COMPARISONS OF CROP YIELD PREDICTION USING BOTH MICROWAVE AND OPTICAL DATA

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ABSTRACT:

Under the ESA study contract NR 9837/92/NL/GS synergy in the modelling of microwave with optical remote sensing data has been studied for agricultural crops. One of the most important issues is whether we could expect synergy from various remote sensing sources for crop yield prediction. Crop yield can be predicted already at an early stage of growth using various kinds of crop growth models with various levels of complexity. However, estimates of crop growth and thus yield predictions often are inaccurate for non-optimal growing conditions, e.g. due to pest and desease incidence, drought, frost damage or fertilizer defiency. Remote sensing can provide information on the actual status of agricultural crops, thus offering the possibility of calibrating the growth modelling.

In this study we will analyse radar backscatter and optical reflectance from sugar beet crops at the MAC Europe 1991 Flevoland test site and we will examine the relations with the growth and development stages of sugar beet. Our final goal is then to answer the question whether radar can monitor sugar beet growth throughout the whole growing season and whether radar measurements can contribute to synergism with optical data in predicting sugar beet yield. The information from radar remote sensing is used in a twofold manner. Firstly, biomass is estimated by inversion of the Cloud model and, secondly, the use of structure changes of the sugar beet crop on the backscatter will be discussed. The Flevopolder dataset of Mac Europe 1991 is used.

Keywords: Radar, optical, remote sensing, inversion, crop growth, energy balance, synergy, biomass, plant structure , modelling.

1. INTRODUCTION

In agricultural market economics knowledge of crop production at an early stage is very important at both national and regional level. The two constituents of crop production are crop acreage and crop yield. In order to estimate or predict crop yield, best results are obtained if the growth of the crops is being monitored during the growing season. The crop variable leaf area index (LAI) is important as a measure for crop growth.

Crop growth can be monitored by using crop growth models. However, estimates of crop growth often are inaccurate for non-optimal growing conditions. Remote sensing can provide information on the actual status of agricultural crops, thus calibrating the growth model for actual growing conditions. Best results are obtained by using (reflective) optical remote sensing data (e.g. some vegetation index) in estimating the LAI regularly during the growing season and subsequently calibrating the growth model on time-series of estimated LAIs (Clevers & van Leeuwen, 1994). However, at national and regional scale in Europe the regular acquisition of optical remote sensing data is hampered by frequent cloud cover. Radar remote sensing data offer a solution in acquiring remote sensing information with a high temporal resolution due to its all-weather capability (van Leeuwen & Clevers, 1994). Moreover, data from both windows provide complementary information and the combined use, either contemporary or at different times during the growing season, can improve the estimation of crop variables.

In this paper we will try to answer the question whether we can expect synergy from optical and microwave remote sensing for crop yield prediction. With synergy we mean that a methodology based on both optical and microwave data in principle is superior to a methodology based on either optical or microwave data solely. In the applied methodology optical and radar remote sensing techniques are combined with crop growth models (in this paper SUCROS is used as an example) through the LAI as the essential link. The LAI is estimated with the derived inverse remote sensing models and brought in the calibration process of the crop growth model with the appropriate weight factor. Data on sugar beet from the MAC Europe 1991 campaign over the Dutch test site Flevoland will be used for illustration. Separate parts of the methodology have been reported before by Clevers & van Leeuwen (1994), van Leeuwen & Clevers (1994) and van Leeuwen et al. (1994a). A detailed description of the MAC Europe campaign for Flevoland and the data gathered has been given by Büker et al. (1992a,b).

2. CROP GROWTH MODELS

Since the 19th century, agricultural researchers have used modelling as a tool to describe relationships between crop growth (yield) 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, site characteristics, environmental characteristics and the initial conditions defined by the date at which the crop emerges.

SUCROS (Simplified and Universal Crop Growth Simulator, Spitters et al., 1989) is a mechanistic crop growth model that describes the potential growth of a crop from irradiation, air temperature and crop characteristics. Potential growth means the accumulation of dry matter under ample supply of water and nutrients, in an environment that is free from pests and diseases. The light profile within a crop canopy is computed on the basis of the LAI and the extinction coefficient. Assimilated matter is first used to maintain the present biomass (maintenance respiration) and for the remainder converted into new, structural plant matter (with loss due to growth respiration). The formed dry matter is partitioned to the various plant organs through partitioning factors introduced as a function of the phenological development stage of the crop. An important variable that is simulated is the LAI, since the increase in leaf area contributes to next day's light interception and hence to next day's rate of assimilation.

When applied to operational uses such as yield estimation, models such as SUCROS often appear to fail when growing conditions are non-optimal (e.g. fertilizer deficiency, 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 through out the growing season. For this checking of the actual growing conditions, an observation technique should be applied that can be operational in practice for very large areas (up to at least national level). Remote sensing can provide such information (Bouman, 1991).

3. OPTICAL REMOTE SENSING

A simplified, semi-empirical reflectance model for estimating LAI of a green canopy was introduced by Clevers (1988, 1989). It is called the CLAIR model. In this model, first, the WDVI (= weighted difference vegetation index) was ascertained as a weighted difference between the measured NIR and red reflectances, assuming that the ratio of NIR and red reflectances of bare soil is constant (the weight factor). In this way a correction for the influence of soil background is performed. Subsequently, this WDVI was used for estimating LAI according to the inverse of an exponential function:

$$LAI = -1/\alpha \, . \, \ln(1 - WDVI/WDVI_{\infty}) \tag{1}$$

with α as a combination of extinction and scattering coefficients describing the rate with which the function of equation (1) runs to its asymptotic value, and $WDVI_{\infty}$ as the asymptotic limiting value for the WDVI.

The exponential relationship between WDVI and LAI means that LAI estimations will be less accurate when approximating the asymptotic value of WDVI ($WDVI_{\infty}$). In other words: the accuracy of LAI estimation will decrease with increasing LAI value. A first order approximation of the standard deviation of the LAI can be derived as:

$$\sigma[LAI] = \exp[\alpha.LAI - \ln(\alpha.WDVI_{\infty})] \, . \, \sigma[WDVI] \tag{2}$$

The validation of the CLAIR model for sugar beet was performed by Bouman et al. (1992). They 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. The residual mean square for the calibration set was 4.1. This value may be used as an estimate of the variance of the individual WDVI measurements. The resulting estimate for the WDVI standard deviation (σ[WDVI] in equation 2) is 2.0. Figure 1 plots the estimated LAI using the CLAIR model against the measured LAI (ground measurements) for the calibration set used by Bouman et al. (1992). In addition, the lines exhibiting deviations +/- two standard deviations from the measured LAI are shown.

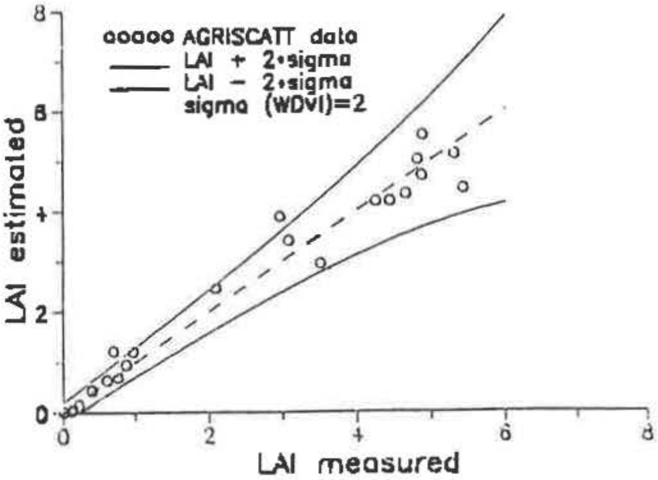


Figure 1. Relationship between estimated LAI using the CLAIR model and measured LAI for sugar beet. Flevoland test site, AGRISCATT campaigns 1987 and 1988.

4. RADAR REMOTE SENSING

4.1 Model-Based Approach

In former studies (Hoekman et al., 1982; van Leeuwen, 1992) it was shown that the Cloud model could be used as a simplified semi-empirical model for the radar backscatter (γ) of agricultural crops:

$$\gamma = C \, . \, (1 - \exp(-D.W.h/\cos\Theta)) + G \, . \, \exp(B.m_s) \, . \, \exp(D.W.h/\cos\Theta) \tag{3}$$

where C, G and D are regression constants, each with their physical meaning. The parameter C represents backscatter at full closure of the crop; G is the dry soil characteristic with roughness information incorporated; D represents the extinction by the canopy layer. B is the sensitivity of backscatter to soil moisture. W is the water content of the vegetation, d is the vegetation height, m_s is the soil moisture content and Θ is the incidence angle. However, in general this model is only valid during the beginning of the growing season, because after closure of the crop a constant backscatter level is reached. Another limitation is the calibration and validation process itself. A high temporal resolution is needed for calibrating the radar model.

For sugar beet a constant relationship (factor A) between the amount of crop moisture (W.h) and the LAI was found (van Leeuwen et al., 1994b):

$$LAI = A \, . \, W \, . \, h \tag{4}$$

For one date in the growing season we may consider the soil moisture content (m_s) and the soil roughness for all sugar beet fields in Flevoland constant. If we put:

$K = C - G.\exp(B.m_v)$ and $D' = D/A$
the Cloud model can be inverted and rewritten as:

$$LAI = -\cos\Theta/D' \, . \, \ln((\gamma - C)/-K) \qquad (5)$$

Similarly as with the CLAIR model we find an exponential relationship between remote sensing measurement and LAI. Again, the accuracy of LAI estimation will decrease with increasing LAI value. A first order approximation of the standard deviation of the LAI can be derived as:

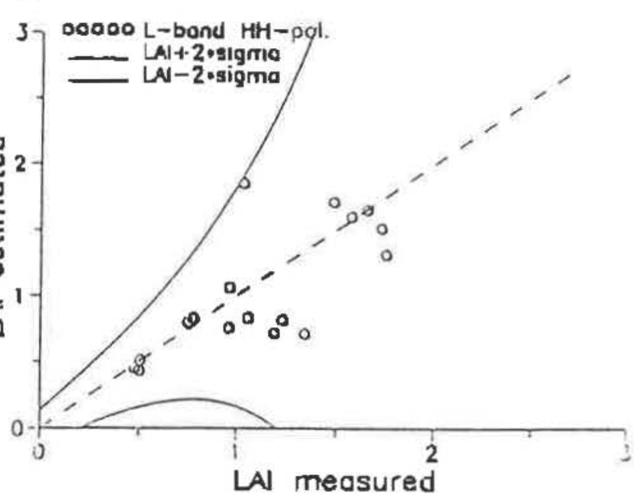
$$\sigma[LAI] = \cos\Theta/(K.D') \, . \, \exp(D'.LAI/\cos\Theta) \, . \, \sigma(\gamma) \qquad (6)$$

Since no LAI measurements were performed during MAC Europe 1991 in Flevoland, (optical) AVIRIS data were used for calibrating the Cloud model (van Leeuwen et al., 1994b). An intersection was made of all sugar beet fields in the AVIRIS image with all sugar beet fields in the AIRSAR image of the beginning of July 1991. Data extraction resulted in a total of 37 sugar beet fields for 2 polarizations (HH,VV) and 3 frequencies of the AIRSAR (C-, L- and P-band; resp. 5.3 GHz, 1.3 GHz and 0.3 GHz). Calibration results showed that L-band HH and C-band VV-polarization were useful to invert. They represent also the configuration of the recently launched radar satellites ERS-1 and JERS-1. To calibrate the Cloud model for L-band HH and for C-band VV, a random calibration set of 20 fields was selected from the available fields (table 1). Figure 2 plots the estimated LAI using the Cloud model against the "measured" LAI (from AVIRIS) for the calibration set of MAC Europe. In addition, the lines exhibiting deviations +/- two standard deviations from the "measured" LAI are shown.

Table 1. Calibration results of the Cloud model for sugar beet using data from MAC Europe 1991.

	L-band HH	C-band VV
D' parameter	0.8967	0.3660
C parameter	0.1369	0.6821
K parameter	0.1767	0.4394
R-square	0.6250	0.6665
$\sigma[\gamma]$	0.022	0.055

(a)



(b)

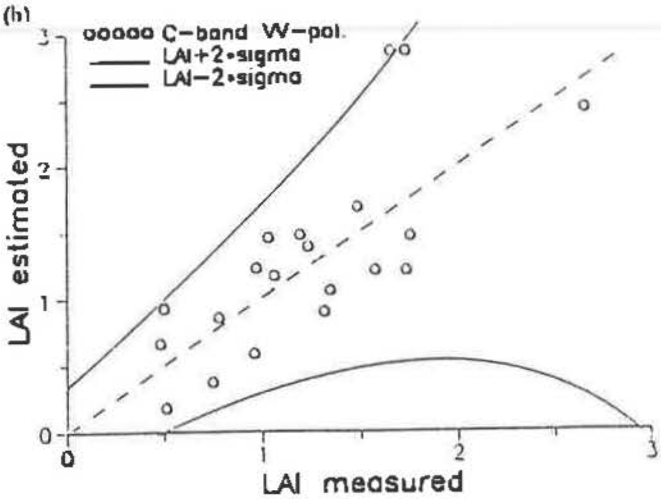


Figure 2. Relationship between estimated LAI using the Cloud model and measured LAI for sugar beet in L-band HH-polarization (a) and C-band VV-polarization (b). Flevoland test site, MAC Europe 1991 campaign.

4.2 Feature-Based Approach

Observed variations in radar backscatter of a crop after closure are mainly attributed to variations in canopy structure (Rijckenberg & van Leeuwen, 1994). The seasonal behaviour of backscatter (X-band) from sugar beet has been studied by de Loor (1984). He showed that the temporal shape of backscatter curves is typical for specific canopies. Bouman & van Kasteren (1990) have detected specific features in wheat and barley, due to transitions in development stages.

In data sets that were obtained over a period of seventeen years in The Netherlands, significant changes in the backscatter of sugar beet canopies were found coinciding with transitions in development stage (Rijckenberg & van Leeuwen, 1994; see figure 3). These transitions could be associated with consistent temperature sums. The temperature sum (T_{sum}) is defined as the integrated daily average temperature from the moment of emergence onwards. The temperature sum is the main environmental factor affecting crop development.

Of interest are the maximum in gamma which occurs at values of T_{sum} between 400 and 500, corresponding with an LAI ~ 2 - 3, and a dip at T_{sum} ~ 900-1000, corresponding with an LAI ~ 4 - 5. By comparing the different backscatter data, these two features, corresponding with two periods in the growing season of sugar beet, were recognized:

(1) at T_{sum} ~ 400-500 (closure of the crop) there is a maximum in the backscatter. This is the top of the characteristic bump in the temporal curve of backscatter from sugar beet.
(2) at T_{sum} ~ 900-1000 (no additional leaf formation) a drop (about 2 dB) in the backscatter is found.

Two changes in the leaf angle distribution (LAD) during the growing season were observed at the Flevoland test site. In the partial coverage situation there is an initial distribution which is a combination of spherical and erectophile leaves (feature 1).

Secondly, a maximal erectophile distribution is reached at the moment that the leaves tend to droop (feature 2). De Wit (1965) and Ross (1981) also found that the LAD changed during the second half of the growing season from erectophile

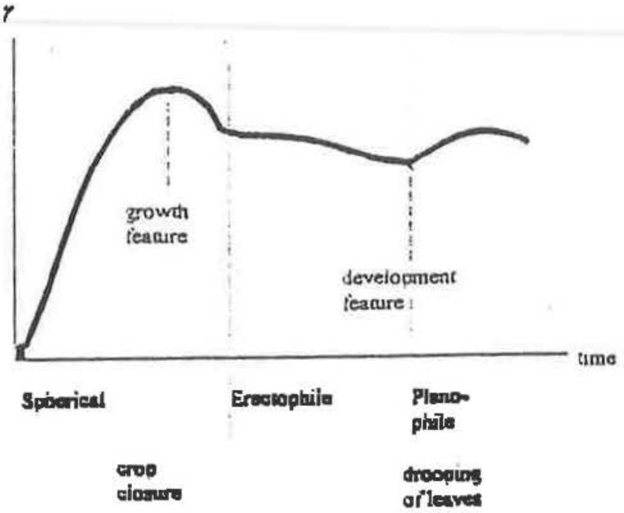


Figure 3. Temporal curve of backscatter from sugar beet with the features indicated as seen in several temporal data sets (ROVE 1980, MAC Europe 1991, ERS-1 1992).

to a more planophile distribution. The increase of the average leaf angle by competition of the neighbouring plants, occurring especially at closure, is therefore development stage related (feature 1, see figure 3). During feature 2 a transition occurs of leaves with an erectophile/spherical LAD into a planophile LAD. This is the point that the outer leaves get more weight and that the tuber of the beet is growing.

When it would be possible to locate the second feature accurately as a function of time, this would yield two kinds of information for the calibration of the crop growth model:

(1) the moment of temperature sum=900, which, in combination with meteorological data, would render a possibility to estimate the actual sowing date by calculating backwards the cumulative temperature;

(2) the moment at which LAI=4.0 occurs.

It must be realized that this is limited a priori information with limited accuracy that one can obtain from radar data. It might get significant in combination with LAI estimates from radar data or optical data or both.

5. COMBINED USE OF CONTEMPORARY OPTICAL AND RADAR DATA

When looking at the results in section 4.1, it is striking that the standard deviation of LAI estimation from radar becomes quite large already at small LAI values. This is quite contrary to the situation in the optical domain as described in section 3. The comparison between standard deviations of LAI estimates from optical and radar measurements is illustrated in figure 4. This figure clearly illustrates that the accuracy of LAI estimation from radar measurements is much worse than from optical measurements except for very low LAI values. So, only little additional value is to be expected from radar measurements for LAI estimation when optical measurements are available and no synergy occurs in the estimation of LAI.

The significance of radar measurements lies in the possibility of obtaining information about crop growth at periods that optical remote sensing is not possible from a practical point of view (mainly caused by bad weather conditions) and in the possibility of obtaining information about the plant structure. Therefore, in the rest of the study emphasis is put on monitoring the growth of crops in a dynamical way using growth models (non-contemporary approach). However, it must be noted that the above-described contemporary approach does yield synergy in the way that optical remote sensing measurements are used for calibrating the Cloud model, which would not have been possible without optical data in this study.

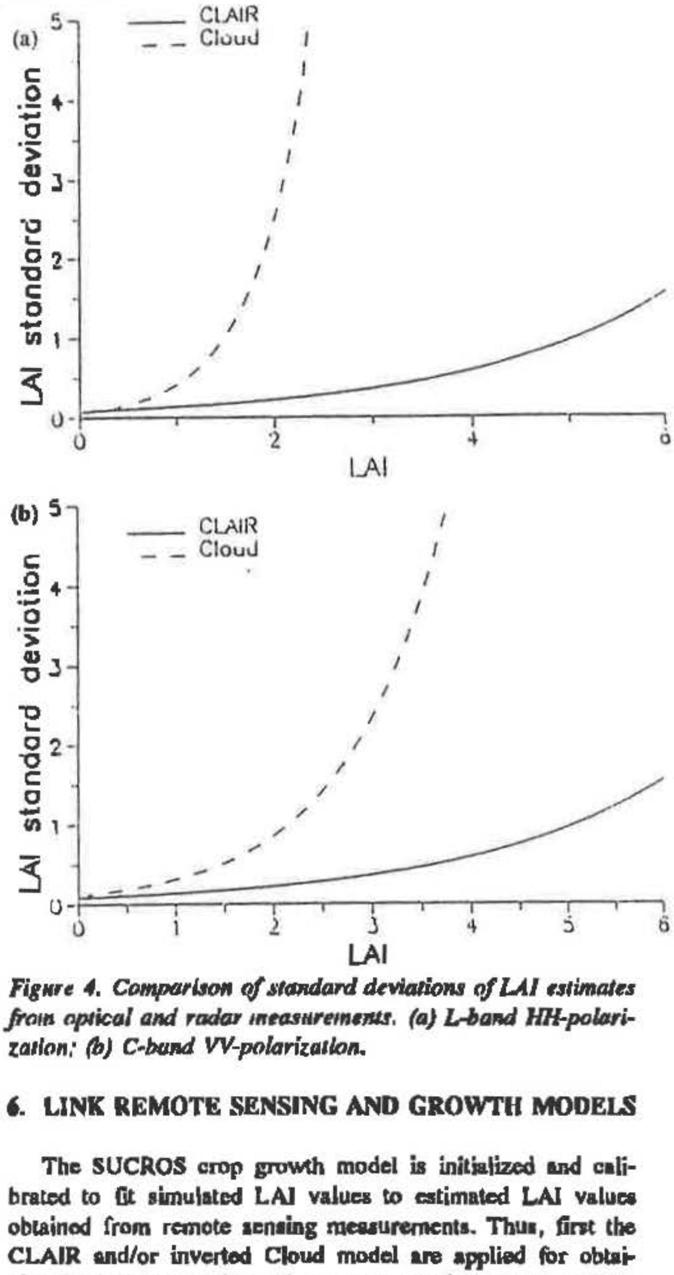


Figure 4. Comparison of standard deviations of LAI estimates from optical and radar measurements. (a) L-band HH-polarization; (b) C-band VV-polarization.

6. LINK REMOTE SENSING AND GROWTH MODELS

The SUCROS crop growth model is initialized and calibrated to fit simulated LAI values to estimated LAI values obtained from remote sensing measurements. Thus, first the CLAIR and/or inverted Cloud model are applied for obtaining LAI estimates from the remote sensing measurements. Subsequently, the SUCROS model is calibrated on these LAI estimates. Since we have seen that the accuracy of the LAI estimates depends on the absolute value of the LAI, the reciproke of the standard deviation of LAI estimation is used as a weight factor for each individual LAI estimate used in the optimization procedure. For LAI estimates from optical measurements equation (1) is used and for LAI estimates from radar measurements equation (5) is used. In addition, parameter estimates obtained during the calibration of CLAIR and Cloud model, respectively, are used in these equations. This approach yields at the same time a proper mutual weighting between optical and radar data when data from both windows are used together in the optimization procedure. Moreover, it is obvious that for the methodology it is not relevant whether one has optical and radar data at the same date or not. In addition, in section 4.2 it was shown that radar remote sensing data may also provide information on crop development stage, which may be used for calibrating the crop growth model in a feature-based combination approach.

7. RESULTS OF MAC EUROPE CAMPAIGN 1991 FOR SUGAR BEET

7.1 Optical Remote Sensing

The crop growth model SUCROS 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 and crop-specific model parameters. This resulted into an estimated beet yield of 60.0 tons/ha. The measurements obtained from three CAESAR recordings (July 4th, July 23rd and August 29th) during the MAC Europe campaign in 1991 over the Flevoland test area were used for testing the calibration procedure for sugar beet using optical data only. The WDVI values obtained from the CAESAR recordings were used for estimating the actual LAI using the fit parameters obtained by Bouman et al. (1992) for sugar beet. Subsequently, SUCROS was calibrated on these three LAI estimates. Results are given in table 2. The comparison between estimated and actual yield is given in figure 5. Results using only three dates during the growing season in the calibration procedure seem to offer quite satisfactory results. On the average, the simulation error of (fresh) beet yield decreased from 13.4 tons/ha (17.5%) using 'standard' SUCROS, to 4.2 tons/ha (5.5%) with SUCROS calibrated on three CAESAR dates (see table 2).

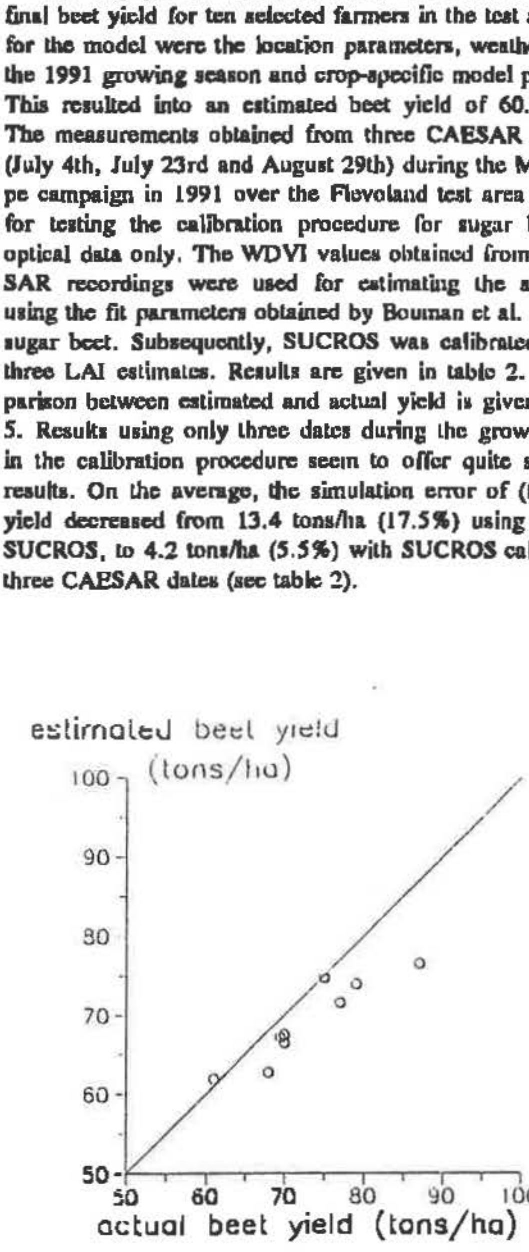


Figure 5. Estimated beet yield using SUCROS calibrated to measured LAI at three optical (CAESAR) recording dates versus actually obtained beet yields.

Table 2. Optical [O] and radar [R] remote sensing configurations with high (10) and lower temporal resolution, used for the combination method and the accompagnying results, represented by yield errors in tons per hectare.

Remote sensing data	category	Average error (t/ha)
Without Remote Sensing	[-]	13.4
CAESAR (3)	[O]	4.2
AIRSAR L-HH (2)	[R]	9.2
AIRSAR C-VV (2)	[R]	7.2
AIRSAR L-HH (2) + CAESAR (3)	[R+O]	3.0
AIRSAR C-VV (2) + CAESAR (3)	[R+O]	3.5
AIRSAR L-HH (2) + CAESAR (3) + feature		3.1
AIRSAR C-VV (2) + CAESAR (3) + feature		2.9

7.2 Radar Remote Sensing

From the MAC Europe campaign 1991 two usable AIRSAR recording dates (July 3rd and July 12th) are available from the beginning of the growing season for sugar beet at the Flevoland test site. It was concluded that the parameters of the Cloud model, as given in table 1, for both L-band HH-polarization and C-band VV-polarization, respectively, may be applied to the measurements of both July 3rd and 12th (van Leeuwen et al., 1994a). As a result, we have two data points during the growing season for a model-based approach using only radar data. By applying equation (5) with the appropriate parameter estimates from table 1, the LAI can be estimated for all sugar beet fields present in both AIRSAR images. Equation (6) offers an estimate of the accuracy of these LAI estimates. Subsequently, SUCROS was calibrated on these LAI estimates from the AIRSAR recordings of July 3rd and July 12th 1991 for the beet fields used before, as far as the corresponding fields were present on both AIRSAR images. Results are given in table 2 for L-band HH and C-band VV. The comparison between estimated and actual yield is illustrated in figure 6 for C-band VV-polarization.
Since we have two recording dates rather early in the growing season, accurate yield estimates cannot be expected. On the average, the simulation error of (fresh) beet yield was 9.2 t/ha (13.0% error) for L-band HH and 7.2 t/ha (9.8% error) for C-band VV, respectively, with SUCROS calibrated on two AIRSAR dates. This is better than the result obtained with "standard" SUCROS without remote sensing information. For sugar beet this is about the best we can expect using only the model-based approach on radar data, since after mid-July (in 1991) the Cloud model cannot be applied anymore.

7.3 The Combination of Optical and Radar Remote Sensing

In this section, LAI estimates from the three CAESAR recordings and the two AIRSAR recordings are integrated and, with their appropriate weight factors, used for calibrating SUCROS. Results are given in table 2 for the three CAESAR recordings in combination with L-band HH and C-band VV radar data. The comparison between estimated and actual yield is illustrated in figure 7. On the average, the simulation error of (fresh) beet yield was 3.0 t/ha (4.2%

error) for L-band HH and 3.5 t/ha (4.8% error) for C-band VV, respecti

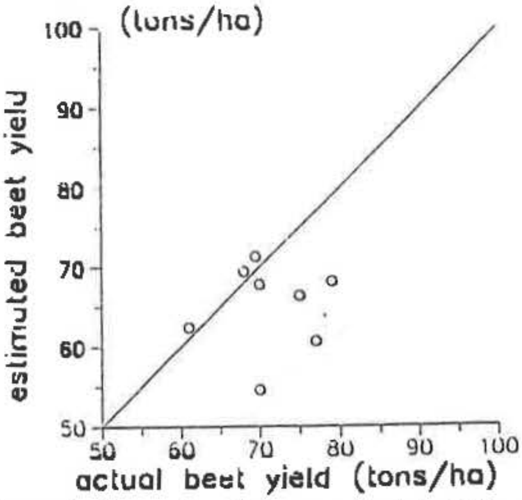


Figure 6. Comparison between estimated yield and actual yield for two AIRSAR recording dates in C-band VV-polarization.

vely. This error is clearly smaller than the one obtained for the three CAESAR recording dates only. These results indicate a synergistic effect by using both optical and radar data for crop growth monitoring. However, under practical conditions only very few optical data during the growing season will be available. For instance, when no optical data from July 4th would be available it is to be expected that radar data from the beginning of July offer a significant improvement to the monitoring of crop growth, particularly at the beginning of the growing season.

7.4 Combination of Model-Based and Feature-Based Approach

As mentioned before, another potential advantage of radar measurements lies in the possibility of obtaining information about crop structure changes. The latter may be related to important transitions in crop development stage.

LAI estimates from the three CAESAR recordings and the two AIRSAR recordings (July 3rd and 12th) in L-band HH-polarization and C-band VV-polarization, respectively, with their appropriate weight factors, were combined with the feature-based information for calibrating the crop growth model. In the optimization of the crop growth model the feature-based information used concerns the occurrence of LAI=4.0 at day number 193 or 209 (and thus the range in between) and a possible range in sowing dates between day 70 and 118. In the optimization procedure the LAI value of 4.0 was given a weight of 1.0 as a first approximation. On the average, the simulation error of (fresh) beet yield was 2.9 t/ha (4.1% error) for C-band VV and 3.1 t/ha (4.5% error) for L-band HH, respectively (see table 2). The comparison between estimated and actual yield is illustrated in figure 8 for C-band VV. These results are somewhat worse for L-band HH and better for C-band VV in comparison to the results obtained with optical and radar data using only the model-based approach.

As a result, the additional value of the feature-based approach is not proven yet. Results indicate that it may get significant when no optical data are available.

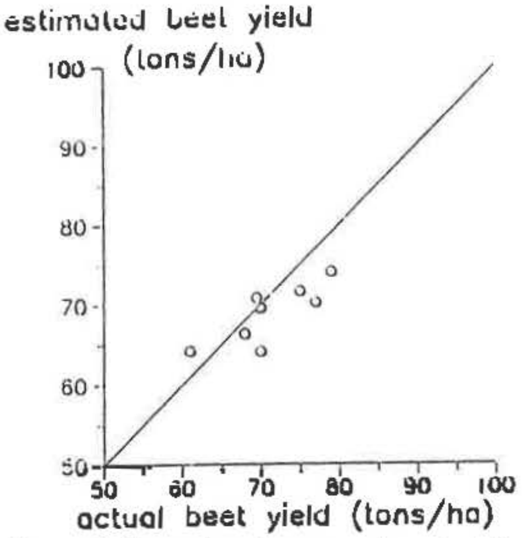


Figure 7. Comparison between estimated yield and actual yield for three CAESAR recording dates and for two AIRSAR recordings in and C-band VV-polarization.

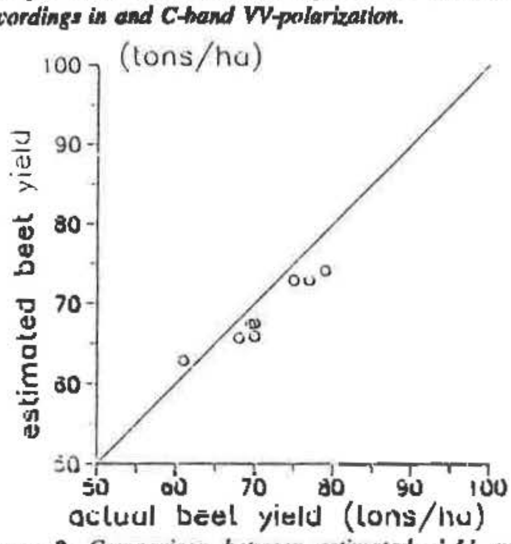


Figure 8. *Comparison between estimated* ***yield and actual yield for*** *three CAESAR recording dates* ***and for two AIRSAR recordings*** *in C-band VV-polarization in* ***combination with the feature-based information.***

8. DISCUSSION AND CONCLUSIONS

For simultaneous (contemporary) observations no synergy occurred in the estimation of LAI. Optical data were most suitable. Calibration of the Cloud model at one date (contemporary) is possible using optical data if enough fields are available for the calibration and the between-field variation is large. Otherwise, more dates must be incorporated.

For operational applications the assumption of non-simultaneous observations is most realistic. For sugar beet, radar data can only be used for estimating LAI early in the growing season (before crop closure). This may be called a model-based approach. After crop closure, radar backscatter is determined by crop structure. However, this still may yield important information for crop growth monitoring. Using the latter information may be called a feature-based approach.

Results for sugar beet indicated that, when a time-series of optical recordings is available, LAI can be monitored well and a good estimate of sugar beet yield at the end of the season is possible by using a calibrated crop growth model. When only a few recording dates with an optical sensor are available, radar recordings at L-band HH-polarization or C-band VV-polarization gave a slight improvement of the results of crop monitoring and yield estimation in comparison to the optical data only. This confirms that the main advantage of radar lies in the possibility to acquire information on crop growth when other techniques (in particular optical techniques) fail.

The additional value of the feature-based approach could not clearly be proven for sugar beet. It is expected that radar features provide more significant information for crops exhibiting more pronounced structural changes during the growing season, e.g. cereals (cf. figure 9).

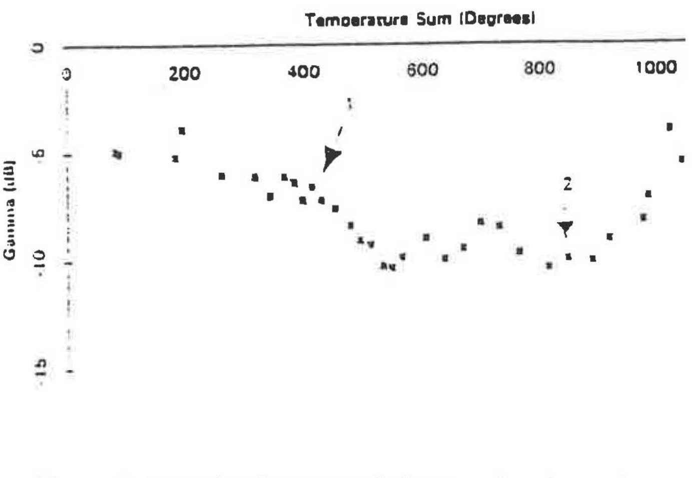


Figure 9: Example of a temporal signature for winter wheat. ROVE measurements, 1979, X-band VV-polarization, 20° incidence angle. Development stage (1) refers to the moment of ear formation, (2) refers to the start of ripening.

ACKNOWLEDGEMENTS

This paper describes a study that was carried out in the framework of the NRSP-2 under responsibility of the Netherlands Remote Sensing Board (BCRS). Parts of it were carried out under contract no. 4530-91-11 ED ISP NL of the Joint Research Centre and contract no. 9837/92/NL/GS of ESA.

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