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Using crop models for multiple fields

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1 Introduction

The original use of crop models was to calculate crop growth and development for a single field with supposedly homogeneous soil, climate, initial conditions and management practices. This is indeed still a basic use of crop models. However, there is also more and more interest in studies that concern multiple fields (see Leenhardt et al., 2003, Hansen and Jones, 2000; Russell and Van Gardingen, 2000; Hartkamp et al, 1999). In some cases each field can be treated independently, but it is the combined result from all fields that is of interest. Examples include the calculation of crop yields or forage yields on a regional or national basis (e.g. Rijks et al., 1998; Thornton et al., 1997; Rosenthal et al., 1998; Chipanshi et al., 1999; Lal et al, 1993; Donet et al., 1999; Faivre; Yun, 2003) the calculation of the water requirements for agriculture within the area served by a water provider (e.g. Sousa and Pereira, 1999; Heineman et al., 2002; Leenhardt et al., 2003) or total emission of nitrogen oxides from agricultural land in a region. In other cases, it is necessary to model not just individual fields but also interactions between fields or between a field and non-crop surroundings. For example, the problem addressed might involve nitrogen, herbicide or pesticide pollution of streams or ground water due to runoff or leaching from agricultural land (e.g. Beaujouan et al., 2001; Gomez and Ledoux, 2001). Another example would involve transfer of genetically modified pollen from one field to surrounding fields. In all of these problems there is a need to use the crop model for multiple fields, perhaps hundreds or thousands of fields, with different soils, climate and management.

A major problem in all these studies is obtaining the input data necessary to run the crop model. This is considered in the next two sections. The first concerns physical input data (climate, soil characteristics, initial conditions) and the next management variables, in particular choice of crop, sowing date and irrigation. For each input variable, we first consider the types of data that are usually available, for example daily weather data from weather stations or soil map data. We then review methods that have been proposed for associating values of the input variables with each point in space. For weather data in particular, there have been a number of studies on zoning, that is on determining the areas which can be considered to have the same weather as the associated weather station, as well as on interpolating the weather data.

Next, we consider approaches that have been used when the input variable has not been measured. This could be the case in simulating the past if some of the input data is not available. It will always be the case for prediction, where future values of the input variable are required. It will also always be the case for scenario testing, where we consider hypothetical situations. The approaches here depend on the input variable, the available information and the specific goal of the study For weather, for example, there may be predictions available for short- or perhaps medium term weather. Otherwise, one often uses

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past data to derive a distribution of possible future weather conditions. Here then one does not predict a single weather pattern but rather takes into account the distribution of possible weather conditions. If scenarios related to global climate change are studied, then the predicted weather conditions will take into account the assumed changes. For soils, one usually assumes that soil type is given. However, if this comes from a soil map, it may not furnish all the information necessary to run a crop model, so there is the problem of determining crop model input values from soil map data.

Management practices are often unknown even for the past. One simple approach is to assume that management practices are fixed for a region. A more complex approach is to assume that management practices are determined by decision rules, which relate practices to other input variables and to the state of the crop. (See the chapter on decision modeling). One can further refine predictions of management practices by taking into account information about farm organization if such information is available. For scenario testing, one must decide if the scenario implies a change in current practices or not. If so, that change must be taken into account.

In section 4 we very briefly discuss the relation of remote sensing data to the problem of running a crop model for multiple fields. Remote sensing provides detailed spatially explicit data for an entire area. However, the data provided are not directly the data needed by crop models. This paragraph describes then how the remote sensing data can be used.

In section 5 we discuss how one obtains the outputs that are sought, for example national yield or nitrate loading of a stream. The two types of situation distinguished above, namely where the interactions between a field and its surroundings are or are not taken into account, are usually treated differently. When the objective involves a sum over non-interacting fields, a common approach is to run the model for a sample of fields and to sum over those fields, giving each an appropriate weighting. In the case of interactions, it is usually necessary to treat each field.

In section 6 we consider briefly the problems of evaluation that are specific to the case where the model is used for multiple fields.

We have distinguished in this introduction a large number of different situations. The problem may involve interactions between fields or not. Each type of input data may be available or not. If available, there may be values at each location or not and if not, there may be a choice as to how to obtain values at each location. If the data is not available, it is necessary to decide how to obtain values for the input variables, and this in turn will depend on the available data and the objectives of the study. Table 1 presents a number of the studies that have been reported, categorized by some of these choices.

The goal of this chapter is not to consider every possible situation involving the use of a crop model for multiple fields, but rather to identify the problems that this use entails, and then to present and discuss the approaches that have been proposed for dealing with these problems.

2 Physical input data

2.1 Weather data

2.1.1 Available data

The required data for crop models typically include precipitation, temperature (min and max), potential evapotranspiration (or the parameters necessary to compute it) and solar radiation. These data are measured at specific locations (meteorological stations) not at the location of every field. For example, the density of the French national meteorological network corresponds to 1 station for 500 km² on the average. There is in addition a rainfall network that provides data with a delay of a month or more, with a density of 1 station per 100 km².

Obtaining meteorological data at locations other than weather stations is a problem that is of importance in many ways, not only for crop models. Two main approaches are used, namely zoning and interpolation.

2.1.2 Defining zones

The zoning approach involves dividing a region into zones considered homogeneous for climate. The same weather data are then used for all locations within a given zone. The weather data are generally those of a meteorological station included in the zone and considered as representative of the zone. The definitions of the zones are determined just once and then are maintained over time.

An example of the zoning method, based on multivariate statistical analysis, is given in Ripert et al. (1990). More recently, the French Meteorological Services has defined the climatic zones of France (Fig. 1).These zones are based on the expertise of local meteorologists.

2.1.3 Interpolating weather data

In the zoning approach, each location within the zone has the same climate data, with an abrupt change at the zone boundaries. An alternative approach is to interpolate climatic data between weather stations, so that the climatic parameters are smooth functions over space. Creutin and Obled (1982) present a review of various interpolation methods including nearest neighbour, arithmetic mean, spline functions, optimal interpolation, kriging or an interpolation method based on empirical orthogonal functions.

Interpolation is generally done separately for precipitation and temperature. Furthermore, the calculations must be redone every day if daily data is used. Although such calculations are very time consuming, they are used by the National French Meteorological services.

An example of an interpolation technique is the Aurelhy method (Bénichou and Lebreton, 1987), which is considered the reference method for interpolating precipitation over France. The first step is to do a principal component analysis (PCA) to identify the major factors that describe topographical variability. In the second step precipitation is regressed on the first components of the PCA..

There has been some effort to use other information to improve the estimation of the spatial variability of precipitation. If weather radar information is available, it can be used to provide information about precipitation at all locations, though the accuracy of the information may sometimes be a problem. There have also been studies that show that surface temperature as measured by satellite is related to precipitation (Seguin et al, 1989). In another study a relation was found between temperature at the cloud surface and the duration of a cold cloud responsible of precipitation (Laurent et al, 1998). However, these relations seem to apply better to West Africa than to temperate countries where the relations between precipitation and clouds are more complex.

In temperate countries, there is more reliance on 3D numerical weather prediction (NWP) than on remote sensing to aid in interpolation. An example is the SAFRAN approach, which bases interpolation on NWP modelling combined with observations. The system has been applied to the whole of France (Le Moigne, 2002) to provide input data for the ISBA soil, vegetation and atmosphere model of Météo-France (Noilhan and Planton, 1989).

2.1.4 <u>Predicting future weather</u>

The prediction of near- or medium-term weather for specific locations is a major goal of meteorological services. We will not consider this problem here.

In crop models, the more common problem is to make predictions not for a specific year but on the average over the different possible meteorological conditions at a site. Two main approaches are used, namely (i) using past data directly, (ii) using a weather generator based on past data.

A common approach when one has past data for say n years is to run the model for the future n times using each weather record in turn and to assume that each result is equally likely. The result is n different model results, each assumed to have equal probability.

A simpler approach is to identify an "average" past climate year and use that for future weather (Launay, Faivre). This simplifies the calculations (one runs the model for only a single weather series) but is unrealistic in that weather uncertainty is replaced by an average value.

In some cases one is not interested in average future results, but rather in results for specific conditions. For example, a water manager might want to make predictions in order to see whether water storage is sufficient for worst-case conditions. In this case, one could use for example only the 10% of driest years from the past for prediction (Leenhardt et al, 2003).

Finally an expanding use of crop models is to evaluate the consequences of climate change. In this case, one does not assume that future climate will be similar to past climate. One can still use past climate series to represent future weather, but now one adds specific changes to the data. For example, to imitate global warming one could simply increase all temperatures by say 2°.

An alternative to the direct use of past climate data is to use a weather generator. This is simply an algorithm that generates the values of climate variables according to some probability distribution. The major effort required here is to create the weather generator. Consider for example just the generation of solar radiation. A very simple approach would be to divide the year into 10 day periods and for each period identify the minimum and maximum values in the past records. Then the generator could generate solar radiation values for each day from a uniform distribution with the given minimum and maximum values. In practice, the generators also take into account the correlations between different variables. For example the smaller values of solar radiation are usually associated with lower temperature, and rainfall events are usually associated with relatively low solar radiation. It is important, in developing or choosing a weather generator, to make sure that it reproduces the aspects of major importance. For example, many weather generators are based on the probability of rainfall events, and generate rainfall days at random using that probability. This need not necessarily give good agreement with other aspects of the weather record. For example, it may not give good agreement with the distribution of the lengths of periods between rainfall events. If the lengths of dry periods are of special concern, then the generator should probably be built explicitly for this purpose.

To build a reliable weather generator requires a substantial amount of past data, so it should not be imagined that a weather generator is a solution to the problem of insufficient data. Rather, its usefulness is that it allows one to transform a finite sample into an infinite number of different climate scenarios.

Notice that for weather generators interpolation can be done either before or after using the generator. In the first case, one interpolates the parameters of the weather generator in order to obtain a weather generator adapted to each field. Then one generates weather scenarios for each field. In the second case one generates weather scenarios only for locations with past data, and then interpolates those data (fig. interp_wgen.ppt).

Weather generators produce climates with properties similar to past climate. There is also interest in scenarios representing global climate change. Climate scenarios can be defined by arbitrary changes in temperature and precipitation, or on the basis of the output from general circulation models. Such scenarios have been used with crop models to determine impacts on agriculture (e.g., Adams et al, 1990; Rozenweig, 1990). Barrow (1993) proposed two methods for constructing climate change scenarios and furnished a series of scenario. These were used to investigate the effects of climate change on the development, yield and distribution of a variety of crops throughout Europe using crop growth models (e.g; Semenov et al, 1993, Bindi et al, 1993, Wolf, 1993). A similar approach has been used with hydrological models. For example, Etchevers et al., 2002, studied the impact of climate change on the Rhone river watershed. To estimate the climate 60 years in the future they used the climate general circulation model ARPEGE but with modified air temperature and precipitation amounts. In another study, Noilhan et al., 2002 generated climate scenarios using global atmospheric climate models (GCMs) with the assumption of a doubling of atmospheric CO_2 concentration.

2.2 Soil properties

2.2.1 Available information

When soil measurements in each field are not feasible, one generally relies on soil surveys which provide information on the spatial distribution of soil properties. Furthermore, since soil properties are considered as stable over time, even old soil surveys can be used.

Standard soil survey procedure is to classify soils according to appearance and measured attributes, to define the geographic zone of each class, and to describe in detail for each class representative profiles from one or more sites (e.g. Soil Survey Staff, 1951; Boulaine, 1980; Bouma et al. 1980; Brus et al., 1992). Either implicitly or explicitly the properties and behaviour at these `representative' sites are assumed to apply approximately to the whole area of the class.

The accuracy of soil maps for providing soil mechanical properties was first investigated in the 1960s by engineers (Morse & Thornburn, 1961; Kantey & Williams, 1962; Thornburn et al., 1966; Webster & Beckett, 1968). Even though the maps that Thornburn and his colleagues evaluated had been made for agricultural purposes rather than engineering, the information provided about mechanical properties was deemed useful. However Webster & Beckett (1968) showed that the maps were not useful for predicting soil chemical properties. Beckett and Webster (1971) suggested that in general if the criteria for classification are not the properties that one wants to predict or not closely related to them, then any success in predicting those properties will be fortuitous. The accuracy of soil surveys should then be reasonable for the spatial estimation of soil properties that are used during the soil survey, e.g. particle size distribution, or for related properties such as the amount of water in the soil at different water potentials.. On the other hand, the accuracy of soil surveys for predicting soil layer thickness, and therefore total available water capacity, will be much lower, since soil surveyors do not in general take into account the thickness pf the different horizons.

Leenhardt et al. (1994) showed that the mean squared error in predicting soil water properties from soil survey information is a sum of terms related to the accuracy of soil stratification and the choice of representative sites. They found that the scale of the soil survey is a key factor in determining accuracy. Maps at the scales 1/10 000 and 1/25 000, where the criteria for classification were intrinsic soil properties, gave good results. The 1/100 000 soil survey performed poorly, partly because it was based mainly on variables not directly related to the soil properties of interest.

2.2.2 Interpolation

More recently attention has turned from classification to interpolation using the methods of spatial statistics. Voltz and Webster (1990) found that the standard kriging technique is unsuited if soil properties changes abruptly, and in that case soil classification is better. In the case where several properties are of interest one enters the complex domain of multivariate spatial statistics. Here soil classification appears to be easier to comprehend. Overall, the classical approach of soil mapping appears likely to remain of value when used in the right circumstances.

2.2.3 Obtaining non measured soil characteristics

Thus soil maps can be the basis for obtaining soil properties at each location, but in general the properties recorded (usually soil type and soil texture) are not those needed for crop models (for example soil depth and water holding capacity or water retention curves and hydraulic conductivity). A common solution to this problem is to develop pedotransfer functions (PTFs), which are functions which relate basic soil properties that are considered as easily accessible to the less often measured soil properties (Bouma, 1989; van Genuchten and Leij, 1992) (table 2). For a recent review of research in this area see the recent review by Wösten *et al.* (2001). The expression “*class-pedotransfer function*” is used when the hydraulic properties are predicted from the soil class (very often classes of texture). Finally, the expression “*pedotransfer rule*” is used when the relationship between the soil composition and the predicted property is based on expert opinion (Daroussin and King, 1997).

Pedotransfer functions are derived using data bases which contain both the input data (readily available soil characteristics) as well as the output data (soil hydraulic properties). Several large databases such as USDA Natural Resource Conservation Service pedon database (USDA Natural Resource Conservation Service, 1994), WISE (Batjes, 1996), UNSODA (Leij et al., 1996 and 1999) and HYPRES (Lilly, 1997; Lilly *et al.*, 1999; Wösten et al., 1999) and much smaller databases (Wösten et al., 2001) have been used for development of PTFs. Since water retention at different water potentials is much easier to measure than hydraulic conductivity, the number of soils with measured water retention properties in databases is considerably greater than the number of soils with measured hydraulic conductivity. As an example, in the European database HYPRES, there are 1136 soil horizons with both water retention and hydraulic conductivity and 2894 soil horizons with only water retention (Wösten *et al*., 1999). A result is that PTFs developed for water retention properties are much more numerous than those that predict hydraulic conductivity (Bastet *et al.,* 1998).

Two types of PTFs for prediction of water retention properties can be distinguished: (i) the first type corresponds to non continuous PTFs because they predict individual points of the water retention curve, and (ii) the second type corresponds to continuous PTFs that assume that all the water retention curves have the same mathematical form so that the PTFs need only predict the parameters of that model. Among the PTFs belonging to the first type, those of Renger (1971), Gupta and Larson (1979), Rawls *et al.* (1982) are non continuous PTFs and those of Hall *et al*. (1977) and Bruand *et al.* (2002 and 2003) are non continuous class-PTFs. Among the PTFs belonging to the second type, those of Cosby et al. (1984), and Vereecken *et al*. (1989) are continuous PTFs while those of Wösten *et al.* (2001) are continuous class-PTFs. Most studies during the last decade have concerned continuous PTFs and class-PTFs because they provide directly a mathematical model for the entire water retention curve (Rawls *et al*. 1992; Minasmy *et al*., 1999; Wösten *et al*. 2001). Despite their possible inaccuracies, non continuous class-PTFs are easy to use because they require little soil information and are well adapted to prediction of water retention over large areas (Wösten *et al*. 1995; Lilly *et al*., 1999; Wösten *et al*., 1999). Although they only give water retention at certain potentials, it is easy to fit a mathematical model to these predictions and thus obtain water retention as a continuous function of water potential (table 3)..

The accuracy of PTFs was discussed in several studies (e.g. Tietje and Tapkenhinrichs, 1993; Kern, 1995; Wösten et al., 1995; Bastet et al., 1999). A common measure of accuracy is root-mean square error (RMSE) defined as:

$$RMSE=\sqrt{\sum\left(\theta_m-\theta_p\right)^2/n}$$

with θ_m and θ_p, the measured and predicted volumetric water content, and *n* the total number of observations. Analysis of the literature showed that RMSE varied from 0.02 to 0.11 m^3 m^{-3}. The smallest RMSE values were obtained in studies where either a preliminary grouping of soils was applied or one or more measured points of the water retention curve were used as predictors (Wösten *et al.*, 2001). The largest RMSE of 0.11 m^3 m^{-3} was obtained in a study where the soil texture was used as sole predictor (table 4).

PTFs have also been used to predict saturated hydraulic conductivity and more recently unsaturated hydraulic conductivity. The accuracy of several of these PTFs was evaluated by Tietje and Hennings (1996) on a set of 1161 soils from Low Saxony in Germany. In fact saturated hydraulic conductivity K_s is closely related to the characteristics (size, shape, connectivity, tortuosity) of macropores in the soil that result from biological activity and from tillage practices. The PTFs studied by Tietje and Hennings (1996) on the other hand are based on soil characteristics such as particle size distribution or organic matter content, which are related to the total porosity but are only distantly related to the presence of macropores. This explains the poor accuracy of prediction found for the PTFs.

Other PTFs are based on the concept of “effective porosity” which in most studies refers to the air-filled porosity at –330 hPa (Ahuja *et al.*, 1989). These PTFs relate K_s to effective porosity (ϕ_e) by the equation

$K_s = a\ (\phi_e)^b$,

where a and b are two parameters. The validity of these PTFs was discussed by Franzmeier (1991) and Tomasella and Hodnett (1997). They showed that a and b are not in fact constant but rather vary according to the characteristics of the soil studied. The prediction of the unsaturated hydraulic conductivity is still very difficult today, progress being limited by the small number of available data.

The rapidly increasing demand for PTFs in the last decade has led to the utilization of available data bases that are not adequate for the purpose. We recommend a wiser utilization of PTFs. There is still a need for acquiring measured hydraulic properties to enrich the databases. The new measured hydraulic properties will enable the improvement of available PTFs and the development of innovative new PTFs. The lack of data is particularly appreciable for the unsaturated hydraulic conductivity in the range of water potential between 0 and –50 hPa, i.e. close to saturation. Indeed, within this range of water potential, the unsaturated hydraulic conductivity varies over several orders of magnitude.

2.3 Initial conditions

The main initial conditions required for crop models are soil moisture and nitrogen in each soil layer. Often this information is not available for the past and so the initial values have to be estimated. The same of course is true for future or hypothetical cases.

A common approach for initial water is to assume that water at sowing is some fixed percentage of maximum available water, for example 80% for all layers. A modification that may be more realistic for some environments is to fix initial conditions not at sowing but several months before. For example, consider initial water conditions at the time corn is sown (around April) in southwestern France. In this region there are usually one or more rainfall events during winter that completely fill the soil profile. It is sufficient then to start simulations at the start of winter with a very rough estimate of initial soil water. At some point before sowing the profile will be filled, both in reality and according to the model, and this provides the correct initial condition for the subsequent calculations.

Initial soil nitrogen at sowing may also be difficult to obtain. Here again it may sometimes be useful to start simulations some time before sowing. In France, for example, there are tables for calculating soil nitrogen at the end of winter as a function of soil type, the previous crop spêcies, its yield and nitrogen applications to the previous crop.

3 Management practices

Management practices include choice of crop and variety, sowing date, fertilization, irrigation, etc;. These inputs are particularly difficult to obtain for fields where they have not been observed, because they depend on individual farmer decisions rather than on physical properties, and these may not vary at all smoothly with location. Thus mathematical interpolation may not be a reasonable approach. One possible approach is to use a unique set of management decisions, for example recommended practices, for an entire region (Hansen and Jones, 2000; Yun, 2003). However, ignoring the spatial variability of practices can lead to prediction errors (Yun, 2003).

3.1 Choice of crop

3.1.1 *Available information*

The information as to which crop species were planted in previous years is usually easily obtainable for a single field or a small number of fields. However, this is no longer the case when running a crop model over a region or an entire country.

One source of information is agricultural statistics. The countries of the European Union use several different procedures (Gallego, 1995). “Local Statistics” are based on an administrative unit (e.g. municipality, small agricultural region, parish). These data are collected by the local administrators or by agricultural organizations. These data are available every year but may be quite imprecise. “Farm census” data result from contacting every farm. The area devoted to each crop is just one of the pieces of information acquired. Only in small countries is the census done annually, otherwise it is usually redone every five or ten years. “Sampling surveys” contact only a sample of farms, and then use statistical techniques to extrapolate to the entire population. In the United States, the National Agricultural Statistics Service (NASS) has been using area frames for agricultural surveys since the early 1960's (Cotter and Nealon, 1987).

If one has satellite images for the region in question, they can be used directly to identify the spatial distribution of crop species (Campbell, 2002; Chuvieco, 2002; Lillesand and Kiefer, 2000). It usually requires several images during the season to provide reliable identification of crop species. Furthermore, though automatic classification is possible, supervised classification usually gives better results.

Another approach is to combine survey data with satellite information. An example is the AgRISTARS program (Agricultural and Resources Inventory Surveys Through Aerospace Remote Sensing), that concernss the use of remotes sensing from space in agriculture (Pinter et al., 2003). Here the satellite data and ground data are combined by means of a regression estimator.

3.1.2 *Determining the crop planted in every field*

The statistical information indicates the area in each mapping unit which was devoted to each crop species, but does not indicate specifically which fields were planted with which crops. Mignolet et al. (2003) proposed a method for recreating this information, using both expert opinion and departmental or national agricultural statistics. The method is based on data mining and statistical cartography techniques proposed by Mari et al. (2000).

3.1.3 *Predicitng which crops will be planted*

The prediction of crop species depends on the time at which prediction is required. If for example a prediction of national yield is required shortly before harvest time, then the agricultural statistics for the current year or remote sensing data may be available, and the approaches described above are applicable.

If on the other hand early prediction is required, then different procedures are required. For example, a water manager in south-western France requires predictions of future water use starting in early summer (Leenhardt et al, 2003), when statistical survey information is not yet available and satellite imagery can at best only distinguish between land with a crop (a summer crop) and uncropped land..

One possible approach in this case is simply to assume that at a regional scale the change in land-use from one year to another is negligible. Such an assumption would be reasonable for a region where single-crop farming dominates and no major changes in economic or regulatory factors have occurred.

A second possibility is to use declared intentions of farmers, where such information is available. The European Agricultural Policy involves asking farmers to declare which crops they intend to cultivate in each field. A minor problem here is that climatic conditions may lead to some changes in plan. A major difficulty is obtaining this information, which is protected by privacy laws. The information is made available in the form of a computer data base, but this only concerns data aggregated by district and furthermore there is considerable delay before this is done.

A third possibility was proposed by Leenhardt et al. (2003). This approach has two stages. First, one obtains an estimate of land use in the preceding year. Then, one uses information about crop rotations to give the probability of having various crops in a field this year, given the crop last year. The crop rotation information is based on TERUTI, which is a systematic land-use sampling program in France. The same locations are sampled each year. Mari et al. (2000) showed how to use these data to identify the major crop rotations of a region. This sampling system is being extended to the entire European Community under the name of LUCAS. Early remote-sensing information could perhaps improve this approach by limiting the possible crop species in a field to those compatible with the satellite information.

In many cases, one wants to study scenarios that imply a change in choice of crop. For example the scenarios might concern changes in climate or in the economic or regulatory context. A number of possible approaches exist (see for example Veldkamp and Lambin,2001). One approach is to assume that each farmer maximizes some objective function, for example net profit, subject to constraints (for example available labor). The problem is then to determine which crop species (and perhaps management decisions) this implies. A simple approach is to suppose that farmers have a choice between a limited number of systems (crops, management), each of which is associated with a certain yield and a certain use of resources. Linear programming can then be used to find the optimal crop and management.

3.2 Sowing date

3.2.1 Available information

For past data one could simply seek to obtain the sowing date for each field, but this can be very difficult for large numbers of fields. Even if one is willing to address direct inquiries to each farmer many may not respond. For example, Leenhardt and Lemaire (2002) had a 39% answer rate to a postal survey.

Information that is generally available is a recommended sowing period for each crop, each variety and each region.

3.2.2 *Estimating or predicting sowing date*

Sowing dates could be based on the recommendations that exist for each variety in each region, but within the possible sowing period the actual sowing date will depend on available manpower, the state of the soil and climatic conditions. This suggests two possible approaches, either using a fixed average sowing date or calculating a sowing date for each field based on information about farm organization and climate.

An example of calculation of sowing date is the SIMSEM model of sowing date proposed by Leenhardt and Lemaire (2002). The model has two elements, one related to soil and climatic conditions and the second to labor availability. In the first step, the days when sowing is possible are determined. This is based on a water balance model run over the sowing period. The rule is that sowing is possible if soil water content is below x% of maximum available water and if rainfall this day is below y mm. The parameters x and y were determined from past sowing data.

The second step in the model is to determine when sowing actually takes place. This is based on the one hand on information about farm organization (as in table 5) (CRAMP, 1988), and on the other hand on expert knowledge concerning recommended sowing periods, priorities among different crops, the time required to sow a hectare of each crop for each soil type and average numbers of working hours per day. The time required to care for livestock is also taken into account. Based on this information the model calculates, for each farm type, what crop is sown on each possible sowing day.

The distribution of farm types per region is input to SIMSEM, but there is no information related to individual fields. The calculations then are averages for the region and not field-specific.

3.3 *Irrigation*

When irrigation dates and amounts are not available, either because many fields are involved and so it is not feasible to get detailed information from each or because it is future or hypothetical situations that are in question, then irrigation behavior has to be simulated.

One approach is to assume that the crop is irrigated to avoid all water stress. The model is used for each field and in each case, as soon as water stress would reduce growth according to the model, water is added up to maximum available soil water. This does not furnish realistic irrigation strategies but it can provide realistic predictions of non water-limited yield.

If more realistic descriptions of irrigation are required, then it is necessary to introduce a realistic model of farmer behavior. A case study with the chapter on decision modeling provides an example of a decision model for irrigation.

4 Remote sensing data

Remote sensing is of great interest when one wants to use a model for multiple fields for past or current conditions, because it gives detailed spatially explicit information on crops over an entire area.

Spatial and spectral resolution of remote sensing data as well as frequency of measurements depends on the sensor/vector configuration. In the past decade, high spatial resolution was generally associated with low frequency (from 1 to 3 images per month, 5-30 m resolution, SPOT-HRV, Landsat-TM, …), while high frequency was associated with low spatial resolution (daily, 1 km resolution : NOAA-AVHRR, SPOT-VGT). New sensors/vectors offer medium spatial resolution (MERIS, MODIS).

We have already discussed the use of remote sensing to identify the crop in a field. Here we consider how remote sensing data can be used to provide other input values for a crop model. Figure 2 shows the general procedure. Suppose that the input variable sought is planting date. The basic idea is to find the planting date that leads to the best agreement between reflectance calculated using the model predictions and the observed reflectance (Bouman, 1995, Moulin, 1995, Guérif et al, 1998, Prévôt et al, 2003). As shown in the figure, this requires a radiative transfer model, which calculates the quantities measured by remote sensing, namely reflectance in the visible or near-infrared or a vegetation index which is a combination of reflectances at different frequencies, and soil and canopy properties such as soil mineral composition, soil surface humidity and rugosity, canopy structure (LAI) and leaf chlorophyll content (Baret, 2000). This procedure is a type of data assimilation (see that chapter), but ignores any prior information about the quantities to be estimated and bases estimation on the observations alone.

The use of remote sensing data for obtaining sowing dates was explored by Moulin (1995) in a simulation study. He used the AFRC-Wheat model coupled to the SAIL radiative transfer model to generate artificial remote sensing observations for wheat canopies. He then used the procedure of figure 2 to go backwards and determine sowing date from the remote sensing data. The study explored the impact of various factors on the quality of the sowing date estimate. The number and dates of images had a large influence on the shape of the cost function that is minimised in the assimilation procedure. The most favourable configurations corresponded to measurements made during the rapid canopy growth period. The precision of the remote sensing observations affected the precision of the sowing date estimate. A 5% error in the observed values led to an error of 2 days in sowing date (and a 4.8 % error in final biomass). A 20% error in observed values led to an error of 20 days in sowing date and and an error of 20.3% in final biomass.

Finally, the assimilation of 4 dates of reflectance data allowed the coupled model AFRC-Wheat+SAIL to better fit the observed data (Figure 3). Starting from 7 first guesses from DOY 266 to DOY 326, the sowing date was re-estimated to 299 with an error of +3 days. This re-estimate allowed to reduce the relative error on biomass prediction from the range
[- 9.8% ; + 17.6%] to – 2.8 %.

Remote sensing data can be used to estimate not only sowing date but also other crop model inputs. In fact, the only obligatory requirement is that the inputs must affect some quantity which can be related to reflectance measurements. However, in practice it may be impractical to estimate several different inputs. An example is provided by the study of Launay (1995), who used the SUCROS crop model coupled with the SAIL radiative transfer model to estimate both sowing date and crop initial condition (specifically LAI at 500°C day after sowing), for 31 sugar beet fields in Picardie in northern France. Note that for crops like sugar beet, sown in spring and with less capacity than wheat of compensating for poor crop establishment, crop initial conditions resulting from emergence and early growth have a major effect on subsequent growth and yield.

This study showed that in the case considered, where few remote sensing data were available during the rapid crop growth period, it did not seem feasible to estimate both sowing date and early LAI. Table 6 shows the errors in the estimated values with or without assimilation of the remote sensing data. When both sowing date and early LAI were estimated from remote sensing data, the errors were as large as or larger than without assimilation. On the other hand, assimilation did bring some improvement when only early LAI was estimated from the remote sensing data.

A different example of the use of remote sensing data is given in Launay et al. (2002, 2003). The purpose of this study was to estimate sugar beet yield in all fields in a region in a using the model SUCROS. Soil properties were available from a soil map associated with pedotransfer functions (Jamagne et al., 1977). However, it was clear that the soil map information was insufficient, in particular for properties related to soil water availability. First of all, the soil map provided information only to a depth of 1.2 m, whereas several experiments in the region have shown that sugar beet roots reach depths greater than 1.2 m. Secondly, the soil map did not provide information on chalk type for soils with a chalk substratum, whereas it is known that there are two different types of chalk with different water availability properties. The first is a hard material, with low sensitivity to frost and impenetrable by roots and the second a soft material, cracked and penetrable by roots. The latter can serve as a reservoir for soil water, which can be mobilised by capillary rise or by direct penetration of roots (Maucorps, personal communication).

The problem then is that soil properties, and as a consequence water availability, are poorly known. This suggests that remote sensing data could be used to provide improved estimates of soil characteristics. However, the situation is complicated by the fact that the crop model does not take properties like penetrability for roots or capillary rise as inputs. It was decided then to use remote sensing data to estimate root growth rate and maximum rooting depth. These parameters also affect soil water availability to the plant, and so can be used to compensate for errors in soil characteristics. Notice that here the objective is not to provide the true inputs for the model, but rather to compensate for errors in the inputs.

Figure 4 shows the effect of using remote remote sensing data for one particular plot, which had a chalky substratum starting at a depth of 0.2-0.3m. The right graph shows predicted (with and without assimilation) and observed values for LAI. The left graph shows predicted and observed values of the vegetation index VI, which is a combination of reflectance values. The radiative transfer model SAIL was used to convert from LAI to VI. The prediction without assimilation assumes that the soil description at 1.2 m can be extended to 1.8 m, and that where chalk is present it has the same water holding properties as silt loam. This led to an overestimate of the soil water holding capacity and to an overestimate of LAI. The available remote sensing data consisted of five SPOT and airborne images. Using these data, the calculated rate of root growth was 0.010 m/day (compared to the standard value of 0.012m/day) and maximum root depth was 0.81m compared to the standard value of 1.8m. Without assimilation the predicted yield was 84.8t/ha and with assimilation 53.8t/ha. The latter value is much closer to the observed yield of 50.3t/ha.

5 Obtaining the outputs for multiple fields

5.1 The output is a sum or average over non-interacting fields

In this case, it is common not to run the model for every field but rather to divide the region into elementary simulation units and to run the model independently for each unit. The simulation units are determined by defining homogeneous zones for the most sensitive input data. For example, a soil map could be overlaid with a climatic zone map in order to obtain a map of homogeneous pedoclimatic units. This could be overlaid with a map of administrative regions, for which there is cropping and management information, to further subdivide the units so that each new unit also belongs to a single administrative region.

The final result would be obtained as a sum (for example of water requirements, Leenhardt et al., 2003) or as an average (for example of yield, Donet et al, 2001) over simulation units. To obtain these results, it might be necessary to run the model several times for each elementary simulation unit. If various weather scenarios are considered, one might want to average over them for each elementary simulation unit. Also, an elementary simulation unit might have a distribution of farm types or cropping choices. Then the model would be run for each choice. For example, Leenhardt and Lemaire (2002) run their model several times for each simulation unit, each time with a sowing date randomly sampled from the modelled distribution of sowing dates. Weighting of simulation units, for example by crop area, might be necessary.

5.2 The fields interact with their surroundings

To account for spatial interaction between fields, the most natural approach is to interface the model with a more global model that represents these spatial interactions. For example, if modelling water flow, a hydrological model is necessary. This model uses output from the crop model (for example, water drainage or amount of nitrate leached beyond the root zone for each field), and furnishes inputs to the crop model (run-on to each field for example). For example, Beaujouan et al (2001) or Gomez and Ledoux (2001), studying water quality in a small watershed or a large river basin, coupled a crop model with a hydrological model in order to obtain water quality at the watershed outlet.

6 Evaluation

6.1 Validation data – few in number and often not totally pertinent

In principle one can evaluate a model used at the regional level by comparing the results with observed data. A basic problem is the lack of data. We are interested specifically in the results for one output in one region, so that by definition there is only one single result for comparison per year (or per season). This is in contrast to evaluating a model at the field level, where one can compare with numerous results each year. Furthermore, it can be very difficult to get reliable data at the regional level. Various approximations may be necessary, leading to a fairly high uncertainty in the observed value. As shown in the chapter on evaluation, when there is measurement error the mean squared error of prediction (MSEP) is augmented by the variance of the measurement error. If that variance is large, as it often will be for regional studies, then the measurement error may be the major part of MSEP, masking the error between the model and the true result which is of primary interest.

Rabaud and Ruget (2002) discuss two specific problems with validation data that are probably quite common. They used expert estimation of forage production in each region of France to obtain data for comparison with the ISOP model. The first problem is that the expert estimates may be more or less accurate depending on the expert. Mignolet et al. (2003) also noted this problem. With regard to past land use, two different experts asked about the same period and the same region did not provide the same information, especially for the more distant past. The second problem noted by Rabaud and Ruget (2002) is that it may not be feasible to get validation data that is exactly comparable to what the model predicts. In their case each expert reported for an administrative region, while the model was run for specially defined forage regions. Another example of this is provided by the study of Leenhardt et al. (2003), who simulated total water demand for irrigation in a region. For comparison they had to rely on data relative to farmers who subscribe to a collective irrigation system, while the simulation concerns all farms in the region including farmers who irrigate from their own reservoirs.

6.2 Relation of overall error to error in individual fields

In the case where the output is the sum or average of outputs from elementary simulation units, it is much easier to obtain validation data for the elementary units, since there are many of them, than for the overall result. It is therefore of interest to consider how the two errors, of the elementary simulation units and of the overall result, are related. Suppose that we have some overall quantity of interest W which is a sum

$W=Y_i$

For example, W might be overall yield and Y_i the yield in elementary simulation unit i. The mean squared error of prediction for W using a model with parameter vector (θhat) is defined by

$MSEP^W(\theta hat) = E\{[W-What(\theta hat)]^2\}$.

where W is the observed quantity and What(θhat) is the corresponding model prediction. The expectation is over all possible situations. (See the chapter on evaluation). The mean squared error for an elementary simulation unit is analogously

$MSEP^Y(\theta hat) = E\{[Y-Yhat(\theta hat)]^2\}$.

It is easy to show that the relation between MSEP for the prediction of W and the individual MSEP values for the Y_i is

$MSEP^W(\theta hat) = \sum MSEP^{Yi}(\theta hat) + 2E\sum_{i<j} [Y_i - E(Y_i|X_i)][Y_j - E(Y_j|X_j)] + 2E\sum_{i<j} [E(Y_i |X_i) - Y_i hat(\theta hat)][E(Y_j |X_j) - Y_j hat(\theta hat)]$

where the notation $E(Y_i|X_i)$ means the expectation of Y_i for fixed values of the model explanatory variables X_i. The first term on the right hand side is just the sum of the MSEP values for the elementary simulation units. The next term has the form of a covariance. If $[Y_i - E(Y_i|X_i)]$ is small and/or uncorrelated for different simulation units, as would be the case if the explanatory variables explain most of the variability in the output Y, then this term will be small. The last term is related to the model bias. If the model has a systematic bias, then this term may be appreciable.

We cannot determine the relation between $MSEP^W(\theta hat)$ and $MSEP^Y(\theta hat)$ without looking in detail at the correlations between elementary units. However, we can define and analyze a most favorable case. If the errors in different simulation units are correlated, it seems reasonable to suppose that the correlation will be positive. If the bias terms for different elementary simulation units are related, it likewise seems reasonable to suppose that they will be of the same sign. This implies that the last two terms on the right in the above equation will be positive. Then the most favorable case is where the correlation and bias are negligible, so the last two terms on the right can be ignored.

In this most favorable case we have approximately that $MSEP^{W}(\theta hat) = \sum MSEP^{Y_i}(\theta hat)$. This corresponds to the case where model errors in different simulation units partially cancel one another. To illustrate this, take the case where all the n individual Y_i values are equal, as are the $MSEP^{Y_i}(\theta hat)$.values. A useful measure of relative error is $\sqrt{[MSEP^{W}(\theta hat)]}/W = \sqrt{[n\ MSEP^{Y}(\theta hat)]}/nY = [1/\sqrt{(n)}]MSEP^{Y}(\theta hat)/\ Y$. That is, in the favorable case the relative error in the global result is smaller, by a factor $[1/\sqrt{(n)}]$, than the relative error for each individual simulation unit. If the correlation and bias terms are not negligible, however, this advantage will be reduced.

6.3 Error propagation studies

The chapters on model evaluation and on sensitivity analysis have insisted on the importance of evaluating how individual errors contribute to overall model error. This information allows one to concentrate the effort of model improvement on the most important errors.

The number of input variables for a crop model used for a single field is already appreciable. When the model is used for multiple fields, then the overall number of input variables is multiplied by the number of fields. Furthermore, additional approximations are usually involved in using a model for multiple fields. In particular, if a total output is based on sampling fields within the study area, then the sampling is an important additional approximation. Given the very large number of possible sources of error, it is even more important here than for single fields to identify which errors are most important.

Analytical methods of decomposition and of propagation of error exist for linear models (cf. for example Heuvelink et al., 1989). For crop models, which are strongly non-linear, these methods do not apply. The procedure then becomes very complex. Indeed, no complete analysis of sources of error and of their propagation has been conducted for spatial applications of crop models. Nevertheless, the procedure has been illustrated by Leenhardt and Voltz (2002) for one kind of crop model input data, namely soil water properties. The aim was to choose among soil maps of different resolution and among different estimators of soil water properties within the mapping units. A more complete approach but without specific application to crop models is given by Crosetto et al. (2000) and by Tarantola et al. (2000). They propose an application of uncertainty and sensibility analyses to GIS-based models in order to estimate the precision needed for the various types of data when the objective is to obtain results with a certain precision.

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TABLE 1. Different situations involving the use of crop models for multiple fields.

Output	Objective	Description of management practices	Interactions between fields	References with examples
Sum over representative fields	Prediction for current season	Actual past practices, future decision rules	No	Launay, 2002 Faivre et al., 2000 Leenhardt et al., 2004
	Diagnosis	Actual past practices	No	Donet et al., 2001 Sousa and pereira, 1999; Heineman et al, 2002
	Scenario testing	Decision rules or hypothetical decisions	No	Lal et al (1993) Priya and Shibasaki (2001)
Result from geographical area	Prediction for current season	Actual past practices, future decision rules	Yes	
	Diagnosis	Actual past practices	Yes	Gomez and Ledoux, 2002
	Scenario testing	Decision rules or hypothetical	Yes	Beaujouan et al (2001)

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TABLE 2. Input variables for PTFs for prediction of water retention at different potentias.

PTFs		Input variables at potential (hPa) of				
		-100	-330	-1000	-3300	-15000
Renger (1971)			Clay Silt			Clay Silt
Hall et al. (1977)	Top- And subsoil	Clay Silt OC ρ_b				Clay
Gupta and Larson (1979)		Sand Silt Clay OM ρ_b	Sand Silt Clay OM ρ_b	Sand Silt Clay OM ρ_b		Sand Silt Clay OM ρ_b
Rawls et al. (1982)	Model 1	Clay Sand OM	Clay Sand OM	Clay Silt OM		Clay OM
	Model 2	Sand OM θ_{15000}	Sand OM θ_{15000}	Sand OM θ_{15000}		
	Model 3	Sand OM θ_{330} θ_{15000}		OM θ_{330} θ_{15000}		
Cosby et al. (1984)		Clay Silt Sand	Clay Silt Sand	Clay Silt Sand	Clay Silt Sand	Clay Silt Sand
Vereecken et al. (1989)		Clay Sand OC ρ_b	Clay Sand OC ρ_b	Clay Sand OC ρ_b	Clay Sand OC ρ_b	Clay Sand OC ρ_b
Bruand et al. (1996)		ρ_b	ρ_b	ρ_b	ρ_b	ρ_b

Clay: clay content, Silt: silt content, Sand: sand content, OC: organic carbon content, OM: organic matter content, ρ_b: bulk density, θ_{330} and θ_{15000}: volumetric water content at –330 and –15000 hPa, respectively.

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TABLE 3. Volumetric water contents at different water potentials using the non continuous class-PTFs based on texture (FAO triangle) and bulk density and parameters of the van Genuchten's (1980) model (Bruand *et al.*, 2003).

Texture class	Class of D_b^c	D_b^h	Volumetric water content $\theta_{\log(-h)}$							Parameters of van Genuchten's model				
			$\theta_{1.0}$	$\theta_{1.5}$	$\theta_{2.0}$	$\theta_{2.5}$	$\theta_{3.0}$	$\theta_{3.5}$	$\theta_{4.2}$	θ_s	θ_r	n	α	R^2
			cm^3 cm^{-3}											
Very Fine	[1.2-1.3]	1.25	0.531	0.514	0.490	0.465	0.428	0.418	0.329	0.527	0.0100	1.0849	0.0098	0.964
		1.15	0.484	0.473	0.451	0.428	0.393	0.384	0.303	0.481	0.0001	1.0868	0.0083	0.966
	]1.3-1.4]	1.35	0.493	0.486	0.467	0.447	0.416	0.401	0.321	0.488	0.0002	1.0930	0.0042	0.971
		1.25	0.456	0.450	0.433	0.414	0.385	0.371	0.298	0.452	0.0006	1.0923	0.0043	0.973
	]1.4-1.5]	1.45	0.489	0.477	0.464	0.445	0.422	0.386	0.318	0.481	0.0001	1.1055	0.0028	0.987
		1.35	0.455	0.444	0.432	0.415	0.393	0.359	0.296	0.448	0.0001	1.1066	0.0027	0.988
Fine	[1.3-1.4]	1.35	0.459	0.429	0.419	0.390	0.369	0.332	0.270	0.449	0.0007	1.0975	0.0088	0.977
		1.25	0.425	0.398	0.388	0.361	0.341	0.325	0.250	0.415	0.0010	1.0927	0.0086	0.952
	]1.4-1.5]	1.45	0.441	0.422	0.400	0.381	0.348	0.323	0.274	0.441	0.0002	1.0802	0.0194	0.992
		1.35	0.410	0.393	0.373	0.355	0.324	0.301	0.255	0.410	0.0007	1.0811	0.0180	0.993
	]1.5-1.6]	1.55	0.383	0.378	0.366	0.350	0.326	0.295	0.259	0.383	0.0006	1.0854	0.0062	0.999
		1.45	0.358	0.353	0.342	0.328	0.305	0.276	0.242	0.358	0.0001	1.0864	0.0059	0.999
	]1.6-1.7]	1.65	0.381	0.363	0.353	0.333	0.312	0.302	0.264	0.384	0.0003	1.0558	0.0377	0.986
		1.55	0.358	0.341	0.332	0.313	0.293	0.284	0.248	0.361	0.0002	1.0560	0.0367	0.986
	]1.7-1.8]	1.75	0.366	0.364	0.341	0.315	0.310	0.292	0.263	0.377	0.0005	1.0518	0.0560	0.981
		1.65	0.345	0.343	0.322	0.297	0.292	0.276	0.239	0.352	0.0001	1.0583	0.0333	0.974
Medium Fine	[1.4-1.5]	1.45	0.381	0.365	0.348	0.313	0.264	0.220	0.193	0.377	0.1402	1.3325	0.0068	0.997
		1.35	0.355	0.340	0.324	0.292	0.246	0.205	0.180	0.352	0.1309	1.3332	0.0068	0.997
	]1.5-1.6]	1.55	0.372	0.357	0.340	0.307	0.262	0.212	0.181	0.369	0.1002	1.2653	0.0068	0.996
		1.45	0.348	0.334	0.318	0.287	0.245	0.199	0.170	0.345	0.0943	1.2631	0.0070	0.997
	]1.6-1.7]	1.65	0.370	0.358	0.343	0.323	0.281	0.236	0.196	0.367	0.0435	1.1707	0.0056	0.996
		1.55	0.347	0.336	0.322	0.304	0.264	0.222	0.185	0.344	0.0583	1.1875	0.0053	0.996
Medium	[1.5-1.6]	1.55	0.356	0.340	0.312	0.274	0.231	0.206	0.175	0.360	0.1125	1.2472	0.0170	0.999
		1.45	0.334	0.318	0.292	0.257	0.216	0.193	0.164	0.338	0.1036	1.2423	0.0176	0.999
	]1.6-1.7]	1.65	0.350	0.338	0.319	0.286	0.241	0.193	0.152	0.350	0.0120	1.1862	0.0078	0.999
		1.55	0.329	0.318	0.299	0.268	0.226	0.181	0.143	0.329	0.0088	1.1820	0.0082	0.999
	]1.7-1.8]	1.75	0.322	0.310	0.299	0.282	0.261	0.226	0.184	0.317	0.0002	1.1231	0.0049	0.992
		1.65	0.304	0.292	0.282	0.266	0.246	0.212	0.173	0.299	0.0005	1.1245	0.0048	0.992
	[1.8-1.9]	1.85	0.311	0.300	0.287	0.272	0.265	0.239	0.181	0.302	0.0003	1.1276	0.0026	0.959
		1.75	0.294	0.284	0.271	0.257	0.250	0.226	0.172	0.286	0.0009	1.1240	0.0028	0.959
Coarse	]1.6-1.7]	1.65	0.315	0.277	0.210	0.182	0.142	0.114	0.089	0.352	0.0334	1.2429	0.0843	0.996
		1.55	0.296	0.260	0.197	0.171	0.133	0.121	0.084	0.339	0.0328	1.2286	0.1123	0.993
	]1.7-1.8]	1.75	0.280	0.252	0.193	0.154	0.121	0.100	0.086	0.294	0.0695	1.4180	0.0339	0.999
		1.65	0.264	0.238	0.193	0.154	0.100	0.094	0.081	0.272	0.0711	1.5179	0.0257	0.996
	[1.8-1.9]	1.85	0.303	0.281	0.257	0.226	0.183	0.165	0.128	0.310	0.0008	1.1434	0.0304	0.996
		1.75	0.287	0.266	0.243	0.214	0.173	0.156	0.121	0.294	0.0008	1.1435	0.0307	0.996

D_b^c : bulk density of centimetric clods; D_b^h : bulk density of the horizon inferred from D_b^c .

TABLE 4. Accuracy of water retention PTFs (modified after Wösten *et al.*, 2001).

Source	Water potential (hPa)	RMSE (m^3 m^{-3})	PTF input variables
Ahuja et al., 1995	–330	0.05	Clay, silt, organic matter content, bulk density
	–15000	0.05	
Bruand et al., 1996	–330	0.03	Bulk density
	–15000	0.03	
Gupta and Larson, 1979	–15000	0.05	Clay, silt, organic matter content, bulk density
Koekkoek and Bootlink, 1999	–100	0.05	Clay, silt, sand, organic matter content, bulk density
	–15000	0.05	
Lenhardt, 1984	–330	0.07	Clay
	–15000	0.05	
Minasny et al., 1999	–330	0.07	Clay, silt, sand, bulk density, porosity, mean particle diameter, geometric standard deviation
	–15000	0.07	
Pachepsky et al., 1996	–330	0.02	Clay, silt, sand, bulk density
	–15000	0.02	
Paydar and Cresswell, 1996	A[a]	0.02	Slope of the particle size distribution curve + one measured point on the WRC
Paydar and Cresswell, 1996	A	0.03	Clay, silt, coarse sand, fine sand, organic matter content
Schapp et al., 1998	A	0.11	Texture class only
Schapp and Leij, 1998	A	0.10	Clay, silt, sand
Sinowski et al., 1997	–300	0.04	Clay, silt, sand, bulk density, porosity, median particle diameter and standard deviation
	–15000	0.04	
Tomasella and Hodnett, 1998	A	0.06	Clay, silt, sand

[a] A-average RMSE along the measured water retention curve obtained after estimating parameters of a water retention equation and using this equation to compute water contents at all suctions where the water retention was measured.

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TABLE 5. Soil-summer crop associations, manpower and number of cows of the farm types with irrigation present in a small agricultural region (Haut-Armagnac) as described by SICOMORE. Among the six farm types are: two mixed crop-livestock farming types (CLF) and four field crop types (FC)

Farm type	Number of farms	Area (ha) of different crop-soil associations				Man-power (in full-time equivalent)	Number of cows
		Maize x loam	Sunflower x clay	Soybean x clay	Sorghum x clay		
CLF1	150	10.1	4.9			2.4	22
CLF2	112	10.4				1.8	10
FC1	181	66.3	29.8	2.6		2.2	
FC2	58	29	25.9	2.4		2.2	8
FC3	105	3			5.1	2.4	
FC4	423				4.7	1.5	7

	Only LAI estimated		LAI and sowing date estimated	
	RMSE without assimilation	RMSE with assimilation	RMSE without assimilation	RMSE with assimilation
Sowing date (days)	-	-	9	9
LAI at 500 °C.days after sowing (m^2/m^2)	*0.34*	0.29	*0.32*	0.40

Table 6. Root mean square errors (RMSE) for 31 fields for sowing date and for early LAI when only early LAI or when both early LAI and sowing date are estimated from remote sensing data. When estimation is not from remote sensing, the average value of early LAI or of sowing date over the 31 fields is calculated and that same value is used for every field.

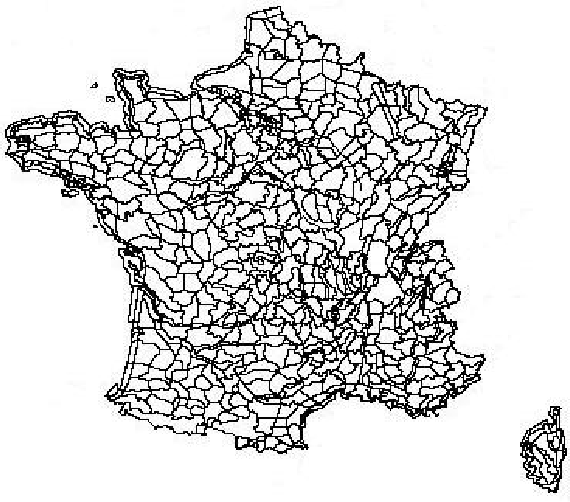

Fig. 1

Figure 1. *The division of France into homogeneous climatic areas.*

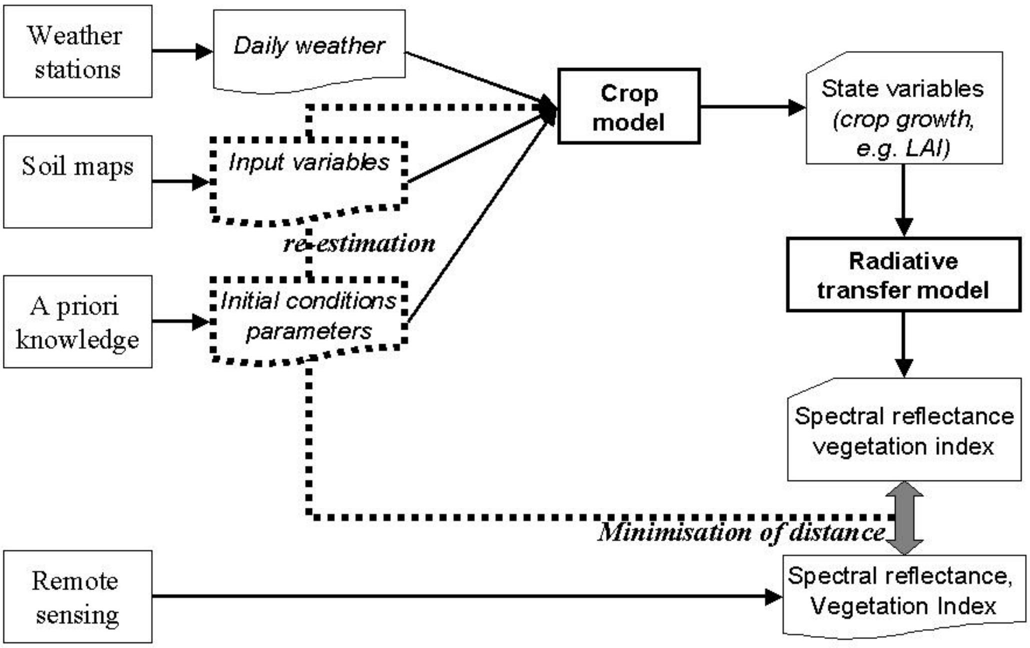

Figure 2: Data actions and models in the assimilation of remote sensing data into a crop model.

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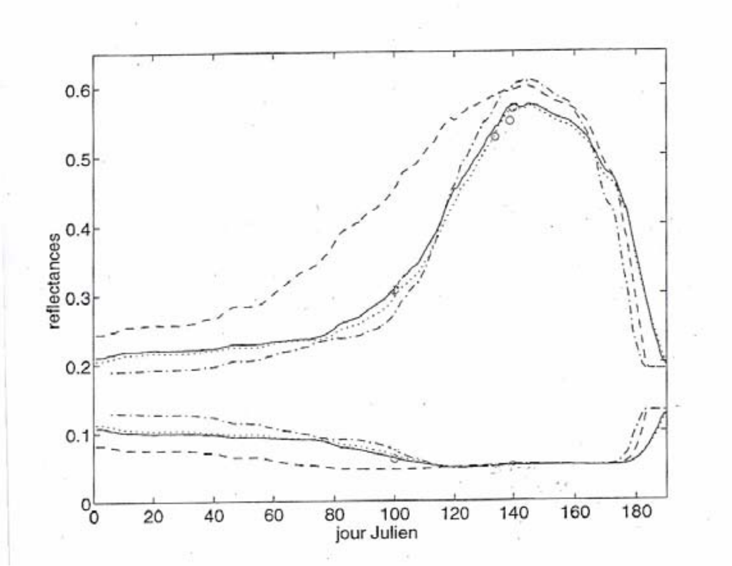

Figure 3. Reflectance profiles simulated by the coupled AFRC-Wheat+SAIL model using the actual (, o), the re-estimated (…), the earliest first guess (---) and the latest first guess (-.-) value for the sowing date.

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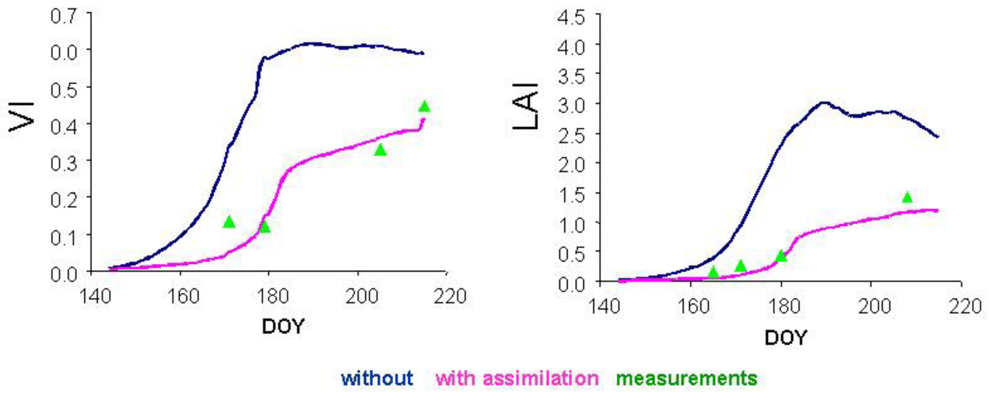

	default	estimated	measured
rooting rate (m.d^{-1})	0.012	0.010	-
max root depth (m)	1.8	1.0	-
Yield (t/ha)	75.5	51.5	50.3

Figure 4. Simulated vegetation index (VI) and leaf area index (LAI) values without (upper curve in each plot) and with (lower curves) assimilation. The data points shown are from a plot with chalky soil.

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