Review article

Combining agricultural crop models and satellite observations: from field to regional scales

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Abstract. This review article gives an overview of how satellite observations are used to feed or tune crop models and improve their capability to predict crop yields in a region. Relations between crop characteristics which correspond to models state variables and satellite observations are briefly analysed, together with the various types of crop models commonly used. Various strategies for introducing short wavelength radiometric information into specific crop models are described, from direct update of model state variables to optimization of model parameter values, and some of them are exemplified. Methods to unmix crop-specific information from mixed pixels in coarse resolution-high frequency imagery are analysed. The conditions of use of the various methods and types of information are discussed.

1. Introduction

Agriculture is a major user of data from satellite remote sensing. For more than a decade, projects have addressed the estimation of crop yield using satellite observations, from the Large Area Crop Inventory Experiment (LACIE) in the USA, which aimed at estimating wheat productions over the world using Landsat MSS information (Erickson 1984), to the Monitoring Agriculture with Remote Sensing (MARS) programme of the European Union, which issues real-time estimations of crop areas and productions at European level using high spatial resolution satellite data (Meyer-Roux 1990). In operational monitoring, satellite data are used only for crop acreage estimations, that is an important part of the agricultural production assessment at a national or continental level (Sharman et al. 1992). However, numerous field experiments and theoretical studies have shown that remotely sensed measurements in the different wavelengths can provide information on crop activity.

Satellite remote sensing supplies observations over large areas at even times and therefore provides other crop monitoring techniques with possible spatial extension. Satellite radiometric observations give help to extend crop models to a regional scale. They allow to account for spatial variations of the environmental conditions which influence crop growth and development, without tedious ground field surveys.

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However, current operational applications only use a very limited area of the potentialities of remote sensing. Most applications are restricted to a descriptive analysis (as described, for example, by Allen 1990, Meyer-Roux and King 1992, and Genovese 1997). Quantitative analysis requires more complex methodologies, including the coupling of satellite data and crop production models to estimate yields at a regional scale, as it was first suggested by Wiegand et al. (1986).

This article attempts to provide a review of some methods and related applications on coupling of remote sensing and production models, and to discuss the current methodological trends. Section 2 analyses the relationships between crop state variables in a model and remote sensing measurements acquired in several wavelengths and gives an overview of different kinds of crop production models (from empirical to mechanistic). Section 3 deals with the strategies identified to couple satellite observations and crop production models. Finally the strategies used to tackle the yield estimation at regional scale with coarse spatial resolution satellite information are presented through section 4.

2. Relations between satellite observations and crop state variables: from empirical to mechanistic crop models

Remote sensing tools can provide information about vegetation in various wavebands: solar spectrum (Guyot 1996), active and passive microwave (for example, for radar: Prévot et al. 1993) and in thermal range (Moran et al. 1994, Seguin et al. 1991b, and Seguin et al. 1994). It appears that remotely sensed measurements can be related to instantaneous values of various canopy state variables. To achieve this, canopy state variables can be connected to remotely sensed information by using physical radiative transfer models or empirical relationships. Canopy variables appear in physiological functions which determine final yield when integrated in time. Crop simulation models (Whistler et al. 1986) provide formal descriptions of state variables and time integration of biophysical processes. Their time step is shorter than the time frequency of remote sensing information. In the microwave range, information about soil moisture and plant water content is obtained (Wigneron et al. 1997, Attema and Ulaby 1978, as discussed by Clevers and van Leeuven 1996); whereas information on plant water status can be derived from thermal infra-red (TIR) range (Taconet et al. 1996). Solar spectral data are related to leaf area index and the photosynthetically absorbed radiation (Asrar et al. 1984). Radar, which gives information on plant structure, is sometimes used to supplement optical data sets (Bouman 1992). Airborne radar data have been successfully coupled with crop models (Clevers and van Leeuven 1996), but satellite data have not been used yet.

2.1. Empirical methods

Ground radiometric measurements performed over winter wheat fields have shown that production is strongly correlated to the cumulative amount of vegetation indices (VIs, which are combinations of visible and near infrared measurements) along the growing season (Tucker et al. 1981). Similar relationships were obtained on various crops (for example, Gilabert et al. 1996, on corn fields). Tucker et al. (1985), obtained the same results using satellite data, and proposed an empirical model for biomass production, based on cumulated indices. According to Hatfield (1983), vegetation index values at heading can be related to potential yield, provided that no accident occurs after that stage. Murthy et al. (1996) also predicted final
yield on paddy via a regression line on NDVI computed from Indian Remote Sensing Satellites (IRS) data. Over several plots, yield is related to NDVI using a single acquisition. Recent works still rely on such simple relationships using satellite data: Hamar et al. (1996) established a linear regression model to estimate corn and wheat yield at regional scale based on vegetation spectral indices computed with Landsat MSS data. Hayes and Decker (1996) used a eight-year time series of global vegetation index (GVI) computed from NOAA AVHRR observations to retrieve yields in a small region through empirical relationships.

Such relationships are due to the fact that the time profile of visible and near infrared signatures is linked with the evolution of: (i) canopy development; (ii) canopy capability to absorb photosynthetically active radiation (fraction of Absorbed Photosynthetically Active Radiation [fAPAR]); and with length of vegetation period, all of these being linked with dry matter production. Relationships between VIs and fAPAR have been established theoretically (for example, Sellers 1985), and experimentally (for example, Asrar et al. 1984 and Bégue and Myneni 1996). But the relationships between cumulated VIs and dry biomass are empirical and only have a local value. To estimate production in any conditions, it is then necessary to describe how photosynthetically active energy is absorbed, converted into dry biomass and partitioned to harvestable organs. More mechanistic or physiologically sound models are therefore necessary to assimilate remote sensing data and predict production of major crops (wheat, maize, soybean, rice, etc.) in intensive agricultural systems of temperate areas.

2.2. Semi-empirical models

A first approach is the Monteith’s efficiency model (1977), adapted to the use of radiometric data by Kumar and Monteith (1981). This model considers that a diagnostic estimation about the status and the activity of the canopy is provided by remote sensing data. According to a semi-empirical formulation, the daily production of dry matter (DM) is computed by integrating incident global solar radiation ($R_g$) (sum of direct sun radiation and diffuse sky radiation) weighted by three efficiencies ($e_c$, $e_i$ and $e_b$):

$$DM(t) = \frac{1}{C} \int_{t_0}^{t_1} e_b(t) \cdot e_i(t) \cdot e_c \cdot R_g(t) \cdot dt$$

(1)

where $C$ is the conversion coefficient of biomass into energy, between 17 and 20 MJ kg$^{-1}$. $e_c$ is the climatic efficiency, i.e., the fraction of photosynthetically active radiation (PAR) in global solar radiation ($e_c R_g(t) = PAR(t)$). Its value is generally admitted as a constant 0.48 (Varlet-Grancher et al. 1982). $e_i$ is the radiation interception efficiency. It represents the ability of the canopy to intercept PAR ($e_i PAR(t) = APAR(t)$ (absorbed PAR)). It ranges from 0 for a bare soil to 0.95 for a close and dense green canopy. As $e_i$ depends on the optical properties of the canopy, it can be derived from reflectance measurements (Baret and Olioso 1989). $e_b$ is the efficiency of conversion of energy into dry matter (total or above-ground) ($e_b PAR(t) = dDM/dt$). It can be 0, when environmental conditions do not allow a positive net primary production and usually ranges between 0.001 and 0.1 according to development stage of the crop. This characteristic reflects the effects of all factors affecting crop carbon assimilation, i.e., C3 or C4 metabolism, air temperature, water and nutrient availability, and phenological development (Garcia et al. 1988). Empirical values are commonly used either from ground measurements (Leblon et al. 1991) or
from literature (Gosse et al. 1986). The daily production of dry matter is integrated during the growing season to estimate final biomass, which is related to the yield.

Monteith’s model allows the estimation of dry matter production for crops using satellite data in different wavelengths. Leblon et al. (1991) used SPOT visible and NIR radiances to estimate $e_i(t)$ on rice. In semi-arid areas, where water conditions can strongly reduce the conversion efficiency (Steinmetz et al. 1990), a water stress index controlling $e_b$ can be computed from TIR radiometric measurements. The difference between surface temperature $T_s$ and air temperature $T_a$ is a good indicator of water stress (Seguin et al. 1991a, 1991b): $T_a$ is meteorological information, while $T_s$ is directly derived from TIR data (Lagouarde et al. 1991). The combined use of satellite data in short wavelengths and in TIR (when acquired by NOAA/AVHRR) has provided reasonable estimates of cereal production in Algeria over two years strongly contrasted in terms of water conditions (Guérif et al. 1993). Loudjani et al. (1995) estimated winter wheat yield at AVHRR resolution using a single $e_b/C$ value (3.2 g DM/MJ APAR, Gosse et al. 1986) for pixels fully covered by this crop. The harvest index (dry matter of harvested parts/total dry matter produced) was set at 0.45 (Russell and Wilson 1994) and a stress index was derived from NDVI. This diagnostic model, which uses satellite data as input, can be used quite simply, provided that a consistent estimation of $e_b$ is available. Its main drawback is the lack of description of the physiological and biological mechanisms which control growth and development (and therefore $e_b$ values). This degree of detail in crop mechanisms is only available in agrometeorological mechanistic models.

2.3. Mechanistic models

Agrometeorological mechanistic models are designed to simulate the time profile of the main crop state variables (leaf area index [LAI], dimensions and biomass of various organs, development stages, etc.) and of energy, carbon, water and nutrient fluxes at the crop/soil/atmosphere interfaces. The simulation of time profiles for those variables depends on soil and climate conditions, and on farming practices. Strictly speaking, these models are suitable at field scale. Models are available for the major crops in the world (IBSNAT 1993). For some of them, yield-driving processes and their interactions are described through mechanistic relationships (for example, AFRCWHEAT from Weir et al. 1984, or SUCROS from Spitters et al. 1989) and generally run at a daily time step. They simulate seasonal profiles of LAI, which is of main importance as it drives absorption of solar radiation and evapotranspiration, and thus carbon assimilation. However, canopy development and allocation of daily assimilates to leaves are described through empirical relationships. The use of inaccurate coefficients within a relation affecting canopy development may lead to important errors on the estimation of biomass production (Porter 1984).

Some modellers therefore suggested replacing the doubtful simulations by an estimation of crop state variables derived from remote sensing along the growing season. Every spectral band is of great interest: visible and NIR for canopy structure and photosynthetic activity, TIR for water status, microwaves (active or passive) for water content, soil moisture and canopy structure (Guyot 1996). The US Department of Agriculture (USDA) first published a review on the combined use of agrometeorological models and remotely sensed data (Wiegand et al. 1986). During the last 10 years, as important improvements were achieved regarding the processing and the interpretation of satellite observations, the concept of coupling crop production models and satellite observations evolved. New strategies consider the use of
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As a way to recalibrate models dynamically. Those strategies are presented and discussed in the next sections. The specific problem of regional yield estimation is also addressed.

3. Coupling crop process models and satellite data

The different ways to combine a crop model with radiometric observations (ground measurements or satellite data) were initially described by Maas (1988) and their classification was revisited by Delécolle et al. (1992). Four methods of data integration have been identified:

(i) the direct use of a driving variable estimated from remote sensing information in the model;
(ii) the updating of a state variable of the model (for example, LAI) derived from remote sensing;
(iii) the re-initialization of the model, i.e., the adjustment of an initial condition to obtain a simulation in agreement with the remotely-sensed derived observations;
(iv) the re-calibration of the model i.e. the adjustment of model parameters to obtain a simulation in agreement with LAI derived from the observations.

Most of those approaches were first tested by Maas et al. (1989) by using a simple model (GRAMI) which simulates gramineous growth and development. For instance, the description of the mechanisms driving canopy development and senescence is replaced by a parameterization of time evolution of LAI. The parameterization is obtained with the initial LAI value at crop emergence, and three parameters for the shape of the LAI seasonal curve. Other works also used one of those methods either with ground radiometric measurements or with satellite data. The general strategy of the model/observations coupling consists of deriving variables or parameters which directly occur in the modelling procedure from radiometric observations. For example, LAI can be derived from a VI computed from visible and NIR spectral bands (for example, Chen and Cihlar 1996), and a stress index (used to reduce daily carbon assimilation), from the TIR channels (Guérif et al. 1993).

The direct use of remote sensing data (i) to derive a driving variable assumes that remote sensing data are available at an adequate time step (from daily to weekly). Due to cloud contamination and intrinsic properties of sensors and platforms, this is rarely the case. Concerning the other strategies (ii, iii, iv) and the current trends, the different studies are here summarized distinguishing two approaches depending on the model/observations coupling method used (Delécolle et al. 1992).

3.1. The ‘forcing’ strategy

The forcing strategy consists of updating at least one state variable in the model using remote sensing data. The crop model requires a value for this state variable at each time step. On the other hand, remote sensing estimations are available only at acquisition dates, generally less frequent than the model step. Gaps between dates must therefore be filled by some interpolation procedure, usually by fitting an empirical curve of time evolution of the state variable to the ‘observed’ data.

Maas et al. (1985) and Maas (1988a) used ground radiometric measurements over maize fields. Optical measurements give access to LAI, whereas TIR data are used to derive surface temperatures which in turn provide a water stress index. In
this case, simulation of above-ground biomass is improved. Delécolle and Guérif (1988) used high spatial resolution satellite data (SPOT/HRV) over wheat fields to improve the predictive ability of a complex deterministic model (ARCWHEAT, Weir et al. 1984). Since the temporal frequency of SPOT data is limited, the derived LAI values are interpolated to a daily time step using a simple model of LAI time course (Baret 1986). The resulting daily LAI values are then used as input variables to ARCWHEAT (figure 1). This coupling leads to a reduction of the mean error on yield estimation.

Substitution of a simulated LAI value by an 'observed' one (actually derived from the observed reflectances) suggests that simulation of the LAI is flawed, and therefore the biophysical processes are not well described by the model. But a good description of those processes is required to obtain a consistent estimation of variables such as crop biomass, which cannot be monitored directly by remote sensing. The derived state variable can also be used to estimate initial conditions or some model parameters. This is a way to improve the description of all processes within the model.

3.2. The 're-initialization/re-parameterization' strategy

This consists of minimizing the difference between a derived state variable or the radiometric signal and its simulation by the re-parameterization and/or reinitialization of the crop production model.

3.2.1. The use of a remotely-sensed derived state-variable

The time profile of simulated state variable must be consistent with observations. For example, the derived LAI is used to constrain the LAI course and its initial value, and the derived stress index allows one to re-initialize the soil water balance routine.

Maas (1988a, 1993) and Maas et al. (1989) used ground radiometric measurements over maize crops to constrain the simulations of the crop production model

Figure 1. Representation of the forcing strategy: the temporal behaviour of one state variable of the crop model is derived from satellite observations and used as input variable within the model (adapted from Delécolle et al. 1992).
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GRAMI. LAI values are derived from optical measurements, and stress index values from thermal measurements. The description of the mechanisms driving canopy development and senescence is replaced by a parameterization of the temporal behaviour of the LAI. The minimization is performed by adjusting the initial LAI value (day of emergence) and three shape coefficients of the LAI seasonal curve. The correct retrieval of those parameters is necessary to obtain a consistent estimation of crop production. Clevers and van Leeuwen (1996) used ground and airborne radiometric measurements over sugar beet fields to calibrate the SUCROS model. They derived LAI from measurements in optical and microwave wavebands. The adjusted parameters and initial conditions were sowing date, a growth rate, light use efficiency and maximum leaf area. Authors point out the ability of optical data to improve yield estimation, whereas radar data are especially useful when optical data are missing. Maas used satellite data (Landsat/MSS) to derive LAI time course for sorghum (1988b) and winter wheat crops (1991) by re-initializing/re-parameterizing the GRAMI model (figure 2). The technique helped estimate yields for different fertilization and irrigation treatments.

All those studies show that the estimation of biomass time profile and final yield are improved as compared to results of the forcing method. Due to the use of optimization procedures, this technique requires more computer time. But the main drawback is the empirical relation used to derive LAI from satellite data. This relation, which must be calibrated locally, has an asymptotic trend for high LAI values (>3 or more, according to the VI used) and is very dependent on soil background for LAI values smaller than 3.

3.2.2. The direct use of the radiometric information (a so-called ‘assimilation’ strategy)

The assimilation strategy is the direct use of radiometric information to re-parameterise and/or re-initialize a crop model. One considers that the temporal

![Figure 2](image-url)  
Figure 2. Representation of the recalibration strategy: by comparing modelled LAI profile and ‘LAI observations’, derived from satellite data some parameters of the crop model (or some initial conditions) are re-tuned (adapted from Delécolle et al. 1992).
behaviour of canopy surface reflectances, as they can be observed from satellite, can be reproduced by coupling a radiative transfer model to the crop production model (Bouman 1992, Major et al. 1992, Moulin et al. 1995a, Fischer et al. 1996, 1997). Analytic reflectance models accounts for view and solar geometries, crop structure and crop and soil optical properties. The minimization of differences between the simulated and observed reflectances is carried out by adjusting initial conditions or model parameters. The pertinent parameters are those which strongly constrain the behaviour of both satellite signals and biological variables of interest, i.e., the parameters which drive the canopy development (figure 3).

Bouman (1992) used ground radiometric measurements over sugarbeet fields to re-parameterise and re-initialize the crop production model SUCROS. A reflectance model and a radar reflectivity model were coupled to the crop model to simulate the measurements acquired in solar spectrum, and in active microwave range. The minimization is performed by fitting the sowing date (important initial condition for the development), and three specific parameters which constrain photosynthetic efficiency and canopy growth rate. The adjustment improves the estimations of crop production. Moulin et al. (1996) and Kergoat et al. (1995) used high spatial resolution satellite data over winter wheat fields of a large agricultural region (figure 4). Four SPOT/HRV scenes were available during the wheat activity period: Three of them were acquired in a six-day period corresponding to the LAI peak period, the other occurred during the growth period. Since satellite data were calibrated and corrected for atmospheric effects, surface bi-directional reflectances were available. The mechanistic crop production model AFRCWHEAT2 (Porter 1993) was linked to the SAIL reflectance model (Verhoef 1984) through daily simulated LAI. Due to the small number of observations, only one parameter can be adjusted to minimize the observations/simulation difference. The sowing date, which strongly influences

![Figure 3. Representation of the assimilation strategy: by comparing simulated reflectance profile (from the coupling of a crop production model and a reflectance model) and satellite reflectances allows some parameters of the crop model (or some initial conditions) are re-tuned.](image-url)
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Figure 4. Seasonal spectral reflectance profiles of winter wheat. (*) : SPOT-HRV observations ±1 standard deviation. Simulations with the sowing date: (---) real (jj 296), (⋯⋯) adjusted (jj 299), (-----) earliest initial (jj 266), and (———) latest initial (jj 326). Upper curves: NIR channel, lower curves: visible channel.

phenology and canopy development and which is hardly known at regional scale was chosen. From a ground survey on a collection of fields, it appeared that the sowing date retrieved was close to reality. Its use within the model provided a yield estimation close to the surveyed yield. A methodological study (Moulin et al. 1995b) has shown that satellite scenes occurring during crop growth are more useful in terms of improving the predictive ability of the model, than observations during the LAI peak period.

Those results make us feel confident in the synergetic potential of coupling crop process models and satellite observations. The assimilation of satellite data leads to the retrieval of one initial condition, subsequently it allows to use the model more confidently over an area where no ground information is available. Unfortunately, the low temporal frequency of high spatial resolution images limits the number of observations during the growth period and thus the number of parameters that can be adjusted. For example, the phenological development of winter wheat is strongly dependent on sensitivity to photoperiod and vernalization, which are variety-dependent. Those characteristics also drive canopy development, and consequently, biomass production. The possible use of low spatial resolution data for this purpose must be evaluated in the future.

4. Spatial resolution and scale

The time frequency of most low spatial resolution sensors allows a constant monitoring of crop growth and development conditions, rarely obtained with high spatial resolution systems. For instance, taking into account the occurrence of clouds, the AVHRR effective time frequency (about one week instead of one day) is adequate to estimate biomass production. The relevance of coupling satellite data with crop
models is actually based on the assumption that the radiometric signal allows the detection of onset of fast processes such as the beginning of crop growth, as well as the occurrence of accidents (for example, severe droughts) which affect yield. Due to the complex land use of agricultural landscapes and the size of agricultural fields (most of time smaller than the AVHRR nadir nominal resolution), the low spatial resolution radiometric measurement is a mixed signal. Therefore, the use of satellite data time series provided by coarse resolution sensors requires a specific attention. Different techniques allowing the retrieval of individual contributions of each component (especially for crops) or to reconstruct the mixed signal are described.

4.1. The so-called ‘spatial decomposition’ approach

This approach considers inter-pixel variability of a coarse resolution image to be mainly due to pixel-to-pixel change in land use. If individual signatures of components are assumed constant over the region, then a simple statistical model retrieves average regional crop signatures (Puyou-Lascassies et al. 1994, over temperate zone, and Kerdiles and Grondona 1995, over Pampa in Argentina). A more complex model accounting for the spatial variability of individual crop reflectances (Faire and Fischer 1997), in addition to average reflectances of each component, also provides the location and magnitude of their positive and negative deviations. Such deviations are due to the spatial variability of soil-climate conditions or farming practices, and are therefore important for crop modelling purpose. A linear mixture model (Ouaidrari et al. 1996) can also be used to extract individual signatures of the components from coarse resolution data. This method restores the spatial variability of each component reflectance over a degree square of the Sahel region using blocks of NOAA AVHRR pixels.

4.2. The ‘temporal decomposition’ approach

This approach relies on the shape of the time profile observed at a regional scale during an annual cycle. Fischer (1994a) used an empirical model to describe the NDVI time profile (a different set of parameters was used for each crop). The regional profile was described as the sum of the various individual profiles weighted by their relative land use percentage. From land use and regional radiometric profiles, individual profiles of the major crops were retrieved.

The spatial decomposition approach requires the location of crops (land use within each pixel), whereas only a statistical knowledge of the land use is necessary for the temporal decomposition (i.e. percentage of a given crop over the considered region). On the other hand, regional observations are required along the whole growing season (Fischer 1994b) to use the semi-empirical model of temporal profile, whereas the spatial decomposition can be applied to a single coarse image.

4.3. The complete modelling of the low resolution signal

All the methods proposed to untangle the mixed signal acquired over heterogeneous agricultural landscapes attempt to extract the individual signature of a given crop. An alternative to this approach is the complete modelling of the low resolution signal (Moulin et al. 1995a), combining the contributions of the different crops considering their relative surface. They simulate the regional radiometric signal over an area planted with 60% of winter cereals. A crop model was used for the winter cereals and empirical reflectance profiles for the remaining components (peas,
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Figure 5. Time profile of observed (x) and modelled (—) NDVI for AVHRR at regional scale (11 km × 20 km). Simulation represented winter cereals by using AFRCWHEAT2 model and other components by empirical values. Observations were from NOAA/AVHRR measurements (averaged pixels) (from Moulin et al. 1995a.)

sunflowers, and woodlands). The simulation fits roughly with the NOAA/AVHRR time signature (figure 5), especially during the growth period.

This result suggests that some crop model parameters could be retrieved with ‘assimilation’ procedure using coarse resolution data.

5. Conclusion

Since satellite data have been used for monitoring vegetation for many years, and have provided information on the behaviour of variables related to canopy activity, their coupling with crop models seems of great interest. Such methodologies can be used, provided that (i) the satellite observations are correctly processed; and (ii) the low spatial resolution signal (if used) is correctly interpreted.

The expected results are limited by the quality of the remote sensing data used. Studies regarding physical radiometric measurements supply a signal allowing to monitor canopy activity at surface level. However, with the ‘assimilation’ strategy, if the radiometric corrections are not performed or the directional effects not accounted for, the effects of atmospheric perturbations and directional properties can lead to a 15-day lag for the retrieved sowing date (Fischer et al. 1996). At regional scale, the atmospheric corrections face the problem of uncertainty about water vapour and aerosol content. The spatial and temporal variability of aerosols drastically affects the measured visible reflectance. Current studies assume that only acquisitions during clear sky days (low aerosol content) remain after data temporal filtering. Some authors also suggest to estimate the aerosol content from AVHRR data (Holben et al. 1992). Many improvements are expected from new sensors (for example,
POLDER on board ADEOS, NASDA 1993) which provide aerosol, ozone, and water vapour estimates. Thanks to multi-angular measurements also provided by these sensors, inversion of physical or analytic reflectance models and subsequent retrieval of canopy properties (LAI, leaf angle distribution (LAD), and leaf optical properties), will be possible (see Clevers and van Leeuwen, 1994). Although, no inversion of LAI is performed with assimilation strategy, the direct modelling of reflectances requires the parameterization of LAD and leaf optical properties (Moulin et al. 1995a). Multiangular satellite data, by providing constraints on the reflectance model parameters will lead to more robust modelling. In any cases, the use of satellite observations implies the correction of raw data or the quantification of residual disturbing effects.

Concerning regional scale studies, the spatial heterogeneity of a mixed low spatial resolution pixel due to the land use occupation can be tackled either with an unmixing technique or with a recomposition method. Whatever the method chosen, the use of mixed pixels, compared to pure ones, adds a degree of complexity to the study, but gives access to the regional scale. Up to now, the crop models used for regional scale studies are not specifically dedicated to regional scale. Initially they were built up to simulate field scale crops. A strategy could consist in implementing a new generation of crop models for regional scale topics. Those models could also be linked to soil/vegetation/atmosphere transfer (SVAT) models which simulate the water and energy budgets at the surface/atmosphere interface. Optical remotely sensed data would be used to retrieve some plant characteristics through the crop model, whereas thermal infrared would be used to adjust some soil characteristics through the SVAT model.

References


IBSNAT, 1993, IBSNAT Views, September, 1. (International Benchmark Sites Network for Agrotechnology Transfer. 2500 Dole Street, Krauss 18, Honolulu, HI 96822, U.S.A.)


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