and external properties may lead to a very similar reflected signal, resulting in ambiguous results or the challenge of solving an ill-posed problem.

Many techniques have been proposed to transform the spectral signal in such a way that a direct statistical relationship can be established with the biophysical or biochemical variable of interest while background effects are minimized. However, these statistical approaches, even though being fast in computational nature, are often confined to local events, lack portability, and substantially decrease in quality at larger scales. We demonstrated that physically based canopy reflectance models help to improve our understanding of the interaction between solar radiation and vegetation canopy elements. For this reason, such models can also be used to design and test new robust and sensitive statistical approaches. The inversion of these types of models appear to be a useful alternative to statistical approaches for the retrieval of biophysical and biochemical variables. Physical models can even be incorporated into agroecosystem models to model reflectance at the top of canopy or atmosphere, which enables a direct comparison with the signal measured by the sensor (Verhoef and Bach, 2003a).

Even if canopy modeling has led to an improved understanding of the multivariate variable space, it still appears to be difficult to cope with the ambiguities emerging when the model is used in the inverse mode for the estimation of canopy variables. Various methods have been proposed to overcome this problem and to contribute to improved estimations of biophysical parameters from earth observation data. These include the use of neighborhood relationships (Atzberger, 2004), the assimilation with data of other origin (field measurements, meteorological data, agroecosystem models; CROMA, 2002; Liang, 2004), and the incorporation of the typical evolution over time of a specific variable (Baret et al., 1989a; Koetz et al., 2005).

As current methods for the retrieval of canopy state variables typically involve analyzing single-sensor, mono-directional, and mono-temporal data, a great potential lies in the fusion of this data with observations with different angular, spectral, spatial, or temporal properties (Bacour et al., 2002b; Chopping et al., 2003; Schaepman et al., 2005). The importance of the increased information content contained in these measurements is acknowledged by the remote sensing community and reflected by the increasing number of initiatives for launching satellites with improved spatial, temporal, spectral, or angular resolution (MERIS, (CHRIS/PROBA; EnMAP (Müller et al., 2004)). Also, earth observation data of a different nature, such as LIDAR, thermal and microwave remote sensing data contain information on canopy state variables and may help to obtain improved canopy variable estimations (Hyyppä et al., 2000; Lefsky et al., 2002; Parker et al., 2001). Radar also provides the opportunity to fill the gaps in temporal sequences of canopy variables in places where optical observations are limited due to frequent cloud cover. The number and timing of the remote sensing observations seem to be a decisive factor for a successful assimilation of remote sensing data in agroecosystem models (Delécolle et al., 1992; Launay and Guérif, 2005).

Parallel and distributed processing will likely prove to be quite useful in dealing with the enormous data amounts involved in the increasingly complex remote sensing and data assimilation strategies discussed in this paper. The use of multiple simultaneous computing nodes seems to offer the potential for enhanced agroecosystem modeling yet, to date, the scope of this potential remains nearly unexplored in this field of research.

Data assimilation based approaches will be of increasing importance in the near future. Not only the increasing growth of in situ measurement networks (so called SensorWebs), but also the challenge to use advanced processing methods to overcome partly discontinuous data sets, as well as minimizing spatial data uncertainties will call for assimilation based procedures (Schaepman, 2007). The inherent nature of agroecosystems and the wish to predict their behaviour in the future more accurately is excellently embedded using assimilation approaches.

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