A CONCEPTUAL FRAMEWORK FOR ESTIMATING CROP GROWTH USING OPTICAL REMOTE SENSING DATA

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ABSTRACT

For monitoring agricultural crop production, growth of crops has to be studied, e.g. by using crop growth models. Estimates of crop growth often are inaccurate for non-optimal growing conditions. Remote sensing can provide information on the actual status of agricultural crops. This information can be used to initialize, (re)parameterize, calibrate or update crop growth models, and it can yield parameter estimates to be used as direct input into growth models: 1) leaf area index (LAI); 2) leaf angle distribution (LAD); and 3) leaf colour (optical properties in the PAR region). LAI and LAD determine the amount of light interception. Leaf (or crop) colour influences the fraction of absorbed photosynthetically active radiation (APAR) and the maximum (potential) rate of photosynthesis of the leaves.

In this paper the above concepts for crop growth estimation will be further elucidated and illustrated with examples for sugar beet using groundbased and airborne data obtained during the MAC Europe 1991 campaign. A simple reflectance model was used for estimating LAI. Quantitative information concerning LAD was obtained by measurements at two viewing angles. The red edge index was used for estimating the leaf optical properties. Finally, a crop growth model (SUCROS) was re-parameterized on time-series of optical reflectance measurements to improve the simulation of beet yield.

KEY WORDS: Growth models, Optical remote sensing, Growth estimation

1. INTRODUCTION

Remote sensing techniques have the potential to provide information on agricultural crops quantitatively, instantaneously and, above all, non-destructively over large areas. In the past decades, knowledge about optical remote sensing techniques and their application to fields such as agriculture has improved considerably (cf. Asrar, 1989; Steven & Clark, 1990). A lot of research has been devoted to land cover classification and acreage estimation with considerable success. Another field of interest in agriculture is yield estimation. Research in this topic, however, has indicated that remote sensing alone is generally not capable to produce accurate yield estimations. This has prompted scientists to look for other techniques that can be combined with remote sensing data to give better results. One of such techniques is crop growth modelling.

In this paper, some views on linking optical remote sensing data with crop growth models are presented. Some concepts will be illustrated with preliminary results from the MAC Europe 1991 campain over the Dutch test site Flevoland.

1.1 Crop Growth Models

From the 19th century, agricultural researchers have used modelling as a tool to describe relations between crop growth (yield) and environmental factors that appear to govern crop growth. In our study, we make use of models and concepts that were developed in The Netherlands by de Wit and his co-workers (de Wit, 1965; Penning de Vries & van Laar, 1982; van Keulen & Wolf, 1986; van Keulen & Seligman, 1987; Spitters et al., 1989). This type of models describes the relation between physiological processes in plants and environmental factors such as solar irradiation, temperature and water and nutrient availability. The models compute the daily growth and development rate of a crop, simulating the dry matter production from emergence till maturity. Finally, a simulation of yield at harvest time is obtained. The basis for the calculations of dry matter production is the rate of gross CO_2 assimilation of the canopy. Input data requirements concern mainly crop physiological characteristics (e.g. maximum CO_2 assimilation rate, respiration and dry matter partitioning), site characteristics (latitude), environmental characteristics (daily irradiation, daily minimum and maximum temperatures) and the initial conditions defined by the date at which the crop emerges.

The main driving force for crop growth in these models is absorbed solar radiation, and a lot of detail is given to the modelling of the solar radiation budget in the canopy. Incoming photosynthetically active radiation (PAR $\approx$ 400-700 nm; more or less synonymous with visible radiation) is first partly reflected by the top layer of the canopy. The complementary fraction is potentially available for absorption by the canopy. Subsequently, the fraction of absorption by the canopy is a function of solar elevation, leaf area index (LAI), leaf optical properties and crop extinction coefficients for diffuse and direct fluxes (which in their turn depend on solar elevation, leaf angle distribution (LAD) and leaf optical properties). The product of the amount of incoming photosynthetically active radiation (PAR) and the absorptance yields the amount of absorbed photosynthetically active radiation (APAR). The rate of CO_2 assimilation (photosynthesis) is calculated from the APAR and the photosynthesis-light response of individual leaves (Fig. 1). The maximum rate of photosynthesis at light saturation is highly correlated to the leaf nitrogen content (Fig. 2). The assimilated CO_2 is then reduced to carbohydrates which can be used by the plant for growth.

Because of this detailed modelling of the solar radiation budget, this type of models is especially suitable for the linkage with optical remote sensing through the use of optical reflectance models.

1.2 Optical Remote Sensing

Crop growth models as described above were developed to formalize and synthesize knowledge on the processes that govern crop growth. When applied to operational uses such as yield estimation, these models often appear

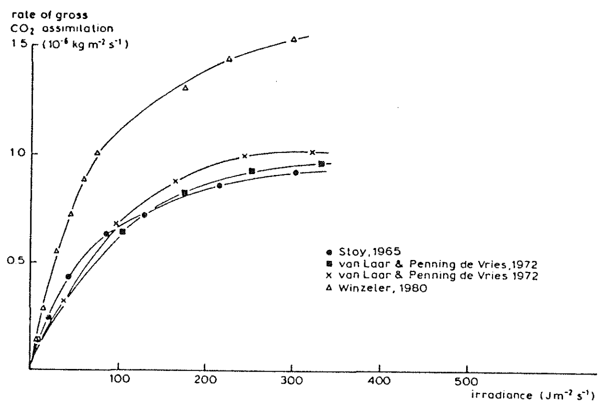

Figure 1. Relation between irradiance and rate of gross CO_2 assimilation for individual leaves of wheat. From: van Keulen & Seligman, 1987, p. 43.

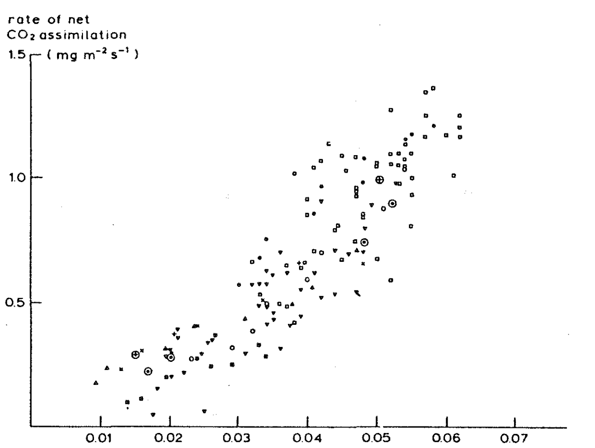

Figure 2. Relation between nitrogen content in the leaf, on a dry weight basis, and its rate of net CO_2 assimilation. The different symbols refer to measurements made by different authors. From: van Keulen & Seligman, 1987, p. 47.

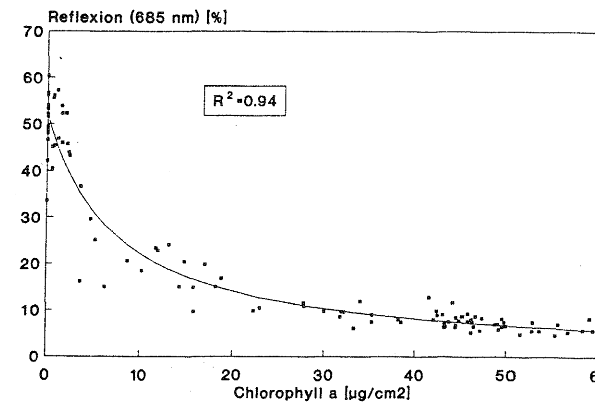

Figure 3. Relation between red reflectance and chlorophyll content of the upper leaves of wheat crops. From: Schellberg, 1990, p.75.

to fail when growing conditions are non-optimal (e.g. pest and disease incidence, severe drought, frost damage). Therefore, for yield estimation, it is necessary to 'check' modelling results with some sort of information on the actual status of the crop throughout the growing season (Bouman, 1991). Optical remote sensing can provide such information. There are three 'key-factors' useful in crop growth models that may be derived from optical remote sensing data: a) LAI; b) LAD; and c) leaf optical properties in the PAR region.

Ad a. The LAI during the growing season is an important variable in crop growth modelling. Also, the LAI is a major factor determining crop reflectance and is often used in crop reflectance modelling (e.g. Suits, 1972; Bunnik, 1978; Verhoef, 1984). The estimation of LAI from remote sensing measurements has received much attention. Much research has been aimed at determining combinations of reflectances, so-called Vegetation Indices, to correct for the effect of disturbing factors on the relationship between crop reflectance and crop characteristics such as LAI (Tucker, 1979; Richardson & Wiegand, 1977; Clevers, 1988, 1989; Bouman, 1992a).

Ad b. LAD (leaf angle distribution) affects the process of crop growth because it has an effect on the interception of APAR by the canopy. With optical remote sensing techniques it has been more difficult to obtain quantitative information on LAD than on LAI. A solution may be found by performing measurements at different viewing angles. Goel & Deering (1985) have shown that measurements at two viewing angles for fixed solar zenith and view azimuth angles are enough to allow estimation of LAI and the LAD by the infrared reflectance.

Ad c. Leaf optical properties (leaf colour) are important in the process of crop growth because:
1) they influence the fraction of absorbed PAR, and
2) they can be indicative for the nitrogen status (or chlorophyll content) of leaves which affects the maximum rate of photosynthesis. Fig. 3 gives an example of a relation between leaf reflectance and leaf chlorophyll content of a wheat canopy (Schellberg, 1990). Leaf chlorophyll content in its turn is related to leaf nitrogen content. Leaf optical properties in the PAR region may be ascertained by spectral measurements in the visible region (VIS) of the electromagnetic (EM) spectrum. However, at low soil cover the measured signal will be confounded by soil influence. As a result, the signals from a crop and from the soil background are difficult to separate, unless the spectral soil signature is known so that a correction of the signals is possible. At complete coverage spectral measurements in the VIS offer information only on leaf colour. However, since the signal in VIS at complete coverage is relatively low, it may be heavily confounded by atmospheric effects for which must be corrected. Only field (spectro)radiometers provide undistorted signals.

Another measure of chlorophyll content may be offered by the so-called red edge index (blue shift) (Horler et al., 1983). The position of the red edge is defined as the position of the main inflexion point of the red infrared slope. A decrease in leaf chlorophyll content results into a shift of the red edge towards the blue.

2. LINKING OPTICAL REMOTE SENSING WITH GROWTH MODELS

2.1 Framework

Two methods can be distinguished to link optical remote sensing data with crop growth models. In the first method, called **'crop parameter estimation'**, crop parameters are estimated from optical remote sensing and 'fed' into a growth model as input or forcing function. Mostly, crop parameters that have been used succesfully so far are measures for the fractional light interception by the canopy, namely LAI and soil cover (Steven et al., 1983; Kanemasu et al., 1984; Maas, 1988; Bouman & Goudriaan, 1989). However, parameters like LAD and leaf colour can also be used as input in more elaborate growth models such as those described in this paper. In section 2.3, some methods for deriving these parameters from optical remote sensing data will be presented.

In the second method, called **'model re-parameterization'**, crop growth models are re-parameterized on time-series of remote sensing measurements. Maas (1988) presented a method in which crop growth model parameters were adjusted in such a way that simulated values of LAI by the growth model matched LAI values that were estimated from reflectance measurements. Bouman (1992b) developed a procedure in which remote sensing models (a.o. optical reflectance) were linked to crop growth models so that canopy reflectance was simulated together with crop growth. The growth model was then re-parameterized to match simulated values of canopy reflectance to measured values of reflectance. In a case study for sugar beet, the simulation of (above-ground) biomass was more accurate after re-parameterization than before re-parameterization on reflectance measurements. The re-parameterization in this procedure is governed by the parameters which link the crop growth model and the remote sensing model (so far mainly LAI). Therefore, LAI, LAD and leaf colour, can in principle be used in the re-parameterization when they are made explicit in both the crop and the optical remote sensing model. Especially for LAD and leaf colour, however, this will take further research.

Central to our approach, in both methods, is that we make use of so-called 'explanatory' models as much as possible. For crop growth this means the use of models that are based on an understanding of physical and physiological processes of crop growth, and for optical remote sensing the use of models that are based on an understanding of the interaction of solar radiation with vegetation canopies. In the next section the models used are briefly described.

2.2 Models

SUCROS. In this study the used crop growth model was SUCROS (Simple and Universal CROp growth Simulator; Spitters et al., 1989). It is a mechanistic growth model describing the potential growth of a crop as a function of irradiation, air temperature and crop characteristics. The light profile within a crop canopy is computed on the basis of the LAI and the 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 used for maintenance respiration and for growth. The newly formed dry matter is partitioned to the various plant organs. An important variable that is simulated is the LAI, since the increase in leaf area contributes to next day's light interception and thus rate of assimilation.

SAIL Model. The one-layer SAIL model (Verhoef, 1984) simulates canopy reflectance as a function of canopy variables (LAI, leaf angle distribution and leaf reflectance and transmittance), soil reflectance, ratio diffuse/direct irradiation and solar/view geometry (solar zenith angle, zenith view angle and sun-view azimuth angle). Recently, the SAIL model has been extended with the hot spot effect (Looyen et al., 1991). Leaf inclination distribution functions used with the SAIL model are given by Verhoef & Bunnik (1981).

PROSPECT Model. The PROSPECT model, as developed by Jacquemoud & Baret (1990), is a radiative transfer model for individual leaves. It is based on the generalized "plate model" of Allen et al. (1969, 1970), which considers a compact theoretical plant leaf as a transparent plate with rough plane parallel surfaces. An actual leaf is assumed to be composed of a pile of N homogeneous compact layers separated by N-1 air spaces. The compact leaf (N = 1) has no intercellular air spaces or the intercellular air spaces of the mesophyll have been infiltrated with water. The discrete approach can be extended to a continuous one where N need not be an integer. PROSPECT allows to compute the 400-2500 nm reflectance and transmittance spectra of very different leaves using only three input variables: leaf mesophyll structure parameter N, chlorophyll content and water content. In the visible region, mainly leaf chlorophyll content determines leaf optical properties.

2.3 Crop Parameter Estimation

LAI

Clevers (1988, 1989) has described a simplified, semi-empirical, reflectance model for estimating LAI of a green canopy. First, a WDVI (Weighted Difference Vegetation Index) is ascertained as a weighted difference between the measured NIR and red reflectances in order to correct for soil background:

$$WDVI = r_{ir} - C \cdot r_r \qquad (1)$$

with r_{ir} = total measured NIR reflectance; r_r = total measured red reflectance; and $C = r_{s,ir}/r_{s,r}$ ($r_{s,ir}$ = NIR reflectance of the soil; $r_{s,r}$ = red reflectance of the soil).

Secondly, this WDVI is used for estimating LAI according to the inverse of an exponential function:

$$LAI = -1/\alpha \cdot \ln(1 - WDVI/WDVI_\infty) \qquad (2)$$

Parameters α and $WDVI_\infty$ have to be estimated empirically from a training set, but they have a physical interpretation. Another possibility is to use a canopy reflectance model for theoretically determining the parameters once the input for the canopy reflectance model is known (e.g. leaf optical properties and LAD). Fig. 4 shows simulation results using the SAIL model illustrating this concept. A sensitivity analysis using the SAIL model revealed that the main parameter influencing the relationship between WDVI and green (!) LAI was the LAD (Clevers & Verhoef, 1990; Clevers, 1992).

Bouman et al. (1992) arrived at the same formulation of the relationship between LAI and WDVI through a similar line of reasoning. They empirically found consistent parameters for various years, locations, cultivars and growing conditions for some main agricultural crops, sugar beet, potato, wheat, barley and oats (Uenk et al., 1992).

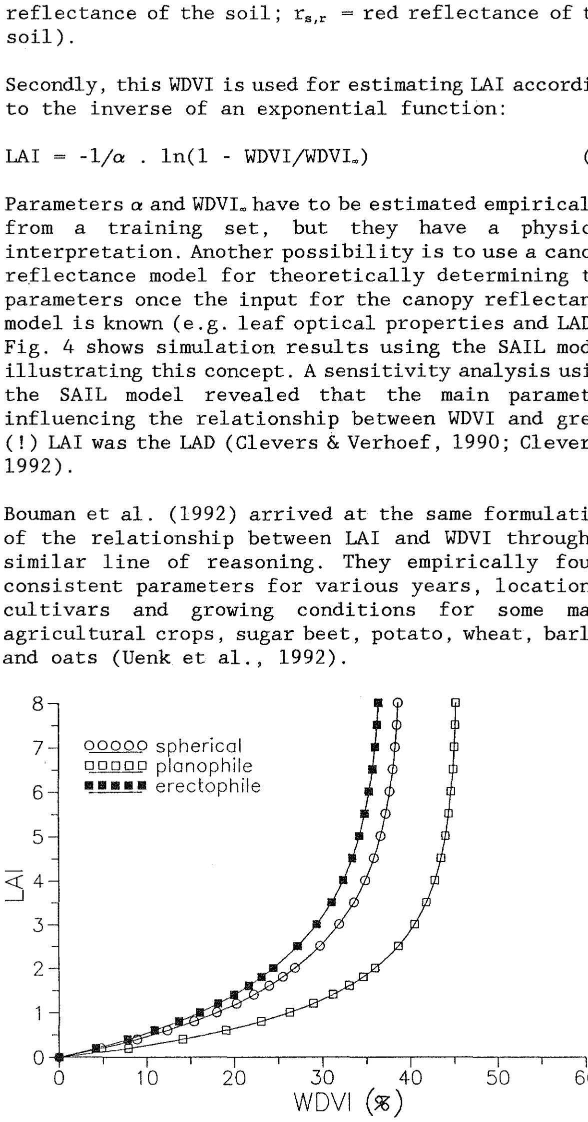

Figure 4. Influence of LAD on a regression of LAI on WDVI as simulated with the SAIL model. From: Clevers & Verhoef, 1990, p.8.

Leaf angle distribution (LAD)

Since the LAD is one of the main parameters influencing the relationship between WDVI and LAI, information on this parameter is very important. In Looyen et al. (1991) the possibilities of acquiring information on both LAI and LAD by means of a so-called dual look (two viewing angles) concept are illustrated. Fig. 5 shows a nomograph of the simulated WDVI (SAIL model) at an oblique viewing angle (52°) plotted against the simulated WDVI at nadir viewing for several LADs and LAI values. By plotting measured WDVI values into this nomograph, an estimate of both LAI and LAD is obtained.

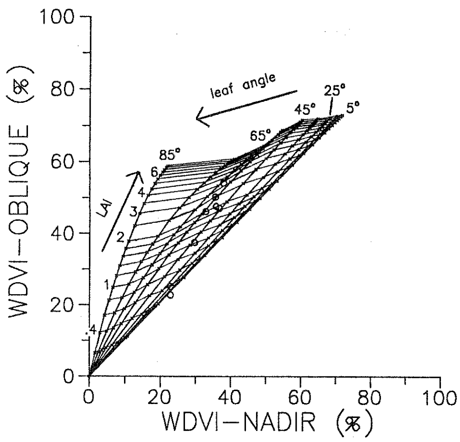

Figure 5. Nomograph illustrating the influence of LAI and LAD (in this graph each LAD consists of just one leaf angle) on the WDVI measured from nadir and the WDVI measured at an oblique viewing angle of 52°. Solar zenith angle of 36° and azimuth angle between plane of observation and sun of 7° as simulated with the SAIL model (measurements are of MAC Europe 1991, CAESAR overflight July 4th - Julian day 185 -, 13.30 GMT).

Leaf colour
As stated before, in practice it will be very difficult to ascertain leaf colour unless leaves are analyzed in the laboratory. A more practical measure may be offered by the red edge index. However, Clevers & Büker (1990) have shown that this index is determined by both LAI and leaf colour (related to leaf chlorophyll content). Two (independent) measurements are therefore needed, one more related to LAI (like WDVI) and one more related to chlorophyll content (like red edge index). Fig. 6 illustrates the simulated influence of LAI and leaf chlorophyll content on the position of the red edge and the WDVI (using a combined PROSPECT-SAIL model). In this study, the method of Guyot & Baret (1988) for determining the position of the red edge was applied, using only four wavelength bands. First,

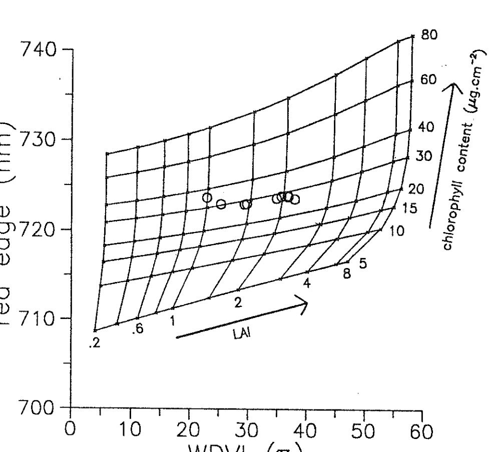

Figure 6. Nomograph illustrating the influence of LAI and leaf chlorophyll content on the WDVI (from nadir) and the position of the red edge as simulated with a combined PROSPECT-SAIL model (measurements are of MAC Europe 1991, Caesar overflight July 4th - Julian day 185 - (WDVI), and AVIRIS overflight July 5th (red edge)).

they estimated the reflectance value at the inflexion point halfway minimum (at 670 nm) and maximum (at 780 nm) reflectance. Secondly, they applied a linear interpolation procedure between the measurements at 700 nm and 740 nm for estimating the wavelength corresponding to the estimated reflectance at the inflexion point. Measurements of the WDVI and the position of the red edge may be combined for ascertaining the leaf chlorophyll content.

3. MAC EUROPE CAMPAIGN - FLEVOLAND TEST SITE

Some of the above principles for linking optical remote sensing with crop growth models will be illustrated with preliminary results from the European multisensor airborne campaign MAC Europe in 1991. A description will be given of the MAC Europe campaign in the Dutch test site Flevoland and of the collected remote sensing and ground truth data.

In the MAC Europe campaign, initiated by the National Aeronautics and Space Administration (NASA) and the Jet Propulsion Laboratory (JPL), both radar and optical airborne measurements were made over selected test sites during the growing season of 1991. One of the test sites was Flevoland in the Netherlands.

In the optical remote sensing domain, NASA executed one overflight with the AVIRIS scanner (for system description, see Vane et al., 1984). In addition, the Dutch experimenters flew three flights with the Dutch CAESAR scanner (for system description, see Looyen et al., 1991). The radar observations made during MAC Europe do not make part of this study and will not be considered here (the synergism between remote sensing data from different sensors is the topic of another study).

Test site. The test site was located in Southern Flevoland in the Netherlands, an agricultural area with very homogeneous soils reclaimed from the lake "IJsselmeer" in 1966. The test site comprised ten different agricultural farms, 45 to 60 ha in extension. Main crops were sugar beet, potato and winter wheat. Due to hailstorms and night-frost damage of the sugar beet in April '91 some of the sugar beet fields were sown for a second time in late April resulting into some yield differences at the end of the season.

Ground truth. Crop parameters concerning acreage, variety, planting date, emergence date, fertilization, harvest date, yield and occurring anomalities were collected for the main crops (Büker et al., 1992). During the growing season, additional parameters were measured in the field. The selected parameters were the estimated soil cover by the canopy (Fig. 7), the

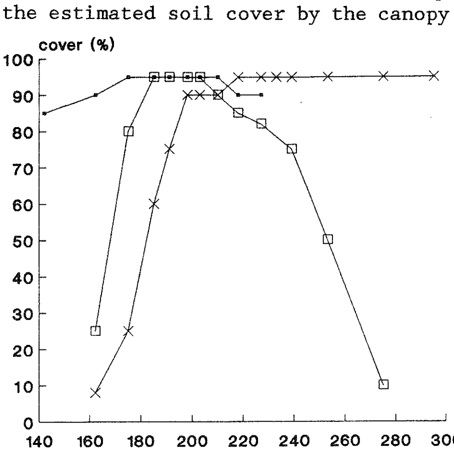

Figure 7. Estimated average soil cover of sugar beet, potato and winter wheat for the 1991 growing season, Flevoland test site.

mean crop height, row distance, plants per m², the soil moisture condition and comments about plant development stage.

Meteorological data. Daily meteorological data are needed as input for crop growth simulation models. For the 1991 growing season these were obtained from the Royal Dutch Meteorological Service (KNMI) for the station Lelystad. Data consisted of daily minimum and maximum temperature, daily global irradiation and daily precipitation.

Leaf optical properties were investigated with a LI-COR laboratory spectroradiometer at the Centre for Agrobiological Research (CABO) in Wageningen. The reflectance or transmittance signature of the upper and lower surface of several leaves was recorded continuously from 400 to 1100 nm wavelength in 5 nm steps. The instrument was calibrated with a white barium sulphate plate.

Field reflectance measurements were obtained during the 1991 growing season with a portable CROPSCAN radiometer (Büker et al., 1992). Eight narrow-band interference filters with photodiodes were oriented upwards to detect hemispherical incident radiation and a matched set of interference filters with photodiodes were oriented downwards to detect reflected radiation. Spectral bands were located at 490, 550, 670, 700, 740, 780, 870 and 1090 nm with a bandwidth of 10 nm. The radiometer was calibrated by pointing towards the sun with both types of photodiodes separately. Percentages reflectance were calculated by the ratio of the signals of both sets of detectors. The sensor head of the radiometer was mounted on top of a long metal pole and positioned three metres above the ground surface. The distance to the crop was 2.5 to 1.5 m depending on the crop height. As the diameter of the field of view (FOV 28°) was half the distance between sensor and measured surface, the field of view varied from 1.23 m² to 0.44 m².

AVIRIS measurements. The ER-2 aircraft of NASA, carrying the airborne visible-infrared imaging spectrometer (AVIRIS), performed a successful overflight over the Flevoland test site on July 5th, 1991. AVIRIS acquires 224 contiguous spectral bands from 0.41 to 2.45 μm. The ground resolution is 20 m as it is flown at 20 km altitude.

CAESAR measurements. The CAESAR (CCD Airborne Experimental Scanner for Applications in Remote Sensing) applies linear CCD arrays as detectors. It has a modular set-up and it combines the possiblities of a high spectral resolution with a high spatial resolution. For land applications three spectral bands are available in the green, red and NIR part of the EM spectrum. One of the special options of CAESAR is the capability of acquiring data according to the so-called dual look concept. This dual look concept consists of measurements performed when looking nadir and under the oblique angle of 52°. Combining these measurements provides information on the directional reflectance properties of objects (Looyen et al., 1991). Successful overflights over the test site were carried out on July 4th, July 23rd and August 29th, 1991.

4. PRELIMINARY RESULTS MAC EUROPE 1991

So far the concepts of chapter 2 have only (partly) been worked out for sugar beet, and these results will be presented here.

4.1 Measurements of Leaf Optical Properties

During July and August 1991 individual leaves of sugar beet were measured in the laboratory with a LI-COR LI-1800 portable spectroradiometer. During this period leaf properties were rather constant. The measurements yielded for a NIR band (at 870 nm) an average reflectance of 46.0% and an average transmittance of 48.4%. These values were respectively 7.3% and 0.6% for a red (at 670 nm) and 15.8% and 13.8% for a green band (at 550 nm). The average scattering coefficient was 0.144 for the whole PAR region.

4.2 Estimating Leaf Angle Distribution (LAD)

Information on LAD was obtained by means of the CAESAR scanner in dual look mode. As explained in Fig. 5, measured WDVI values at an oblique and nadir viewing angle plotted into such a nomograph, based on the actual recording geometry and the leaf optical properties from section 4.1, can yield estimates of both LAI and LAD. Fig. 8 gives the results of July 4th for the CAESAR scanner (note: CROPSCAN measurements over bare soil yielded an estimate for C in Eq. (1) of 1.15) together with simulated curves for a spherical, uniform and planophile LAD (LADs as defined by Verhoef & Bunnik, 1981). In this figure we have shown more realistic LADs as opposed to Fig. 5 with LADs consisting of just one angle. Results for all three dates showed that sugar beet mostly matched the curve for a spherical LAD rather well, except for the beginning of the growing season (LAI<1.5) when the LAD was more planophile. This information is important for determining the relationship between WDVI and LAI. It can also be used to derive extinction coefficients that are input for crop growth models. Currently, SUCROS uses an extinction coefficient for diffuse PAR, which is calculated to be 0.69 for a spherical LAD.

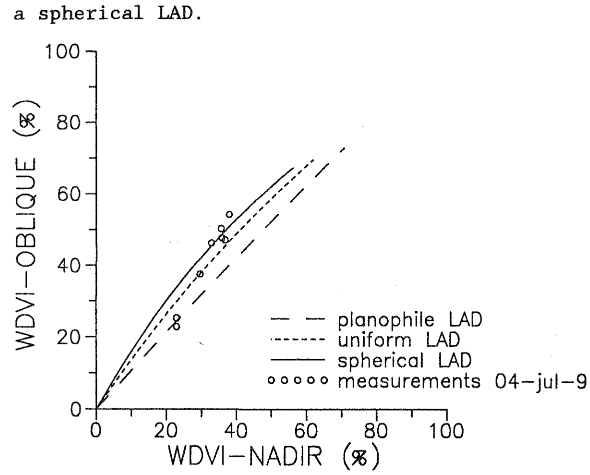

Figure 8. Relationship between the WDVI measured from nadir and the WDVI measured at an oblique viewing angle of 52° for a spherical, uniform and planophile LAD (SAIL model with a hot spot size-parameter of 0.5 for sugar beet) and measurements obtained with CAESAR, July 4th - Julian day 185 -, 1991 (13.30 GMT). Solar zenith angle of 36° and azimuth angle between plane of observation and sun of 7°.

4.3 Estimating Leaf Area Index (LAI)

Using the optical leaf properties found in section 4.1 and the spherical LAD in section 4.2, the relationship between WDVI and LAI was simulated using the SAIL model (cf. Fig. 4). The regression of LAI on WDVI (Eq. 3) yielded for α an estimate of 0.418 and for $WDVI_\infty$ an estimate of 57.5 (spherical LAD). Bouman et al. (1992) found for sugar beet empirically for α an estimate of 0.485 and for $WDVI_\infty$ an estimate of 48.4, whereby the WDVI was based on green reflectance instead of red reflectance. CROPSCAN measurements and SAIL simulations yielded a ratio between green and red reflectances for sugar beet of 1.16. As a result, a value of 48.4 for $WDVI_\infty$ corresponds with a value of 56.3 for a $WDVI_\infty$ based on red reflectances. Fig. 9 illustrates that the simulated relationship and the empirical relationship correspond rather well. Applying the empirical function to measured WDVI values yielded temporal LAI signatures for the sugar beet fields (Fig. 10).

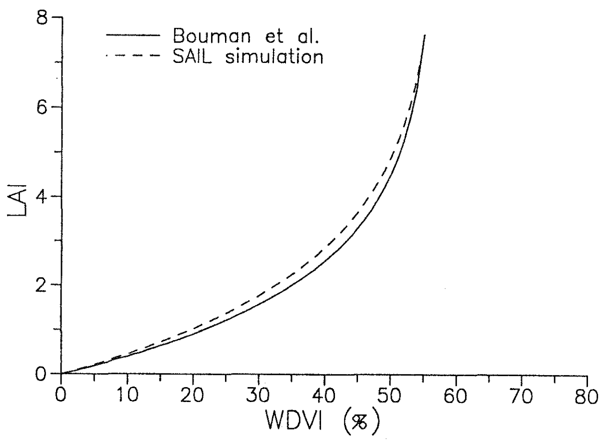

Figure 9. Theoretical (SAIL model) and empirical (Bouman et al., 1992) relationship between WDVI (based on NIR and red reflectances) and LAI for sugar beet.

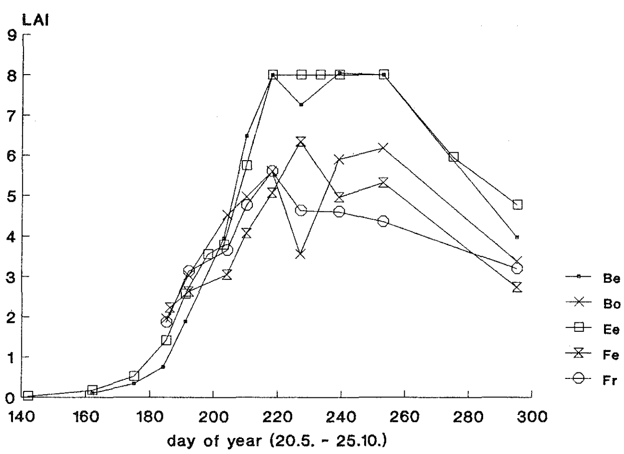

Figure 10. Temporal LAI signatures for sugar beet in 1991.

4.4 Estimating Leaf Optical Properties

Fig. 6 illustrated the influence of LAI and leaf chlorophyll content on the position of the red edge and the WDVI as simulated with a combined PROSPECT-SAIL model. By plotting both the measured WDVI (acquired with CAESAR) and the red edge values (acquired with AVIRIS) into such a nomograph for actual recording conditions, an estimate of both LAI and leaf chlorophyll content is obtained (see Fig. 6). Since AVIRIS data were yet calibrated up to radiances and not to reflectances, WDVI values of CAESAR were used. For calculating red edge values, radiances may be used instead of reflectances (Clevers & Büker, 1991). Results for sugar beet yielded an estimated chlorophyll content of about 28 $\mu g.cm^{-2}$, except for the beginning of the growing season (LAI<1.5) when the chlorophyll content was somewhat higher. By using the PROSPECT model this leaf chlorophyll content yielded an average leaf scattering coefficient in the PAR region of 0.134. This value is comparable to the one found in section 4.1. Also note that the LAI values found in Fig. 6, based on CAESAR/AVIRIS measurements, correspond very well with LAI values derived from CROPSCAN measurements on that day, see Fig. 10. Currently, SUCROS uses a scattering coefficient of 0.20 for all crops.

4.5 Re-parameterizing SUCROS

The crop growth model SUCROS, extended to simulate WDVI from the growing crop (Bouman, 1992b), was run to estimate the final beet yield for ten selected farmers in the test area. Input for the model were the location parameters, weather data for the 1991 growing season, sowing date, harvest date and crop-specific model parameters. The difference between simulated yield and attained yields by the farmers is given in Fig. 11.

Next, SUCROS was re-parameterized so that simulated WDVI during the growing season matched measured WDVI (as measured with the CROPSCAN) as close as possible for all ten fields individually. Since in operational yield estimations information on exact sowing dates are not readily available, SUCROS was also **initialized** on the WDVI measurements (i.e. the sowing date was also parameterized). For the time being, actual harvest dates were used because the reflectance measurements were stopped well before harvest time. Fig. 12 gives the simulated beet yields after model re-parameterization versus actually obtained yields, and the differences between simulated and actual yields are again given in Fig. 11. For all except one fields, the simulated yield after re-parameterization was closer to actually obtained yields than before re-parameterization. On the average, the simulation error of (fresh) beet yield decreased from 6.6 t/ha (8.6%) using 'standard' SUCROS, to 4.0 t/ha (5.2%) with SUCROS re-parameterized to time-series of WDVI.

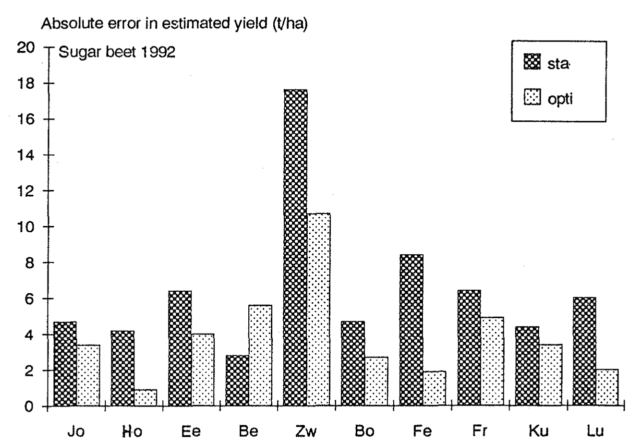

Figure 11. Absolute error (tons/hectare) in estimated beet yield using standard SUCROS (sta) and using SUCROS re-parameterized to measured time-series of WDVI (opti). The different pairs of bars relate to different farmers.

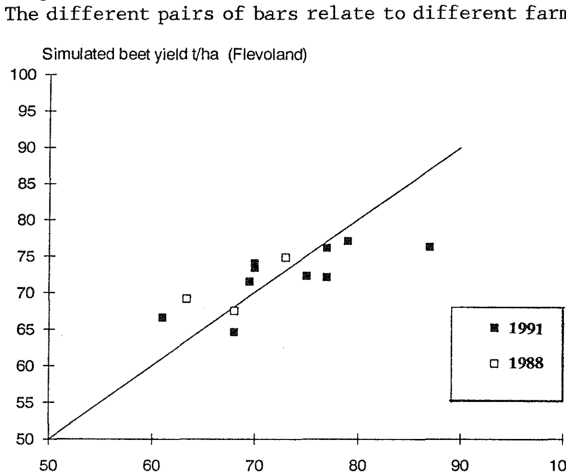

Figure 12. Simulated beet yield using SUCROS re-parameterized to measured WDVI versus actually obtained beet yields for ten farmers in 1991, and for three farmers in 1988, in the Flevopolder test site.

5. SUMMARY AND DISCUSSION

A framework was presented to integrate crop canopy information derived from optical remote sensing with crop growth models for the purpose of growth monitoring and yield estimation. Within this framework, two methods were described. In the first method, crop parameters that play an important role in both the processes of crop growth and canopy reflectance were estimated from optical remote sensing data. These crop parameters were LAI, LAD and leaf colour. For each parameter, an estimation methodology was developed or taken from literature. The estimated parameter values can be used as direct input into crop growth models. In the second method, a crop growth model called SUCROS was extended with a canopy reflectance model to calculate remote sensing signals from the growing crop. The extended growth model can be re-parameterized, or calibrated, on time-series of remote sensing data. The main linking parameter between growth model and the reflectance model was LAI.

The framework was applied to data gathered during the MAC Europe 1991 campaign over the Dutch test site Flevoland. Initial results for sugar beet indicated the feasibility of estimating LAI, LAD and leaf colour from optical reflectance measurements. As yet, these parameter estimations have not been implemented in the growth model (SUCROS). A critical point to consider is the precision and additional value of the parameter values derived from remote sensing compared to the standard values already used in the growth model. For instance, the LAD value that was derived for sugar beet from the CAESAR measurements confirmed the spherical LAD currently used in SUCROS (section 4.2). Leaf scattering coefficient was found to be about 0.14 (sections 4.1 and 4.4) instead of 0.20, but the simulation of biomass is not very sensitive to leaf scattering coefficient in the range of 0.1 to 0.3. In contrast, much relative benefit might be obtained from the estimation of leaf colour expressed in leaf nitrogen/chlorophyll content. Especially the modelling of leaf nitrogen status in canopies is extremely complicated (but equally important through its effect on maximum leaf photosynthesis rate) and actual information derived from optical reflectance would be valuable. However, it will take more research and dedicated experiments together with crop physiologists to investigate the potentials of optical remote sensing for the assessment of leaf (or canopy) nitrogen status.

The method of model re-parameterization was also tested on sugar beet. For nine out of ten fields, the simulated yield was better in agreement with actually obtained yields after model re-parameterization than without model re-parameterization. Since the re-parameterization procedure mainly concerned the calibration of the simulated LAI, these results indicate the importance of LAI for accurate growth simulation.

Within the framework for integrating remote sensing data and crop growth models, both methods 'crop parameter estimation' and 'model re-parameterization' have to be used together in a combined approach. Crop parameter estimation can best be used to estimate crop model inputs (crop parameters) that are relatively stable throughout the growing season, such as LAD and leaf colour of sugar beet. Model re-parameterization is especially suited to calibrate the simulation of relatively dynamic variables, such as LAI.

By using inversion techniques, remote sensing model parameter estimation is also possible. Depending on the amount of physiological and hydrological relations which could serve as *a priori* information, the parameter estimation by inversion might be successful. Subsequently, crop growth model parameters may be adjusted so that simulated values of LAI by the growth model match LAI values estimated after inversion of reflectance models (cf. Maas, 1988).

The framework can be extended to include other parameters that are relevant to both crop growth and optical reflectance. Moreover, the framework can incorporate other remote sensing techniques as well, such as radar, passive microwave or thermal remote sensing (Bouman, 1991).

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REFERENCES

Allen, W.A., H.W. Gausman, A.J. Richardson & J.R. Thomas, 1969. Interaction of isotropic light with a compact plant leaf. J. Opt. Soc. Am. 59: 1376-1379.

Allen, W.A., H.W. Gausman & A.J. Richardson, 1970. Mean effective optical constants of cotton leaves. J. Opt. Soc. Am. 60: 542-547.

Asrar, G. (ed.), 1989. Theory and applications of optical remote sensing. New york: John Wiley & Sons, Inc., 734 pp.

Bouman, B.A.M., 1991. Linking X-band radar backscattering and optical reflectance with crop growth models. Thesis Agricultural University Wageningen, Wageningen, the Netherlands.

Bouman, B.A.M., 1992a. The accuracy of estimating the leaf area index from vegetation indices derived from crop reflectance characteristics, a simulation study. Int. J. Rem. Sensing (in press.)

Bouman, B.A.M., 1992b. Linking physical remote sensing models with crop growth simulation models, applied for sugar beet. Int. J. Rem. Sensing (in press.)

Bouman, B.A.M., H.W.J. van Kasteren & D. Uenk, 1992. Standard relations to estimate ground cover and LAI of agricultural crops from reflectance measurements (in prep.)

Bouman, B.A.M. & J. Goudriaan, 1989. Estimation of crop growth from optical and microwave soil cover. Int. J. Rem. Sensing 10: 1843-1855.

Büker C., J.G.P.W. Clevers, H.J.C. van Leeuwen, B.A.M. Bouman & D. Uenk, 1992. Optical component MAC Europe ground truth report - Flevoland 1991. Wageningen Agricultural University, Dept. Landsurveying & Remote Sensing, Report LUW-LMK-199204.

Bunnik, N.J.J., 1978. The multispectral reflectance of shortwave radiation by agricultural crops in relation with their morphological and optical properties. Thesis Agricultural University Wageningen, Wageningen, the Netherlands.

Clevers, J.G.P.W., 1988. The derivation of a simplified reflectance model for the estimation of Leaf Area Index. Rem. Sens. Envir. 25: 53-69.

Clevers, J.G.P.W., 1989. The application of a weighted infrared-red vegetation index for estimating Leaf Area Index by correcting for soil moisture. Rem. Sens. Envir. 29: 25-37.

Clevers, J.G.P.W., 1992. Modelling and synergetic use of optical and microwave remote sensing. Report 4: Influence of leaf properties on the relationship between WDVI and LAI: a sensitivity analysis with the SAIL and the PROSPECT model. Wageningen Agricultural University, Dept. Landsurveying & Remote Sensing, Report LUW-LMK-199202, 31 pp.

Clevers, J.G.P.W. & C. Büker, 1991. Feasibility of the red edge index for the detection of nitrogen deficiency. Fifth Int. Coll. on Physical Measurements and Signatures in Remote Sensing, Courchevel, France, ESA SP-319, pp. 165-168.

Clevers, J.G.P.W. & W. Verhoef, 1990. Modelling and synergetic use of optical and microwave remote sensing. Report 2: LAI estimation from canopy reflectance and WDVI: a sensitivity analysis with the SAIL model. BCRS report 90-39, 70 pp.

Goel, N.S. & D.W. Deering, 1985. Evaluation of a canopy reflectance model for LAI estimation through its inversion. IEEE GE-23: 674-684.

Guyot, G. & F. Baret, 1988. Utilisation de la haute resolution spectrale pour suivre l'etat des couverts vegetaux. Proc. 4th Int. Coll. on Spectral Signatures of Objects in Remote Sensing, Aussois, France, 18-22 January 1988 (ESA SP-287, April 1988).

Horler, D.N.H., M. Dockray & J. Barber, 1983. The red edge of plant leaf reflectance. Int. J. Rem. Sensing 4: 273-288.

Jacquemoud S. & F. Baret, 1990. PROSPECT: a model of leaf optical properties spectra. Rem. Sens. Envir. 34: 75-91.

Kanemasu, E.T., G. Asrar & M. Fuchs, 1984. Application of remotely sensed data in wheat growth modelling. In: Wheat growth modelling: 357-369, Edited by Day, W. and R.K. Atkin (Plenum Press, New York and London, Published in cooperation with NATO Scientific Affairs Division).

Keulen, H. van & J. Wolf (eds.), 1986. Modelling of agricultural production: weather, soils and crops. Simulation monograph, PUDOC, Wageningen, The Netherlands.

Keulen, H. van & N.G. Seligman, 1987. Simulation of water use, nitrogen nutrition and growth of a spring wheat crop. Simulation monograph, PUDOC, Wageningen, The Netherlands.

Looyen, W.J., W. Verhoef, J.G.P.W. Clevers, J.T. Lamers, & J. Boerma, 1991. CAESAR: evaluation of the dual-look concept. BCRS report 91-10, 144 pp.

Maas, S.J., 1988. Use of remotely sensed information in agricultural crop growth models. Ecological modelling 41: 247-268.

Penning de Vries, F.W.T. & H.H van Laar (Eds.), 1982. Simulation of plant growth and crop production. Simulation Monographs. Wageningen: Pudoc, 308 pp.

Richardson, A.J. & C.L. Wiegand, 1977. Distinguishing vegetation from soil background information. Photogram. Eng. Rem. Sensing 43: 1541-1552.

Schellberg, J., 1990. Die spektrale Reflexion von Weizen - ein Beitrag zur Zustandsbeschreibung landwirtschaftlicher Kulturpflanzenbestände durch Fernerkundung. PhD Thesis, Rheinischen Friedrich-Wilhelms-Universität, Bonn, 160 pp.

Spitters, C.J.T., H. van Keulen & D.W.G. van Kraailingen, 1989. A simple and universal crop growth simulator: SUCROS87. In: Simulation and systems management in crop protection. Ed.: R. Rabbinge, S.A. Ward & H.H. van Laar. Simulation Monographs 32. Wageningen: Pudoc, 420 pp.

Steven, M.D. & J.A. Clark (Eds.), 1990. Applications of remote sensing in agriculture. London: Butterworths, 427 pp.

Steven M.D., P.V. Biscoe & K.W. Jaggard, 1983. Estimation of sugar beet productivity from reflection in the red and infrared spectral bands. Int. J. Rem. Sensing 2: 117-125.

Suits, G.H., 1972. The calculation of the directional reflectance of a vegetation canopy. Rem. Sens. Envir. 2: 117-125.

Tucker, C.J., 1979. Red and photographic infrared linear combinations for monitoring vegetation. Rem. Sens. Envir. 8: 127-150.

Uenk, D., B.A.M. Bouman & H.W.J. van Kasteren, 1992. Reflectiemetingen aan landbouwgewassen. CABO Verslag 156, 56 pp.

Vane, G., M. Chrisp, H. Enmark, S. Macenka & J. Solomon, 1984. Airborne Visible/Infrared Imaging Spectrometer: An advanced tool for Earth remote sensing. IGARSS '84, SP215, 751.

Verhoef, W., 1984. Light scattering by leaf layers with application to canopy reflectance modelling: the SAIL model. Rem. Sens. Envir. 16: 125-141.

Verhoef, W. & N.J.J. Bunnik, 1981. Influence of crop geometry on multispectral reflectance determined by the use of canopy reflectance models. Proc. Int. Coll. on Signatures of Remotely Sensed Objects, Avignon, France, pp. 273-290.

Wit, C.T. de, 1965. Photosynthesis of leaf canopies. Agricultural Research Report 663, Centre for Agricultural Publications and Documentation (PUDOC), Wageningen, The Netherlands.