Netherlands Journal of Agricultural Science 43 (1995) 143-161

Crop modelling and remote sensing for yield prediction

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Received 17 December 1994; accepted 7 April 1995

Abstract

Methods for the application of crop growth models, remote sensing and their integrative use for yield forecasting and prediction are presented. First, the general principles of crop growth models are explained. When crop simulation models are used on regional scales, uncertainty and spatial variation in model parameters can result in broad bands of simulated yield. Remote sensing can be used to reduce some of this uncertainty. With optical remote sensing, standard relations between the Weighted Difference Vegetation Index and fraction ground cover and LAI were established for a number of crops. The radar backscatter of agricultural crops was found to be largely affected by canopy structure, and, for most crops, no consistent relationships with crop growth indicators were established. Two approaches are described to integrate remote sensing data with crop growth models. In the first one, measures of light interception (ground cover, LAI) estimated from optical remote sensing are used as forcing function in the models. In the second method, crop growth models are extended with remote sensing sub-models to simulate time-series of optical and radar remote sensing signals. These simulated signals are compared to measured signals, and the crop growth model is re-calibrated to match simulated with measured remote sensing data. The developed methods resulted in increased accuracy in the simulation of crop growth and yield of wheat and sugar beet in a number of case-studies.

Keywords: simulation, yield forecasting, region, uncertainty, spatial variation.

Introduction

Timely and accurate crop yield forecasting and prediction on regional to (supra-)national scales is increasingly becoming important both in developing countries (e.g. early warning systems) and in developed countries. Yield forecasting is defined here as the estimation in advance what the yield of a certain crop will be at the end of the growing season, whereas yield prediction is the estimation of actually realised yields after harvest. Especially for yield forecasting, methods are being investigated that are based on new, objective techniques such as crop growth modelling and remote sensing. For instance in the European Union (EU), a ten year project is underway at the Joint Research Centre for the improvement of agricultural statistics of its member states. This project, commonly known as MARS (Monitoring Agriculture with Remote Sensing) aims at, among others, using remote sensing methods and crop growth models for timely yield forecasting of the most important crops of the EU (Meyer-Roux & Vossen, 1994). Reasons to explore new techniques for crop yield prediction are that current yield forecasts suffer from a lack of consistency across regions and countries, are subjective in many cases ('expert guesses') and are not delivered on time by all member states (Heath, 1990).

In The Netherlands, crop growth modelling was initiated and developed from the mid-sixties onwards by C.T. de Wit and his co-workers in Wageningen. After initial emphasis on quantifying and synthesising insight in processes of crop growth, research attention is now shifting to operational application possibilities, such as crop yield prediction and forecasting. Research on the application of remote sensing to agriculture has been stimulated in The Netherlands from the early seventies through successive government-sponsored programs, i.e. NIWARS 1971–1976 (Netherlands Interdepartmental Working community for the Applications of Remote Sensing techniques) and NRSP-1, 1986–1990, and -2, 1990–2000 (National Remote Sensing Program). The DLO-Research Institute for Agrobiology and Soil Fertility (AB-DLO) has participated in these programs from the early days with research on the use of optical and radar remote sensing for crop classification, growth monitoring and yield estimation. This paper presents some concepts and methodologies developed to apply both crop growth models and remote sensing for yield prediction. Future prospects and consequences for further research are discussed.

Crop growth modelling

Crop growth models simulate growth and development of agricultural crops based on an understanding of underlying physical and physiological processes. The most simple crop growth model is of the 'light-interception' type (Gallagher & Biscoe, 1978; Monteith, 1981):

$$W_d = \int \varepsilon . S . f . dt \qquad (1)$$

Where:
W_d = dry weight of the crop [g m^{-2}]
ε = light use efficiency factor [g J^{-1}]
S = incoming global irradiation [J m^{-2} d^{-1}]
f = fraction light interception [–]
t = time [d]

The driving variable of crop growth is incoming photosynthetic active radiation (light), that is converted into biomass via a light use efficiency factor. This efficiency factor ε has to be derived from field experiments and, under non-stressed conditions, has shown to be rather stable for several crops. For agricultural crops, ε has been reported to be in the order of 1–3 g MJ^{-1} (Monteith & Elston, 1983) and 1.3–4.2 g MJ^{-1} (Charles-Edwards, 1982). Some reported values for specific crops are: 1.5–2 g MJ^{-1} for sugar beet (Steven *et al.*, 1983), 0.64–1.42 g tuber dry matter MJ^{-1} for potato (Haverkort & Harris, 1986) and 2.3–2.7 g total dry matter for potato MJ^{-1} (Spitters, 1990), about 3 g MJ^{-1} for maize (Maas, 1988) and 2.4 g MJ^{-1} for barley (Christensen & Goudriaan, 1993).

In the practical use of eq. 1 for yield prediction, the development of the fraction of intercepted light by the canopy has to be known. Fraction light interception can be measured with tube-solarimeters, estimated with grid-frames (Haverkort *et al.*, 1991) or calculated from Leaf Area Index (LAI):

$$\text{fraction light interception} = (1\text{-}\exp(-k.\text{LAI})) \qquad (2)$$

Where k is extinction coefficient for visible radiation (0.5–0.8, depending on crop type). With equation 2, the problem of quantifying the fraction light interception is transferred to that of quantifying LAI. Another way to estimate fraction light interception is by the use of remote sensing techniques (see next section). When the development of fraction light interception in time can not be measured or estimated, it has to be dynamically simulated.

Of course a simple formulation of crop growth such as equation 1 does not consider individual processes of crop growth (e.g. photosynthesis, respiration, assimilate partitioning, phenology), nor does it consider the (interactive) effects of other environmental variables beside solar radiation. Complex crop growth models that describe growth processes and feed-back mechanisms on a higher level of detail have been developed by many researchers all over the world, e.g. the CERES and CROPGRO models in the DSSAT system (Tsuji *et al.*, 1994), EPIC (Williams *et al.*, 1989), SIMTAG (Stapper & Harris, 1989) and ARCWHEAT (Weir et al., 1984), to name only a few. In The Netherlands, de Wit and his co-workers developed a whole series of dynamic simulation models based on the light-interception concept (de Wit, 1965; Penning de Vries & van Laar, 1982; van Keulen & Wolf, 1986; Penning de Vries *et al.*, 1989). The basic outline of these 'School of de Wit' models is as follows: The light profile within a crop canopy is computed on the basis of the Leaf Area Index and the light extinction coefficient. At selected times during the day and at selected depths within the canopy, photosynthesis is calculated from the photosynthesis-light response of individual leaves. Integration over the canopy layers and over time within the day gives the daily assimilation rate of the crop. Assimilated matter is first used for maintenance respiration and for the remainder converted to new, structural plant material. This newly formed material is partitioned to the various plant organs through partitioning factors introduced as a function of the phenological development stage of the crop (Spitters, 1990). A diagram of this type of models is found in the left-hand side of Figure 1, representing potential production situations (i.e. with ample supply of nutrients and water, and with no weeds, pest or disease infestation). This basic model has been extended to simulate water-limited production and, in some cases, nutrient-limited production. Examples of crop models of the 'de Wit School' are SUCROS (Spitters *et al.*, 1989; van Laar *et al.*, 1992); WOFOST (van Diepen *et al.*, 1989) and MACROS (Penning de Vries *et al.*, 1989). These models simulate growth and development of agricultural crops with time steps of one day.

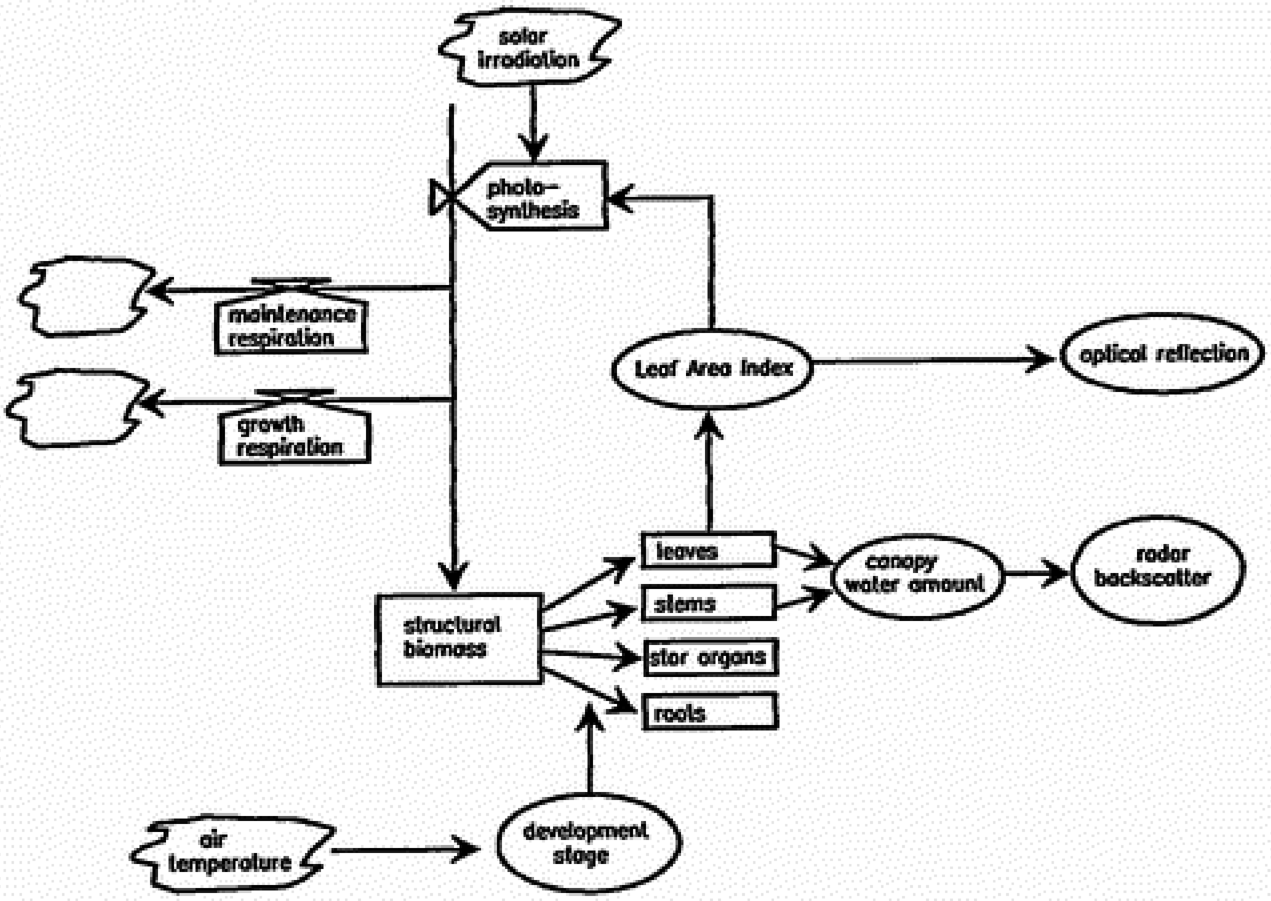

Figure 1. Functioning of the crop growth model SUCROS (Simple and Universal Crop Growth Simulator) with extensions to simulate optical reflectance and radar backscatter.

Input are daily weather data (driving variables) and crop, management and soil (for non-potential production) parameters.

Regional yield prediction and forecasting

General methodology

Crop growth models have been applied on regional scales to assess crop yield potentials and land-use options in a number of studies (e.g. Buringh *et al.*, 1979; van Lanen, 1991; Anonymous, 1992). In the framework of the MARS project, the model WOFOST has recently been integrated with a Geographic Information System (GIS) into the Crop Growth Monitoring System (CGMS) by the DLO-Winand Staring Centre for yield forecasting in the EU (Van Diepen, 1991; Meyer-Roux & Vossen, 1994). In these regional studies, the concept of 'homogeneous land unit' is followed, Figure 2. The geographic area under study is divided into land units that are considered homogeneous in soil, weather and agricultural land use characteristics. For each land unit, weather data are obtained from meteorological stations in the area by spatial interpolation. Crop parameters should ideally be derived from dedicated field experiments, but are often adopted from the original model developer. Soil parameters are costly and time-consuming to measure and are mostly estimated from infor-

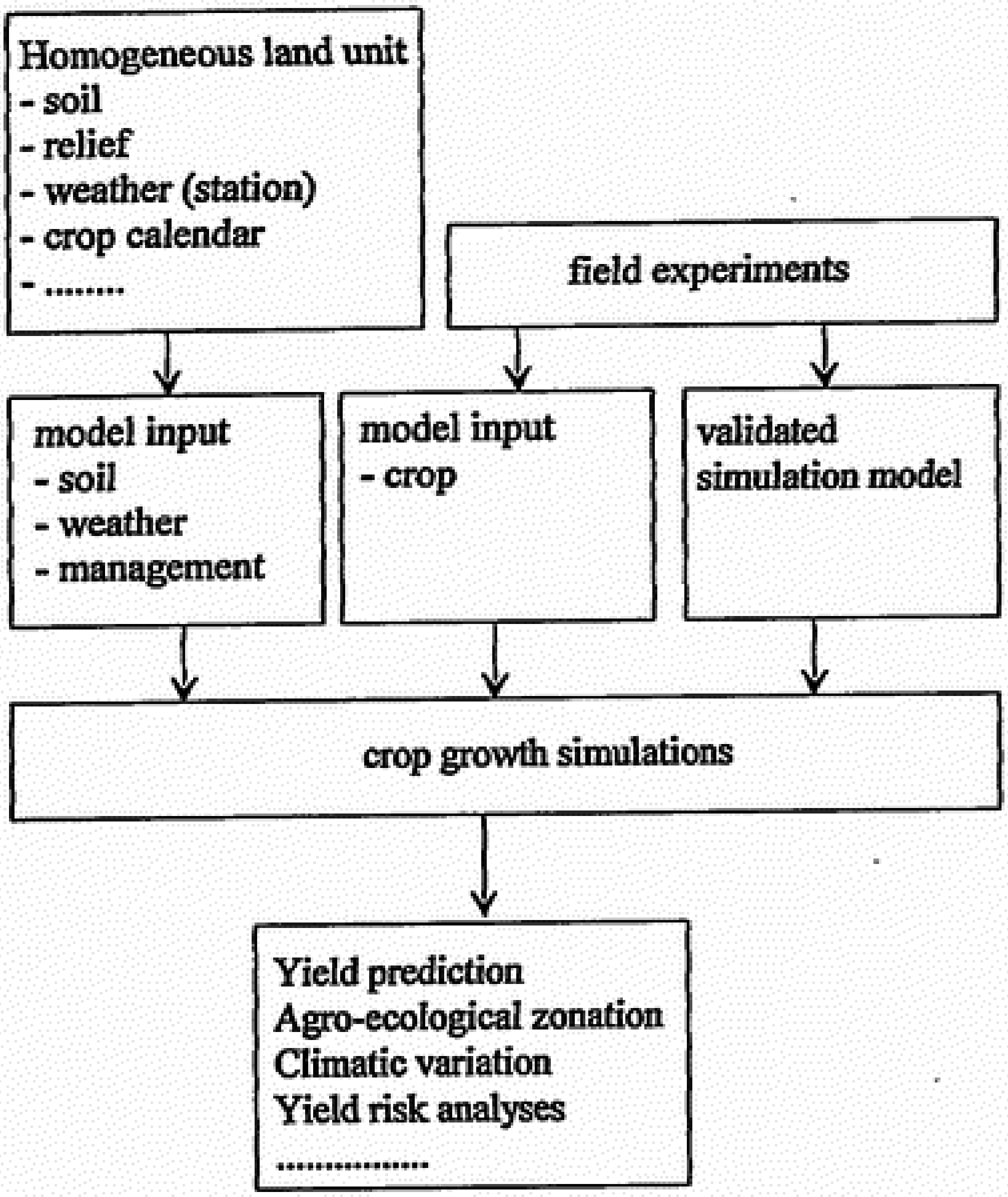

Figure 2. Diagram of steps in applying crop simulation models on regional scales using the 'homogeneous land unit' concept.

mation on existing soil maps using pedotransfer functions (e.g. Van Genuchten *et al.*, 1989). Management parameters, such as sowing date, are estimated from expert knowledge or from local field enquiries. Thus, for a particular land unit, there is one set of measured weather data, one set of experimentally derived crop parameters, and one set of estimated soil and management parameters that are supposedly representative for the whole land unit. Using these input sets, crop growth models are run to obtain quantitative indicators of crop growth, such as total above ground weight, weight of storage organs, or final yield. The simulated yield at the end of the growing season can be used for yield prediction, whereas simulated crop growth indicators during the growing season can be used for crop yield forecasting. In both cases, the simulated yield/crop growth indicators need to be regressed against actually realised yields for a number of years to obtain a practical crop yield predictor/forecasting algorithm. Mostly, actually realised yields are taken from official yield statistics that may be compiled from various sources of information (ranging from pure expert guesses to farmers' sampling strategies). Therefore, it should be kept in mind that, strictly speaking, most forecasting algorithms forecast yield statistics and not actual yields.

Crop growth and final yield as simulated by crop growth models is generally not the same as actually realised on farmers' fields. A number of reasons exist for this discrepancy. First, models are by definition simplifications of reality, and some processes may be over-simplified, or even wrongly represented, to describe practical field situations accurately. Secondly, a number of biotic (e.g. diseases) and a-biotic (e.g. micro-nutrient deficiency) stress factors may operate on farmers' fields that are not incorporated in crop growth models. For instance the model WOFOST in CGMS only simulates crop growth and development under potential and water-limited production situations whereas all other conditions for crop growth are considered optimal (i.e. optimal supply of nutrients and no pests, diseases or weeds present). Thirdly, input data to the models may not be accurately known on the scale of application for yield forecasting (a problem elaborated further in this paper, see below). A critical review of the record of crop models for practical applications such as yield forecasting has been given by Seligman (1990). In yield forecasting algorithms based on crop model simulations, all the 'distorting' effects of over-simplification and errors in the model and input data are supposed to be dealt with by the regression of simulated yield (and growth indicators) against the yield statistics. However, even then, discrepancies may still exist between actually forecasted or predicted yields and official yield estimates in statistics (e.g. for CGMS see De Koning *et al.*, 1993). Crop simulation models and the methods for regional application need to be further improved. However, it should also be realised that the quality of many official yield statistics is hardly quantified, and that it suffers from lack of consistency across regions and countries. This hampers an unbiased comparison between forecasted and statistical yields.

Effects of uncertainty and spatial variation

Some discrepancies between simulated and actual crop growth and yield on regional scales may arise from a too simplified approach in applying so-called point models (here the one-dimensional crop model) on extended geographic areas. The use of a single set of representative model parameters for a particular land unit ignores the uncertainty that is present in the - often estimated - value(s) of these parameters on a regional scale. For example, soil parameter values that are estimated from descriptive information on soil maps are inherently uncertain. Also, there is generally spatial variation in parameter values, of which the magnitude can also be uncertain. Especially for soil properties, evidence is increasing that spatial variation can be considerable, and its effect on crop growth simulation can no longer be neglected (e.g. Finke, 1993). Management parameters may also vary in space. For example, in a given land-unit, all farmers do not sow their crops on the same single date, but sowing is spread in time according to e.g. access to labour, local field conditions or socio-economic factors. Sowing date, though a temporal phenomenon, can be considered here as a model input parameter of which the value varies in space. Lastly, even the values of some crop parameters may vary for the same crop type among cultivars (e.g. Kooman, 1995).

An example of spatial variation in crop growth within a homogeneous land-unit is given for winter wheat in Flevoland, The Netherlands, Figure 3. The use of average, representative input parameters in SUCROS resulted in a fair average simulation of development of LAI and biomass; the seasonal-average error between simulated and actual canopy biomass over 1987 and 1988 was 1740 kg ha^{-1}. However, the variation in growth as expressed by the sample fields was not represented by the simulation results.

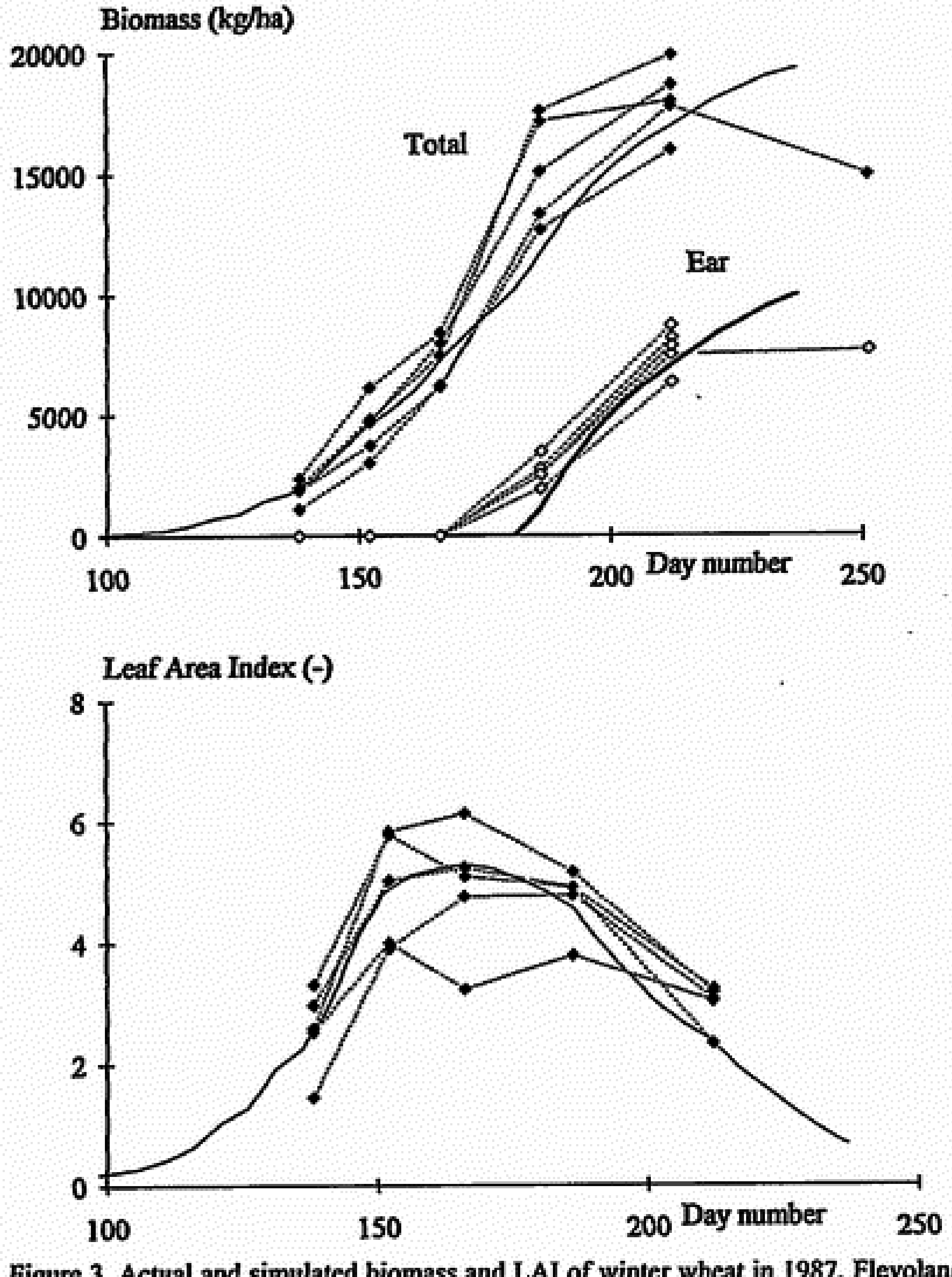

Figure 3. Actual and simulated biomass and LAI of winter wheat in 1987, Flevoland, The Netherlands. The diamonds are measurements at farmers fields, the solid line is the area-representative SUCROS simulation.

To quantify the effects of uncertainty in model parameters and their spatial variation on simulated crop yield, a combination of sensitivity analysis and Monte Carlo techniques can be used. Sensitivity analysis is first used to identify model parameters that significantly affect model output (yield) in the environment under consideration. For these parameters, probability distributions are constructed that represent the uncertainty about their true values and/or spatial variation. These probability distributions can be obtained from expert knowledge, literature data or actual measurements. When a large number of actual measurements have been made, the *probability* distribution becomes a *frequency* distribution that quantifies the actual spatial variation in the parameter values within that land-unit. Monte Carlo simulation is then used to calculate crop yield using a large number of combinations of input parameters that are randomly chosen from their probability distributions. The distribution of the resulting simulated crop yields represents the probability in crop yield as result of the uncertainty in model parameter values and their spatial variation.

An example is given for the simulation of rainfed, lowland rice yield in the Philippines. The used crop growth model was ORYZA–W (Wopereis *et al.*, 1995); daily weather data were taken from the International Rice Research Institute (IRRI) at Los Baños, 1979; crop data were derived from field experiments at IRRI; management and soil data were taken from expert knowledge and field measurements. The case-study concentrated on uncertainty and spatial variation in soil and management data. Sensitivity analysis revealed five parameters that had a significant effect on simulated rice yield, and (uniform) probability distributions were constructed (Table 1). Using Monte Carlo simulation, it was found that there was 67% probability of complete crop failure. For the crops that 'survived', the probability distribution of simulated yield is given in Figure 4. Given the very broad distribution of probable yields, the accuracy of yield simulation for this land-unit is small, and can only be increased when the uncertainty in the model parameter values is reduced by more observations. On the other hand, when the distribution of parameter values given in Table 1 would be a measured frequency distribution of actually occurring values, then Figure 4 would quantify the frequency distribution of yields as caused by the - known - spatial distribution of input parameters in that land unit. The average yield (of successful crops) of 3.47 t ha^{-1} would then be a simulation of the average yield from this land-unit. For comparison, the mean yield simulated with average, representative model parameter values for this land-unit was 4.24 t ha^{-1}.

To improve the accuracy of yield forecasting and prediction on regional scales,

Table 1. Model parameters for ORYZA-W, with ranges for a uniform probability distribution for a hypothetical land-unit in the Philippines.

Parameter	Range
Sowing date	150–180 days
Thickness puddled layer	15–250 mm
Days in seed-bed	10–21 days
Seepage & percolation rate	5–10 mm d^{-1}
Shrinkage of puddled layer	0.65–0.90 (–)

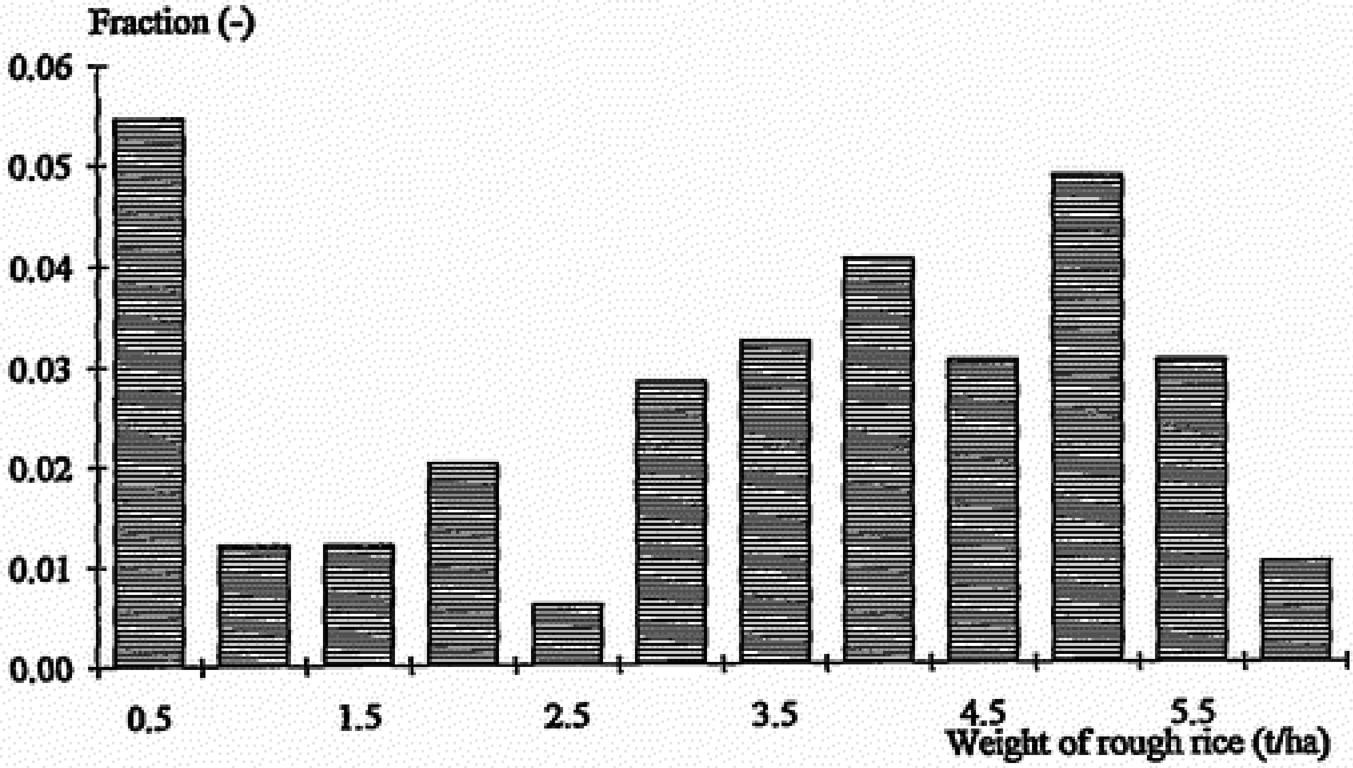

Figure 4. Frequency distribution of simulated rainfed lowland rice yield in 1979, with model input distributions as specified in Table 1.

methods must be sought to decrease the uncertainty in crop growth simulation. In this respect, remote sensing offers techniques that can be useful.

Remote sensing

Remote sensing is the measurement of electromagnetic radiation that is reflected or emitted from the surface of the earth. Reflected electromagnetic waves may have been emitted by the sun (optical remote sensing) or by artificial sources (e.g. laser, radar). In this paper, only optical and radar remote sensing are considered. In the optical domain, a large number of satellites currently monitor and map the surface of the earth (e.g. the high resolution Landsat and SPOT series). Experience has been gained in using data from these satellites in agriculture already since the early seventies. Unfortunately, frequent cloud cover is a large drawback for monitoring purposes at many parts of the world. Microwaves are relatively unhindered by clouds, and satellites such as ERS-1 and JERS-1 provide radar images of the earth on a regular basis since the early nineties. Compared with optical remote sensing, however, methods for using radar in agriculture are, up to know, less well developed.

Optical remote sensing

For the estimation of crop characteristics from optical remote sensing data, measurements of reflected solar radiation in single wavelength bands (e.g. green, red, near-infrared) are generally combined into so-called Vegetation Indices (VI). Many VI's have been constructed that have a good relationship with various crop growth indicators (e.g. Rouse *et al.*, 1973; Richardson and Wiegand, 1977; Clevers, 1989). The most interesting crop growth indicator to measure in relation to crop growth simulation models is fraction light interception by the canopy. From a comparative analysis, the Weighted Difference Vegetation Index (WDVI) as developed by Clevers (1989) was found to be the most suitable VI to estimate fraction soil cover and LAI of agricultural crops (Bouman, 1992a):

$$WDVI = IRc - VISc \frac{IRs}{VISs} \tag{3}$$

where:
IR_c = Infrared reflectance of the crop
IR_s = Infrared reflectance of the soil
VIS_c = Visible reflectance of the crop
VIS_s = Visible reflectance of the soil

Standard relations between WDVI and fraction ground cover and LAI were established for wheat, barley, oats, sugar beet and potato from 10 years of field observations (Bouman *et al.*, 1992). The used data set was gathered on different locations in The Netherlands, and spanned a range of cultivars, treatments, soil types, soil moisture regimes, and growing conditions from severely stressed to near-potential growth. Figure 5 gives an example of the relationship between WDVI and fraction

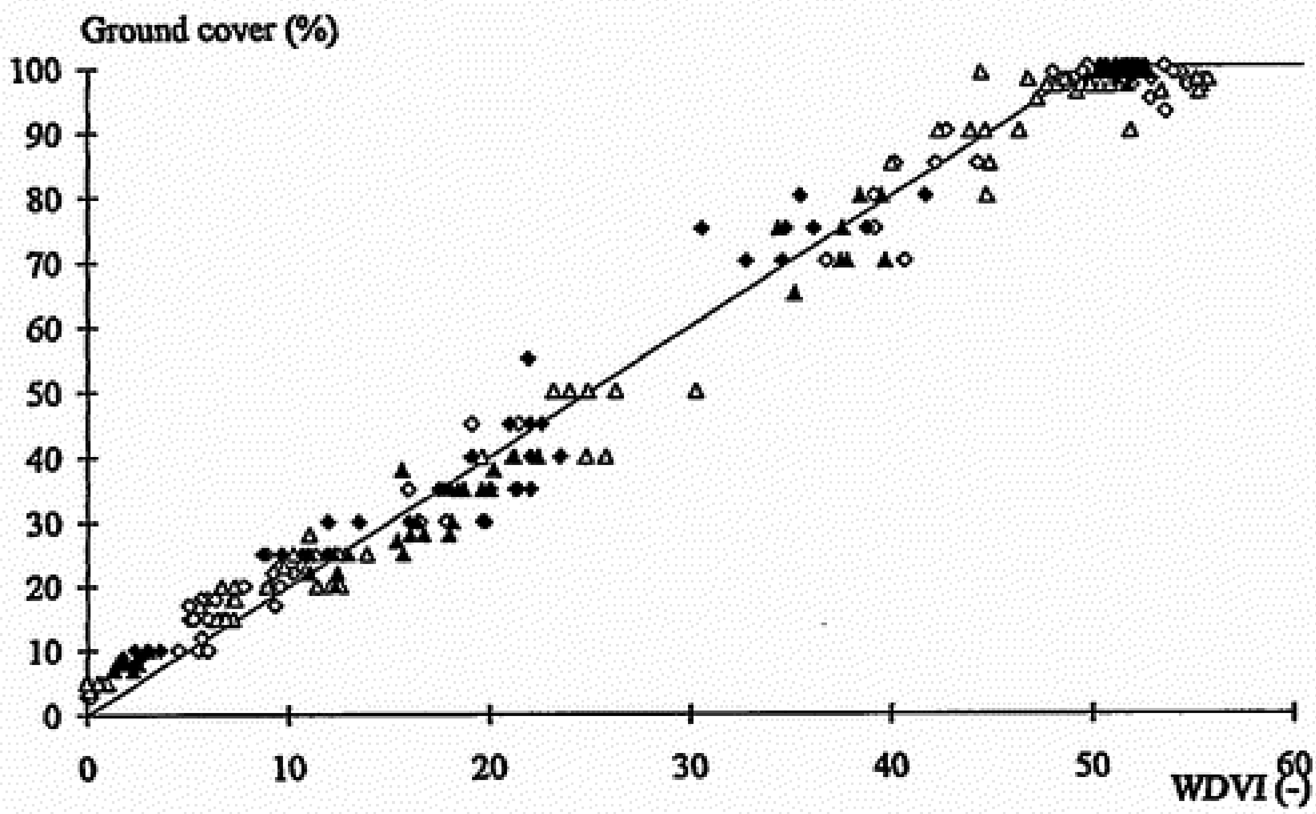

Figure 5. Ground cover (%) versus WDVI of potato, early growing season. Different symbols indicate different varieties (N = 285); the line is the regression line (r^2=0.97). Crop growth ranged from severely stressed to near-potential.

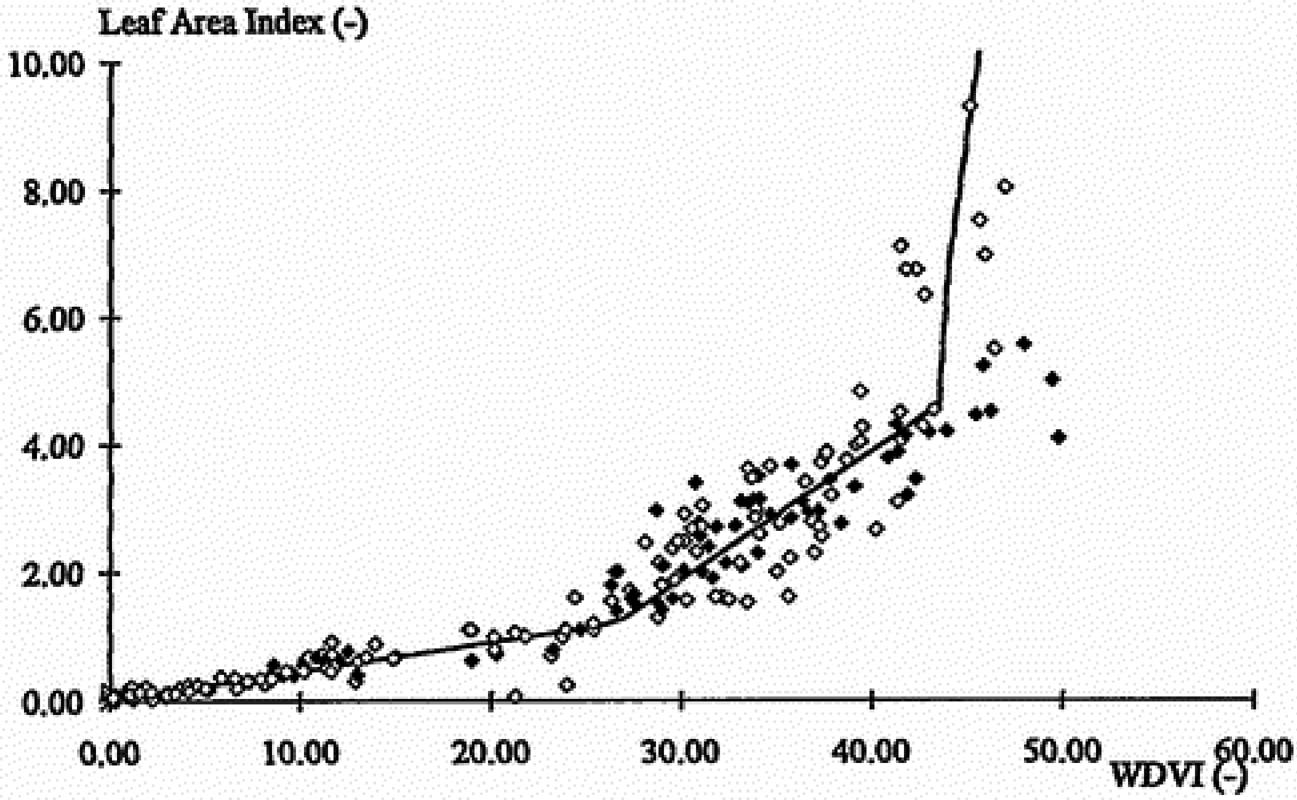

Figure 6. Leaf Area Index versus WDVI for barley. White diamonds are measurements in the vegetative phase, black diamonds in the reproductive phase. Data from 5 different experiments (N=298). The line segments are the regression line (r^2=0.95).

ground cover for potato; Figure 6 gives an example of the relationship between WDVI and *LAI* for barley. Using the developed standard relations, the estimation accuracy of fraction ground cover and LAI from WDVI was the same as that of measurements using conventional techniques (i.e. 5% absolute accuracy for ground cover; 10-15% relative accuracy for LAI up to LAI values of 4).

Radar remote sensing

Since the early seventies, the Dutch national research group ROVE (Radar Observation on VEgetation) measured radar backscatter of agricultural crops with ground-based and airborne instruments (De Loor *et al.*, 1982). Measurements were made at various frequencies (35 to 1.2 GHz), incidence angles (10-80°) and polarisations (VV, HH, VH and HV). From extensive analyses, it was concluded that radar backscatter of agricultural crops is extremely sensitive to the structure of the canopy and that of the underlying soil surface (with low soil cover). This sensitivity is especially large for crops with distinct vertical, elongated canopy elements such as found in cereals: stems, leaves and ears (Bouman & van Kasteren, 1990; Hoekman & Bouman, 1993). An example is given in Figure 7 that shows the X-band radar backscatter of three barley crops with different row spacings. All three crops had a comparable rate of growth as measured by biomass and LAI. Row spacing had a pronounced effect on the radar backscatter. But, even more striking was the effect of ear direction: Before day 182, the barley ears were directed towards the radar, and backscatter was relatively low. After day 182, wind changed the direction of the ears

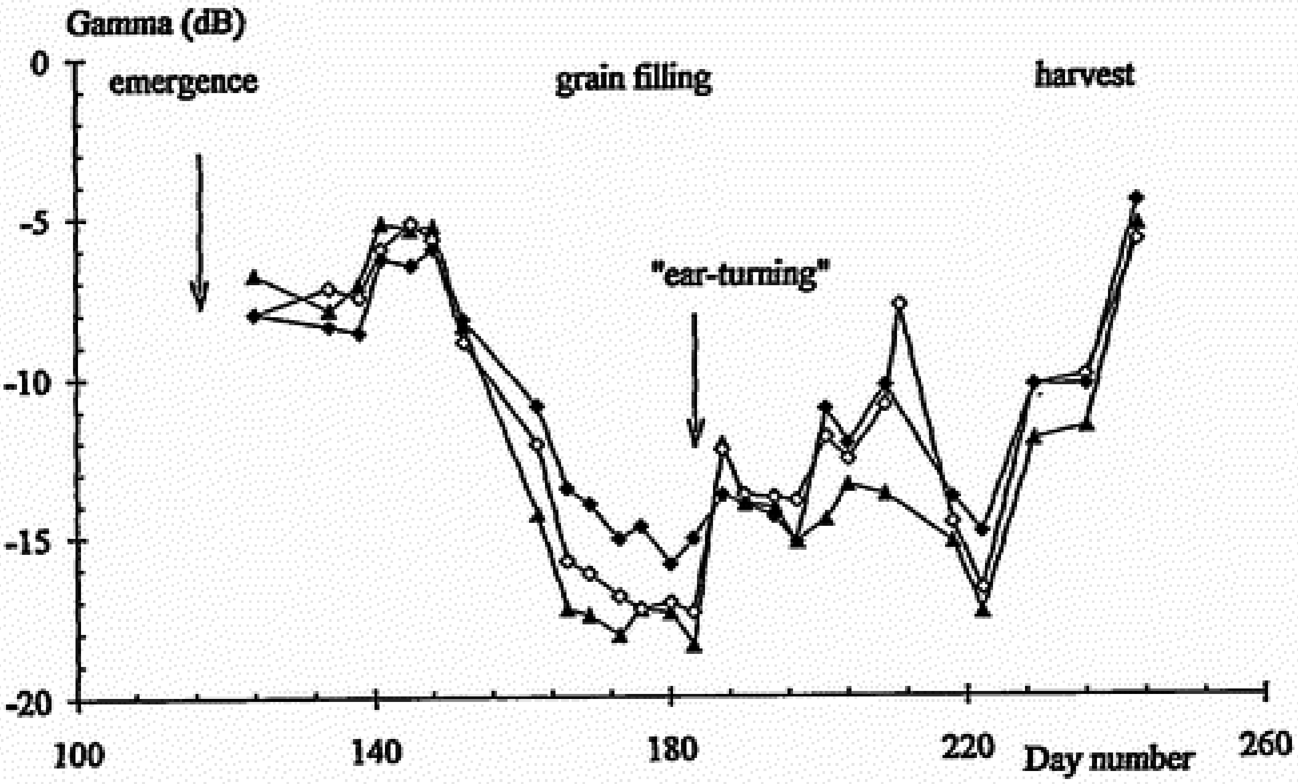

Figure 7. X-band VV radar backscatter of three barley crops with different row spacing: black diamonds = 37.5 cm; white diamonds = 25 cm; black triangles = 12.5 cm. Radar look direction was parallel with row direction.

180° with respect to the radar look direction, and radar backscatter increased dramatically. Other fluctuations in the backscatter curves were mostly caused by changes in canopy structure as a result of wind and rain (also soil moisture). In other observations, lodging of barley even increased radar backscatter with 10 dB! (Bouman & van Kasteren, 1990). All these effects of canopy structure on radar backscatter hampered the development of any useful relationship between radar backscatter and crop growth indicators for cereals.

For crops with a 'uniform' canopy structure and relatively large and broad leaves (compared to the wavelength of incident radiation), the sensitivity of radar backscatter to canopy structure was found to be less. For example in sugar beet, a relationship was found between X-band radar backscatter and the amount of water in the canopy. Using the inverted Cloud model (Attema & Ulaby, 1978), crop water of sugar beet could be estimated from radar measurements in two or more different angles of incidence. However, realistic estimates of crop water were limited to values up to 2.5 kg m^{-2} only (i.e. a crop of some four weeks old, 80–100% soil cover and 2.8 t ha^{-1} dry matter), and fitted Cloud model parameters varied with experiments in different locations.

Reducing model uncertainty with remote sensing

Uncertainty in crop growth simulation modelling on regional scales can be reduced by the use of remote sensing data in two ways. First, remote sensing images can be used to classify and geo-reference agricultural fields and crop types. Using GIS, the classified crops can be located on soil maps, and from this, specific crop models can be selected and combined with the geographically corresponding soil input data. Crop classification from remote sensing data has been shown to be feasible for both optical (e.g. Janssen, 1994) and radar techniques (Hoogeboom, 1983; Nieuwenhuis & Scholten, 1993). Second, remote sensing can be used to estimate crop growth indicators, that can be integrated with crop grow simulation models. There are two methods for this integration: direct data input, and 'steering' simulation results.

Direct data input

Time-series of estimated fraction light intercepted by the canopy are ideally suitable to be used as input in crop growth models. For example, fraction ground cover as derived from WDVI (e.g. Figure 5) can be used directly in simple models such as equation 1 for growth simulation. This approach has been worked-out by Steven *et al.* (1983), Garcia *et al.* (1988) and Christensen & Goudriaan (1993). With more complex growth models, such as SUCROS, LAI values estimated from WDVI (e.g. Figure 6) can be used to replace subroutines in the crop model that simulate the development of LAI from environmental variables. This approach will lead to better simulation results when LAI is estimated more accurately from remote sensing than it is simulated by the model. Model simulations of LAI may be inaccurate because of uncertainty in the model input data, because of the occurrence of growth-reducing factors in the field or because of over-simplification of growth processes. In a number of case studies, it was found that the use of estimated LAI as 'forcing function' increased the accuracy of growth simulation. In the example of winter wheat in Figure 3, the use of LAI values that were estimated from WDVI, as forcing function in SUCROS for the individual fields decreased the seasonal-average error between simulated and actual canopy biomass from 1740 kg ha^{-1} to 1376 kg ha^{-1} (as 'regional' average over 1987 and 1988), Figure 8. In this example, it should be noted that SUCROS only explains potential crop growth and yield formation from weather data (minimum and maximum temperature and solar radiation) and crop characteristics.

Two conditions must be fulfilled for the successful use of estimated LAI as forcing function. First, a sufficiently large number of remote sensing observations needs to be available with a regular frequency (e.g. weekly observations). Daily values of LAI can then be interpolated between observations without making too much error. A high frequency of observations is especially needed in the early growing season when LAI increases exponentially from 0 to about 3, and at the end of the growing season when LAI decreases again with senescence of the crop (e.g. as in cereals). With high resolution satellites, such as the Landsat and SPOT series, a high frequency of (optical) remote sensing observations is often not realised due to cloud cover. Low resolution (meteorological) satellites, that make daily observations, are not suitable because farmers fields are not individually recognized. A solution could be the use of airborne remote sensing over selected, representative test-sites as has been carried out by the former Soviet Union (Kleschenko; pers. comm., 1994). Second, the starting point of crop growth in time (sowing or emergence date), should be rea-

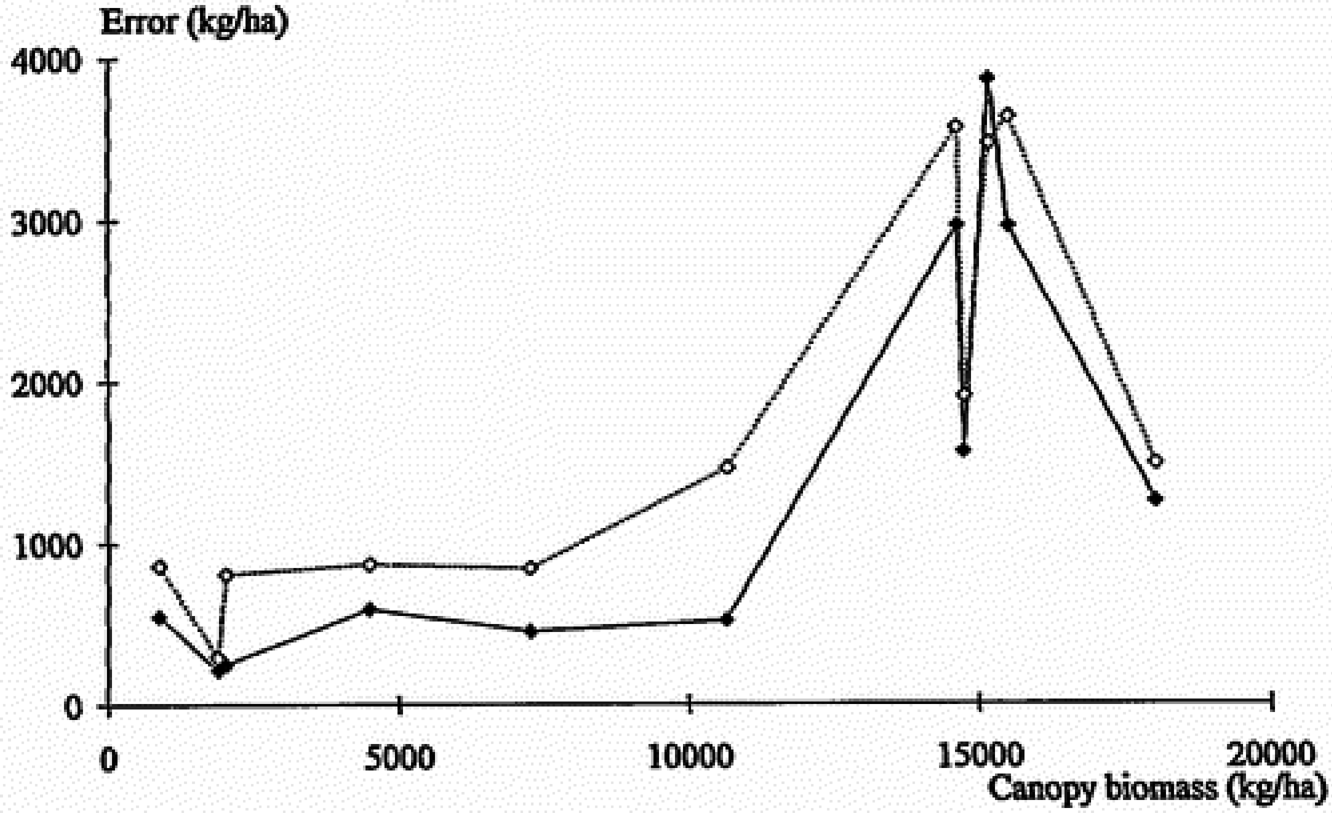

Figure 8. Average error in simulated canopy biomass of winter wheat in Flevoland (1987, 1988) as function of actual biomass value. White diamonds: using standard SUCROS; black diamonds: using SUCROS with LAI estimated from WDVI as forcing function.

sonably well known. Otherwise, the externally forced LAI estimations may not be 'in phase' with the simulated phenological development of the crop. For selected areas, such information could be collected by field-surveys or by enquiries early in the growing season. This stresses the importance of combining multiple sources of information in crop yield forecasting (e.g. the Regional Inventories action of the MARS project, Meyer-Roux & Vossen, 1994).

Steering simulation results

When the number of remote sensing observations is limited and/or initial conditions are not well known, remote sensing can be used to 'steer' crop growth models by adapting the values of model parameters so that simulated time-series of LAI match estimated time-series of LAI. For instance, the unknown value of sowing/emergence date can be found by fitting the simulated LAI curve to the estimated LAI curve from (optical) remote sensing (Maas, 1988). In a 'multi-sensor' approach, Bouman (1992b) extended SUCROS with remote sensing models for optical reflectance and for radar backscatter (right-hand side of Figure 1). The extended model simulates crop growth and development together with optical reflectance and radar backscatter. These simulated remote sensing signals can be compared with observed time-series of remote sensing signals. The values of selected model parameters can then be optimised, within plausible ranges, so that simulated remote sensing signals match the observed ones as good as possible. For sugar beet, this 'calibration' procedure improved simulations of crop growth in a number of field-experiments using only

Table 2. Seasonal-average error between measured and simulated biomass using *SUCROS* with 'standard' input data ('Standard' error) and using *SUCROS* optimised to remote sensing observations ('Optimised' error). N-radar and N-optical indicate the number of observations of X-band radar backscatter and optical reflectance. From 1975 to 1983, the data pertain to one single test field; in 1987 and 1988 the data are the average for three test fields. In 1980, the same test field was observed with both radar and optical reflectance instruments.

Year	N radar	N optical	'Standard' error (kg m^{-2})	'Optimised' error(kg m^{-2})
1975	20	–	451	231
1979	35	–	424	388
1980	36	–	680	463
1980		34	680	306
1980	36	34	680	259
1981	17	–	700	261
1983	–	32	548	227
1987	–	6	561	286
1988	–	9	386	434

optical, only (X-band) radar and combined optical and radar observations (Table 2). On the average, the seasonal-average error between simulated and actual canopy biomass decreased from 400–700 kg ha^{-1} using only SUCROS (but with actual emergence dates as input) to 225-475 kg ha^{-1} using the optimisation methodology (and without actual input on sowing date). Only in one out of seven years did the calibration procedure result in simulation errors that were slightly larger than using SUCROS with 'standard' (i.e. non-optimised) input data. In a validation study in 1991, simulations of tuber yield of sugar beet of ten farmers in Flevoland improved on the average from 19% error using only SUCROS with mean sowing date for the area as input, to 3% using the optimisation procedure with time-series of (ground-based) WDVI (Table 3). On the same test site, a modified optimisation procedure resulted in 4.2% average simulation error using only three airborne recordings with the Dutch optical CAESAR scanner (van Leeuwen & Clevers, 1994).

So far, the integration of SUCROS with remote sensing data has been most successful using optical reflectance data. Radar observations have only proven some value in steering SUCROS for sugar beet in the very early part of the growing season. For other crops, such as cereals, the sensitivity of radar backscatter to canopy structure might be useful when changes in radar backscatter can be linked to morpho-phenological development of the crop. The simulation of phenological development of the crop might then be steered by radar observations in the same way that LAI simulations are steered by optical reflectance measurements.

Conclusions and discussion

Crop growth models and remote sensing techniques increasingly find their way in regional to national yield prediction and forecasting systems, e.g. USA (Hanuschak, 1990), Canada (Goulet, 1990) and Europe (Meyer-Roux & Vossen, 1994). They are

Table 3. Actual and simulated tuber yield of sugar beet of 10 farmers in Flevoland, The Netherlands, 1991.

Farm	Yreal	Ysim1	Ysim2	Ysim3	N
1	87	60	69.4	80.0	9
2	79	60	70.6	76.7	9
3	75	60	70.3	74.3	9
4	77	60	70.6	71.5	9
	81	60	74.6	–	–
5	70	60	63.5	70.5	8
6	68	60	63.3	65.3	11
7	70	60	65.6	69.9	12
8	61	60	58.2	68.1	11
9	70	60	63.6	72.2	15
10	77	60	72.8	75.7	12
	78	60	74.8	–	–
Average	74.3	60	68.1	72.2	11

Yreal = actual farmers yield (t ha^{-1})
Ysim1 = simulated farmers yield, using average sowing date of the region
Ysim2 = simulated farmers yield, using actual sowing date for each field
Ysim3 = simulated farmers yield, calibrated on optical remote sensing
N = number of remote sensing observations

part of a whole set of information and analysis tools that are used to eventually determine crop yield and production estimates: actual sampling and crop measurements, farmer enquiries by post, telephone or field-visits, expert-knowledge, weather reports, statistical regression analyses, newspaper articles and even ‘agricultural spies’ in foreign countries. The added value of crop models and remote sensing is that they are objective, quantitative and consistent over large areas. However, one should always keep in mind that any crop growth model, by its very nature, is a simplification of reality and that it may contain shortcomings in the description of complex, actual field conditions. Also, the quality of the simulated output depends on the quality of model data input.

Two methods were presented to use remote sensing observations from farmers' fields to adjust simulations made by a crop growth model to account for effects of uncertain data input and/or possible stress factors that are not included in the model. Though the presented methods were illustrated using SUCROS, the underlying principles are general and can be applied using other crop growth models as well. These integrative methods have proven their usefulness in several case-studies using ground-based remote sensing observations, and need now to be tested using airborne and satellite data. Follow-up projects will be carried out the coming years to investigate the feasibility of using high resolution optical satellite data.. A pre-requisite for the developed integration methods is that farmers' fields can be individually identified in satellite images. Low resolution satellite data such as AVHRR are therefore not suitable. With radar remote sensing, capabilities of polarimetric systems to monitor changes in canopy architecture, and linking those to phenological development, should be investigated. Further research on the crop modelling part will have to focus on improving the models to incorporate the effects of yield-reducing factors. Because the accuracy and quality of yield statistics on regional scales is unknown, the models should be calibrated and validated first on accurate data from experimental fields and farmers' fields. The analysis of uncertainty and spatial variation has demonstrated the need for a soil data base that contains measured data on physical properties that are directly relevant for crop growth modelling. Moreover, measured data should not be aggregated and averaged over pre-defined land units, but all original data should be available so that probability distributions can be derived.

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