Methodology for combining optical and microwave remote sensing in agricultural crop monitoring

The sugar beet crop as special case

Hans van Leeuwen

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ter verkrijging van de graad van doctor
op gezag van de rector magnificus,
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des namiddags om vier uur in de aula
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The cover is a painting from Toon Janse: 'Synthesis of nature"

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STELLINGEN

1. In vergelijking met het optisch venster leiden waarnemingen in het microgolfvenster voor de monitoring van gewasgroei op veldniveau op dit moment tot minder bruikbare gegevens, omdat het huidige begrip van interactie tussen microgolfstraling en gewas nog ontoereikend is. *(dit proefschrift)*

2. In de afgelopen 2 decennia zijn remote sensing projecten gestuurd door de ontwikkelingen met betrekking tot sensoren. Het zou beter zijn als toekomstige projecten gestuurd zouden worden door de dynamiek van de gewasgroei. *(dit proefschrift)*

3. Karakteristieke groeicurven per gewastype zijn met microgolf remote sensing op regionaal niveau beter te bepalen dan op veldniveau. *(dit proefschrift)*

4. De verandering in gewasstructuur tijdens het groeiseizoen kan door microgolf remote sensing goed bepaald worden. Voor zover deze verandering duidelijk gerelateerd is aan de ontwikkeling van het gewas (zoals bij granen) en indien er voldoende waarnemingen worden gedaan kan deze informatie gebruikt worden voor ijking van het gewasgroeimodel. *(dit proefschrift)*

5. Voorkennis vanuit gewasgroeimodellen, natuurlijke omgeving en bedrijfsvoering geven voorwaarden voor effectief toepassen van eenvoudige semi-empirische remote sensing modellen in gewasgroeimonitoring. *(dit proefschrift)*

6. Na bestudering van microgolf satelliettijdseries (ERS-1/2) van gewassen met veel bladmassa (zoals suikerbieten en aardappelen) in 3 opeenvolgende jaren in de Flevopolder blijkt dat bodemvocht een veel grotere invloed heeft dan voorspeld met microgolf remote sensing modellen. *(ESA study 11154/94/NL/NB)*

7. Vanuit gewasfysiologisch oogpunt is de informatie afkomstig van het groene deel van het spectrum interessant. De dynamiek van vegetatieindices mede gebaseerd op deze informatie verdient verdere aandacht in het onderzoek op het gebied van gewasgroeimonitoring.
   (Gitelson A., M.N. Merzylak and Y. Grits, 1996. Novel algorithms for remote sensing of chorophyll content in higher plant leaves. Proceedings IGARSS'96, Vol IV: 2355-2357)

8. Voor de bestudering van natuurlijke processen op meerdere ruimtelijke schaalniveaus zijn methodieken gebaseerd op het gebruik van remote sensing en geografische informatie systemen onontbeerlijk. De inzet van deze technologie vraagt om een eigen conceptuele benadering, hetgeen de aanwezigheid van een hierop gerichte discipline op leerstoelniveau binnen de Landbouwuniversiteit rechtvaardigt.

9. Kleine bedrijven met postdoctorale kennis kunnen een verbindende rol spelen tussen universiteiten, instituten en bedrijven, doordat ze in het toegepaste onderzoek de specialistische kennis van deze organisaties kunnen integreren.

10. De zuigkracht van de arbeidsmarkt op AIO's in de remote sensing en geografische informatie verwerking is zo groot dat met werkgevers een aparte regeling getroffen zou moeten worden om ex-AIO's binnen hun nieuwe werkverband de gelegenheid te geven hun proefschrift af te ronden.

11. Specialisatie in het onderzoek is pas verantwoord, indien fragmentatie van kennis wordt voorkomen.

12. De duurzaamheid van onze samenleving is omgekeerd evenredig aan het aantal kilometers dat afgelegd wordt om een alledaags bord vol met eten te krijgen.

Stellingen behorend bij het proefschrift:
Methodology for combining optical and microwave remote sensing in agricultural crop monitoring: the sugar beet crop as special case.
Hans van Leeuwen, 18 september 1996.

Voor mijn Vader en Moeder
Broer en Zus

Preface

In 1989 a preparatory study has been carried out for the Dutch Remote Sensing Board (BCRS) in order to inventarize the possibilities to combine optical and microwave remote sensing data for agricultural and forestry applications (Clevers & Hoekman, 1989). This study was the start of the socalled 'Synergy project'. The project was subsidized by the BCRS for 4 years and started in December 1989. During this period I was employed as assistant research trainee (AIO) and financed by the Department of Landsurveying and Remote Sensing at the Wageningen Agricultural University. My supervisor was Prof. Molenaar.

Normally, the PhD research lasts about 4 years in the Netherlands. Because of additional research projects and duties at the Department, the period was extended to 6 years. Besides the mentioned BCRS project, a study was granted from the European Space Agency. It was one of the first studies tendered by ESA on synergy of optical and microwave remote sensing for agricultural applications. For half a year I was asked to replace Henk Schok, who has been a fine colleague to me and great support in image processing. Together with Jan Clevers I had the opportunity to work on the educational aspects of remote sensing like guidance of students and setting up practical lectures in the last year.

During the last years I felt a great urge to bring theories into practise and took (sometimes nightly) efforts to found the company 'Synoptics' together with my mates of the early hour, Guido Lemoine, Jeroen Huising, Jos Bakker, Paul van Ingen and Lucas Janssen. Sometimes naive, but enthousiastic discussions around the campfire near the stone factory in the 'Uiterwaarden' of Wageningen formed the start of a mature consultancy which forms my present challenge of work.

My first introduction to remote sensing was given by Toon Janse, who has left behind an unforgettable impression. His eccentric attitude strongly appealed to me and he gave me the opportunity to do my MSc thesis in the Faculty of Electrical Engineering, Telecommunication and Teleobservation at the Delft university. With his help and that of Professor Leo Krul, Paul Snoeij and Peter Swart I learned to abridge the gap between theory and practical application of microwave remote sensing during my MSc study in the mid eighties, which appeared to be very helpful in my PhD study and probably in my future career as well.

The first years of my PhD study were difficult, because of the great amount of remote sensing campaigns and data to be processed. Sometimes the objective of the study was complete out of sight and thanks to my guidance group of Martien Molenaar, Henk Buiten, Gert-Jan Rijckenberg, Dirk Hoekman, Jan Goudriaan (later Bas Bouman) and especially Jan Clevers I was brought back on the right trail.

Sometimes it was difficult to separate my social life from work because I experienced the work as very motivating and pleasant. I want to thank Edith Gijsen for the support during the first stages of this study. Especially I want to thank Fons van Leeuwen (Fønske) for his great and warm friendship and who was always there when I needed him as a friend.

The flexibility and great patience of my colleagues at the department were much appreciated and formed the boundary conditions for my activities. Especially Dick de Wit (Diederik) gave me a warm nest feeling at the department and he took care of all the necessary logistics. Furthermore Dirk Joghems, Philip Wenting and Ank Hoeneveld are greatly acknowledged for their help in everyday problems. I want to thank my room mates and PhD colleagues Joost van der Sanden for giving me room in a literally sense as well and Silvia de Hoop also for sharing her thoughts with me on information science. Furthermore discussions with Wim Droessen, Nanna Suryana, Rene van der Schans and Gerrit Epema contributed to this thesis.

Martien Molenaar, my promotor, is much appreciated for his vision and insight helping me to stick to the core of the study and keeping me away from the various side-walks I would have made. The critical questions and remarks of Martien resulted sometimes to a total revision of my draft thesis, which led to better formulation and structure of the work. Together with him and Lucas Janssen we managed to organize the IAPR-TC7 Workshop in Delft in (1992) on integration of GIS and remote sensing.

I want to express my deep admiration for Jan Clevers, my co-promotor, who must have had much patience with his first PhD student, certainly in the writing stage of this thesis, which took me quite some effort to accomplish. Jan and I have had many projects together and I felt strongly motivated by his enthusiasm and work attitude which led us many times into synergy.

All the years during my MSc and PhD, Guido Lemoine (LeMoen) has been a great friend and a fine colleague to me, who supported me (Leo) many times. Together with Ron Schoenmakers (de Schoen; rest in peace) we enjoyed times during conferences, visits to JRC and the writing of several papers together.

Furthermore, I want to thank my PhD colleague Gert-Jan Rijckenberg for the many discussions I had with him on the issues of modelling and microwave remote sensing, which really helped me to get on. The pigheaded discussions with Gert-Jan sometimes led to difficult and hilarious but mostly to very fruitful situations.

Martin Vissers has been a fine colleague and friend during my study and helped me many times in processing and managing the microwave remote sensing and field data.

I want to thank for the support of my MSc students Ina Derksen and Onno Luimstra and PhD student Luce Castagnas for sharing their critical remarks and discussions.

I appreciated the many discussions I had with Bas Bouman, which enlarged my insight in the complex world of crop growth modelling. Gerard Nieuwenhuis is acknowledged for his critical and pragmatical attitude, which put me back to reality once more in my study.

The discussions I had with Maurice Borgeaud en Josef Noll on the synergy topic during several ESA contract studies are very much appreciated and helped me in finishing my thesis.

Hanneke Drijvers is acknowledged for correcting the syntax and the spelling of the manuscript.

In the last stages of my study I experienced the new blind love from Floor de Wit inspiring me to finish the last chapters of my thesis and puberty. Thanks to her patience and help I found the energy to finish my thesis.

Finally, I want to thank my family for their great confidence in me for accomplishing this study.

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PART II APPLICATION OF CONCEPTS

PART III CONCLUDING REMARKS

List of acronymes

AB-DLO	: DLO-Research Institute for Agrobiology and Soil Fertility
Agriscatt	: Campaign with Delft University of Technology scatterometer ('87-'88); ESA. Southern Flevopolder
AIRSAR	: Airborne synthetic aperture radar (polarimeter)
APAR	: Absorbed Photosynthetically Active Radiation
AVIRIS	: Airborne Visible InfraRed Imaging Spectrometer
BCRS	: Begeleiding Commissie Remote Sensing.
CAESAR	: CCD Airborne Experimental Scanner for Applications in RS
CCD	: Charged coupled device
CEO	: Centre for Earth Observation, Joint Research Centre, (EU) Ispra, Italy
CLAIR	: Clevers Leaf Area Index by Reflectance
CROPSCAN	: Hand held radiometer in the visible and NIR region
DISIMP	: Device-Independent Software For Image Processing.
DLO	: Dienst Landbouwkundig Onderzoek
DUTSCAT	: Delft University of Technology Scatterometer
EM	: Electro-Magnetic (spectrum)
ERDAS	: Image processing software.ERDAS Inc. Atlanta, US.
ERS-1	: Environmental Radar Satellite from ESA
ERS-2	: Update of ERS-1
ESA	: European Space Agency
TNO-FEL	: Technical scientific research Centre: Physics and Electronics Laboratory , The Hague, The Netherlands
FMCW	: Frequency modulation by continuous waves: ground based radar used in ROVE period.
FPAR	: Fraction absorbed Photosynthetically Active Radiation
HHR	: Hand held radiometer like CROPSCAN
IRIS	: Canadian X-band airborne synthetic aperture radar
JERS-1	: Japanese L-band Earth Resources satellite synthetic aperture radar
JPL	: Jet Propulsion Laboratory (Pasadena, USA)
JRC	: Joint Research Centre (EU), Ispra Italy.
LAD	: Leaf Angle Distribution
LAI	: Leaf Area Index
LICOR	: laboratory spectroradiometer
LMK	: Landmeetkunde, Department of Landsurveying and RS, Wageningen Agricultural University, The Netherlands.
LOWTRAN	: Atmosperical correction algorithm
KNMI	: Royal Dutch Meteorological Service, de Bilt.

MAESTRO	: First European Campaign on polarimetry for microwaves
NASA	: National Aeronautic Space Administration
NIR	: Near Infra Red
MIMICS	: Michican microwave model for scattering surfaces
PAR	: Photosynthetically Active Radiation
ROVE	: Radar Onderzoek Vegetatie: Dutch research team on microwave RS with respect to agricultural crops ('75-'81)
RS	: Remote Sensing
SAR	: Synthetic Aperture Radar
SAIL	: Scattering by Arbitrarily Inclined Leaves
SBFLEVO	: Prototype software for combining crop growth with RS for sugar beet
SIR-C	: Space Shuttle Imaging Radar (C experiment)
SLAR	: Side Looking Airborne Radar
SPOT	: Système Probatoire d'Observation de la Terre
SQL	: Standard query language, used in common database software like ORACLE, DBASE, etc
SUCROS	: Simplified and Universal Crop Growth Simulator
TM	: Landsat Thematic Mapper
TUD	: Technical University Delft, The Netherlands
WAU	: Wageningen Agricultural University
WDVI	: Weighted Difference Vegetation Index
WWFLEVO	: Prototype software for combining crop growth with RS for winter wheat

INTRODUCTION TO THE STUDY

1 Introduction

1.1 Background to the present study

Accurate and up-to-date information on agricultural production is a vital component in running market economies. At European level, considerable differences between countries in their agricultural production have led to a complex system of rules and subsidies which all rely on a certain level of accuracy regarding agricultural statistics (such as acreage and yield). Such statistics, when collected using conventional methods are, inevitably, out-of-date by the time they are available and there is a growing realization that it may be possible to use a combination of modern information techniques and knowledge to provide realistic estimates of crop yield and production.

Yield prediction is an important tool for industry, farmers and policy makers, facilitating logistic planning of transportation and production, storage and sale at national level and planning at farm level. For the present study some common agricultural crops in The Netherlands were chosen for monitoring crop growth using different sources of information. Crop growth models describe crop growth as a function of time. When assuming standard growing conditions, these models could supply us with a prediction of yield at a certain day later in the growing season.

Since technology for civil purposes has developed dramatically in the last two decades, tools such as computers and sensors have greatly enhanced our understanding of biological processes. In this perspective another source of potential information for yield prediction purposes has presented itself lately, namely observations from the air or space by sensors. Remote sensing (RS) may become a tool to provide useful information for crop growth monitoring and certainly when combined with additional knowledge about crop growth. This thesis focuses on the crop sugar beet and to a lesser extent on winter wheat.

1.2 Crop growth monitoring using growth models

Since the 19th century, agricultural researchers have used modelling as a tool to describe relationships between crop growth and yield and environmental factors that appear to govern crop growth. The majority of the crop growth models that have been developed are in general not applicable at higher aggregation levels other than field level as the description of biophysical relationships is mostly very detailed. In Figure 1.1 the crop growth process is schematized in a general manner.

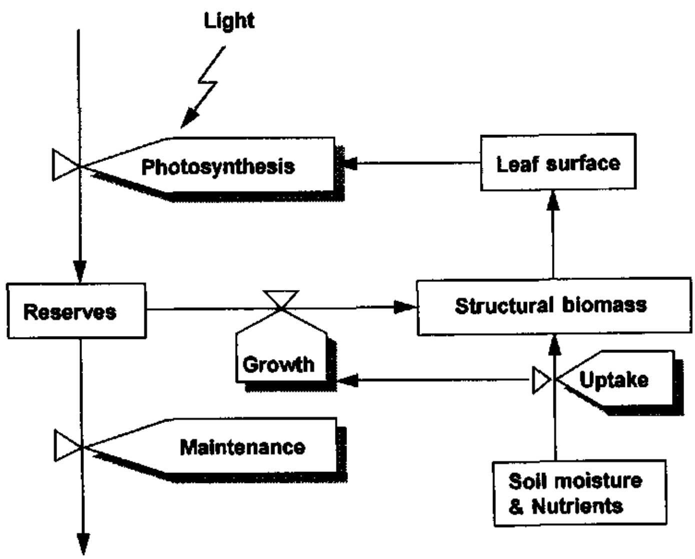


Figure 1.1 *The crop growth process schematized*

Starting point for this study are models and concepts that were developed in The Netherlands by De Wit and co-workers (De Wit, 1965; Penning de Vries & Van Laar, 1982; Van Keulen & Wolf, 1986; Van Keulen & Seligman, 1987; Spitters *et al.*, 1989). These types of model describe the relationship 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 (see also Figure 1.2), simulating the dry-matter production from emergence until maturity. Finally, a simulation of yield at harvest time is obtained. The basis for the calculation of dry matter production is the rate of gross CO_2 assimilation of the canopy. The 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. When applied to operational use, such as yield prediction, crop growth models often appear to fail when the growing conditions are nonoptimal (e.g. pest and disease incidence, nutritional deficiency, severe drought, frost damage). Therefore, for yield estimation, it is necessary to "check" the modelling results with some kind of information on the actual status of the crop throughout the growing season. To check the actual growing conditions, an observation technique is needed that can be applied in practice to very large areas (up to at least national level). Remote sensing (RS) techniques may provide such information.

In this study detailed crop growth models, such as SUCROS (Spitters *et al.*, 1989) are used for the prediction of yield at field level. The use of RS information together with field and meteorological data is studied in more detail.

1.3 Monitoring with the use of RS information

RS techniques have the potential of providing information on agricultural crops quantitatively, instantaneously and, above all, nondestructively over large areas. In the past decades, our knowledge of optical RS techniques and their application to fields such as agriculture has improved considerably (cf Asrar 1989; Steven & Clark 1990). Much research has been devoted to land cover classification and acreage estimation with considerable success. Another field of interest in agriculture is yield prediction. Research on this subject, however, has indicated that RS alone is generally not capable of producing an accurate yield prediction. This has prompted scientists to look for other information that can be combined with RS data in order to give better predictions. Already existing knowledge of the object observed by the remote sensor could be provided by crop growth modelling and serve as a useful piece of information for better interpretation of RS data. In recent years, RS and crop growth simulation models have become increasingly recognized as potential tools for growth monitoring and yield prediction.

Optical RS techniques operating in the spectral window from 0.4 μm to 2.5 μm with respect to this thesis study, receiving reflected solar radiation, have great possibilities for application in agriculture. The status of the physical modelling of solar energy reflected by the earth's surface is better developed than that of microwave energy that is backscattered. For crop growth monitoring good results have already been obtained by using (reflective) optical RS data (e.g. some vegetation index) in estimating the leaf area index (*LAI*) regularly during the growing season. However, the regular acquisition of optical RS data is hampered by frequent cloud cover.

Microwave RS techniques (active RS) operating in the spectral window from 0.01 m to 0.7 m with respect to this thesis study, offer a solution in acquiring RS information with a high temporal resolution owing to its all-weather capability. For operational agricultural applications, optical and microwave sensors and data should be integrated. In this study the emphasis is on the combined use of optical and active microwave RS data linked to crop growth models.

Former research (Bouman, 1991c) on crop growth monitoring with RS was conducted mainly on yield estimation at field level by applying crop growth models calibrated with ground-based measurement techniques. An experiment performed by Bouman (1991c) showed that there might be some superior value in combining optical and microwave RS with crop growth models. Subsequently, the development of methodologies based on airborne and even spaceborne RS needs to be studied for operational purposes.

The major research question here is whether the combined use of both RS windows yields synergy. In this study, synergy is defined as the additional benefit in yield estimation of agricultural crops by using optical and microwave RS together compared to the use of optical or microwave RS separately.

In an article of Space News (July 1993) the following was stated about yield prediction with respect to the crop sugar beet:

' All of British Sugar's activities are really based on the forecast of the sugar beet yield, which is done several months before the harvest. They have to book lorries [trucks], book storage space and decide the date of opening of the factories. All of this costs money. Operational savings can be made by making sure that the amount is optimum. British Sugar could save 1.8 million pounds a year using RS technology, in distribution costs, storage and fuel for factories. Using data from Earth observation satellites such as the French SPOT or the American Landsat spacecraft, experts can determine the status of the crop and how much it is likely to yield.'

The use of RS techniques as a potential tool (e.g. subsidy control, agricultural statistics, etc.) in policy making receives more attention from governmental organizations. However, certain research questions still remain after having read the above statement. These questions will be formulated with the objective of the study in mind as defined in Section 1.4.

1.4 Objective and methodology of the study

The research objective of the thesis can be formulated as follows:

The objective is to understand how optical and microwave remote sensing may be used in a synergetic way in order to develop a methodology, that can be used to monitor crop growth and predict crop yield together with existing knowledge.

The thesis objective includes the search for answers to the following questions:

a Which information on biophysical properties of agricultural crops estimated with airborne remote sensing is useful for crop growth monitoring and yield prediction?
b How can this information be integrated in the methodology for combining crop growth and remote sensing?
c Can the developed combination methodology be applied for operational crop growth monitoring and yield prediction and are the present spaceborne sensors appropriate?

The proposed methodology to meet the objective is a combination method in which various pieces of information come together. It will be obvious that the combined use of RS and crop growth information needs to be studied in more detail to answer the questions mentioned above. As the information has been gathered on fields of farms, the scale of study is at field level to begin with.
To answer the first research question (*a*) an inventory of information sources is needed. The following information is relevant:

- variables retrieved from optical or microwave interaction models, which describe the observation of the "crop-soil system", leading to crop status information;
- the accuracy of the estimation of these variables;
- the accuracy of the RS observation;
- information retrieved from RS signatures or time-series possibly leading to information on development of the crop;
- plant physiological parameters and their plausible biophysical ranges (field measurements);
- a crop growth model;
- growing conditions (meteorology, farm management, etc.).

The next research question (*b*) can be answered by making an inventory of the links between information obtained from RS and crop growth and their use to the prediction procedure. These links are visualized in Figure 1.2.

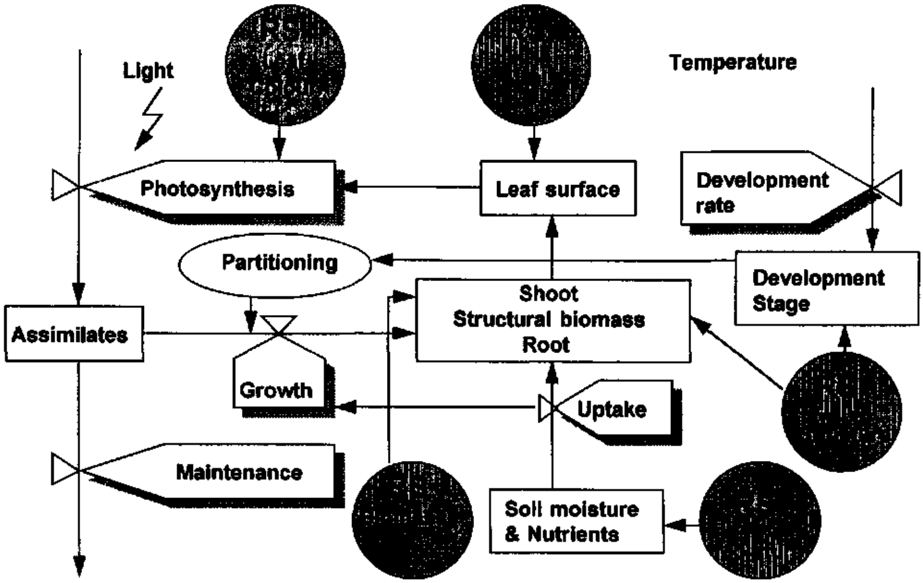


Figure 1.2 *RS information with links to the crop growth model*

The significance of the information obtained from RS to crop growth monitoring must be studied in more detail for RS in the first place; this is dealt with in Chapter 2.

The accuracy of estimating the various crop variables with RS will indirectly answer the question of the significance of RS to agricultural crops. In Chapter 3 the various combination methods using the links of RS models and crop growth models are discussed (question *a* and *b*). In Chapter 4 the data acquisition and the quality of RS and field data are discussed in the scope of the study objective. In Chapter 5 and 6 the success of the combination techniques is studied and discussed regarding crop growth monitoring and yield prediction. Important is the step from groundbased RS measurements towards airborne and even spaceborne RS with respect to yield prediction (question *c*). The question whether the developed combination methodology might be applied in an operational sense is dealt with in Chapter 6, where the application of the method on field and regional is discussed.

The four relevant crop growth calibration or combination methods applied in this study (Chapter 3, Section 3.4) are :

I Crop growth model calibration using an RS model predicting the RS signal at a certain moment in the growing season (or so-called direct use of RS models; direct modelling method);

II Crop growth model calibration using an inverted RS model estimating crop variables at a certain moment in the growing season (inverse modelling method);
III Crop growth model calibration using RS information by means of typical RS features in time-series related to the crop development stages;
IV A combination of approaches 2 and 3.

The first method was developed by Bouman (1991c). It combines the crop growth model SUCROS (Spitters *et al.*, 1989) with RS data; calibration of the crop growth model is performed by comparing the measured and predicted RS signals.

The second method is based on the inverted use of RS models. The crop growth model is calibrated by comparing the estimated variable of the RS measurement by model inversion and the variable in the crop growth model.

In the third method, the changes of one crop development stage into another, possibly corresponding to structural changes in the above-ground canopy, may result in a considerable change in RS observations. The interpretation of such a feature in RS time-series is then based on the change of a certain biomass level and/or spatial distribution of plant parts, such as leaves or stems, over a period of time.

In the first two methods calibration of the model occurs when an RS measurement is available. The four calibration methods have in common that the variables *LAI*, biomass and canopy structure all play their specific role in the combination methodology as a link between RS and crop growth. The second and the third method are studied in more detail in this thesis and can be regarded as an extension of the first approach (Section 3.4.2), which lead to a better understanding of the yield prediction process. The fourth method is the integrated representation of methods 2 and 3.

To discuss the second combination method more in detail, the biophysically relevant variables from the inverse RS model are compared with the corresponding variables in the crop growth model. The retrieved variables from RS are the *LAI* and biomass, because these variables play an important role in optical and microwave RS models and of course in the crop growth model. In this manner weighted contributions (by means of the standard deviation of the estimated *LAI* or biomass) from different sensors can be combined simultaneously (same time), contemporaneously (during same period assuming no change in crop status) or at different times (with clear changes in crop status between different points in time). Further, in this approach the RS measurement error is incorporated by using the standard deviation of the RS measurement. The crop growth model is calibrated for every new RS measurement so that new predictions of *LAI* and biomass can be made (so-called model-based approach, see Figure 1.3).

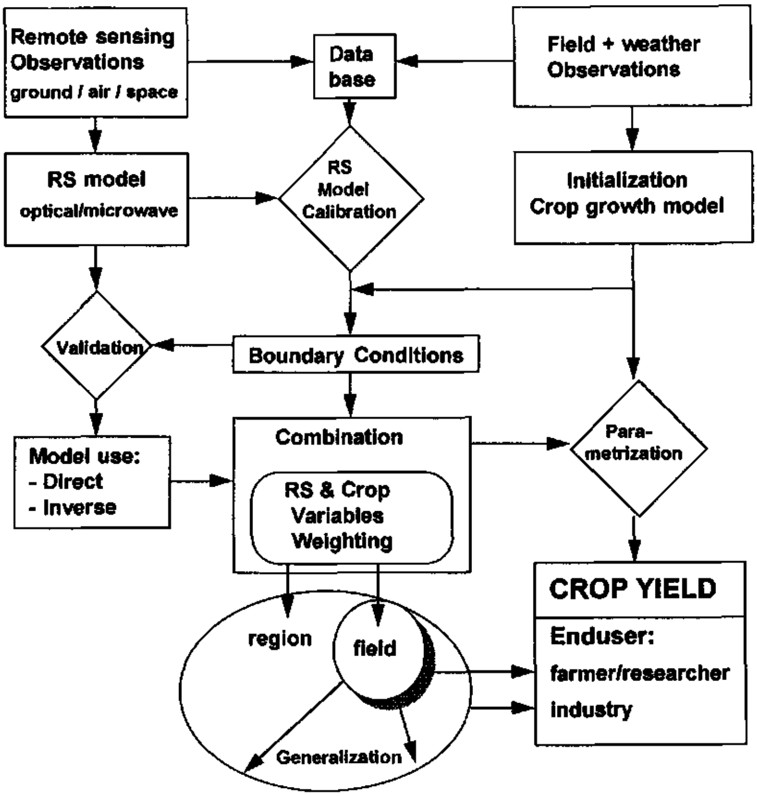


Figure 1.3 *Proposition to use RS information in combination (model-based) with a crop growth model for yield prediction in general*

In the third combination method a possibility for introducing incidental features, such as changes in canopy structure, is proposed. For dense leafy vegetation (sugar beet, potato, etc.) the canopy structure can be represented by the leaf angle distribution (*LAD*). Canopy structure is in fact accounted for in the simplified semi-empirical RS model by adjusting its regression parameters. For cereals, like wheat, crop structure is more evidently related to the various crop growth stages in which the spatial distribution of stems, leaves and ears changes clearly during the growing season (see Figure 1.4). As canopy structure cannot be estimated by the inversion of simple models, structure information may be derived from time-series of RS measurements. Changes in canopy structure are expected to be detected by multitemporal microwave measurements (the so-called features in microwave signatures). Of course this depends on the sensor configuration (frequency, polarization, etc.) and crop type, and presumably even crop cultivar.

Transition from one development stage into another can result in a change in canopy structure. This accounts especially for cereals. Microwave RS time-series can be used to find these changes in canopy structure, which in turn might lead to information on crop development. This structure information is evaluated for calibration of the crop growth model (so-called feature-based approach; see Figure 1.4). The accuracy of finding these calibration points in RS time-series depends amongst others on the frequency of observation.

The fourth approach is based on the integration of the model and the feature based combination method. It is a new approach that makes use of the available information from RS observations, so far, weighted with the accuracy of estimation of each piece of information for the purpose of crop growth monitoring.

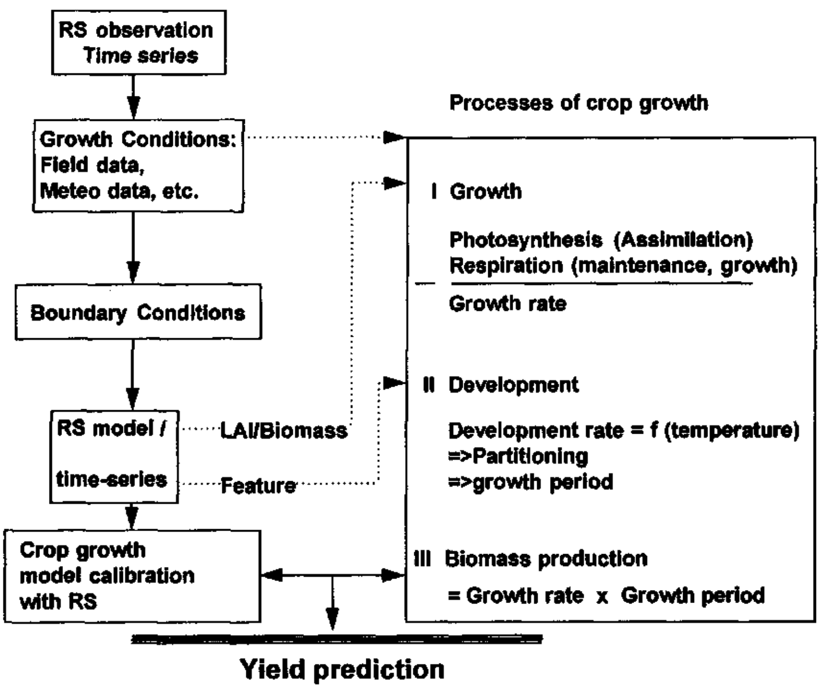


Figure 1.4 *The integration of RS model based and feature based information with the crop growth model. Growth and development of the crop give changes in biomass and crop structure during the growing season. RS can play a role to monitor these changes in order to assist in crop yield prediction.*

Variations on these static and dynamic approaches can be made by introducing factors such as the RS measurement timing, the sensor configuration (optical or microwave, resolution etc.) and the observation platform (ground-based, airborne or spaceborne).

To meet the objective, the monitoring potential of RS needs to be studied by making an inventory of the characteristic calibration points in RS time-series for agricultural crops. This is carried out in detail for sugar beet at field level. In future studies an inventory could then be made of analogies for other crops. Part of the methodology scheme (model-based) as given in Figure 1.3 is outlined in Figure 1.4 for sugar beet as an example of possible calibration points (model- and feature- based).

To test the developed methodology a demonstration crop has been chosen (Chapter 4), namely the sugar beet which is a common crop in the Southern Flevoland Province in The Netherlands. At the start of this study the crop growth model had already been initialized for growing conditions in the Southern Flevoland Province. This region had been chosen numerous times in the past as a test site for ground-based, airborne and spaceborne calibration experiments under contract of the Dutch Remote Sensing Board (BCRS), ESA, NASA, etc.. Apart from this, the newly reclaimed Flevoland Province (in the 1950s) provides large and homogeneous agricultural fields. Several airborne experiments have been conducted there to calibrate and test the spaceborne measurements (SIR-B, SIR-C X-SAR, ERS-1, JERS-1, SPOT, Landsat). In other words, the airborne measurements were planned to offer a link between ground survey measurements and spaceborne measurements. During the ROVE period (1975-1981; De Loor, 1982) ground-based measurements with microwave (X-band FMCW scatterometer) and optical (field reflectance radiometer) sensors had been done on a frequent (three-daily) basis during the growing season.

Furthermore, the MAC Europe campaign offered RS data coming from different airborne sensors, which provided the necessary information to study the step from ground-based to airborne crop growth monitoring (Chapter 5).

In order to produce regional yield figures a proposition for application of the combination methodology is made in Chapter 6 using a crop growth model in combination with RS information of presently operational platforms such as spaceborne optical (SPOT, Landsat) and microwave sensors (ERS-1, JERS-1), However, this is not further elaborated and tested with field data because of lack of data for validation of the methodology on a higher scale level (regional or national).

1.5 Structure of the thesis

The thesis work is subdivided into three parts. Part I outlines the theory and background supporting the thesis methodology and the combination methodology itself. In Part II, the test data are presented and, for the case study, the synergy of the combination of information is studied, especially for the multisensor airborne campaign MAC Europe 1991. The application of the methodology described in this thesis is evaluated in Part III, accompanied by concluding remarks and recommendations.

To monitor growth and production of agricultural crops with RS techniques, an inventory of the information estimated with RS must be made. A review of the state of the art in modelling in the reflective optical and microwave region of the electromagnetic (EM) spectrum is required since a major objective of this study is the investigation of the possibilities of a synergistic use of both optical and microwave RS data (Chapter 2). Furthermore, the most suitable models need to be selected and validated with RS measurements.

Furthermore, the underlying physiological processes of crop growth have to be studied in order to link them with RS information. The knowledge concerning these processes can be summarized in crop growth models. For practical use, a crop growth model must be calibrated to the actual growing conditions in the specific growing season. This calibration can be performed by using actual information from the field or information supplied by remote sensing from airborne or spaceborne platforms. Chapter 3 proposes a methodology for combining the information (RS data, field data and models) from different sources in order to meet the research objective. The ultimate goal is to monitor crop growth and to predict the yield. This immediately raises the question how to do this with RS. In other words, can RS provide relevant biophysical variables and with what accuracy can these be estimated to actualize the description of crop growth? This information can be provided by inverting the selected RS interaction models. Knowledge needs to be included in the inversion approach in order to reduce the number of unknown object (read crop) variables or to limit the range of these variables so that the model can be linearized or simplified. Then, the growth model can be calibrated with the actual estimates of variables from RS.

In order to meet the research objectives, Chapter 4 deals with data gathering and data analysis in order to work out and test the combination methodology applied in Chapter 5. Most of the information has been gathered from incidental campaigns, stimulated by the introduction of new sensors (polarimetry, interferometry) and strategic funding. In order to study the effect of synergism of optical and microwave RS data, conditioned data sets are required. A theoretical RS model or interaction model needs to be calibrated with experimental data and validated with other experimental data sets. This has certain consequences for the quality and the quantity of data.

With the analysis of RS data by image processing and information extraction in Chapter 4 a thorough data preparation and data fusion of several campaigns is accomplished. A synergetic data set is selected and tested. It appeared that the MAC Europe data set of 1991 from the Flevoland test plot was suitable to test the synergism of combining multisource data in Chapter 5. The combination methods of Chapter 3 are tested with contemporaneous (simultaneous) and non-contemporaneous recordings of optical and microwave sensors. A new methodology to introduce structure information from microwave data into the procedure of crop growth model calibration is applied on the MAC Europe data set.

Chapter 6 discusses the practical application of the methodology. The various methods using airborne RS in the previous chapters are reconsidered and compared with spaceborne RS. An important aspect is that the level of study is translated from field to regional level in order to evaluate practical use or potential of the combination method in conventional prediction strategies of the present processing industry.

Chapter 7 presents the main conclusions and recommendations for further research.

PART I THEORY AND CONCEPTS

2 Information from remote sensing for crop growth monitoring

2.1 Introduction

In order to monitor the growth and production of agricultural crops with remote sensing (RS) techniques, an inventory needs to be made of the information retrieved from the optical and microwave region of the EM spectrum during RS observations in the growing season. This study was done for leafy crops like sugar beet and also for cereals like winter wheat, which are two important crops in the Netherlands.

The models describing the observation of crops by remote sensors are reviewed in Sections 2.3.1 and 2.4.1. The models that are available and most appropriate for the study are selected in Section 2.3.2 for optical and in Section 2.4.2 for microwave applications. In Section 2.3.3 and 2.4.3 the selected RS models are calibrated with field measurements and RS observations and validated for use in the test area in the Southern Flevoland Province in The Netherlands.

Results of sensitivity analysis of RS interaction models which describe the observation of crops in a theoretical and detailed manner are presented in Section 2.3.4 and 2.4.4. Respectively, the SAIL model in the optical region and the 'Eom and Fung' model in the microwave region provided us with the main variables influencing the RS signal in general. The main variables when observing a crop during the growing season are *LAI*, biomass and plant structure. Optical and microwave RS models appeared to supply similar and complementary information, which can be used for crop growth monitoring.

Reflective optical RS data provide the possibility of estimating the leaf area index *LAI* and leaf angle distribution *LAD* of agricultural crops (Section 2.3.5). The CLAIR ("Clevers Leaf Area Index by Reflectance") model offers a practical algorithm for describing the relationship between reflectances and *LAI* and can be used as a practical algorithm for estimating *LAI* from RS. The more detailed (or complex) SAIL model is used for understanding the observation by sensitivity analysis and is somewhat less practical for inversion. The variable *LAD* can be estimated with this model using additional independent informations, from the sensor (several look angles, wavelength, field data, etc.).

Microwave RS data can be used for estimating the amount of plant moisture related to above ground biomass by using validated RS models (Section 2.4.5). As the physical interpretation of the microwave measurement process is not fully understood yet, complex theoretical models can serve as tools for sensitivity analysis and trend studies. Analogously to the CLAIR model in the optical domain, the Cloud model can serve as a simplification of more complex models and offer a practical algorithm for describing the relationship between backscatter and plant moisture and soil moisture.

In addition, microwave RS data can provide information on plant structure by studying time signatures of backscatter values (Section 2.5). Specific features found in these backscatter signatures may yield important information on specific development stages of crops as this is often accompanied by structural changes in the plant.

2.2 General approach to evaluation of RS information

There are several possible applications for RS information in agriculture. For example, using RS information acreages (1) can be estimated and crop types classified (2). Using the same RS information, crop characteristics can be retrieved (3) by means of inversion of a validated RS model describing the observation of the "crop-soil system". In order to prepare this, a general approach is visualized in Figure 2.1.

On the other hand, multitemporal RS information can give indications of recognizable and characteristic RS time signatures (4) related to soil or vegetation. More RS applications may be available, but in the scope of crop growth monitoring with remote sensing these four applications of RS are considered as the main elements for operational use for the moment. In the scope of this thesis crop classification can be regarded as a means of preparing data; acreage estimation is not further dealt with. This thesis focuses on the derivation and estimation of crop variables by using RS models and RS time-series for the purpose of crop growth monitoring and yield prediction. The scheme in Figure 2.1 will be followed accordingly in the next sections of this chapter.

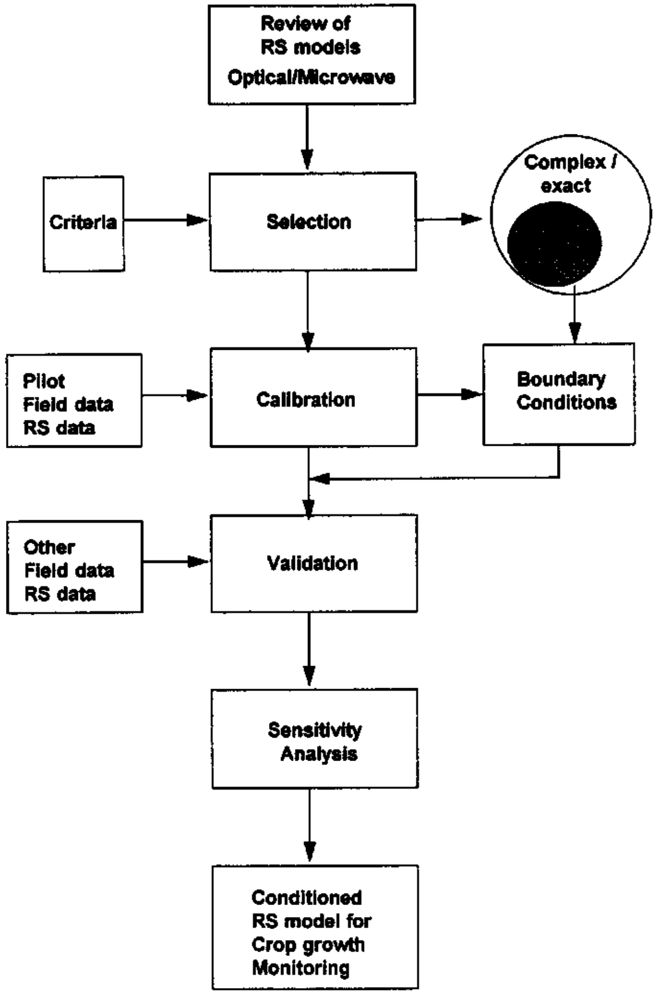


Figure 2.1 *General evaluation of RS information*

2.2.1 Review of RS models

A profound review of RS models with respect to agricultural crops is inevitable in order to interpret RS information. Estimation of physical characteristics related to crop growth variables is one way to interpret RS, besides other techniques like classification (identification), segmentation (estimation of area), etc. In this study information from RS is restricted to the optical and microwave region of the Electro-magnetic (EM) spectrum. As a consequence, optical and microwave RS models are used here. A distinction can be made between models which are still in development and those that can already be applied in practice. Another distinction in RS models can be made between complex (physical) and simple (semi-empirical) model representations of the observation by remote sensing. The development of these RS models depends on crop type and cultivar (and corresponding growth conditions) and on the physical assumptions underlying the modelling in a specific part of the spectrum. Furthermore, one can say that in general the modelling activities in the optical region are better understood compared to those in the microwave region.

2.2.2 Selection of RS models

Criteria for the selection of RS models in this study are:

1 Validity of the specific RS model and its applicability to a specific crop type and crop cultivar;
2 Interchangeability of variables of the specific RS model with variables in crop growth models;
3 Interchangeability of variables of the specific RS model with those in another RS model;
4 The scale level for predicting variables with the specific RS model (field, regional, national, supranational) or in other words level of aggregation, assuming homogeneous objects (crop-soil system);
5 The level of complexity of the RS model.

Each crop has its specific impact on the RS signal. Biomass level and the phenological development of each crop have characteristic consequences for the observation with remote sensing. Here, the selection of RS models is based on their validity and consequently on model boundary conditions with respect to each crop.

The application of RS models in a crop growth monitoring study depends on the interchangeability of variables in optical RS models and microwave RS models. Secondly, the interchangeability of variables of RS models and crop growth models is of great importance to monitoring and yield prediction in the end. On the one hand, models of the optical and microwave domain need to have comparable and corresponding model variables for reasons of interchangeability, especially with contemporaneous RS observations (from the same period) or simultaneous RS observations (at the same time). On the other hand, independent and different variables in RS models can give synergetic results in the prediction of crop growth and yield as well. Another requirement is that the RS model variables can interact with the crop growth model itself by having overlap in variables.

Modelling at field level will be the central issue here. Fields form the elementary spatial units with a homogeneous crop-soil system, where statistically sound RS signal averages are assumed to be representative for the spectral properties of the specific crop. Within-field variability is expressed by the standard deviation of the RS signal of the field.

Once the RS observation has been described in detail, a sound sensitivity analysis can be made as more variables are theoretically assumed to be responsible for the RS signal. Through simple representation of the same observation with less variables the inversion of the RS model is easier and with that the estimation of crop variables.

2.2.3 Calibration and validation of RS models

RS models can be calibrated on the basis of conditioned and experimental studies (Ulaby *et al.*, 1986). Simulations of a theoretical algorithm are compared with measured data in a (conditioned) experiment for ideal situations of a pilot test data set. This comparison can be performed statistically by introducing regression or fit parameters in the theoretical model and adjust them in order to match the simulated RS data with the measured data. The variables of the RS model have mostly direct or indirect relationships with the crop and soil model variables measured in the field. For calibration of the RS model data from the remote sensor as well as from the field are needed at the same time (Hoekman *et al.*, 1982).

Validation of these calibrated RS models is needed in order to determine the applicability of the model to other data sets of the same crop and the corresponding growing conditions. This can be done by applying the model to another measurement situation in another season or to fields other than those used for the calibration procedure of the same growing season. As a result of these measurements the validation of the model is restricted to subranges of the input RS model variables under study and used in the calibration. These subranges are nothing more than the plausible biophysical ranges of crop variables of the specific crop type under certain growing conditions. These ranges of crop variables have been measured in the field.

An RS model is considered to be valid when the RS signal prediction with the calibrated RS model fed by actual field measurements matches the measured RS signal of the same fields. It can occur that a calibrated RS model of a specific measurement programme cannot be applied to another programme (another season, weather or different location) because of non-comparable measurements and/or crop growing conditions (Bouman, 1991a).

2.2.4 Sensitivity analysis of RS models

Once the RS model has been calibrated and validated for the specific conditions of a test plot, it can be applied for simulating RS signals. In order to find out which crop (or soil) variables dominate the reflection or backscattering of EM radiation, a sensitivity analysis must be performed with these RS models.

If the RS models are not calibrated and/or validated, theoretically a sensitivity analysis can still be performed. In that case one may discover certain trends or the relative importance of the variables involved, which may lead to better insight into the different physical processes.

For the sensitivity analysis of RS models a distinction in complexity level of the model must be made. The description of an RS observation with a physically based model deals with many variables. In contrast, a simplified description of the measurement process can be represented by semi-empirical (semi physically based) regression functions with only a few variables.

A sensitivity analysis of complex RS models is important in order to determine the most dominant variables of the crop-soil system. In this way an important subspace of the total solution space, in which probably all practical solutions are embedded, can be selected for inversion purposes. This subspace can be represented by a semi-empirical model. In this way other important variables affecting the measurement signal can be found.

However, the regression parameters of this semi-empirical model may be a function of certain other crop variables which are not accounted for in this simplified description. By changing the corresponding input variables the complex RS model produces simulated RS signals and this dependency can be studied. These produced "RS measurements" can be used for fitting (or new calibration) with the semi-empirical description resulting in new regression parameters. In fact these regression parameters quantify the validity region of the sub model or semi-empirical RS model.

2.2.5 Boundary conditions for RS models

The use of semi-empirical models is more practical than the use of the complex multi-variable RS models as the models are already confined to a subpart of the total solution space as in Figure 2.2 and are easy to invert. The boundary conditions of the practical semi-empirical models cannot be defined by field measurements only, but can theoretically be predicted by simulations of the complex RS models as mentioned in Section 2.2.4.

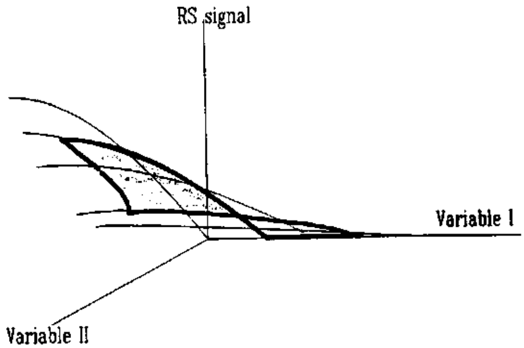


Figure 2.2 *A subspace formed by combinations of two different model variables representing local solutions of a complex RS observation model with more than two variables*

RS modelling of the crop-soil system must account for the dynamic changes during crop growth in the season. Crop growth is accompanied by changes in plant geometry (spatial distribution of plant parts) and the amount of plant material (biomass). Besides this, the nature of the plant material (e.g. dielectric properties), the structure and dimensions of individual constituents (like leaf mesophile structure), the density of the canopy medium, etc. are important for RS observation modelling.

These different variables are embedded in the physical RS model. The semi-empirical RS models, which have local validity, still do model the various properties of the crop-soil system. However, these are not explicitly present as model variables but are embedded in the regression parameters. Therefore, it is important to define boundary conditions on the basis of these regression parameters as a function of the properties of the crop-soil system. Once these conditions have been clearly defined, inversion is allowed.

2.3 Reflective optical modelling

2.3.1 Review of optical RS models

The incoming solar radiation is partly reflected by the top layer of the canopy. The direct reflectance of the canopy is a function of solar elevation, leaf area index (*LAI*), leaf angle distribution (*LAD*) and optical properties of the leaves. The complementary fraction is potentially available for absorption by the canopy. The absorptance by the canopy is a function of *LAI*, scattering coefficient and extinction coefficient. The extinction coefficient is a function of solar elevation, leaf angle distribution and scattering coefficient. The product of the amount of incoming photosynthetically active radiation (*PAR*) and the absorptance yields the amount of absorbed photosynthetically active radiation (*APAR*).

The main purpose of physical modelling in the reflective optical region of the EM spectrum is the understanding of the interaction between solar radiation and vegetation elements. Such understanding is then incorporated into a model that relates the vegetation characteristics to its spectral signature or reflectance. For homogeneous vegetation this modelling requires specification of the following elements:

1 the area of the vegetation elements (leaves, stems, branches, fruits, etc.);
2 the optical properties of the vegetation elements;
3 the geometry of the vegetation;
4 the optical properties of the soil background;
5 the illumination and viewing geometry.

Since the leaves constitute the main vegetation element for many crops that can be seen from an RS platform, the *LAI* will be the main characteristic describing element 1. Concerning element 2, also leaf characteristics determining the optical properties (such as chlorophyll content, water content and mesophile structure) may be used.

RS canopy-modelling enables the study of relationships between reflectances and crop characteristics. An understanding of the interaction between EM radiation in any wavelength region (visible, infrared, microwave, and thermal) and any object is developed by using the Maxwell equations. However, since vegetation canopies are so complex, one cannot hope to solve these equations in a direct way. To meet this problem different approaches have been developed with various levels of complexity. Methods to model the radiation regime in the vegetation canopy can be divided into the following categories:

A. Geometrical models

In this type of model the canopy is described in terms of mathematical shapes and dimensions with certain optical properties. Such models may adequately represent the reflectances of sparse canopies but, since multiple reflectance is neglected, they are not suitable for dense canopies as in this study.

B. Turbid-medium models

These models describe the canopy in terms of small absorbing and scattering particles with given optical properties assuming a random distribution of these particles. Moreover, the canopy is assumed to be homogeneous in horizontal direction and the effective distance between leaves is not taken into account. The canopy architecture is mainly expressed in *LAI* and *LAD*. The models seem to be particularly suitable for the present study.

C. Hybrid models

These are geometrical models of vegetation with multiple reflectance included. They are needed for non-homogeneous canopies since they are a combination of categories A and B. At the moment, there are only very few models of this category available (e.g. ROW model, Goel & Grier, 1986).

D. Computer-simulation models

In this type of model the canopy is described by a 3-D realistic simulation with numerical calculations at photon level. These models are very computer-intensive and generally cannot be inverted. As such these models are not suitable for this study.

Essentially, in the group of turbid medium models, there are two classes of physical reflectance models: numerical and analytical models. Bunnik (1984) has reviewed several models.

An example of a numerical model was described by Idso and De Wit (1970). In this model, radiative transfer is determined for discrete leaf layers by scattering and absorption. Goudriaan (1977) improved and extended this model by calculating a numerical solution for upward and downward diffuse fluxes within nine sectors of each hemisphere for each discrete layer. Den Dulk (1989) described a crop as a stack of thin crop layers. He defined 46 directions in a semi-space, each representing an equal solid angle. These model directions were used to represent radiation patterns as well as to define leaf angle distributions.

One of the earliest analytical models was that described by Allen and Richardson (1968). It was based on a theory of Kubelka and Munk (1931) which describes the transfer of isotropic diffuse flux in perfectly diffusing media. In the analytical model, the scattering and absorption of upward and downward fluxes are expressed by differential equations. Allen *et al.* (1969) extended this model in order to include scattering of direct solar flux by using the Duntley equations (Duntley, 1942). The first analytical model incorporating both illumination and observation geometry was that developed by Suits (1972), and is an extension of the model developed by Allen and his colleagues. Suits' model also incorporates plant canopy structural (with a drastic simplification) and optical properties. When model simulations are carried out with varying viewing angle, Suits' simplifications appear to be too drastic (Verhoef & Bunnik, 1981). Therefore, Verhoef (1984) extended Suits' model further by including scattering and extinction functions for canopy layers containing fractions of oblique leaves (inclined leaves). He did not introduce the drastic simplification of canopy geometry exclusively to horizontal and vertical components as Suits did, but used a set of frequencies at distinct leaf angles. This model is called the SAIL model (Scattering by Arbitrarily Inclined Leaves).

SAIL model (complex)

The one-layer SAIL radiative transfer model (Verhoef, 1984, 1985a,b) simulates canopy reflectance as a function of canopy variables (leaf reflectance and transmittance, leaf area index and leaf inclination angle distribution), soil reflectance, ratio diffuse/direct irradiation and solar/view geometry (solar zenith angle, zenith view angle and sun-view azimuth angle). Recently, an extension of the SAIL model with the hot spot effect was made (Verhoef, 1990). The latter extension is based on equations given by Kuusk (1985). The hot spot situation occurs at equal zenith angles of sun and observation with no azimuthal angle between the two. The additional parameter required by this model is called the hot spot size-parameter which equals the ratio of horizontal correlation length and canopy height. The horizontal correlation length depends on the average size of the leaves and on the shape of the leaves.

PROSPECT model (complex)

PROSPECT is a radiative transfer model that simulates the optical properties of plant leaves in the spectral range from 400 nm to 2500 nm (Jacquemoud & Baret, 1991). Leaf scattering is described by a spectral refractive index and a parameter characterising the leaf mesophile structure. Absorption is modelled using pigment concentration, water content and the corresponding specific absorption coefficients. The spectral refractive index and the specific absorption coefficients have been fitted using experimental data corresponding to a wide range of plant types and status. PROSPECT allows estimation of the leaf reflectance and leaf transmittance from three input parameters: characterising the leaf mesophile structure, chlorophyll concentration and leaf water content respectively.

CLAIR model (simple)

Complicated physical reflectance models are very useful for sensitivity analyses in order to investigate the influence of crop characteristics and external variables on reflectances or simple vegetation indices. Moreover, they are quite valuable for investigating boundary conditions of the application of certain simplifying relationships. However, they are difficult to invert and too complicated for practical purposes.

A simplified, semi-empirical reflectance model for estimating the *LAI* of a green canopy (vegetative stage) was introduced by Clevers (1988, 1989b). In this model it is assumed that in the multitemporal analysis the soil type is known and that the soil moisture content is the only varying property of the soil. For estimating *LAI* a "corrected" (adjusted) near infrared (*NIR*) reflectance was calculated by subtracting the contribution of the soil in line of sight from the measured reflectance of the composite canopy-soil scene. This corrected *NIR* reflectance was ascertained as a weighted difference between the measured *NIR* and red reflectances (called weighted difference vegetation index *WDVI*), assuming that the ratio of *NIR* and red reflectances of bare soil is constant, independent of the soil moisture content (which assumption is valid for many soil types). Subsequently, this *WDVI* was used for estimating *LAI* according to the inverse of an exponential function.

The simplified reflectance model derived by Clevers (1988, 1989b) consists of two steps. Firstly, the *WDVI* is calculated as:

$$WDVI = r_{ir} - C \bullet r_r \qquad (2.1)$$

with

r_{ir} = total measured *NIR* reflectance

r_r = total measured red reflectance

and $C = r_{s,ir}/r_{s,r}$ (2.2)

$r_{s,ir}$ = *NIR* reflectance of the soil

$r_{s,r}$ = red reflectance of the soil.

Secondly, the relationship between *WDVI* and *LAI* is modelled as:

$$LAI = -1/\alpha \bullet \ln(1 - WDVI/WDVI_{\infty}) \qquad (2.3)$$

in which α is a combination of extinction and scattering coefficients describing the rate at which the function of Equation (2.3) approaches its asymptotic value and $WDVI_{\infty}$ as the asymptotic limiting value for the *WDVI*. The parameters $WDVI_{\infty}$ and α have to be estimated empirically from a training set by means of regression, but they have a physical interpretation (Clevers, 1988). Another possibility is to use a canopy reflectance model for theoretically determining the parameters of Equation (2.3) once the input for the canopy reflectance model is known (e.g. leaf optical properties and *LAD*). This so-called *WDVI*-concept has proven to be a very useful concept for estimating the *LAI* of various agricultural crops under practical conditions (Uenk *et al.* , 1992; Bouman *et al.*, 1992f). The combination of Equations (2.1) and (2.3) is the simplified, semi-empirical, reflectance model or CLAIR model.

2.3.2 Selection of optical RS models

For the synergy study the group of turbid medium models has been selected, because variables like *LAI* and *LAD* play an important role in them. The aggregation level of the modelling is field level. At this scale modelling at crop level is still possible if the crop-soil system is representative for the whole field. This already forms a good perspective in meeting the selection criteria mentioned in Section 2.2.2.

The SAIL model can be regarded to be valid for sugar beet as it meets criterion 1. The interchangeability of variables like *LAI* and *LAD* between crop growth models and RS models meet criteria 2 and 3. In the same way other agricultural crops can be investigated. The SAIL model can be considered as a complete description (complex) of the observation by RS of crops at field level meeting criteria 4 and 5.

The PROSPECT model (scale at leaf level and at field level, assuming homogeneity of the crop) was selected as its output can be used as input for the SAIL model (leaf transmittance and leaf reflectance) following criteria 3 and 4.

The CLAIR model was chosen because of its simple semi-empirical form and because it can be regarded as a conditional submodel of a multidimensional variable space of another more complex RS model (SAIL) following selection criteria 1, 2, 3, 4 and 5. The CLAIR model as in Equation (2.3) is already an inverted RS model.

2.3.3 Calibration and validation of optical RS models

Extensive calibration and validation of the PROSPECT model has already been performed by Jacquemoud (1990). Simulations with the PROSPECT leaf model appeared to be valid for the leaves from crops on the Flevoland test plot, by providing a very good match with the measured spectra of leaf reflectance and leaf transmittance of individual sugar beet leaves (Büker *et al.*, 1992a). For linking PROSPECT with SAIL, leaf chlorophyll content and leaf mesophile structure were used as input for SAIL instead of leaf reflectance and leaf transmittance, both depending on wavelength.

The study by Clevers *et al.* (1992b) showed that simulations of the canopy reflectance obtained with the SAIL model correspond well with airborne reflectance measurements of various crops. The SAIL model can be considered valid for different growing seasons as well as for different measurement situations. However, it is important to correct for different atmospheric conditions when observing with airborne or spaceborne optical remote sensors.

The CLAIR model appears to be a practical way of describing the relationship between reflectances and *LAI*. The results are quite satisfactory.

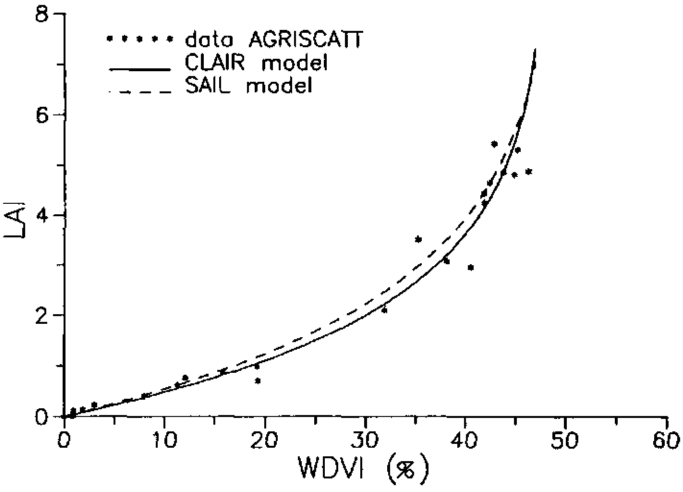


Figure 2.3 *Relationship between LAI and WDVI for sugar beet. The data are taken for the whole growing season. Flevoland test site AGRISCATT campaigns 1987 and 1988 (Source: Clevers et al., 1992b)*

Recently, standard relationships (indices) have been established for the derivation of the proportion soil cover and *LAI* from measured *WDVI* for potato, sugar beet, wheat, barley and oats (Uenk *et al.*, 1992; Bouman *et al.*, 1992f). These standard relationships were derived from field reflectance measurements on agricultural crops during several years on different locations in The Netherlands. Uenk *et al.* (1992) found regression parameters for sugar beet with an α of 0.485 and $WDVI_{\infty}$ of 48.4 (based on green reflectance instead of red reflectance). The CLAIR model was fitted to reflectances measured with a field spectrometer and *LAI* measured in the field during the Agriscatt 1987 and 1988 campaigns on sugar beet. Results can be found in Figure 2.3.

2.3.4 Sensitivity analysis of optical RS models

The sensitivity analysis of complex optical RS models focuses on the PROSPECT-SAIL combination model by studying the empirical relationship of *WDVI* and *LAI* or the fraction absorbed photosynthetically active radiation *FPAR* conform the methodology described in Section 2.2. The analysis is carried out by Clevers *et al.* (1993) by systematically changing the RS model variable in question, at the same time keeping the other RS model variables constant. A standard sugar beet crop as defined by Clevers *et al.* (1993) was chosen. ("Standard" is defined as follows. Input PROSPECT: chlorophyll content = 34.24 μg cm^{-2}, *N* homogeneous layers within a leaf assumed = 1.8320, water content = 0.0137 cm as given for dicotyledonous plants by Jacquemoud and Baret (1990). Input SAIL: hot spot size parameter = 0, soil reflectance = 20%, only direct solar irradiation, solar zenith angle = 45°, nadir viewing).

2.3.4.1 Relationship between *WDVI* and *LAI* (CLAIR model)

A sensitivity analysis using the SAIL model revealed that the main variable influencing the relationship between *WDVI* and *LAI* is the *LAD* (Clevers & Verhoef 1990; Clevers 1992a). Other leaf and canopy variables and external factors only have a minor influence on optical RS in agricultural applications. Concerning the estimation of the *LAI* by means of the *WDVI*, the sensitivity analysis with the combined PROSPECT-SAIL model resulted in the following conclusions (restricted by the validity of these models):

- The influence of soil background on the regression of *LAI* on *WDVI* was only minor. This was independent of the leaf angle distribution function (*LAD*). So, the *WDVI* corrected satisfactory for the influence of soil background.
- The sensitivity of the regression of *LAI* on *WDVI* to errors in solar zenith angle was quite small, especially for practical circumstances in western Europe.
- The influence of the diffuse/total irradiation was only minor.
- The leaf inclination angle had a huge influence on the regression of *LAI* on *WDVI*. This influence cannot be neglected.
- The influence of the hot spot size parameter on the relationship between *WDVI* and *LAI* for nadir viewing was small. Largest effects occurred at large *LAI* for small values of the size parameter (small leaves).
- The chlorophyll content had a considerable influence on the relationship between *WDVI* and *LAI* only for values smaller than 10-20 g cm^{-2}. So, *WDVI* should be used as an estimate of green *LAI*. The effects are small for green leaves.
- The influence of the mesophile structure on the regression of *LAI* on *WDVI* for the defined "standard crop" was small up to *LAI* values of about 4.0.
- Off-nadir viewing effects were only of minor importance for satellite observations. For sensors looking off-nadir the effects can not be neglected, especially when looking into the hot spot.

As stated in the report on the project 'Modelling and synergetic use of optical and microwave RS' (Clevers & Hoekman, 1989), light interception (or better the absorbed photosynthetically active radiation, *APAR*) is particularly interesting from an agricultural point of view. This applies particularly to the possible combination of RS with crop growth models. Clevers *et al.* (1993) studied the relationship between *LAI* and the fraction of absorbed photosynthetically active radiation (*FPAR*). The amount of leaves showed an exponential relationship with the amount of light being intercepted and used for photosynthesis. In the same way the relationship between *WDVI* and *FPAR* could be studied with the combined PROSPECT-SAIL model.

2.3.4.2 Relationship between *WDVI* and *FPAR*

Regarding the estimation of the *APAR* (multiplication of the daily photosynthetically active radiation *PAR* and the fraction of absorbed *PAR* or *FPAR*) by means of the *WDVI*, the sensitivity analysis using the combined PROSPECT-SAIL model resulted in the following conclusions (Clevers *et al.*, 1993, 1994a):

- A linear relationship may be applied as an approximation for estimating *FPAR* from the *WDVI*. This appeared to be a simple and practical concept for linking RS information with crop growth models.
- The influence of soil background on the regression of *FPAR* on *WDVI* was only minor. So, the *WDVI* showed the expected behaviour: it corrected satisfactorily for the influence of soil background, not only for estimating *LAI*, but also for estimating *FPAR*.
- The sensitivity of the regression of *FPAR* on *WDVI* for errors in solar zenith angle was quite small, especially for the circumstances prevailing in The Netherlands. By assuming a solar zenith angle of 45°, the maximum error was about 10% *FPAR*.
- The influence of the ratio diffuse/total irradiation was only minor.
- As expected, the leaf inclination angle had a huge influence on the regression of *FPAR* on *WDVI*. This influence cannot be neglected and is mainly caused by the effect on the simulated *WDVI*.
- The influence of the hot spot size parameter on the relationship between *WDVI* and *FPAR* for nadir viewing is only small.
- The influence of the leaf chlorophyll content on the regression of *FPAR* on *WDVI* is small, from a chlorophyll content of 2 μg cm^{-2} onwards. A considerable effect was only found with albino leaves (lacking chlorophyll).
- The leaf mesophile structure forms only a minor influence on the regression of *FPAR* on *WDVI*.

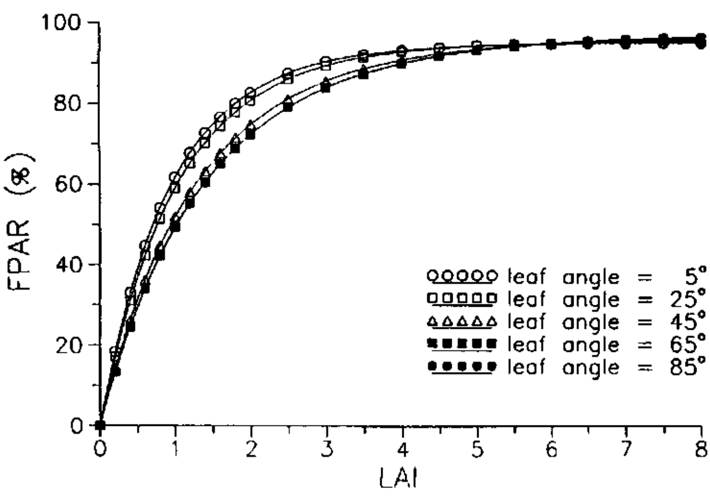


Figure 2.4a *Influence of the LAD on simulated FPAR as a function of LAI for the standard crop as defined by Clevers et al. (1993)*

The influence of the leaf inclination angle is important for the relationship between *WDVI* and *FPAR*, similar to the influence on the relationship between *LAI* and *WDVI*. However, its influence on *FPAR* itself is rather small (note the small deviation in Figure 2.4a). Figures 2.4a and 2.4b summarize the sensitivity analysis in a clear graphical manner for the main variables.

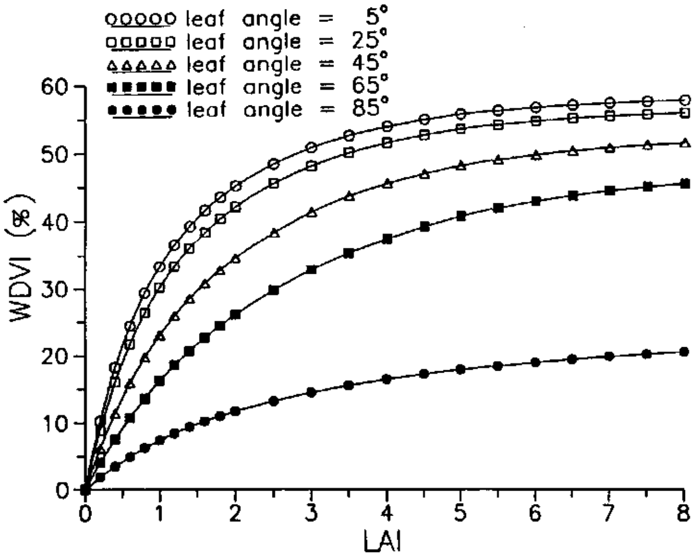


Figure 2.4b *Influence of LAD on simulated WDVI as a function of LAI for the standard crop (adapted from Figure 34, Clevers & Verhoef 1990)*

2.3.5 Boundary conditions: optical RS

In the optical region the boundary conditions for the application of interaction models can be determined with the aid of the conclusions drawn from the validity of these models. The validity of the RS model was tested (see Section 2.3.3) by fitting it to experimental data (ground data and RS data). The experimental data consist of measured crop variables, varying within their natural biophysical ranges, regarding the whole growing season. The consequence is that the validity of these models is restricted to the range of the measured variables in the field.

In the validation procedure of the optical models for sugar beet in Figure 2.3, the *WDVI* becomes saturated at a value of about 45, corresponding with an *LAI* of 5 towards the end of the growing season. After *LAI* = 5 the standard deviation of the *LAI* increases significantly. This was shown by Bouman (1991a) for several campaigns and for other crops in the past, assuming the crop structure to be constant during the growing season (Table 2.1). Improvement of optical modelling may be achieved by introducing structure information on plant parts (e.g. the function ear angle distribution for cereals or *LAD* for leafy canopies like sugar beet or potato).

Uenk *et al.* (1992) concluded that the *WDVI* (green) - *LAI* relationship in several crops can be described even better by using (empirical) linear expressions (Table 2.2) instead of the semi-empirical exponential CLAIR relationships as used in Table 2.1.

Table 2.1 *Regression coefficients α and β (= $1/WDVI_\infty$) for the relationship between LAI and WDVI (green) in Equation 2.3; accompanying regression output $\sigma(\alpha)$ and $\sigma(\beta)$ are standard errors of the regression coefficients, % var is the percentage of variance accounted for and N the number of observations (Uenk et al., 1992)*

Crop	α	$\sigma(\alpha)$	β	$\sigma(\beta)$	*%var*	*N*
Potato	0.588	0.065	1.940	0.090	82.8	156
Beet	0.485	0.032	2.056	0.073	94.7	37
Barley	0.545	0.026	2.223	0.045	94.8	231
Wheat	0.400	0.025	2.128	0.067	92.7	223

Table 2.2 *Boundary conditions expressed by regression parameters and validity ranges of WDVI* (green) *from optical RS models (LAI as function of green WDVI) for different crops with the equation $LAI = A + B \cdot WDVI$, in which $\sigma(A)$ and $\sigma(B)$ are standard errors of the regression coefficients, % var is the percentage of variance accounted for, A and B the regression coefficients and N the number of observations (Uenk et al., 1992)*

Crop	*WDVI*	*A*	$\sigma(A)$	*B*	$\sigma(B)$	*%var*	*N*
Potato	[0; 29]	-	-	0.048	0.003	68.8	75
	[29; >]	-0.867	0.401	0.091	0.009	56.7	72
Wheat	[0; 12]	-	-	0.050	0.003	69.9	59
	[12; 38]	-1.030	-0.253	0.134	0.008	65.3	136
	[38; >]	-10.44	-	0.378	-	-	28
Barley	[0, 26]	-	-	0.045	0.001	76.8	107
	[26, 43]	-4.150	-0.429	0.201	0.013	62.8	110
	[43, >]	-85.68	-	2.100	-	-	14

Based on these findings and considerations Uenk *et al.* (1992) concluded that the *WDVI-LAI* relationship does not account for the following situations:

- plant structural changes in general during the growing season;

- contribution to reflectance by the ear layer for wheat, barley, etc.;
- contribution to reflectance by the stems of the potato crop, later in the growing season;
- yellow and brown leaves.

The sensitivity analysis showed that the most sensitive variables were *LAI* and *LAD*. All combinations of these two variables (assuming the other variables to be constant) lead to a range of predicted *WDVI* values, assuming the SAIL model to be valid. The semi-empirical CLAIR model can be fitted to simulations of the multivariable SAIL model. Theoretically this fit procedure can provide another α and $WDVI_{\infty}$ belonging to the various combinations of *LAI* and *LAD* input variables of the SAIL model.

The boundary values for the application of the CLAIR model are imposed by the restricted ranges of the fit parameters resulting from this theoretical study. Moreover, these fits of the simple CLAIR equation to a valid complex model like SAIL provide a simple inversion scheme, later to be used in the combination method (Chapter 3).

However, to describe these boundary values quantitatively and for practical situations, the fit procedure must be based on experimental data. The problem is that during most campaigns only the *LAI* was measured. During the MAC Europe 1991 and ERS-1 1993 field campaign *LADs* were measured for sugar beet. Also, *LAI* was estimated using a field reflectance meter, the "Cropscan", for sugar beet (Rijckenberg & Van Leeuwen, 1994).

These *LAD* measurements show that the average leaf angle of the sugar beet crop changes during the growing season. In the CLAIR model this *LAD* is considered to be constant (spherical). In the case of sugar beet it is not unrealistic to say that the calibration parameters for the CLAIR model as obtained by Bouman *et al.* (1992f) are not valid during the second half of the growing season because of the changing canopy structure.

2.3.5.1 Example of the conditioned CLAIR model for sugar beet adapted for structure

For sugar beet a spherical or erectophile *LAD* is applicable until the stage of tuber filling starts. After that stage the *LAD* is more extremophile, which was confirmed by measurements in the field by Rijckenberg and Van Leeuwen (1994). Dividing the growing season of sugar beet into these two phases, *LAI* values can be estimated from *WDVI* measurements using the CLAIR model.

In the beginning of the growing season the regression parameters of the CLAIR model as used thus far, are valid (cf Section 2.3.3). The regression parameters of the CLAIR model for the second part of the growing season can be estimated by simulating the relationship between *LAI* and *WDVI* using the SAIL model with the input parameters of the "standard crop" (and the measured extremophile *LAD*). The *LAD* input derived from the actual field measurements is visualized in Figure 5.12. The new regression parameters resulted in 0.491 for α and 55.58 for $WDVI_\infty$.

2.4 Microwave modelling

2.4.1 Review of microwave models

In the microwave region of the EM spectrum various scattering models have been developed in the past to interpret the measurements of a crop-soil medium. A short review of the current development in microwave modelling is presented with respect to this study, based on findings by Rijckenberg and Van Leeuwen (1994) and Lemoine *et al.* (1991). In general, scattering from a surface covered with vegetation consists of a surface scattering term and a volume scattering term, including a ground-vegetation scattering term. Most models use a heuristic approach based on an intuitive understanding of the relative importance of the different components of the scattering mechanism. Scattering by the ground surface depends on the roughness of the surface and its dielectric properties. Commonly used models for scattering by the ground surface are the Kirchoff model, the small perturbation model, and the IEM model (Fung & Pan, 1987).

Two major modelling methods for volume scattering with respect to vegetation can be distinguished :

1. *The wave approach*, based on the Maxwell equations (see also Ulaby, 1982). It predicts backscatter for a certain medium. It will not be discussed here any further.
2. *The intensity approach*, based on the radiative transfer theory. With this theory the interaction of the electromagnetic radiation and the vegetation matter can be described by the extinction, or the loss of intensity of the radiation while it is traversing the vegetation medium. The extinction by the medium accounts for scattering and absorption by the medium.

A different modelling approach is the so-called *modified radiative transfer theory* (MRT). With this theory the coherent effects, which are caused by the boundaries of the medium (like soil or canopy layers), can be accounted for.

Both the radiative transfer theory and the modified radiative transfer theory are considered to be related to the wave theory. This then means that the equations which govern the backscatter predictions can be derived directly from the Maxwell equations with certain approximations (Tsang *et al.*, 1985).

In the case of agricultural crops having several layers, like cereals (vegetative and generative layer), multiple scattering is expected to be important and this makes the wave approach less favourite, since multiple scattering can only be accounted for to a certain extent (Rijckenberg & Van Leeuwen, 1994). As far as the coherent effects (e.g. backscatter enhancement) are concerned, these mainly occur when the density of the medium is greater than 1%. Since this is not the case for the vegetation canopies under study, the conventional radiative transfer theory will be followed.

2.4.1.1 Cloud model (simple description)

The physical and geometrical properties of agricultural crop-soil systems determine the microwave backscatter. Attema and Ulaby (1978) formulated a simplified model derived from the radiative transfer theory as:

$$\sigma^0_{total} = \sigma^0_{canopy} + \tau_1 . \sigma^0_{soil} + \tau_2 . \sigma^0_{interaction} \tag{2.4}$$

where $\sigma^0 = \gamma \cdot cos(\theta)$
and

σ^0_{canopy}	=	the canopy backscattering coefficient;
σ^0_{soil}	=	the soil backscattering coefficient;
$\sigma^0_{interaction}$	=	the backscattering coefficient due to the interaction between the canopy constituents and the soil surface;
τ_1 , τ_2	=	the transparency coefficients of the canopy layer covering the soil surface;
θ	=	the incidence look angle of the sensor (degrees).

In Equation (2.4) the interaction term and the soil term are expected to be significant in the case of crops with considerable surface effects, like rows (e.g. potato). For most agricultural crops the interaction term is not taken into consideration and thus the Cloud model will be used as in Equation (2.5). The Cloud model can be considered as a simplified solution (first order) of the radiative transfer theory. The original formulation of the Cloud model was based on the assumption that the vegetation consisted of a collection of water droplets which are represented as small identical particles uniformly distributed in space. Equation (2.5) is the original equation as formulated by Attema and Ulaby (1978).

$$\gamma = C \cdot (1 - e^{\frac{D \cdot W \cdot d}{\cos\theta}}) + G \cdot e^{\frac{k \cdot m_s \cdot d}{\cos\theta}} \qquad (2.5)$$

with

γ = total backscatter (or $\sigma^0/cos\theta$) [-];
W = canopy moisture [kg.m^{-3}];
m_S = soil moisture content [vol%];
d = height of vegetation [m];
θ = incidence angle [degrees];
k = frequency and soil type dependent factor: k=0.1 • ln10 • S;
S = sensitivity to soil moisture in dB/vol%;
C,D,G = regression parameters [-].

The first term in Equation (2.5) represents the backscatter contribution by the canopy layer and the second term represents the contribution of backscatter by the soil (corrected for the attenuation by the canopy layer).

Soil contribution in the Cloud model

The soil contribution in Equation (2.5) is represented by a very simple model depending mainly on soil moisture and soil roughness. From experiments the soil contribution appears to be linearly dependent on soil moisture (m_s) when the scattering coefficient is expressed in dB. Parameters like the dry soil characteristic (G) and the sensitivity to soil moisture (S) are assumed to be constant at a given frequency, polarization and soil roughness.

If the soil roughness remains the same during measurements, then the parameters S and G can be estimated with a regression analysis at the beginning of the growing season with measurements over bare soil. On the other hand, the soil term in the Cloud model may be replaced by a more complex representation of the soil backscatter contribution.

The theoretical first-order integral equation method (IEM model) by Fung and Pan (1987) is a recent example of a model with a reliable description of the soil backscatter contribution. In contrast with theoretical soil backscatter models like the Kirchoff (high frequencies) or small perturbation (low frequencies) soil model (Ulaby *et al.*, 1986), the IEM model has a wider range of applicability in the frequency domain.

Higher-order models include multiple scattering effects (including volume interaction). For evaluation of the soil backscatter contribution and comparison with more practical soil models, the first-order representation (IEM model) is used and tested for applicability with the Agriscatt 88 airborne RS data (Chapter 4, Section 4.2.3.3) in which a wide range of frequencies is used.

Canopy contribution in the Cloud model

The direct backscattering from the underlying soil, which is attenuated by the canopy layer, is included in the model as a separate term. The model is driven by two parameters *C* and *D*. These parameters can be determined by means of a regression analysis (Hoekman *et al.*, 1982; Van Leeuwen, 1992b). Knowing *C* and *D*, the backscatter can then be predicted as a function of incidence angle, canopy height and the amount of canopy water. The expression for the backscatter can be derived directly from the radiative transfer theory, if contributions by some interaction mechanisms can be assumed negligible. For sugar beet and potato the problem lies in the fact that the backscatter saturates very quickly with fresh biomass (approximately 1 to 1.5 kg water per m^2) so that a high temporal resolution is required in the first growth stage before closure, in order to get statistically reliable regression results. The *D* parameter is difficult to determine because of the saturation when the complete growing cycle is used. The model has also been extended to two layers in the case of cereal crops (Hoekman *et al.*, 1982) by introducing an additional (ear)layer, for which a second "Cloud equation" is to be applied separately. Results are reasonably consistent with the data found by the ROVE team, but unfortunately no indication is given of the accuracy of their fit parameters, which now have become four C1 and D1 of layer 1 and C2 and D2 of layer 2 instead of C and D of one canopy layer, see also Appendix B (Van Leeuwen, 1992b).

2.4.1.2 'Eom and Fung' model (complex description)

Several applications can be found in literature of the radiative transfer theory in modelling the backscatter from vegetation-covered surfaces. Exact solutions of the equations have been studied as well (Eom & Fung, 1984; Tsang *et al.*, 1985; Ulaby *et al.*, 1986, 1990; Kong, 1990). In general, these solutions are very complicated and are only suitable for numerical inversion. Exact solutions of the radiative transfer equations are possible by means of the so-called "matrix-doubling" (MD) method

(Eom & Fung, 1984), which is not further elucidated here. Eom and Fung derived a model which is applicable to a single-layer canopy medium, which consists of randomly oriented circular disks (leaves) or cylinders (needles). The soil backscatter was modelled by using the Kirchoff approximation.

2.4.1.3 MIMICS (complex description)

A recent development based on the radiative transfer theory is MIMICS (Michigan Microwave Canopy Scattering model, Ulaby *et al.*, 1990). MIMICS is a first-order solution of the radiative transfer equations, which is applicable to a vegetation canopy consisting of two layers above a rough surface. The model is fully polarimetric, and an earlier developed dielectric model for soil and vegetation has been integrated (Ulaby and El-Rayes, 1987). The presented version is valid for a continuous canopy, in later versions this and other limitations will be eliminated. The model can be considered to be semi-empirical. The microwave backscatter from the crop-soil system is related to the physical characteristics of the canopy and the soil medium. The dielectric constant of the canopy medium has an empirical relationship with the moisture content in the canopy and its spatial distribution and, related to this, to the density of the moisture in the canopy medium. In the same way, an empirical relationship between soil moisture and its distribution in space, and the dielectric constant of soil can be used (Dobson *et al.*, 1985).

2.4.1.4 Karam model (complex description)

Another recent development is the model developed by Karam *et al.* (1992). The model is based on a second-order solution of the radiative transfer theory and can be applied to a three-layer canopy. The model is fully polarimetric, so for different polarizations contributions of the observed object may be simulated. Comparisons with measurements from coniferous and deciduous trees are in consistence at several frequencies, for both cross and like polarizations. The model is applicable to continuous canopies only .

2.4.2 Selection of microwave models

The selection of a complex RS model (criterion 5) is useful for a better physical understanding of the microwave backscatter phenomena. The most dominating variable can then be found by sensitivity analysis. The model of Eom and Fung was selected and used for the sensitivity analysis. This model contains various crop and soil variables but also physical variables like dielectric constant of soil, vegetation, etc.. The Cloud model is a relatively simple and semi-empirical model. The selection criteria 2 and 3 can be fulfilled because the Cloud model and the 'Eom and Fung' model have some variables in common (soil moisture, the amount of moisture of the canopy layer) and also complementary variables (canopy structure). An example of this was shown by Prevot *et al.* (1992) who compared the Cloud model with a subspace of the MIMICS model for winter wheat in France by feeding both models with the same variables obtained from field measurements of moisture in the canopy layer and the soil. This can be compared to the method in Section 2.3.5 with the CLAIR and the SAIL model. The 'Eom and Fung' model was selected for this study as it was available at the time. The more recent model by Karam *et al.* (1992) was not used as it appeared later. The 'Eom and Fung' model was used for the sensitivity analysis resulting in trends in backscatter by changing the variables of the RS model (crop-soil system related variables). The Cloud model can be considered valid during one growing season for several agricultural crops like sugar beet, wheat, potato, etc. The Cloud model meets criteria 2, 3 and 4, because of its interchangeability of variables (biomass, possibly related to *LAI*) with those of other complex RS models (optical and microwave) and crop growth models.

The soil model can be added separately to the canopy model as the contributions of soil and canopy backscatter are assumed to add incoherently. When no bare soil microwave measurements of the particular campaign are available, which is realistic, the proposed IEM model can be used. Soil moisture supplied by field measurements or even by a calibrated hydrological model (by meteorological data, standard soil data as texture, hydraulic conductivity, etc.) for the specific test site and soil roughness which is rather constant for the crop (Lemoine *et al.*, 1994), can be used for the soil contribution in backscatter of the crop-soil system.

2.4.3 Calibration and validation of microwave models

Analogous to calibrating optical models, microwave models can be calibrated by comparing the RS observations with the RS model simulations by regression analysis. The RS model is fed with the field variables measured at the time of RS observation. The output of the regression analysis is a set of regression or fit parameters. With the calibrated RS model the RS signal from other fields can be simulated with additional field data and then be compared to the observed RS signal. If the RS signal can be reproduced by the RS model, the model can be considered as valid within the boundary conditions. It is within these boundary conditions that the inverted model supplies estimations of crop-soil variables (see Figure 2.5).

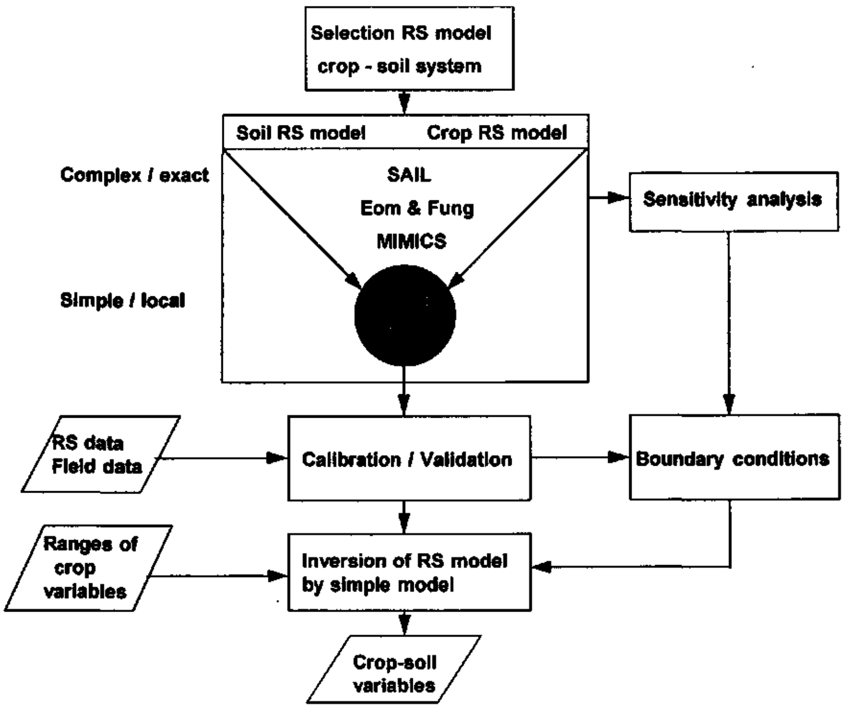


Figure 2.5 *Model selection for predicting variables in the crop-soil system (Van Leeuwen et al., 1992a)*

2.4.3.1 Calibration and validation of the Cloud model

Cloud model validation was performed for sugar beet using microwave data of former campaigns at the Flevoland test plot. This was carried out by Hoekman *et al.* (1982) for the ground-based ROVE data (X-band) and for the Agriscatt 1988 campaign (multi-frequency) by Van Leeuwen (1992b). The fit results for the Agriscatt 1988 campaign were produced with a regression procedure written in FORTRAN without standard deviations for every fit parameter. It is, however, useful to present the results in Table 2.3 and compare them with results of other campaigns in Table 2.4. The Cloud fit parameters C and D can be obtained by means of a regression analysis. Rijckenberg and Van Leeuwen (1994) used the non-linear algorithm of Marquardt-Levenberg, which was available in the SAS mathematical library (courtesy Dr. M. de Gee, Department of Mathematics, Dr. J. Bontsma, Department of Agrophysics of WAU).

It was not possible to fit the Cloud model on the Agriscatt 1988 data with sufficient accuracy (see Table 2.4; the standard deviation is in the order of magnitude of the backscatter itself), since these sets do not contain enough microwave data from the beginning of the growing season to the moment of the crop closure, which is particularly important for the assessment of D parameter.

An interesting attempt to calibrate the Cloud model was performed for the ERS-1 data set for sugar beet at the test site in the Southern Flevoland Province. By using estimated LAI values from field reflectance measurements with a Cropscan radiometer through the CLAIR model, the canopy moisture content W (related to fresh biomass, Equation 3.7) could be estimated on the days of ERS-1 overpasses and the Cloud model calibrated. However, the standard deviation of the fit parameters was very high and the fit parameters of the airborne and the spaceborne Cloud model calibration procedure were not comparable (see Table 2.4).

Parameter D can only be determined if the exponential curvature of the backscatter as function of the amount of moisture W in the canopy layer (in kg m^{-3}) is recognizable. From Figure 2.6 taken from the ROVE campaign (Rijckenberg & Van Leeuwen, 1994) it can readily be seen that there are too few points at low LAI values before closure of the crop ($LAI < 2$) to have a reliable fit at about 30 degrees incidence angle. If an incidence angle dependent γ is considered, a large dispersion in γ can be noticed in Figure 2.6. The variations in backscatter can probably be related to structure in combination with the viewing geometry of the remote sensor.

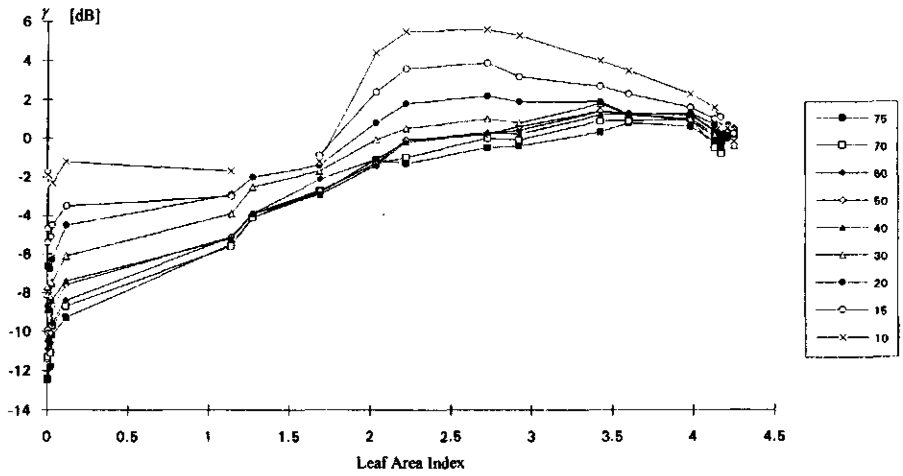


Figure 2.6 *X-band backscatter at VV polarization from sugar beet at various incidence angles as a function of LAI (measured with an hand-held radiometer) (Source: Rijckenberg & Van Leeuwen, 1994)*

The X-band data set of the ROVE period provided detailed ground and RS data sets (see Figure 2.6) to fit the Cloud model, see Table 2.4.

Table 2.3 *Fit results of radar data for sugar beet in the Agriscatt 1988 campaign; airborne scatterometer with multifrequency (L, S, C, X, Ku-1, Ku-2, see also Table 2.5) and incidence angle θ (20°, 30°, 40°, 50°, 60°; HH polarization) (Source: Van Leeuwen, 1992b). Regression parameters Cloud model: G, C, D and k (see Eq. 2.5)*

	G					
θ	*L*	*S*	*C*	*X*	*Ku-1*	*Ku-2*
20°	0.00190	0.013024	0.019637	0.125781	0.163298	0.077177
30°	0.00085	0.009141	0.011464	0.067289	0.102148	0.074368
40°	0.00070	0.004448	0.049184	0.034643	0.120707	0.076001
50°	0.00082	0.003735	0.004577	0.021858	0.065574	0.070116
60°	0.00079	0.002933	0.003907	0.025829	0.107194	0.029653
	C					
θ	*L*	*S*	*C*	*X*	*Ku-1*	*Ku-2*
20°	0.19115	0.32000	0.58845	1.04065	1.94800	1.37346
30°	0.12776	0.27578	0.50725	0.83942	2.66803	1.14837
40°	0.11424	0.30995	0.44199	1.22765	2.57024	1.14212
50°	0.11386	0.34963	0.32138	1.13502	2.59050	1.33077
60°	0.10328	0.36640	0.49978	0.96138	1.95570	1.20513
k	0.100	0.069	0.058	0.048	0.044	0.041
D	1.1025	0.2314	0.1009	0.2099	1.0000	1.0000

The validation of the Cloud model for X-band was reliable, and the results were more stable over the years (Bouman, 1991) than those of the airborne and spaceborne campaigns. However, in the ROVE period validation of the Cloud model ground-based measurements was performed for a few fields only.

Table 2.4 *Fit results of radar data of sugar beet at the Southern Flevoland Province test site at three different observation levels at an observation angle of about 30 degrees and three different frequencies. σ(C) and σ(D) are standard errors of the regression coefficients (Source: Rijckenberg & Van Leeuwen, 1994)*

Campaign	*C*	*σ(C)*	*D*	*σ(D)*	*residuals*
ROVE X-HH 1980	1.06	0.035	1.58	0.56	0.03
ROVE X-VV 1980	1.05	0.04	1.29	0.33	0.04
Agriscatt C-HH 1988, 20°- 30°	0.30	0.29	0.65	0.83	0.71
Agriscatt C-VV 1988, 20°-30°	0.73	0.06	1.64	0.62	0.20
Agriscatt L-HH 1988, 20°-30°	0.34	0.23	0.10	0.10	0.05
ERS-1 C-VV,1992, ~20°	0.30	0.02	13.7	18.1	0.11

These results show immediately that the Cloud model for C-band and VV polarization can not be applied to the seasons of 1988 and 1992 because of the large difference in the regression parameters *C* and *D* (see Table 2.4). This is most likely because of the differences in canopy structure of the sugar beet crop and possibly because of the differences in observation level (airborne Agriscatt 1988 versus spaceborne ERS-1 1992). Despite the fact that Table 2.3 does not show fit accuracy, the figures for parameter *C* and those in Table 2.4 are in the same order of magnitude for the Agriscatt campaign. The fit parameter *D* is very different in both tables. Besides the lack of enough field and RS data, another important factor of disturbance can be the large variance in total backscatter within one sugar beet field. For every RS observation of one field a certain measurement error can be calculated, which can be expressed by the standard deviation of the backscatter (see Chapter 4). It seems that for every campaign, sensor configuration, crop type (and cultivar) and region a new calibration of the Cloud model needs to be performed.

Another reason for the poor transferability of regression parameters between different seasons and sensors could lie in the fact that so far the Cloud model is not the most appropriate description of RS interaction mechanisms concerning the crop-soil system. A weak point is the description of the soil contribution and canopy structure in the Cloud model. In this sense the soil backscatter term and possibly the ground-vegetation interaction term should be studied in more detail. Therefore, it is interesting to study the calibration procedure for the Cloud model in combination with a more detailed soil model.

2.4.3.2 Validation of the Cloud model integrated with a soil model

In previous studies Hoekman *et al.* (1982) and Van Leeuwen (1992b) presented calibration and validation results of the Cloud model by estimating the soil and canopy contribution for several crops. The soil component was estimated by using soil backscatter data from the bare soil period of the crop under study, also used in the direct modelling method by Bouman (1992a). The roughness was assumed to be constant in the bare and in the covered period of the growing season. Only soil moisture in the top 5 to 10 cm was assumed to be of importance to changes in the soil backscatter contribution. In this way the soil backscatter contribution could be corrected for changes in soil moisture. The sensitivity of microwave backscatter to soil moisture B was estimated by De Loor (1987) and experimentally validated on Agriscatt 1987 data by Van Leeuwen (1991), with the model of Attema, Kats and Krul (1982) or the so-called AKK model (see Table 2.5). This model is not further discussed here.

Table 2.5 *Sensitivity S_1 (in dB/vol%) of microwaves of different wavelengths to soil moisture determined theoretically (De Loor, 1987);S_2 determined experimentally with the AKK model from the Agriscatt 1987 campaign (Van Leeuwen, 1991). "-" means: no data available*

Frequency (GHz)	*Wavelength* (in cm)	*Military* Code	S_1 (dB/vol%)	S_2 (dB/vol%)
1.2	25.00	L	0.41	0.434
3.2	9.38	S	0.33	0.300
5.3	5.66	C	0.26	0.252
9.7	3.11	X	0.24	0.210
13.7	2.19	Ku-1	-	0.190
17.3	1.74	Ku-2	-	0.179
35.0	0.86	Ka	0.11	0.152

Effects like slaking (smoothening of the soil surface by heavy rain on loamy to silty soils) during the growing season, which could be a major factor of influence on the roughness situation, have not been taken into account (Janse, 1993). Instead of the AKK model, the model of Equation (2.6) is used. The soil contribution to total backscatter can be found using the following equation (cf Eq. 2.5):

$$\gamma_{soil} = G * e^{(K.m_s)} \tag{2.6}$$

Parameter G incorporates the roughness effect and is frequency and incidence angle dependent. The sensitivity of backscatter to soil moisture S (dB/vol%) is represented by the frequency dependent factor k *(k=0.1 •ln10 •S)* which is frequency and soil type dependent (see Table 2.5).

The soil contribution to the total received backscatter in the covered situation is attenuated by the canopy layer with thickness d and extinction properties represented by factor D.

The canopy contribution to total backscatter can be estimated with a least squares method estimating the fit parameters C and D. However, when there are no measurements of the bare soil period present, it would be useful to represent the soil backscatter contribution by a validated (semi-empirical and theoretical) soil model. Different theoretical soil models for the direct soil backscatter are available (small perturbation, physical optics, etc.). Depending on the frequency, different validity boundaries are given in order to apply the correct soil backscatter model (Table 2.6).

Table 2.6 *Validity conditions for some present soil radar backscatter models. With k' = wave number; σ= root mean square roughness (rms in m);*
l = correlation length (in m); $m = \sqrt{(2\sigma/l)}$

Model	*Validity Conditions*
Physical optics	$m < 0.25$; $k'l > 6$; $l^2 > 2.76\sigma\lambda$
Geometric optics	$(2\sigma\cos\theta)^2 > 10$; $k'l > 6$; $l^2 > 2.76\sigma\lambda$
Small perturbation	$k'\sigma < 0.3$; $m < 0.3$
Integral Equation Method (IEM)	$m < 0.4$

The Integral Equation Method (IEM) by Fung and Pan (1987), however, can be applied for many frequencies. The soil term in the Cloud model can easily be replaced by such a model. The advantages of the IEM model over other theoretical soil backscattering models are the following:

- the use of the model is not as tightly restricted to the surface roughness parameter domain as the conventional models, such as the small perturbation, and Kirchoff models (Ulaby *et al.*, 1982)(see Table 2.6);
- the use of the model is permitted for most of the roughness conditions normally found in agricultural fields and for most operational microwave systems (i.e. with frequencies lower than 10 GHz);
- the low and high frequency limits of the IEM correspond to the small perturbation and physical optics model;
- the first-order model can easily be used in inversion exercises on multifrequency and dual-polarization (HH and VV) data sets.

The obvious advantage of the IEM in comparison with semi-empirical models (such as described in Equation 2.5) is that the IEM does not contain empirical parameters which need to be calibrated for various frequencies and polarizations.

The IEM contains three parameters describing the soil system, the dielectric constant ε, the surface rms-height σ and the surface correlation length l. In fact, the choice of the surface auto-correlation function is another variable in the IEM. In this study, an exponential function has been assumed. To relate the dielectric constant of the soil to its material properties, such as soil texture and soil moisture content, a dielectric mixing model has to be used. In this study, the empirical formulae given by Dobson *et al.* (1985) have been applied, with fixed values for the mixing model parameters.

2.4.3.3 Some validation results of the IEM soil model

Some inversion results will be discussed which were obtained from Agriscatt 1988 data in order to validate the IEM soil model (Lemoine *et al.*, 1994; Van Leeuwen *et al.*, 1992a). Data from the first two sorties (22 April 1988, 2 May 1988) were used, since most fields were bare at that time. The relevance of soil backscattering under partially covered conditions is illustrated by an example involving potato crops.

Figure 2.7 shows the possibility of using the IEM model on multifrequency data for smooth potato fields. The measured L-band and C-band (both VV polarized) data were used in a Marquardt-Levenberg fit procedure, in which the dielectric constant ε was fixed. ε was calculated by applying the dielectric mixing model for the marine clay in the Flevoland Province and a volumetric moisture content of 0.20 (Vissers *et al.*, 1988). Note that the fit performs quite well, except for incidence angles of 10° and 15°. The fitted surface *rms* height corresponds very well with the *in situ* measurements (between 0.0050 and 0.0095 m). The correlation lengths were not measured.

Figure 2.8 illustrates the Marquardt-Levenberg inversion scheme with a nomogram for pairs of L-band HH and C-band VV data. In the nomogram the measured pairs are compared to IEM simulations for various combinations of surface rms-height σ and volumetric moisture content m_v (the surface correlation length was fixed). This is done for three different crops at the beginning of the growing season (day 122). This means that RS and field observations were made at the time of bare soil for sugar beet and potato and partial coverage for winter wheat. Regarding *rms*-height the various crop type related soil classes are clearly clustered. However, the fit results are somewhat different from the field measurements. This is most obvious for m_v, for which the fitted results are significantly lower than those in the measured soil moisture samples (0.20 -

0.34 m³ m⁻³). This discrepancy is probably partially caused by the use of the Dobson dielectric mixing model. Still, the relative positions of the potato, (most) sugar beet and wheat clusters in the nomogram compare quite well with the relative soil moisture and rms-height differences measured for the various fields.

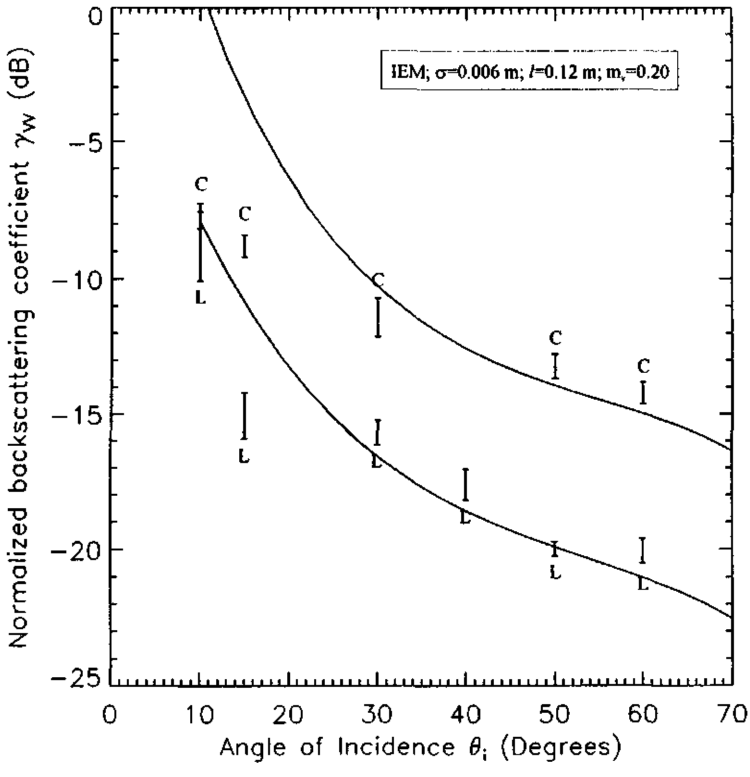


Figure 2.7 *IEM fit results of the Marquardt-Levenberg method on L and C band data (VV polarization) of the Agriscatt 1988 data set. The measured data from three reference potato fields (320, 520 and 710) were averaged (error window of 1 x standard deviation in backscatter) for day 122. The soil moisture content was fixed to the averaged in situ value. The Dobson dielectric mixing model was used to estimate the dielectric constant*

The actual fit procedure yields the IEM parameters indicated in the nomogram, except for the two sugar beet fields situated just outside the range of the simulation grid. The use of nomograms is a graphical way of predicting and checking the performance of the numerical fit procedure. Note that measurement pairs have been selected from the Agriscatt 1988 data set that approximately correspond to that of the operational JERS-1 (L-band, HH, 30°) and ERS-1/2 (C-band VV, 23°) satellites.

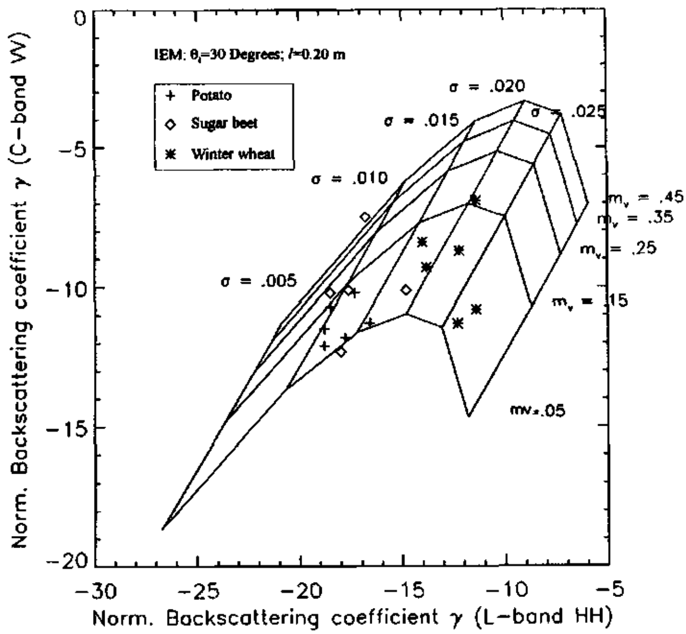


Figure 2.8 *Nomogram of backscattering pairs simulated with the IEM model compared with measured data of the Agriscatt 1988 data set. The data for the various fields are shown for day 122*

The relevance of the soil component in the backscattering from the crop-soil system is illustrated in Figure 2.9. The L-band backscattering signatures of two potato fields are shown which are viewed from different directions. Field 422 (Fieldno. 320 in Vissers *et al., 1988)* had its typical potato ridges orientated parallel to the flight direction, while for field 520 the ridges were orientated perpendicular to the line of flight. The viewing direction has a very distinct impact on the signatures (Beaudoin *et al.*, 1990). The viewing direction modulation is especially large under bare soil conditions (approximately 15 dB at 40° incidence angle, day 122), but is still present when the potato crop is fully developed (day 195). Obviously, in the latter case the underlying soil still contributes significantly to the overall backscattering. Knowledge about the soil component, therefore, should be an integral part of inversion exercises on backscattering signatures, especially before and during crop emergence.

The combination of the Cloud model with the IEM model shows that theoretical models can be used for describing the observation of the crop-soil system and replace the empirical soil model (Equation 2.6), but the accuracy of fit must be taken into consideration for operational application of the model. However, the case study in this thesis does not incorporate the IEM model in its methodology any further owing to the assumption that the soil contribution of the crop-soil system is constant at the time of observation in the MAC Europe 1991 campaign (see Chapter 5).

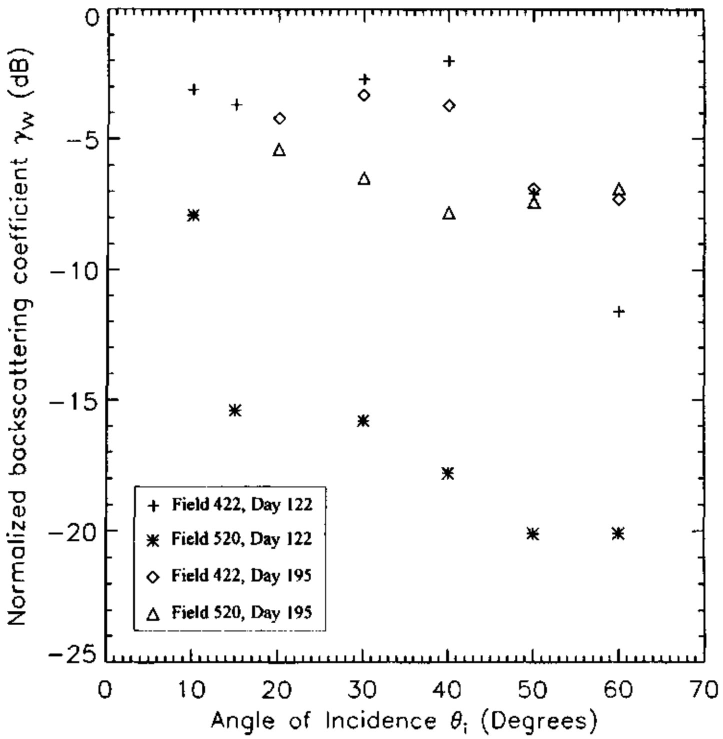


Figure 2.9 *L-Band VV polarized backscattering signatures for two potato fields with different orientation of the ridges towards the microwave line of flight. The ridges of field 422 were parallel and 520 perpendicular to the flight line. On day 122 both fields were completely bare, while on day 195, the potato crop was fully (and approximately equally) developed on both fields in the Agriscatt 1988 campaign*

2.4.3.4 Validation of the selected complex models

The validation of the complex models (MIMICS and the 'Eom and Fung' model) was not successful (Rijckenberg & Van Leeuwen, 1994). The main reasons were the lack of ground data as mentioned in Chapter 2, Section 2.4.3.2, the complexity of the canopy constituents, and their geometrical dimensions and configuration in the canopy medium. MIMICS also showed some inconsistencies concerning the scatter matrix of circular disks (Perez *et al.*, 1994). Orientation of the leaves will remain a problem with these approaches. Structure is very important to the microwave backscatter and little is known about leaf orientations. It is beyond the scope of this study to consider theoretical approaches in detail as this belongs to the field of development of RS models. This would, however, be interesting for the continuation of theoretical research in The Netherlands.

The link between the Cloud model and the theoretical models is difficult to investigate, because of the validation problems mentioned earlier. These problems may be solved by using more complex representations of the canopy constituents, for which numerical solutions of the scatter matrix exist. Instead of fitting an effective leaf diameter to the data, one could also try to find an object which would be a closer resemblance to the curved sugar beet leaf, by fitting a class of curved plates or clusters of small disks to the data. A direct measurement of the scatter matrix from, for instance, a sugar beet leaf is also feasible.

The complex RS models like the 'Eom and Fung' model can still be used for sensitivity analysis. The dominating variables of the RS model could be found theoretically and trends in backscatter observations related to characteristics of the crop-soil system be interpreted and explained in a relative way.

2.4.4 Sensitivity analysis of models

In a manner similar to the optical modelling (with the SAIL model), a sensitivity analysis was performed by Rijckenberg and Van Leeuwen (1994) by varying the input variables of a complex microwave model within the ranges of biophysical reality (field measurements). In this study the 'Eom and Fung' model (1984) was selected. Analogous to the CLAIR model fitted to the SAIL model in the optical sensitivity analysis procedure, the semi-empirical microwave Cloud model with the regression parameters C and D has been fitted to the simulated data of the more detailed 'Eom and Fung' model. With the ERS-1 configuration in mind, C-band VV simulations at 20° incidence angle were performed. Rijckenberg and Van Leeuwen (1994) concluded that the variables that caused detectable changes in C and D of the Cloud model were the moisture content W of the canopy, the canopy height d, the fraction of leaves of above ground canopy volume *Volfr* and the average leaf inclination angle *Avl* (Figure 2.10). The dynamic behaviour of these input variables is summarized in Table 2.7. The figures were derived from the Agriscatt 1988 data set.

Table 2.7 *Steps in input variables for simulations with the Eom & Fung model (1984) (Source: Rijckenberg & Van Leeuwen, 1994)*

input variable	*Minimum value*	*Medium value*	*Maximum value*
d (m)	0.1	0.42	0.75
Volfr	0.0022	0.0069	0.015
Avl	30.	45.	60.
W	0.1	0.5	0.9

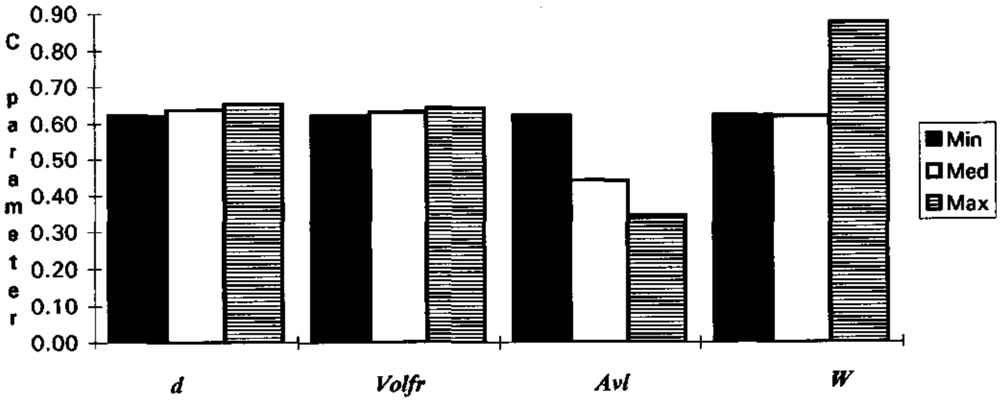


Figure 2.10 *Sensitivity of the C-parameter from simulations at C-band, VV, 20° incidence angle (Source: Rijckenberg & Van Leeuwen, 1994)*

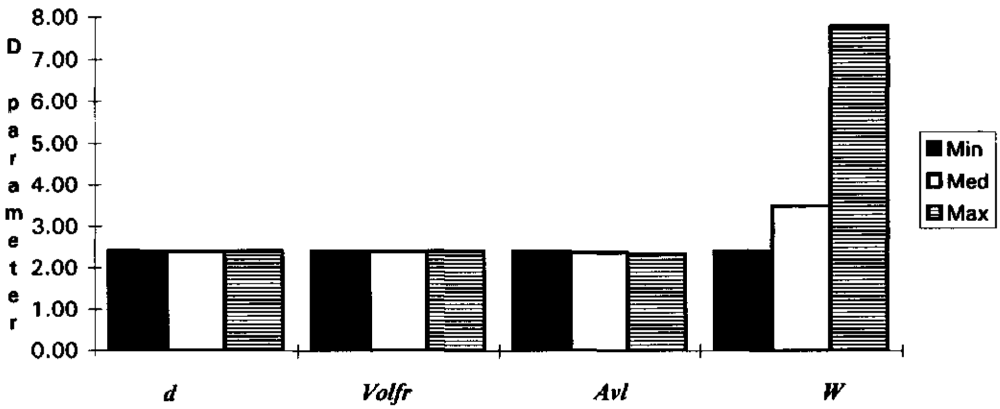


Figure 2.11 *Sensitivity of parameter D from simulations at C-band, VV, 20° incidence angle (Source: Rijckenberg & Van Leeuwen, 1994)*

When studying Figures 2.10 and 2.11 the fact that the moisture content in the canopy layer *W* and the leaf inclination angle *Avl* have dominant impacts on regression parameter *C* in the Cloud model, is especially striking. However, a change in the average leaf inclination *Avl* had no influence on parameter *D* in the Cloud model, while this parameter also strongly depends on *W*. The volume fraction *Volfr* and the canopy layer height *d*, have hardly any influence on the regression parameters.

It can readily be seen from Figure 2.10 that the parameter *C* clearly depends on the amount of moisture in the canopy layer, a smaller dependency on orientation and negligible effects caused by the height of the layer and the occupied volume by the leaves. Parameter *D* accounts for extinction and depends on the amount of moisture in the canopy layer and very little on orientation (see Figure 2.11). The moisture content of sugar beet leaves is more or less constant, but the orientation of the leaves can change. The structure differences in the canopy layer might cause different backscatter behaviour. The canopy structure is not represented by a variable in the Cloud model. The complex model of Eom and Fung, however, could explain these structural changes with proper variables. This could explain the fact that structure and related to that the distribution of moisture in the canopy have an important influence on the measured RS signal. In this case the Cloud model, not being able to model canopy structure properly, tries to incorporate the additional mechanisms in the fit parameters *C* and *D*. This may support the idea that explaining variables like *W* and the regression variables *C* and *D* of the Cloud model are not independent from each other.

Measurements in other studies confirmed the impact of plant architecture on the backscatter for wheat and barley (Hoekman and Bouman, 1992).

The results of the sensitivity analysis are that the amount of moisture in the canopy layer and average leaf inclination angle (related to the *LAD*) greatly influence the microwave backscatter. This means that external influences like wind, water stress, etc. could cause trouble in interpreting the microwave data. On the other hand, it also means that information on canopy structure can be obtained from microwave data, in addition to information on the amount of moisture in the canopy layer from models like the Cloud model.

2.4.5 Boundary conditions of microwave models

In analogy with the optical modelling we may say that the validity region of the microwave models based on calibration experiments form the basis for defining the boundary conditions. The semi-empirical Cloud model can be seen as a submodel with the proper boundary conditions of more complex (multivariable) microwave RS models. In Section 2.4.4 the 'Eom and Fung' model was taken to study theoretical trends in backscatter with the various input variable combinations of the complex RS model. The fit parameters *C* and *D* of the Cloud model appeared to be dependent on the changes in the amount of moisture in the canopy layer and the average leaf angle. However, the complex microwave model, different from the SAIL model in the optical region, could not be validated for the sugar beet crop (Rijckenberg & Van Leeuwen, 1994). This means that the boundary conditions for the Cloud model are difficult to define too. Besides that, it can be concluded from the calibration exercises of different campaigns that the regression parameters of the semi-empirical Cloud model are not constant for the various campaigns. This is probably due to different factors which could affect the crop structure (Sections 2.4.4 and 2.5).

The approach that the development of biomass in time imposes a certain condition on the microwave model (convexity of the Cloud curve) can be applied in order to examine fit parameter *D*. When enough microwave measurements are available in the range of plant moisture values between 0 and 2 kg m^{-2} and a constant crop structure can be assumed, parameter *D* can be determined with a certain standard deviation.

Another restriction is the saturation of the backscatter signal at high frequencies (5.3 GHz and higher) when the amount of moisture in the canopy layer reaches the value of about 2 kg.m^{-2}. This is the case when closure of the sugar beet canopy has been completed. A moisture content of the canopy higher than 2 kg m^{-2} seems to have a minor impact on the backscatter. However, structural changes in the canopy due to water stress or development stage of the crop are more likely to be detected instead (see Section 2.5). This structure effect is not represented in the Cloud model by an explaining variable, but is probably embedded in the regression parameters *C* and *D*. Just as in the optical modelling, the regression parameter might be adapted at the moment when the average leaf angle changes (see Section 2.3.5). As this effect of canopy structure is expected to be more pronounced in the microwave region than in the optical domain, special attention is given to this feature in microwave time-series or signatures in the next section.

2.5 Features in microwave signatures

2.5.1 Introduction

The previous section showed that only with a conditioned Cloud model RS microwave measurements may be used for estimating the amount of moisture in the canopy layer by using microwave RS models (model-based approach). In addition, microwave measurements may provide information on canopy structure. This information on canopy structure can be obtained by studying backscatter signatures as a function of time.

In this section microwave backscatter from the crop-soil system is studied and its relationship with biomass and development stages will be examined (Rijckenberg & Van Leeuwen, 1994). Furthermore, the question whether microwave RS can monitor growth throughout the whole growing season is dealt with. In addition, the impact of structure changes in the canopy layer on the backscatter will be discussed. Only a qualitative explanation can be given, since no detailed structural measurements are at hand to validate the findings. The latter are based on reported structure changes in the crop at a certain development stage. The changes are of course gradual and do not occur in the order of a few days. Further support is given by field measurements on average leaf angles and their distributions (in Chapter 5).

Observed variations in microwave backscatter of a sugar beet crop after closure of the crop are mainly attributed to variations in canopy structure. In a study by Le Toan *et al.* (1984) it is stressed that canopy structure is important to microwave modelling. It is not clear, however, whether these changes are supposed to be caused by weather conditions (e.g. wind) (Bouman & Van Kasteren, 1990a) or by specific orientations of the constituents of the crop, independent of weather conditions (Ernst & Fischbeek, 1984). From backscatter experiments conducted on wheat, barley and oats, it appeared that the geometrical architecture of the canopy (which changed by the wind) was of importance to the backscatter (Bouman & Van Kasteren, 1990b). Ernst and Fischbeek (1984) give a description of backscatter measurements in crops in Germany. The studied crops were winter wheat, barley, sugar beet and potato. Their major conclusion was that plant structure is the most important factor influencing backscatter. They attributed the high levels of backscatter from sugar beet to the erectophile leaves of the crop with *LAI* of about 4. Measurements on orientations of sugar beet leaves, performed by De Wit (1965), also showed that the leaves have an erectophile distribution at this stage.

Average time-series of backscatter (X-band) from various agricultural crops of the ROVE period were studied by De Loor (1984). Sugar beet backscatter series showed a characteristic feature before reaching a maximal *LAI* value and after an exponential increase in biomass. The backscatter decreased after this feature.

The structure of the canopy layer of sugar beet can partly be described in a quantitative way by the leaf angle distribution (*LAD*). The radar can detect changes in the structure of the canopy layer, which are assumed to be related to a transition of one crop development stage into another. This is more plausible than explaining structure changes by diurnal effects or stress caused by water shortage (Rijckenberg & Van Leeuwen, 1994). In data sets from different campaigns in The Netherlands, that were obtained over a period of seventeen years, significant changes in the backscatter of sugar beet canopies were found coinciding with transitions in crop development.

These transitions in development in time can be described by the development rate which is a function of the integrated average daily temperature from the moment of emergence (or sowing) onwards. In detailed crop growth models like SUCROS (Spitters, 1989), decision criteria of partitioning assimilates to various plant parts can be defined by specific values of the temperature sum T_{sum}. T_{sum} is the principal environmental factor affecting crop development.

By studying the changes in backscatter as a function of temperature sum, the capability of microwave RS to measure changes in development stage will be examined in Section 2.5.2. The possible impact of diurnal effects and stress should be considered as well. The final goal is to answer the question whether microwave RS can be used in order to study the evolution of crop growth throughout the entire growing season, resulting in a certain crop yield. Since Chapter 5 focuses on sugar beet, in the next section characteristic features found in temporal microwave signatures of this crop will be discussed in more detail. Another crop, in which a much better relationship between structural changes in the crop and changes in development stages is expected, is winter wheat (or other cereals). For this crop type the canopy structure is more clearly a function of morphological-physiological development of the crop.

2.5.2 Observed changes in microwave signatures of agricultural crops

De Loor (1984) studied the temporal curvature of microwave signatures of the ROVE period and found characteristic average microwave signatures for different crops over a period of several years, measuring with a ground-based radar system (X-band radar). However, these signatures are only averages so that specific points are difficult to locate. Furthermore, the study covered a number of years as a function of time, while temperature regimes during the growing season changed over the years and with them the development of the crop.

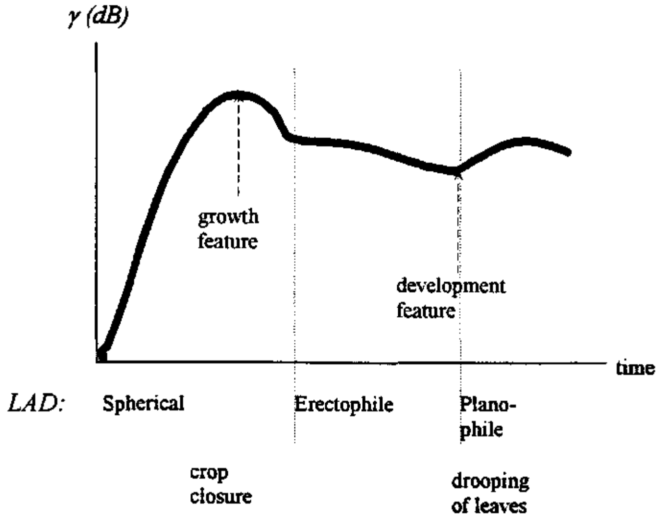


Figure 2.12 *Schematized temporal curve of backscatter from sugar beet with two features indicated (Source: Rijckenberg & Van Leeuwen, 1994)*

While studying time-series of backscatter, changes in backscatter from sugar beet canopies were found in data sets that were obtained over a period of seventeen years. These so-called features could be the result of transitions in biomass and/or development stage. Figure 2.12 summarizes these phenomena in a general sense, in which the average backscatter over a period of ten years (ROVE period) is given as a function of temperature sum in the growing season. Bouman and Van Kasteren (1990a, 1990b) detected similar features in wheat and barley, caused by transitions in development stages.

Figure 2.13 illustrates backscatter (γ) as a function of T_{sum} for the ROVE data set. Of interest is the maximum γ which occurs at values of T_{sum} between 400 and 500, corresponding with an *LAI* of about 2-3, and a dip at T_{sum} ~ 900-1000, which corresponds with an *LAI* ~ 4-5 (varying for different test sites; 'De Bouwing', Southern Flevoland Province). By comparing the different backscatter data, these two features were recognized by Rijckenberg and Van Leeuwen (1994), corresponding with two periods in the growing season of sugar beet:

- at T_{sum} ~ 400-500 there is a maximum in the backscatter. This is the top of the characteristic feature in the temporal curve of backscatter from sugar beet. This is however not caused by a change in development but probably by the closure of the sugar beet canopy;
- at T_{sum} ~ 900-1000 a drop was seen in the backscatter (about 2 dB). At this moment the plant partitions assimilates to the root and no more additional leaf formation is expected.

In Figure 2.13 the first feature appears around T_{sum} ~ 500 and the second at T_{sum} ~ 950 in the 1975 and 1980 curves. No specific features can be distinguished in the 1979 curve, which implies some inconsistency in detecting structural changes. However, Rijckenberg and Van Leeuwen (1994) listed the observed dips in the different data sets and found that the second feature appeared consistently. The first feature was not consistently found in all data sets, probably because of differences in plant density or other reasons. The latter affects the average leaf angle at crop closure. Crop closure is not development stage related. The average dip lies in the order of 2 dB for C- and L-band VV of the Agriscatt 1988 and MAC Europe 1991 data. In the next chapter, the implications of canopy structure information for crop growth monitoring, will be considered.

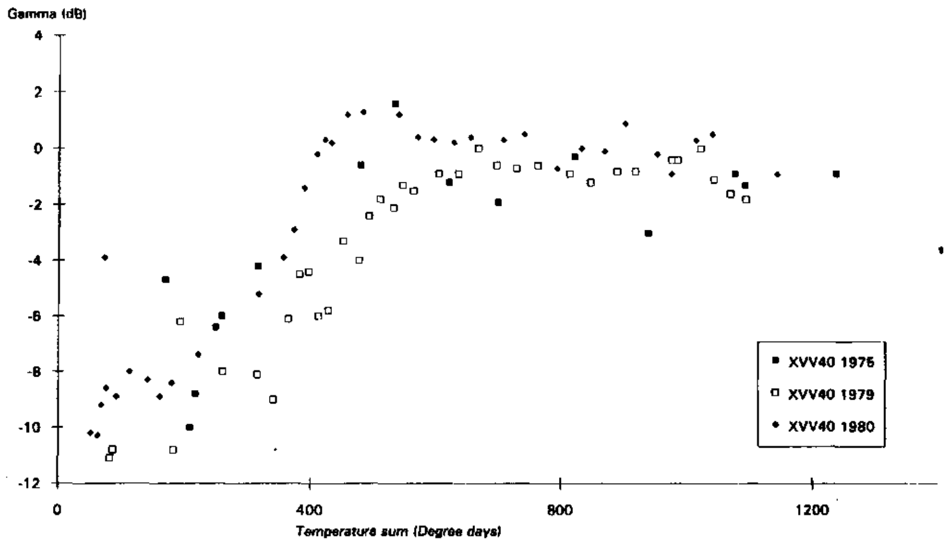


Figure 2.13 *ROVE backscatter from sugar beet, at X-band, VV, 40° (incidence angle) in 1975, 1979 and 1980 (Source: Rijckenberg & an Leeuwen, 1994)*

Rijckenberg and Van Leeuwen (1994) noticed that the dip in γ increases with incidence angle (ROVE data), which could be caused by the fact that the backscatter becomes more sensitive to structure variations with increasing incidence angle. For winter wheat X-band VV ROVE data gave the signature shown in Figure 2.14.

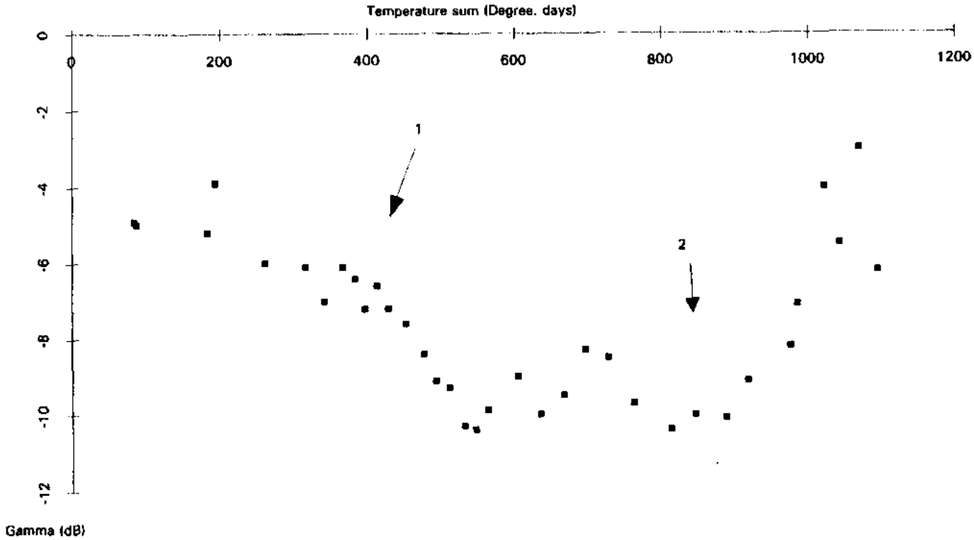


Figure 2.14 *ROVE backscatter from winter wheat, at X band VV 20 degrees (incidence angle) in 1979, 'De Bouwing' Wageningen*

At T_{sum} ~ 400 a decrease in backscatter was found which was due to ear formation (change in crop structure) and at about T_{sum} 800 the ears start ripening (increase in biomass: here the second layer could be modelled by a Cloud model), see also Table 2.8 in which ROVE field observations are summarized.

Figure 2.14 and Table 2.8 allow the conclusion that crop development related to canopy structure can indicate the moment when a new RS model or semi-empirical relationship with the proper boundary conditions should be used. This is more pronounced for cereals than for sugar beet. For cereals two important moments of increase in biomass could be noticed: the moment of leaf and stem formation and, later in the growing season, the moment of ear formation and filling. In Figure 2.14 only the latter can be seen in the microwave backscatter time-series, because the measurements started later on in the growing season. Winter wheat had already started growing at the end of the previous year. The latter is the reason that the temperature sum is relatively low, because it was calculated from the 1st of January instead of the sowing date.

Table 2.8 *ROVE 1979, 'De Bouwing' Wageningen; development of winter wheat as a function of temperature sum counting from 1 January 1979 and corresponding day numbers (Source: Van Kasteren, 1993)*

T_{sum}	*Day nr*	*Growth stage*
83	202	cover 20-50
183	216	cover >50, height <50
246	224	1st shoot, 2nd leaf
383	237	ear formation
429	244	ear stem formation
511	253	filling of ears, yellowing
814	285	ripening, % dry biomass of ear >40%
918	295	dying of leaves (brown)
986	302	harvest possible, ears bent
1022	306	stubs

2.6 Summary

In this chapter several RS models were dealt with. In the optical part of the EM spectrum as well as in the microwave region these models can be complex or more simple in character. They are all (implemented) solutions of the radiative transfer theory. In crop growth monitoring accurate estimates of the *LAI*, for example, are required during the whole growing season.

For the optical part of the EM spectrum two models were selected, the CLAIR model and the SAIL model. The CLAIR model, using the *WDVI* concept, appears to be a practical algorithm describing the relationship between reflectances and *LAI*. The results of *LAI* estimation are quite satisfactory. The CLAIR model is a simplification of the SAIL model. Both models were validated. A sensitivity analysis of a combined SAIL-PROSPECT model revealed that the leaf angle distribution is the major disturbing factor in the relationship between *WDVI* and *LAI*. Similar conclusions can be drawn for the estimation of the *APAR* from the *WDVI*.

For the microwave region of the spectrum, the Cloud model was selected. The canopy and soil contribution to total backscatter of the crop-soil system could be modelled in an acceptable manner. The IEM soil model appeared to be useful for understanding microwave soil backscatter phenomena, but is not further used in this study simply because the Cloud model takes canopy contribution as well as soil contribution into account .

More complex models such as the 'Eom and Fung' model were used for sensitivity analysis. As with the optical RS models, leaf angle distribution (or better plant structure; also stem distribution) is a major factor influencing the backscatter signal, besides plant moisture. The Cloud model may appear to be a practical algorithm describing the relationship between backscatter and the amount of moisture in the canopy layer. However, in contrast with optical modelling, the Cloud model has not yet been calibrated for most crops and is not transferable over the years. This implies that the Cloud model needs to be calibrated for every season or measurement campaign.

Canopy structure is not explicitly incorporated in the semi-empirical CLAIR and Cloud RS models. However, the more detailed RS models such as SAIL and the 'Eom and Fung' model do include canopy structure as it is recognized as an important factor in the change of the RS signal. The impact of canopy structure on the microwave RS signal can be discovered as a specific and important feature in time-series of microwave RS measurements. Remark that the validation of RS models is based on a few fields only so far.

Chapter 3 deals with the use of the various RS models and features for monitoring crop growth. The study of information from RS models and temporal series, especially as function of development rate, will improve the combination methods for linking both optical and microwave RS data with crop growth models.

3 Crop growth monitoring with remote sensing

3.1 Introduction

New methods for crop yield prediction in The Netherlands are based on crop growth modelling and remote sensing techniques. In the mid-sixties C.T. de Wit and his co-workers at the Department of Theoretical Production Ecology of Wageningen Agricultural University and at the DLO-Research Institute for Agrobiology and Soil Fertility (AB-DLO) developed techniques for crop growth modelling. In the late eighties AB-DLO introduced methodologies that combined remote sensing (RS) models and crop growth models. The information on crop growth provided by RS needs to be evaluated on its applicability as RS measurement and modelling techniques change with time.

In the previous chapter the potential of RS information for crop growth monitoring was evaluated (research question a of Section 1.4). However, it would be interesting to know how and to what extent this information can contribute to the improvement of crop yield prediction (research question b). The sensitivity analysis of remote sensing interaction models as performed in Chapter 2 showed that the most important variables influencing the RS signal are *LAI*, biomass and canopy structure.

Reflective optical RS data offer the possibility of estimating the *LAI* of agricultural crops. The CLAIR model offers a practical algorithm for describing the relationship between reflectances and *LAI*. This inverted RS model is simple and has already been validated. Furthermore, in the CLAIR model it is assumed that the leaf angle distribution (*LAD*) is constant throughout the growing season, which is not always the case for some crops (for example sugar beet).

Chapter 2 also showed that microwave RS data can be used for estimating the amount of canopy moisture with a validated microwave RS model. When doing so, the Cloud model may provide a practical algorithm for describing the relationship between backscatter and canopy moisture. However, this model has not been calibrated yet for most crops nor for various remote sensor configurations. Because of this, the regression parameters of the Cloud model cannot be reused for the various seasons. This might imply that the Cloud model needs to be calibrated for every season or RS campaign.

Microwave RS data may also provide information on canopy structure by studying the time-series of backscatter values. Specific features observed in such signatures may give important information on specific development stages of the crop as these features can correspond with canopy structural changes in most crops, certainly in cereals.

In this chapter a methodology is described for linking the RS information described above with crop growth models. First of all, in Section 3.2 several crop growth models are briefly reviewed. Next, the key crop variables that may be used for linking RS and crop growth models are described in Section 3.3 Various combination methods for the purpose of crop growth monitoring will then be described in Section 3.4, followed by the conclusions in Section 3.5.

3.2 Overview of crop growth models

3.2.1 Introduction

Crop growth modelling serves two main aims (Spitters, 1990):

1 acquiring insight into the system under study: how crops grow in dependence of environmental conditions and management;

2 predicting growth (yield) in future situations.

Two main types of crop growth models will be reviewed here: comprehensive models and regression models, being complex and simplified descriptions of crop growth respectively .

For prediction purposes, regression models and/or simple physiological models have the advantage over comprehensive models, because of the small amount of parameters involved and their simple structure. In regression models, the parameters are estimated by straightforward and objective, statistical procedures. The use of regression models in crop growth analysis has been reviewed by Causton and Venus (1981).

In contrast, in the comprehensive models the parameters are estimated by means of iterative procedures in order to tune the model to the experimental data. This often involves tedious computation. Also, comprehensive models are unnecessary complex with regard to their prediction accuracy.

Crop management requires predictive (regression) crop growth models, whereas research asks for comprehensive (or explanatory) models. It is expected, therefore, that for predictive purposes, simple physiological models should be used.

The crop growth models developed by De Wit and his co-workers at the AB-DLO are comprehensive in nature and particularly suitable to study possible links with RS model variables. The main driving force is absorbed (intercepted) solar radiation. Many studies were carried out on the modelling of the solar radiation budget in the canopy (De Wit, 1965; Ross, 1981; Goudriaan, 1977, etc.). However, another important basis for crop growth modelling could be the phenology of the crop.

The comprehensive model has a wider range of application, especially as a research tool. It predicts yields better than a regression model, but requires more information as input. When there is insufficient information available, the use of a regression model may be the best option (Seligman, 1990). In the following sections some models will be studied in more detail and selected on their potential application in combination with RS data.

3.2.2 Comprehensive description of crop growth based on light interception

The incoming photosynthetically active radiation (*PAR*, 400-700 nm, representing more or less the visible radiation) is partly reflected by the top layer of the canopy and partly potentially available for absorption by the canopy. Subsequently, the fraction of absorbed radiation 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 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. The maximum rate of photosynthesis at light saturation is strongly correlated to the leaf nitrogen content. The assimilated CO_2 is reduced to carbohydrates which the crop can use for growth.

Because of this detailed modelling of the solar radiation budget, this type of model, based on light interception, is especially suitable for the linkage with optical RS through the use of reflectance models operating in the same spectral region (especially red). An example of implementation of this type of model is the SUCROS model (Spitters *et al.*, 1989b). SUCROS (Simplified and Universal Crop Growth Simulator) is a mechanistic crop growth model that describes the potential growth of a crop using irradiation, air temperature and crop characteristics. Potential growth here means the accumulation of dry matter under conditions of ample supply of water and nutrients, and an environment that is free from pests and diseases (Bouman, 1992a). A schematic illustration of the model is given in Figure 3.1.

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 (partly from Spitters *et al.*, 1989b).

The assimilated matter is first used to maintain the present biomass (maintenance respiration) while the remainder is converted to new, structural plant matter (with loss due to growth respiration). The crop growth rate is determined by the difference between the energy used for daily assimilation and respiration of the crop. The development rate which is a function of temperature determines the growth period. Biomass production of the various plant organs is a product of the growth rate and growth period of the crop. The newly 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. This is an important issue for the combination with RS as above-ground biomass appeared to be one of the variables (Chapter 2) dominating the RS signal reflection. Phenological development of the crop has, in its turn, an effect on the distribution of the newly formed dry matter in a spatial sense, which could cause changes in plant structure, which will be shown in Section 3.4.2.3. As presented in Figure 1.4, the biomass production and the development section of the crop growth scheme represent the most important links with RS information. These main links are the variables biomass, *LAI* and plant structure.

Multiplication of the simulated leaf dry matter with the specific leaf area of new leaves gives the increase in leaf area (*LAI*). This is an important variable in the simulation since the increase in leaf area contributes to the next day's light interception and hence to the next day's rate of assimilation. As a result, the development of *LAI* depends on the growing conditions in the previous period. As such, the *LAI* is a suitable indicator of crop growth and a major variable to be monitored. Also, this variable is important to the combination of crop growth and RS.

The parameters in the model can be divided into species parameters (e.g. partitioning factors, light use efficiency), location parameters (geographical latitude), initialization parameters (e.g. sowing date, number of plants per m^2) and driving variables (daily irradiance, daily maximum and minimum temperature). Species parameters have to be estimated from field and laboratory measurements. Location and initialization parameters need to be known for each simulation condition, and driving variables have to be measured daily throughout the growing season.

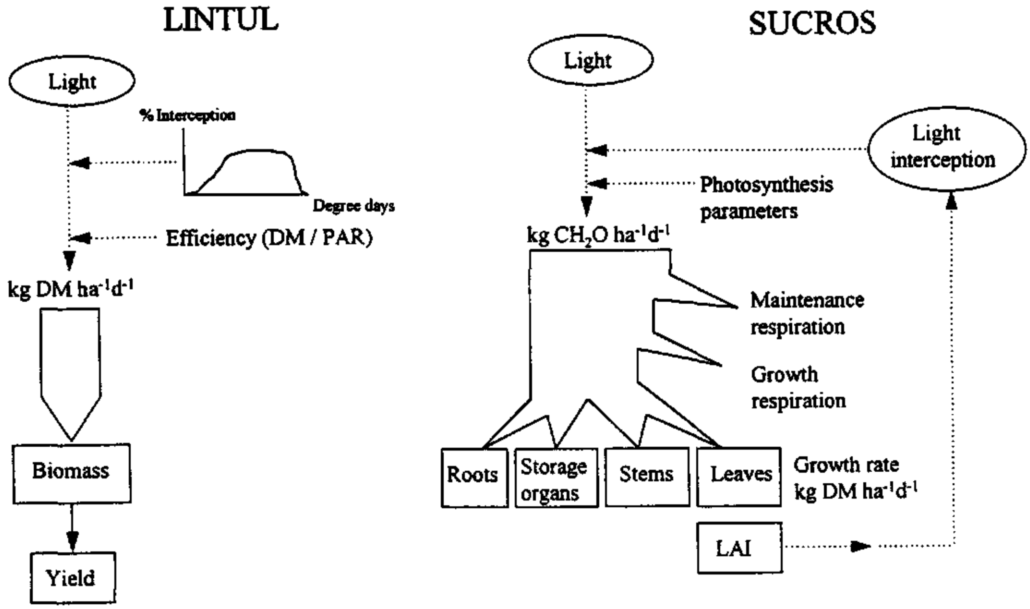


Figure 3.1 *Schematic representation of the calculation of crop growth: (a) a relatively simple approach (LINTUL) and (b) a complex approach (SUCROS)*
(Source: Spitters et al., 1989b)

SUCROS was calibrated, i.e. the species parameters were determined, by Spitters *et al.* (1989) on a number of Dutch field experiments, and by taking parameter values from literature. Spitters *et al.* (1989) also updated and improved the SUCROS version as published by Van Keulen *et al.* (1982) and named their version SUCROS87. A good description of SUCROS87 with an explanation of the abbreviations (parameter and variable names) is presented by Spitters *et al.* (1989). In his study Bouman adapted and initialized the SUCROS87 model for the Southern Flevoland Province. During the growing seasons of 1987 and 1988 an extensive field survey was carried out at the test site of the Southern Flevoland Province supporting the Agriscatt 1987 and 1988 RS campaigns.

3.2.3 Validity of the SUCROS model

SUCROS simulates potential production. In most field situations, conditions for potential production are rarely met. The Southern Flevoland Province, however, is an area where growing conditions are generally favourable to reach the potential production. Water shortage is rarely a problem, and farmers apply (more than) sufficient fertilizer and pest, disease and weed control measures. In the calibration and validation years 1987 and 1988 (Agriscatt campaigns), SUCROS gave good simulations of actual crop growth for sugar beet (Bouman, 1992b). At the time of this research Bouman showed that the SUCROS model predicts the growth of sugar beet quite well, which was, at the time, not the case for winter wheat as the partitioning of newly formed dry matter was rather difficult to simulate.

For operational use (such as yield estimation), models like SUCROS often appear to fail when growing conditions are nonoptimal (e.g. pest and disease incidence, severe drought, frost damage). Therefore, for yield estimation it is necessary to check the modelling results with some kind of information on the actual status of the crop throughout the growing season. RS may provide such actual information (Section 3.3).

3.2.4 Simple description of crop growth based on light interception

3.2.4.1 LINTUL

LINTUL is the acronym for "Light INTerception and UtiLization simulator" (Spitters, 1987, 1988). The concept of this model is based on the experience that under proper growing conditions, the growth rate is proportional to the amount of intercepted light. This concept can be elaborated on in the following procedure (Spitters, 1987, 1988). The growth rate is calculated on the basis of the incoming photosyntically active radiation (*PAR*), the fraction of *PAR* intercepted by the foliage (*FPAR*) and the average light utilization efficiency (see Figure 3.1). This fraction can be calculated in the period from emergence to full ground coverage with a logistic function, in which plant density and the relative growth rate play a dominant role. During the phase of foliage senescence the decline in light interception is assumed to be linear. The different phases are described as a function of temperature sum (or T_{sum}). The temperature sum is calculated using the daily average minimum and maximum air temperature just above the ground (common meteorological data). Total biomass is obtained by integrating the daily growth rates over time.

3.2.4.2 Approach by Maas

Maas (1988) developed a simple semi-empirical crop growth model to simulate the daily above-ground growth for white maize over the period from emergence to anthesis. To validate the model, the average daily temperature and integrated *PAR* were measured. Furthermore, biomass and *LAI* were measured every week. The model developed to simulate this growth is shown schematically in Figure 3.2. Modelling daily growth involves quantifying three basic activities in the following order:

1 absorption of light (based on *L*);
2 production of new above-ground biomass (based on *Q*);
3 determination of the new *LAI* together with the increase of *M*.

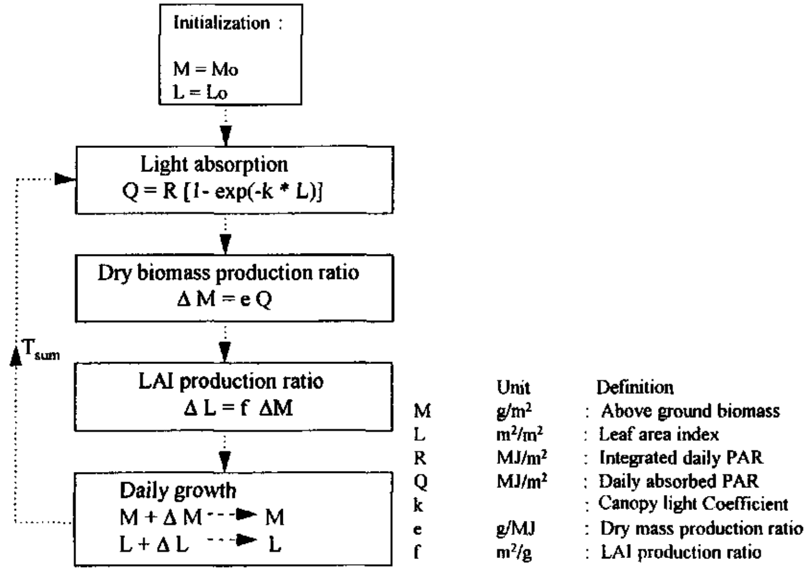


Figure 3.2 *Schematic description of crop growth by Maas*

The increase in *LAI* and biomass on one day resulting in new values for *L* and *M*, forms the new start for the next simulation of the following day. The modelled growth is driven by environmental conditions through the input of *R* (global radiation) and temperature. The latter is not included in the model. Since the model simulates growth between two fixed dates representing emergence and anthesis, development of the crop is not taken into consideration.

However, recently Maas (1993) introduced the daily increase in accumulated degree-days, or the increase in the so-called temperature sum in this type of modelling. As the development of the crop is closely related to the temperature conditions, this option in the modelling could indirectly indicate the crop growth development stage. The development stage of a crop could be accompanied with a certain canopy structure. The latter offers specific opportunities for the application of RS (especially radar RS).

3.2.4.3 Description of growth by using regression functions

Various regression functions for crop growth can be used, like those by Gompertz, Richards, etc. (Clevers, 1986). The model by Schnute can describe all these different models with the proper boundary conditions mentioned in Table 3.1. The model of Schnute (1981) is another type of regression model. The regression parameters must be determined on the basis of a non-linear fit of existing temporal growth data. However, this model describes the growth of a single biophysically relevant variable Y as a function of time (e.g. $Y = LAI$ or biomass, etc.). The function is mathematically flexible and can be used for non-symmetrical crop growth curves (mostly sigmoid in shape):

$$Y(t) = (y_1^b + (y_2^b - y_1^b) \cdot \frac{1 - e^{-a(t-t_1)}}{1 - e^{-a(t_2-t_1)}})^{1/b} \qquad (3.1)$$

in which

t_1 = first specific age (time)
t_2 = second specific age (time)
a = fit parameter 1
b = fit parameter 2
y_1 = size of crop variable at t_1
y_2 = size of crop variable at t_2

with the boundary conditions for the different growth functions derived from Equation (3.1) in Table 3.1. The advantage of this kind of modelling is that crop growth (boundary conditions, error analysis, etc.) can be simplified and formulated in a mathematical way. A disadvantage is that the curve is based on experimental data, which are often not available or not representing the crop in general (over the seasons).

Table 3.1 *Special cases of the general Schnute model*

Boundary Condition		*Model*
$a > 0$	$b = 0$	Gompertz
$a > 0$	$b < 1$	Richards
$a > 0$	$b = -1$	Logistic
$a = 0$	$b = 1$	Linear
$a = 0$	$b = 0.5$	Quadratic
$a < 0$	$b = 1$	Exponential

In Figure 3.3 the Schnute model is fitted to a sequence of *LAI* values and biomass values simulated by the standard SUCROS model (Bouman, 1991c). The parameters a and b are the regression or fit parameters. The size parameters y_1 and y_2 represent the initial *LAI* or biomass at time t_1 and the *LAI* or biomass at the end of the growing season at time t_2 respectively.

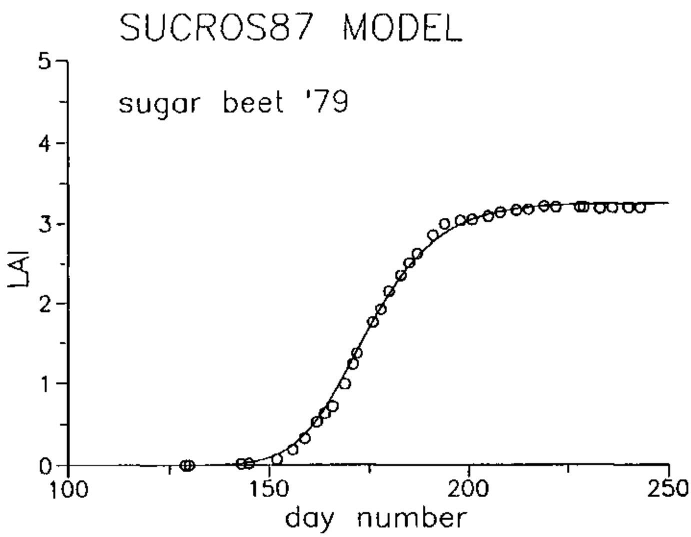


Figure 3.3 *The Schnute model fitted to simulated data of the SUCROS model (LAI sugar beet, meteo data of 1979)*

In order to compare the different growth functions, regression is performed with dry biomass also simulated by the same SUCROS model. The results of this exercise, presented in Table 3.2, indicate that various forms of the general model by Schnute are suitable enough to describe crop growth.

Table 3.2 *Regression results with various forms of the model of Schnute applied to experimental ROVE data (dry biomass in g/m²) of 'De Bouwing', 1979*

Name curve			a	b	y_1	y_2	r
Gompertz	a > 0	b = 0	0.009	0.0	24.5	816.8	0.9760
Richards	a > 0	b < 1	0.028	0.048	0.0	765.8	0.9942
Logistic	a > 0	b = -1	0.091	-1.0	0.4	661.5	0.9968
Linear	a = 0	b = 1	0.0	1.0	267.0	630.0	0.7336
Quadratic	a = 0	b = .5	0.0	0.5	267.0	630.0	0.7336
Exponential	a < 0	b = 1	-.014	1.0	0.2	886.5	0.9718

3.2.5 Selection of crop growth models in relation to RS

In this study, the SUCROS model is an appropriate model to combine with RS as it includes several crop variables that can be estimated with RS. Important is that the SUCROS model (from now on the SBFLEVO model for sugar beet) has been validated for several crops on the test site in Southern Flevoland where many RS campaigns have been conducted (Bouman, 1992a). For this study, the SBFLEVO model was chosen and will be used in Chapters 5 and 6 to test the developed combination methodology. The crop characteristics estimated using RS data could either initialize or calibrate the crop growth model. On the other hand, when the crop growth model is validated, and growth can be summarized with more simplified models such as those by Maas or Schnute, or the LINTUL model, it would be more appropriate for practical applications (yield estimation on regional scale) as it has fewer parameters and requires less computation.

3.3 Key variables for linking RS and crop growth models

3.3.1 *LAI* and biomass estimation

The estimation of *LAI* and biomass by inversion of RS models is quite straightforward when semi-empirical models like the Cloud model for the microwave and CLAIR for the optical part of the EM spectrum are used. However, as these models are semi-empirical, the fit parameters in the model are based on local conditions and have limited validity. Inversion of these models should be performed carefully within the boundary conditions (Chapter 2). The fit parameters are determined on the basis of former campaigns. It is important to realize that disturbing factors such as wind, water stress and with that biophysical parameters like *LAD*, could influence these fit parameters. From literature (Uenk *et al.*, 1992) and from past experiments the fit parameters appeared to be constant over the years (see Table 2.2).

3.3.1.1 LAI estimation with the CLAIR model

The CLAIR model is an already inverted algorithm (Clevers, 1989b):

$$LAI = -1/\alpha \cdot \ln(1 - WDVI/WDVI_{\infty}) \tag{3.2}$$

in which *WDVI* is the so-called weighted difference vegetation index, either based on green reflectance or red reflectance.

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* values. It is expected that the accuracy of *WDVI* measurement will not depend on the absolute value of the *WDVI* itself. However, the accuracy of *LAI* estimation cannot simply be expressed in terms of accuracy of the individual WDVI values, because *LAI* is a non-linear function of *WDVI*:

$$LAI = f(WDVI) \tag{3.3}$$

An approximation can be derived in the following way (Van Leeuwen & Clevers, 1994a): Consider a non-linear function f(x); a first-order approximation of the variance of this function is:

$$\mathrm{var}[f(x)] = (\delta f/\delta x)^2 \cdot \mathrm{var}(x) \tag{3.4}$$

For the relationship given in Equation (3.2) this gives:

$$\mathrm{var}[LAI] = (\alpha \cdot WDVI_{\infty})^{-2} \cdot (1 - WDVI/WDVI_{\infty})^{-2} \cdot \mathrm{var}[WDVI] \tag{3.5}$$

Combination of Equation (3.5) and Equation (3.2) yields for the standard deviation of *LAI* estimation:

$$\sigma[LAI] = \exp[\alpha \cdot LAI - \ln(\alpha \cdot \cdot WDVI_{\infty})] \cdot \sigma[WDVI] \qquad (3.6)$$

As presented in Chapter 2, Section 2.3.3 for sugar beet Bouman *et al.* (1992a) found an estimated 0.485 for α and 48.4 for $WDVI_{\infty}$, whereby *WDVI* was based on green reflectance. The residual mean square error 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 ($\sigma[WDVI]$ in Equation (3.6)) is 2.0. This value seems quite reasonable. Figure 3.4 plots the estimated *LAI* using the CLAIR model against the measured *LAI* (ground measurements) for the calibration set of Agriscatt. In addition, the lines exhibiting deviations +/- twice the standard deviation (using Equation (3.6)) from the measured *LAI* are shown.

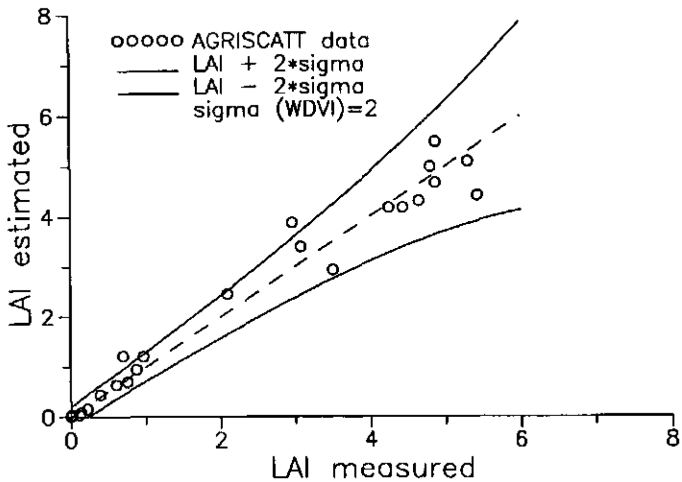


Figure 3.4 *Relationship between estimated LAI using the CLAIR model and measured LAI for sugar beet (test site Southern Flevoland Province, Agriscatt campaigns 1987 and 1988)*

3.3.1.2 Biomass (LAI) estimation using the inverted Cloud model

The main variable in the Cloud model is canopy moisture with partially or totally closed canopy. In addition, soil moisture and soil roughness can play a role of importance depending on the measurement situation and the crop geometry (rows, etc.). But first the attention will be focused on the relationship between canopy moisture and *LAI*.

In order to meet the criteria in Chapter 2, Section 2.2 interchangeability of variables between models would be preferable. In this sense the relationship between biomass (related to canopy moisture) and *LAI* in the case of the sugar beet crop was studied. Ulaby *et al.* (1986) performed a similar study for corn to calibrate the Cloud model. However, their conclusion was that the calibrated Cloud model could not be used for other experiments in other growing seasons. The fit parameters appeared not to be similar.

Relationship between LAI and the amount of water in the canopy layer (sugar beet)

A possible relationship between *LAI* and canopy moisture is interesting for the synergy study as it provides a link between optical and microwave RS models. The amount of moisture in the canopy layer is represented by the amount of water (gravimetric) in leaves and stems of the above-ground parts of the crop. The leaves distributed in space play the most important role in the observation of the crop-soil system, certainly at high frequencies. Since sugar beet can be considered as a rather dense crop it is assumed that the microwave sensor only sees the above-ground canopy. Soil backscatter contribution to total backscatter is assumed to be neglected. The relationship between *LAI* and canopy water of the sugar beet crop is based on the detailed ground truth measurements of the Agriscatt 1988 campaign (see Figure 3.5)

$$W \cdot d = LAI \cdot 1.21 \qquad (3.7)$$

with $R^2 = 0.95$ and correlation coefficient $r = 0.97$

In reality this simple linear relationship between canopy moisture and *LAI* is not valid for the whole growing season. In the beginning of the growing season *LAI* measurements in the field are rather difficult and less accurate compared to biomass measurements. The relationship is expected to be non-linear. As in Figure 3.3, *LAI* can be modelled by the Schnute regression function. This can be done for biomass as well. In this way, theoretically a nonlinear relationship between biomass and *LAI* can be derived by substitution of the mutual variable time of both regression functions! For reasons of simplicity, the linear Equation (3.7) was used. If we consider only the leaf layer to be important for the microwave modelling, leaf moisture could be estimated with *LAI* as well, see Appendix A.

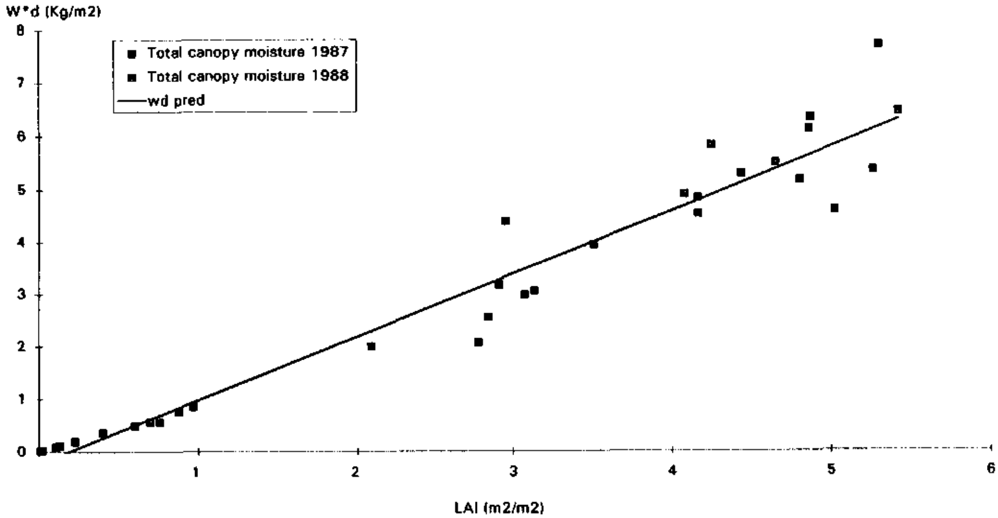


Figure 3.5 *Relationship between canopy moisture and LAI for sugar beet (test site Southern Flevoland Province, Agriscatt 1987 and 1988 campaign)*

Considering that total canopy moisture is responsible for the backscattering the Cloud equation can be written as (with A = 1/1.21; cf Equation (2.5)):

$$\gamma = C \cdot (1\text{-}\exp(\text{-}D \cdot LAI/A \cdot \cos\theta)) + G \cdot \exp(k \cdot m_s/\cos\theta) * \exp(\text{-}D \cdot LAI/A \cdot \cos\theta) \qquad (3.8)$$

For a single day in the growing season we may consider the soil moisture content and the soil roughness constant for all sugar beet fields at the Flevoland test site. Thus, we can simplify the Cloud model. In practical operational situations, the soil moisture can be predicted by a hydrological model calibrated with meteorological data and representative soil moisture samples from the field for the typical soil in question.
The simplified Cloud model can be inverted when we put $K = C - G \cdot \exp(k \cdot m_s/ \cos\theta)$ and $D' = D/A$. Equation (3.8) results in:

$$\gamma = C - K \cdot \exp(\text{-}D' \cdot LAI/\cos\theta) \qquad (3.9)$$

Under the assumptions given above, this equation can be inverted:

$$LAI = \text{-}\cos\theta/D' * \ln \cdot ((\gamma\text{-}C)/\text{-}K) \qquad (3.10)$$

Similar to the CLAIR model we find an exponential relationship between the RS measurements and *LAI*. Again, the accuracy of *LAI* estimation will decrease with increasing *LAI* value.

Analogously to the CLAIR model, we are dealing with a non-linear function. A first-order approximation of the variance of the *LAI* can be derived as follows:

$$\mathrm{var}[LAI] = -\cos\theta / D' / (\gamma - C)^2 \cdot \mathrm{var}[\gamma] \tag{3.11}$$

Combining this Equation (3.11) with Equation (3.10) yields the following estimation for the standard deviation of *LAI*

$$\sigma[LAI] = \cos\theta / (K \cdot D') \cdot \exp(D' \cdot LAI / \cos\theta) \cdot \sigma(\gamma) \tag{3.12}$$

The standard deviation of the *LAI* estimation can serve as a means for weighting the contribution of *LAI* coming from radar or from optical remote sensing in the combination methodology.

3.3.2 *LAD* estimation

As significant changes in leaf angle can occur during the growing season due to changes in development stage or local disturbances (like wind, water stress, nutrient depletion, etc.) the leaf angle will influence the RS signal as was shown by a sensitivity analysis (see Chapter 2). The simplified semi-empirically RS models like CLAIR or Cloud do not take the *LAD* into account as a separate variable, as opposed to the more complex models such as SAIL or MIMICS. In the calibration of the CLAIR and Cloud model structure information is not accounted for. Therefore it is somehow related to the regression (or fit) parameters.

Theoretically, one could determine the fit parameters of the CLAIR model belonging to a certain *LAD* by fitting this model to SAIL model simulations with different *LAD* and varying *LAI* (Chapter 5). Jacquemoud *et al.* (1994) tried to invert the PROSPECT-SAIL combination for five variables (a.o. *LAI* and *LAD*) with the CAESAR optical airborne sensor in the MAC Europe 1991 campaign. The inversion with different numerical techniques failed more or less, because of numerical instability and too few independent measurements (the dual-look concept of CAESAR was used).

3.3.3 *APAR*

Estimating *APAR* over a certain interval of time (e.g. daily *APAR*) requires both incident *PAR* and the (average) fraction of *PAR* absorbed by the vegetation (*FPAR*). Daughtry *et al.* (1992) showed that the daily *APAR* for crops may be reliably computed from measurement of the *FPAR* near solar noon and daily incident *PAR*. As a result, they conclude that the *FPAR* yields a good estimate of the plant's capacity to absorb radiation throughout most of the day. This *FPAR* can be estimated from an RS platform.

The relationship between *LAI* and *FPAR* has been defined by e.g. Baret and Guyot (1991) (cf also Asrar *et al.*, 1984; Sellers, 1985) as:

$$LAI = -1/K_{par} \cdot \ln(1 - FPAR/FPAR_{\infty}) \tag{3.13}$$

with K_{par} as the extinction coefficient for photosynthetically active radiation, which depends on canopy geometry and the illumination conditions (of the sun) (see Figure 2.4a), and $FPAR_{\infty}$ as the asymptotically limiting value for *FPAR* (0.94 according to Baret and Guyot, 1991). When comparing Equations (3.2) and (3.13), a clear analogy becomes obvious. However, α is particularly related to the NIR region where scattering is the dominating phenomenon (measured in terms of *WDVI*) and K_{par} is related to the visible region in which absorption dominates (measured in terms of *FPAR*). Although α and K_{par} are related to different spectral regions, they are influenced by variables such as leaf angle distribution (*LAD*) or solar angle in a similar way. Assuming the rough approximation that α and K_{par} are equal, the following linear relationship between *WDVI* and *FPAR* (Clevers et al., 1994c) is found:

$$FPAR = WDVI \cdot FPAR_{\infty}/WDVI_{\infty} \tag{3.14}$$

Finally, the *FPAR* can be related to the total photosynthetic activity of a canopy by integrating the *FPAR* over time. This is what is done in crop growth models. The inputs in these models are often estimates of parameters such as the canopy scattering coefficient for visible light and the extinction coefficient for *PAR*.

3.3.4 Optical properties of leaves

The optical properties of leaves are characteristics such as leaf reflectance and transmittance. These characteristics can only serve as input and initialization of the optical RS model and also of the crop growth model (e.g. extinction coefficient). As mentioned in Chapter 3, Section 3.1 leaf reflectance and transmittance can be estimated using the PROSPECT model .

As the optical properties are more or less constant for each crop under specific growing conditions, governed by nature (climate and regional aspects), predictions by RS might be able to provide additional information on the (development) state of the crop. For example, the greenness of the leaves gives an indication of the photosynthetic activity, and as yellowing occurs mostly at the end of the growing season or for reasons of disease, changes in leaf reflectance and transmittance are to be expected. Another reason for the change in greenness of the leaves could be the amount of nitrogen. There are indications that nitrogen depletion may be detected with RS (Clevers and Van Leeuwen, 1994c). They studied the chlorophyll content of agricultural crops by using airborne hyperspectral measurements, which are related to the optical properties of leaves.

3.4 Combination methods of RS and crop growth models

3.4.1 Introduction

The main advantage of RS information is that it provides quantification of the actual state of the crop using methods that are less labour and material intensive than *in situ* sampling. While models provide a continuous description of plant growth over the period of interest, RS observations are discrete time events. Also, models provide a physiologically based record of the interaction between plants and their environment. In contrast, RS information can give little indication how the plant community achieved its observed state. These basic differences make the incorporation of RS information into crop growth models more than a trivial exercise.

Two general techniques can accomplish this objective (Wiegand *et al.*, 1986), and these can be described as follows: RS observations can be used to provide estimated values for one or more variables that “drive” the model; secondly, RS observations can be used to "adjust" or "correct" the simulation during the growth period. Several previous attempts to apply these techniques to agricultural crop growth models have been reported (Brakke & Kanemasu, 1979; Kanemasu *et al.*, 1982, 1985; Maas *et al.*, 1988; Wanjura & Hatfield, 1985; Maas, 1993; Delecolle *et al.*, 1992).

In the first method, the so-called *crop parameter estimation*, the crop parameters are estimated from optical RS and fed into a growth model as input or forcing function. Mostly, crop parameters that have been used successfully so far are measures for the fractional light interception by the canopy (Steven *et al.*, 1983; Kanemasu *et al.*, 1984; Maas, 1988; Bouman & Goudriaan, 1989). However, parameters like *LAD* and leaf optical properties can also be used as input in more elaborate growth models such as those described in this chapter. Some methods for deriving these parameters from optical RS data are published in Clevers and Van Leeuwen (1994c) and Clevers *et al.* (1994b).

In the second method, known as *model calibration*, crop growth models are calibrated on time-series of RS measurements. Maas (1988) presented a method in which crop growth model parameters were adjusted in such a way that values of *LAI* simulated by the growth model matched *LAI* values that were estimated from reflectance measurements. Bouman (1992b) developed a procedure in which RS 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 calibrated 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 calibration than before calibration on reflectance measurements. The calibration in this procedure is governed by the parameters that link the crop growth model and the RS model together (so far mainly *LAI* and crop biomass).

3.4.2 Calibration methods for crop growth models

In this study the relevant methods for crop growth model calibration with remote sensing can be schematically ordered in the following way:

I Crop growth model calibration using a direct RS model predicting the RS signal at a certain moment in the growing season (or so-called direct use of RS models; direct modelling method);

II Crop growth model calibration using an inverted RS model estimating crop variables at a certain moment in the growing season (inverse modelling method);

III Crop growth model calibration using RS information by means of typical RS features in time-series related to the crop development stages;

IV A combination of approaches II and III.

In the first two approaches calibration of the model occurs at every specific moment an RS measurement is available. This is a specific *moment* during crop growth at a specific growth stage with a certain biomass level and a certain spatial distribution of the various parts of the crop above ground. The third approach is based on the development of the crop in which transitions of one crop development stage into another could be the cause of a change in level of the RS signal. The interpretation of such a feature in an RS time curve is then based on the change of a certain biomass level and/or spatial distribution of plant parts above the ground or, in other words, a change in canopy structure over a *period* of time.

These four calibration methods have in common that the key variables *LAI*, biomass and canopy structure play their specific role in the combination methodology as a link between RS and crop growth. The key variables *LAI* and biomass are used in Method I, *LAI* (and indirectly biomass) in Method II and structure information of the canopy in Method III; finally in Method IV all variables are used as Methods II and III are combined.

For reasons of consistency, in the combination methodologies RS information was combined with the SBFLEVO model as this model is a detailed description of crop growth, which is important for the necessary links with RS. Bouman (1992a,b) combined crop growth models with RS and tested and calibrated Method I with ground-based optical and radar measurements from ROVE campaigns. Assuming the fact that RS model regression parameters can be used for different growing seasons of different crops (especially sugar beet and wheat), Bouman (1992a,b) implemented direct RS models (Method I) in combination with the crop growth model in the SBFLEVO and WWFLEVO (developed for wheat analogously to sugar beet) prototype software.

At the time, the WWFLEVO prototype was not suitable for testing the methodologies as the validation for growing conditions for winter wheat at the Southern Flevoland Province posed some problems. This concerned especially the partitioning of dry matter to the different plant organs. However, the SBFLEVO prototype (for sugar beet) gave better results, because the crop growth model had been initialized and validated successfully for the growing conditions in the Southern Flevoland Province. This was the main reason for conducting our research on sugar beet as a crop.

This prototype was the starting point for this study in which optical and microwave airborne RS measurements were used for the next step in application of RS in crop growth monitoring in an operational sense. Secondly, the problem of non-transferrable RS models over the different growing seasons was dealt with by using the validity of RS models and additional RS time-series information. The combination methods II, III and IV were tested with the synergetic airborne data of the MAC Europe campaign 1991 as described in Chapter 5. The prototype as a starting point for the thesis study will be described in the following section in which also the reasons for modification will be given.

3.4.2.1 Method I: Direct modelling method

The crop growth simulation model SUCROS (Spitters et al., 1989) was extended with the Cloud model and the reflectance models EXTRAD and CLAIR to simulate RS signals in the SBFLEVO programme (Bouman, 1992a). The Cloud model regression parameters were provided by Van Leeuwen (1992b) using the Agriscatt 1988 data for different crops, only no regression accuracy was presented. The SBFLEVO model simulated crop variables, such as biomass and *LAI*, together with radar backscatter and canopy reflectance during the growing season. The growth model had been calibrated for the Southern Flevoland Province to fit the simulated RS signals to the measured RS signals. The initialization of the model for the Southern Flevoland Province was carried out by determining the species parameters (e.g. partitioning factors, light use efficiency, etc.), initialization parameters (e.g. plant density) and location parameters.

In reality, most crop species parameters in the growth model do not have one specific value but are characterized by a biological plausible range (Rouse *et al.*, 1991). This variation in parameter values allows for a range in simulation results by the SBFLEVO programme. The model may thus be calibrated within the biologically plausible ranges to fit the simulated RS signals to the measured ones. The calibration of the starting conditions (e.g. sowing date, number of plants per m^2) of the growth model is known as initialization. Initialization and calibration of the growth model were based on a controlled random search procedure as developed by Price (1979) and extended by Rouse *et al.* (1991). Per simulation condition this procedure yielded "optimum" initialization conditions and species parameter values. "Optimum" here refers to parameter values that resulted in the smallest (absolute) difference between simulated and measured RS signals (either optical or radar, or both), averaged over the whole growing season. With optimum parameter values, the simulated time course of RS signals fitted the measured signals best. Thus the growth model could be optimized to both optical and radar RS measurements (and to any other type of observation), for any combination of (radar) incidence angles (cf Figure 3.6). The prototype programme for this optimization (or calibration) procedure was called SBFLEVO_OPT by Bouman (1992b).

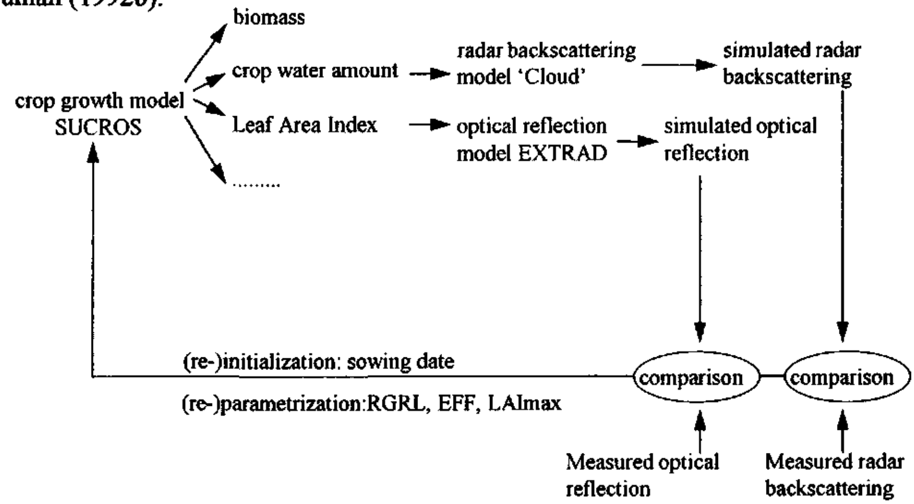


Figure 3.6 *Methodology of calibrating the crop growth model SUCROS with simulated and measured radar and optical RS data using the models in a direct modelling method (Source Bouman, 1991c)*

A sensitivity analysis of the crop growth model was carried out to select the initialization conditions and crop species parameters to be calibrated (Bouman, 1991c). The growing season of the sugar beet crop was divided into three distinct growing periods: initialization, exponential growth, and linear growth. Per growing period, parameters were selected that had a great effect on both the RS signal and the canopy biomass and/or *LAI*. Because of the redundancy in the effects of parameter changes, the selection of parameters was kept to a minimum. For radar data only, sowing date, relative growth rate and light use efficiency were selected. Optimizing all parameters during linear growth hardly had any effect on γ. For optical data, sowing date, relative growth rate, light use efficiency and maximum leaf area were selected. The maximum leaf area (defined here as the leaf area above which the leaf dies owing to shading) especially had a great effect on the *WDVI* and the *LAI* in the second half of the period of linear growth.

Because the calibration procedure optimized a number of parameters at the same time, the obtained optimum values may deviate from the true physical values. The optimum values only fitted the simulated RS signals to the measured signals in order to improve the simulations of canopy biomass.

An extensive description of this calibration procedure, including programme listings, is given by Bouman (1992a, 1992b).

Discussion and modifications for the present study

It is important to realize that the present method (I), using the Price algorithm, can be regarded as an inverse procedure to estimate the four most important crop growth model variables (sowing date, relative growth rate, light use efficiency and maximum leaf area) in order to predict the dry matter formation of different plant organs in time. These variables vary within plausible ranges as input to SBFLEVO model simulations resulting in simulated RS signals, which are compared with the measured RS signals from the specific campaign in order to find the best combination of the four crop variables with the lowest error. The method is evaluated on one overall error. This could give local solutions of the crop growth status at the time of observation and thus of the calibration, which might be beside the truth.

At the present state of RS modelling the RS signal cannot yet be fully explained as a function of *LAI*, biomass, *LAD*, not to mention the additional variables such as soil moisture, roughness or even row effects. A distinction must be made for optical and radar modelling for reasons of validity (see Chapter 2). So, the simulation of RS signals with the SBFLEVO model introduces errors which have their impact when they are compared with the actual measured RS signals. As this problem does not lie in the crop growth modelling itself but more in the RS modelling, in the following more attention will be paid to the information supplied by RS and its appropriate link with the crop growth model.

At this stage the SBFLEVO model uses the RS models in a forward or direct manner. The inverse use of RS models could give the opportunity to take the RS measurement error into consideration (see Equations (3.6) and (3.12)). Another characteristic point in the new combination method is the clearly defined use of the inverse RS models by the introduction of the boundary conditions found in the calibration and validation phase (see Chapter 2, Sections 2.3.5 and 2.4.5).

Especially for present microwave modelling (Cloud model), the biomass is estimated while assuming a constant crop morphology or structure. The latter is embedded in the regression parameters of the Cloud model (see Chapter 2). The previous description provides a means to adapt the SBFLEVO_OPT prototype (Bouman, 1992b) in order to test the combination methods II, III and IV for crop growth model calibration (see Figure 3.7) by:

- implementing inverse RS models;
- introducing airborne RS measurements;

- introducing a new weighting method in order to introduce the estimation accuracy of the RS variable and the accuracy of the RS measurement itself;
- implementing the noncontemporaneous combination of RS information by calibration on the same variable estimated from either optical and/or microwave RS;
- introducing structure information related to development stage in the crop growth model by means of temperature sum intervals.

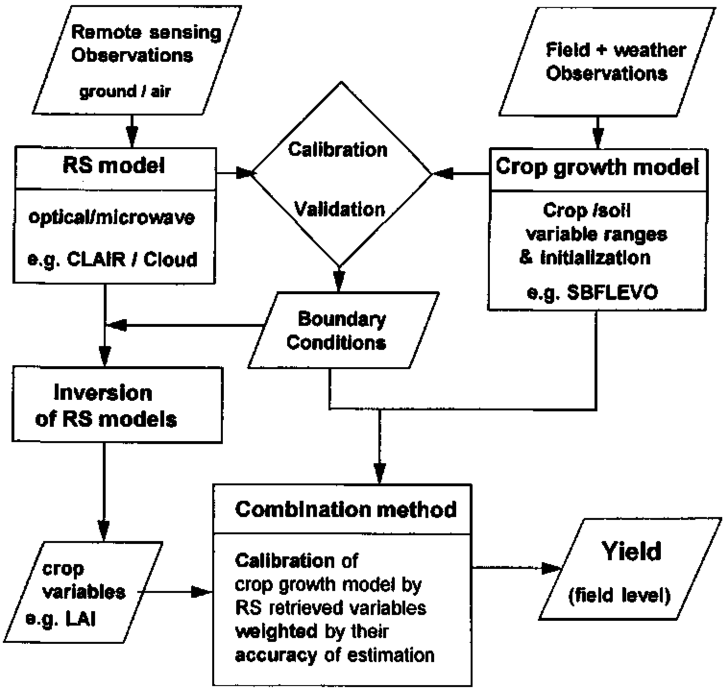


Figure 3.7 *Methodology of calibrating the crop growth model SBFLEVO with simulated and measured radar and optical RS data using the models in an inverse modelling method*

In the SBFLEVO_OPT prototype developed so far, the simultaneous optimization of both optical and radar data can only be performed when at a specific date both optical as well as radar data are available. This problem can be solved by introducing crop variables (*LAI*, biomass) and the corresponding proper weighting factor. With each variable supplied by RS at any moment, whether the estimation is for the optical or the microwave region, calibration of the crop growth model can be performed on contemporaneous RS data as well as noncontemporaneous RS data.

For practical reasons of adaptation and because of criteria 2 and 3 (Chapter 2, Section 2.2.2) , *LAI* will form the main integrating link between optical and microwave RS models and crop growth models with Equation (3.7). When no direct relationship between *LAI* and leaf biomass exists, use can be made of prior knowledge of a standard description of *LAI* and biomass as a function of time (or temperature sum) by using the Schnute model (Equation (3.1)). The regression parameters of this model are based on the daily simulations of *LAI* and biomass by the standard SUCROS crop growth model, initialized for the specific growing conditions valid at the site. However, the relationship between *LAI* and (leaf) biomass (with known plant density) needs to be handled with care (see the discussion in Section 3.3.1.2 and Appendix A), certainly at the end of the growing season when the leaves are yellowing and/or dying (sugar beet, wheat). Another option which has not been used in this thesis is to make use of a weighted estimate of biomass (related to the amount of moisture in the canopy layer) from the Cloud model and the weighted estimate of *LAI* from the CLAIR model and feed them into calibration Method I (direct use of RS models) in a noncontemporary manner as well.

Of course, at the proper moments in this calibration procedure the relevant variables need to be selected by using prior information from field knowledge or standard crop growth models of the specific growing conditions of the crop under study. Some discussion on the uniqueness of the solution of the optimization procedure of SBFLEVO_OPT will follow in Chapter 4.

Radar model development has not reached the stage yet where it can supply us with structure information for directly applying combination method III. A simple mathematical representation (for reasons of inversion) is needed to estimate biomass (or *LAI*) and *LAD*. Therefore, an inverse modelling methodology has been developed (see next section).

3.4.2.2 Method II: Inverse modelling method

With the modifications of Method I mentioned in Section 3.4.2.1 the inverse RS modelling in combination with the crop growth model was developed. In the inverse modelling method the SBFLEVO crop growth model is initialized and calibrated to fit simulated *LAI* values to estimated *LAI* values obtained from RS observations. Thus, first the CLAIR and/or inverted Cloud model are applied for obtaining *LAI* estimates from the RS measurements. Subsequently, the SBFLEVO model is calibrated on these

LAI estimates. Since we have seen in Sections 3.3.1.1 and 3.3.1.2 that the accuracy of the *LAI* estimates depends on the absolute value of the *LAI*, the reciprocal of the standard deviation of *LAI* estimation is used as a weighting factor for each individual *LAI* estimate used in the optimization procedure. For *LAI* estimates from optical measurements, Equations (3.2) and (3.6) were used and for *LAI* estimates from radar measurements, Equations (3.10) and (3.12) were used. In addition, regression parameters obtained from the calibration of the CLAIR and the Cloud model respectively, must be used in these equations. This approach yields at the same time a proper mutual weighting between optical and radar data when the data from both windows are used together in the crop growth model calibration procedure. Moreover, it is obvious that for the methodology of this approach it is irrelevant whether one has optical and radar data at the same date or not. Since it was found that quite different combinations of optimized calibration parameters yielded similar fit results, it was decided to select the mean calibration parameter values of the 200 best combinations after optimization. This mean value appeared to yield more stable results, particularly concerning simulated yield and calibrated sowing date.

For the rest, the same procedure with the same crop growth model calibration parameters as in direct modelling was used in the inverse modelling approach.

3.4.2.3 Method III: Feature-based combination method

As mentioned in Section 3.2.2 crop growth depends on environmental conditions like temperature, nutrients, water availability, etc. The temperature sum is one of the main factors determining the development rate of the crop. The formation and partitioning of dry matter is different for each development stage during the corresponding growth period of the crop. The change into another development stage has therefore consequences for the spatial distribution of dry matter or the structure of the canopy.

The canopy structure can be quantified with a leaf angle distribution (*LAD*), as leaves are dominantly present in the case of, for instance, the sugar beet crop. Measurement of the *LAD* of sugar beet leaves is complicated because the leaves are very curved. For cereals measuring the orientation of plant parts (or so-called constituents) like leaves (shoot), stems or even ears are even more difficult. Up till now no extensive measurements in the field have been done.

For sugar beet the relationship between canopy structure (morphology) and phenological development stage is not as evident as for instance winter wheat. In general, sugar beet stays in the vegetative stage during the whole growing season, forming a rosette of leaves. Cereals, however, exhibit a clear transition from vegetative stage with predominantly leaves to generative stage during stem elongation, resulting in the formation of ears. If this relationship was evident, the temperature sum (T_{sum}) could serve as a useful indicator of changes in the development stage of the crop. As these changes could be accompanied by changes in canopy structure, microwave RS could help in identifying these transitions by finding certain features in microwave RS time-series as was already suggested in Chapter 2, Section 2.5. The microwave backscatter features make the following contribution to the optimization procedure SBFLEVO_OPT:

1 *Information for optimization.*With the meteorological data (daily temperature) a sowing date or emergence date of the crop in the observed field can be reconstructed with the help of the backscatter features that were found. As the sowing date is one of the four main parameters in the growth model optimization procedure SBFLEVO_OPT, the backscatter features can be used to calibrate the crop growth model.
2 *Boundary conditions for application of simple RS models in the optimization.* The occurrence of a certain temperature sum during the growing season can be used for application of the RS model valid during this development stage. When a new development stage coincides with a change in the distribution and amount of above-ground biomass, the temperature sum can be used as a decision maker to apply the simple RS model (e.g. two-layer Cloud model when ear layer of winter wheat is to be formed) with the proper regression parameters within these boundary conditions.

Optical RS has shown to be dependent on structure as well (see Chapter 2, Section 2.3.5). Varying the leaf angle distribution *LAD* in the EXTRAD model of the SBFLEVO prototype gave no significant consequences for the light interception and photosynthesis in the crop growth modelling (Goudriaan, 1988). However, the information on canopy structure from microwave (and optical) RS could offer the proper boundary conditions for applying the optical (and microwave) model at the right *moment* in the combination method (Method IV) as well (see Chapter 2, Section 2.3.5 and Chapter 5, Section 5.5.3). The features to be found in microwave time-series are only of value to the combination method when these features can be detected within a period of about a week in the case of sugar beet. In this way the sowing date can be reconstructed from this point with help of meteorological data. In temperate climatological conditions (e.g. Flevoland province in The Netherlands) growth can increase quickly when a long period of successive warm days occurs. For example, for sugar beet in its vegetative stage the *LAI* can increase with about one unit within one week in the period from emergence to closure. The increase in dry matter in the stems and storage organs of winter wheat occurs also in a short period. It is therefore necessary to have frequent observations by RS sensors to follow these growth dynamics. Next, in relation to crop growth the value of microwave RS information will be discussed in more detail as a basis for the combination method (Method III).

Case study: feature-based combination method for sugar beet

De Wit (1965) found that during the second half of the growing season the *LAD* changed from erectophile to a more planophile distribution, represented by a move from the right (high average leaf angle) to the left in Figure 3.8. Figure 3.9 shows the distributions that were measured by De Wit (1965). It was also noticed by Ross (1981) that a change in canopy structure occurs during the growing season. He noticed a drooping of the outer leaves (because of increasing weight) at the moment when no more additional leaves were generated. At this point the *LAI* remains more or less constant. The change in *LAD* can be either caused by a change in biomass (e.g. closure of a crop with high plant density results in erected leaves) or by the phenological development stage of the crop, depending on the plant density or nutrient application as decided by the farm management. This needs to be proven yet by conditioning the experiment in combination with *LAD* measurements.

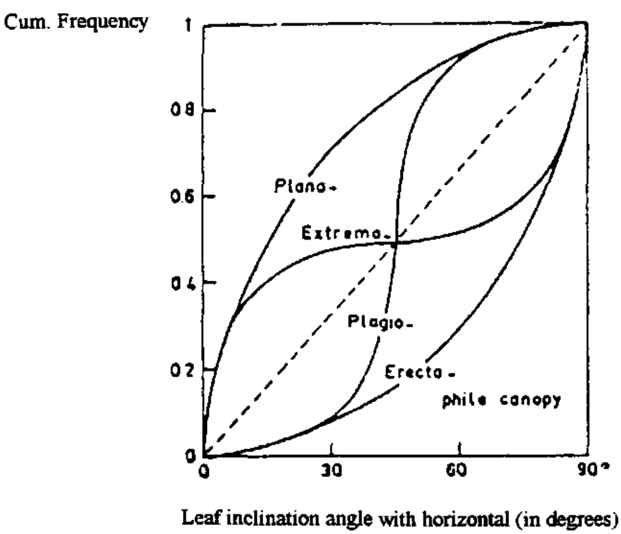


Figure 3.8 *Leaf angle distribution, with on the X-axis leaf inclination angle (in °) with the horizontal plane and on the Y-axis the cumulative frequency (after De Wit, 1965)*

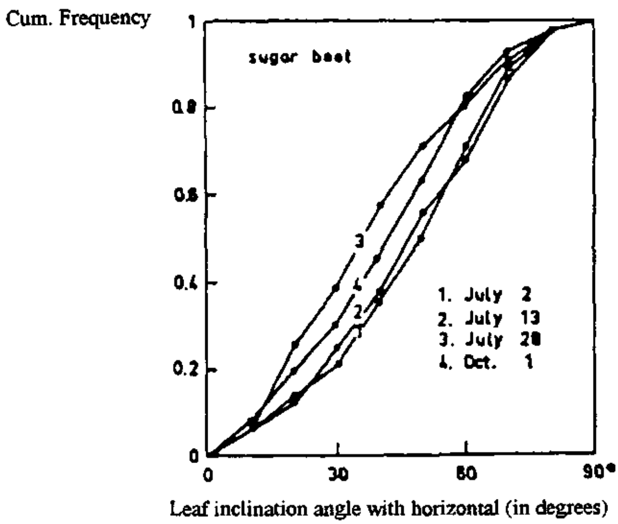


Figure 3.9 *Leaf angle distributions as measured by De Wit (1965) for sugar beet with on the X-axis leaf inclination angle (in °) with the horizontal plane and on the Y-axis the cumulative frequency.*

Table 3.3 gives an overview of how the dry matter production in sugar beet is allocated to the different organs (for the SBFLEVO programme). It shows that at T_{sum} ~ 400-700 the tuber formation starts. This is also the period in which the crop closes at the Southern Flevoland test site. At T_{sum} ~ 900-1000, almost all of the dry matter production is allocated to the tuber and here the outer leaves seem to droop according to recent measurements (see Chapter 5, MAC Europe campaign 1991).

Table 3.3 *Fractions of dry matter growth allocated to the various sugar beet plant organs, as a function of temperature sum (T_{sum}) (Source: Bouman, 1992a)*

T_{sum}	shoot leaves	shoot petiole	shoot crown	shoot total root	fiber root	tuber	root total
0	0.52	0.24	0.04	0.80	0.20	0	0.20
370	0.46	0.21	0.04	0.71	0.29	0	0.29
400	,,	,,	,,	0.70	,,	,,	0.30
665	0.27	0.29	0.06	0.61	0.20	0.20	0.39
820	0.16	0.34	0.06	0.55	,,	,,	0.45
900	,,	,,	,,	0.52	,,	,,	0.48
901	,,	,,	,,	0.22	,,	,,	0.78
1000	,,	,,	,,	,,	0.080	0.70	,,
2000	,,	,,	,,	,,	0.002	0.78	,,
3000	0.06	0.13	0.02	0.22	0.002	0.78	0.78

In Chapter 2 it was shown that the temporal backscatter signature of sugar beet exhibits a clear dip at a T_{sum} of about 900, which is related to a change in leaf orientation from spherical/erectophile to extremophile. This feature coincides with a transition in development stage from leaf formation to tuber filling (Table 3.3) and it occurs at an *LAI* of about 4.0 at the Southern Flevoland test site. This transition is very important for crop growth monitoring and yield prediction. Care should be taken with the various cultivars of sugar beet as these have their own crop growth schemes and partition tables. This has not been taken into consideration in this study.

If it were possible to locate the change in radar backscatter accurately as a function of time (or even better temperature sum), this would provide three kinds of information:

1 the moment when T_{sum} = 900 which, in combination with meteorological data, would provide the possibility of estimating the actual sowing date (by calculating back in time);
2 the moment at which *LAI* ~ 4.0 occurs, when the sugar beet crop starts to fill its tuber;
3 which regression parameters must be used in the simple RS models (such as CLAIR) in relation to the development stage.

It must be realized that the value of the above mentioned information depends on the accuracy in detection of features in microwave time-series. It might become significant in combination with *LAI* estimates from radar data using a model-based approach or in combination with *LAI* estimates from optical data or both (see next section). This will be tested in Chapter 5.

3.4.2.4 Method IV: Model-based and feature-based combination method

In the previous sections different sources of RS information have been distinguished leading to the estimation of *LAI* or a reference point in time for a specific temperature sum, which provide means for calibrating the crop growth model. These information sources were optical RS data (using the CLAIR model), radar RS data used in a model-based approach (using the Cloud model) and the information of radar RS providing a reference point used in a feature-based approach.

In order to reach the best possible estimation of crop growth, one needs all possible information there is, i. e. a combination of the model-based and feature-based method, Methods II and III respectively, resulting in combination Method IV.

However, not all information contributes in the same way to this estimation. In fact, each contribution is weighted in its own way related to its accuracy in the optimization procedure.

As the relationship between radar signature changes and the transition of development stages is much more obvious for cereals than for sugar beet, it would be better to test cereals with the proposed combination methodology. However, the prototype software of the winter wheat combination method (WWFLEVO; Bouman, 1992a) was not suitable for practical use at the time of this study. However, it is interesting to illustrate the theoretical aspects of combination Method IV for winter wheat as an example, as various information sources from RS on crop growth can be used in this method to calibrate the winter wheat crop growth model.

In Table 3.4 the fractions of dry matter growth allocated to the various plant organs for winter wheat are summarized for the growing conditions in the Southern Flevoland Province. These partitioning factors are used in the WWFLEVO programme and give an indication of phenological development of the crop. When these figures are compared with those of Table 2.8, the temperature sum relationships in the development stages of winter wheat at 'de Bouwing' site were totally different. This is caused by the moment from which the temperature sum is calculated; at sowing date in the previous year or at the first of January.

Table 3.4 *Fractions of dry matter growth allocated to the various winter wheat plant organs, as a function of temperature sum (T_{sum} in degrees days; leaves and stems and organs represent fractions of shoot). Source WWFLEVO programme (Bouman, 1992a)*

T_{sum}	*Shoot*	*Leaves*	*Stems*	*Storage*	*Roots*
0	0.50	0.66	0.34	0.00	0.50
100	0.50	0.66	0.34	0.00	0.50
200	0.60	"	"	"	0.40
250	"	0.66	0.34	0.00	"
350	0.78	"	"	"	0.22
400	0.83	"	"	"	0.17
500	0.87	0.63	0.37	0.00	0.17
600	0.90	"	"	"	0.10
700	0.93	0.29	0.71	0.00	0.07
800	0.95	"	"	"	0.05
900	0.97	"	"	"	0.03
950	"	0.00	1.00	0.00	"
1000	0.98	"	"	"	0.02
1100	0.99	0.00	0.00	1.00	0.01
1200	1.00	"	0.00	"	0.00
2500	1.00	0.00	0.00	1.00	0.00

Table 3.4 shows some important transitions in dry matter allocation which can be schematized as in Figure 3.10. In winter wheat the dry matter is partitioned between root and shoot in the first development stage from emergence to anthesis (T_{sum} 0-

1000). The increase in biomass of the first layer can be observed with microwave RS and modelled with the simple Cloud model, applying the proper regression parameters for that growth period (assuming a constant leaf/stem distribution incorporated in the regression parameters). The above-ground formation of dry matter becomes even more important in the second development stage, from anthesis to maturity (T_{sum} >1000). The increase in biomass by the filling of the ears (storage organs) of winter wheat can be observed by microwave RS and can be modelled by a second-layer in the Cloud model with new regression parameters (Hoekman *et al.*, 1982). The accuracy of these regression parameters are expected to be relatively small (see Chapter 2), owing to differences in ear and stem angle distribution of winter wheat caused by wind or water stress, etc. during the successive (microwave) RS observations. It is therefore expected that the value of microwave model inversion for winter wheat is not very high in the combination method, but that the information at the moment of change in canopy structure is more important here (feature).

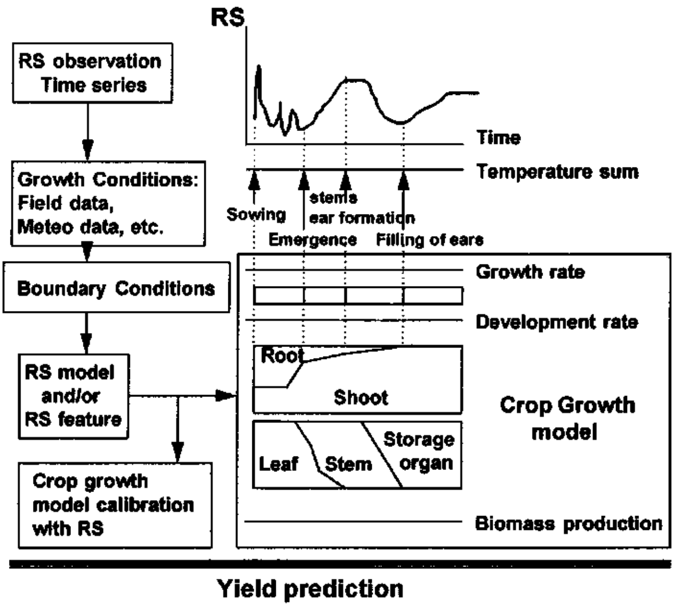


Figure 3.10 *Combination Method IV: Methods II (model based) and III (feature based) combined in one scheme. Growth and development in the crop growth model (here winter wheat as example) provide links to RS models (LAI, biomass, LAD) boundary conditions and input for the use of the RS model.*

3.5 Summary

In this chapter various crop growth models have been reviewed and selected for combined use with RS models. The SBFLEVO prototype appeared to be suitable because of its links with the variables of RS models at field level.

The RS models have the potential to provide input parameters of the crop growth model. On the other hand, RS can be used for calibrating the crop growth model to actual growing conditions. This can be done either with the direct or the inverse (Methods I and II respectively) use of the RS model. The latter is preferred here as it provides possibilities of integrating optical and microwave RS in a weighted manner. The weights, represented by the estimation accuracy of the RS model variables, like *LAI* and biomass, offer a flexible way of combining RS information from different recording times and different sensors. The weights reflect, at the same time, the ability in estimating variables by inverse RS models related to the RS measurement accuracy and the present state of the art in RS modelling. When in future better RS models will have been developed, these could be inserted into the combination methods with the proper boundary conditions of these models.

Information from microwave RS time-series on canopy structure provides a new approach to combine RS with crop growth modelling (Method III). However, detailed time-series are needed in order to locate the features exactly in time. The features found in microwave RS time-series coincide (especially for cereals) with changes in the development of the crop when related to changes in canopy structure (e.g. ear formation, or leaf/stem angle distribution changes, etc.). Furthermore, microwave RS is not hampered by clouds or bad weather situations and can therefore provide interesting measurement time-series. By combining all RS information from optical and radar sensors at a specific time or at various recording times, an integrated combination method is formulated (Method IV).

In Chapter 4, a description will be given of the data sets and the analysis methods for preparation and reduction of the RS data and ground data for testing the combination methodologies. The various methodologies of combining RS information with crop growth models will be illustrated by data from the MAC Europe campaign in Chapter 5 .

PART II APPLICATION OF CONCEPTS

4 Material and methods

4.1 Introduction

An inventory of the datasets presently available to agricultural studies in the Southern Flevoland Province in The Netherlands is presented in Section 4.2 and selected on the basis of the criteria set for the study objectives. In general, the present RS and ground data were gathered by conducting several campaigns, stimulated by the introduction of new measurement techniques (e.g. scatterometry, polarimetry, spectrometry) and strategic funding in the last two decades. Therefore, with the present state of the art in RS and crop growth modelling (as described in Chapters 2 and 3) and bearing in mind the research objectives, only few RS campaigns (described in Section 4.2.3) appeared to be useful to the study. The measurements of crop variables in the field at the time of the RS campaigns are described in Section 4.2.3 and selected for the modelling exercise in Chapter 5.

The different types of information from the RS campaign need to be processed and analyzed. In Section 3, a processing methodology is outlined in order to prepare and integrate RS data and ground data for the crop growth monitoring study. Acquisition of information for studying (biophysical) processes is considered to be an iterative procedure as the insight into these natural processes increases with time and scientific experience. It is therefore important that the information is easily accessible and be used in a conditioned manner for model analysis and combination methods of different sources of information (RS with crop growth or hydrology). This requires flexible data handling for analysis and visualization.

4.2 Campaigns

4.2.1 Brief historical overview of RS data campaigns

In the past two decades numerous RS campaigns have been organized in The Netherlands. In Table 4.1 several campaigns are mentioned (Van Leeuwen *et al.*, 1995b), with their respective objectives. Some important microwave RS campaigns are listed. Of course numerous campaigns with optical sensors have been organized. The objective of this study is related to crop growth monitoring at field level, and interesting ground-based optical and microwave RS archives were gathered from the Dutch NIWARS period (1975-1981) by the AB-DLO institute in Wageningen. At that time the ROVE programme (De Loor, 1982) was one of the most intensive microwave and optical measurement programmes (Van Kasteren, 1993). This period has provided detailed multi-temporal series with a ground-based FMCW radar system (X-band) for several agricultural crops and bare soils on different test sites (De Bouwing, Flevoland). The use of radar for applications like crop growth monitoring and forestry studies was studied in airborne campaigns like Agriscatt 1987/1988 (Bouman, 1991c; Hoekman, 1990). During the MAC Europe campaign in 1991 (Van Leeuwen *et al.*, 1995a) a synergetic airborne RS data set was obtained for the purpose of agricultural crop studies for operational application in particular. The development of new sensors together with the step from ground-based to airborne measurements and even spaceborne systems has provided researchers with an enormous amount of data of high research potential.

Table 4.1 *Historical overview of the main RS campaigns for agricultural and forestry applications at the test site of the Southern Flevoland Province in The Netherlands. Note: Nonexhaustive list of campaigns available for this study*

Campaign	*Year*	*Main purpose*	*Sensors*
ROVE	1980-1981	Ground based; crop growth; soil	FMCW & HHR
Agriscatt	1987; 1988	Airborne scatterometry & SAR sensor intercalibration, airborne	DUTSCAT & HHR SAR, IRIS, SLAR
	..	Crop growth and soil modelling	
MAESTRO	1989	Airborne; polarimetry; calibration	AIRSAR
MAC-Europe	1991 ..	Airborne synergy; crop growth, spectrometry; polarimetry	AIRSAR,CAESAR,SPOT AVIRIS, GERIS, HHR
ERS-1	1991; 1992	Spaceborne; acreage, pre-season crop classification, crop growth monitoring	ERS-1
ERS-1,	1993	Sensor calibration; crop growth monitoring	ERS-1, JERS-1, HHR, SPOT, TM
SIR-C	1994	Sensor calibration, validation of interpretation for agriculture, forestry	SAR (X,C,L)

However, the technology push has not always contributed to a constructive measurement programme serving the specific research objectives of this study and limitations will be briefly evaluated in Section 4.2.3.

4.2.2 Selection criteria for synergy study

An inventory needs to be made of the available data sets of the campaigns in the Dutch Flevoland test site and appropriate data selected for the synergy study. RS and crop growth modelling with respect to agricultural crops are the central issue for the synergy study. The selection criteria for the use of data sets in this research project can be formulated as follows:

1. Crop type and location and, related to this, availability of initialized crop growth models;
2. Availability of ground truth variables corresponding to the RS model variables (calibration set);
3. The frequency of time-series of RS data should meet the dynamic behaviour of the crop growth process, so that RS models can be calibrated;
4. The measurement configuration (frequency, polarization, incidence angle, phase information, measurement accuracy, etc.) should be chosen in such a way that crops and their growth stages can be discriminated and analyzed with valid RS models;
5. Combination of criteria 1, 2, 3, and 4, providing the conditions for retrieval of crop characteristics like the amount of biomass and leaves or crop architecture, and their change in time during the growing season.

4.2.3 Description of data sets and their limitations

Four multi-temporal data sets mentioned in Table 4.1 that at least had the potential of monitoring crop growth during the growing season and that met nearly all the above mentioned criteria, were selected for the synergy study. However, each data set was very different from the other.

The ROVE data set was chosen (Criteria 1, 2 and 3) because it comprises data from experiments covering several years at different test sites, and because of its detailed multitemporal observations of various agricultural crops (only X and Ka band, which are not common configurations in present operational satellites). The Agriscatt database (Criteria 1, 2 and 4) is especially interesting for its extensive ground truth and different frequencies, while the MAC Europe data are interesting because of the multi-sensor programme serving the synergetic research objectives (Criteria 1-5). ERS-1 (Criteria 1, 2 and 3) might have the potential to be a monitoring tool, therefore its 1992 data set was also examined for suitability. Unfortunately, the ERS-1 1993 and JERS-1 data appeared too late to be incorporated fully in this study, apart from some illustration of time-series in Chapter 6.

To estimate variables with RS, the accuracy of the RS measurement is of great importance (see Chapter 3 and Criterion 4 in Section 4.2.2). Table 4.2 shows the measurement accuracy of different sensors in units of radar backscatter (dB) or optical reflectances (%). The figures are an estimation of error in the RS signal as for each sensor configuration (frequency, polarization, etc.) different accuracies at ground level are expected. These errors are caused by calibration of the RS signal or by calculation of a representative RS signal for one field. The latter is calculated on the basis of enough independent measurements within the observed fields (objects). For example, for radar images from SAR sensors one needs about 200 independent samples (pixels) to have a statistically sound backscatter coefficient. The effect of the measurement error on the variance in *LAI* can be studied by Equations 3.5 and 3.11 for optical and microwave RS measurements respectively.

Table 4.2 *Estimated accuracy of RS observations representing one field for various remote sensors of relevant campaigns at the test site of the Southern Flevoland Province the last two decades at field level*

Campaign	*Sensor*	*Measurement accuracy*
ROVE	ground-based FMCW radar	+/- 0.5 dB
	field spectrometer	+/- 2 %
Agriscatt	airborne scatterometer	+/- 2.0 dB
MAC Europe	airborne SAR	+/- 1.0 dB
	airborne optical CCD scanner	+/- 2 %
SPOT	spaceborne optical sensor	2-5 %
ERS-1	spaceborne SAR	+/- 1.0 dB

Table 4.2 shows that the accuracy of measurements varies rather, which is not directly related to the sensor itself at the various observation levels, but more to the internal and external calibration of each measurement configuration. In the optical part, an atmospheric model correction is important for spaceborne observations. An absolute calibration with the aid of known reference objects must be carried out for microwave sensors (corner reflectors, transponders) and for airborne optical sensors (reference plates or stable natural objects or a valid atmospheric model).

4.2.3.1 Test site

The test site was located in the Southern part of the Flevoland Province in The Netherlands (see Figures 4.1 and 4.2), an agricultural area with very homogeneous (heavy clay) soils reclaimed from the lake IJsselmeer in 1966. The test site comprised various agricultural farms, each covering 45 to 60 ha. The main crops were sugar beet, potato and winter wheat.

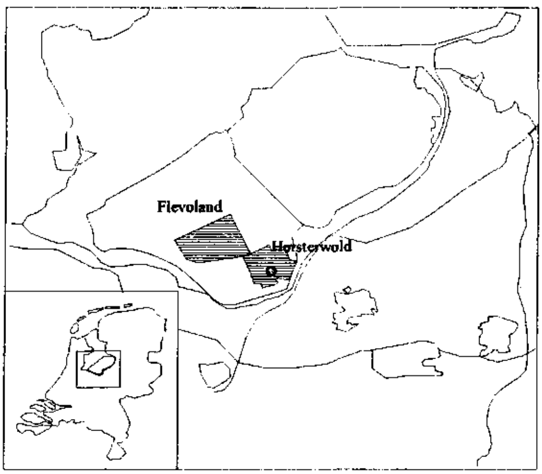


Figure 4.1 *Location of two test sites in the Southern Flevoland Province (agriculture and forestry) in The Netherlands. The upper area (agriculture) is used for the study*

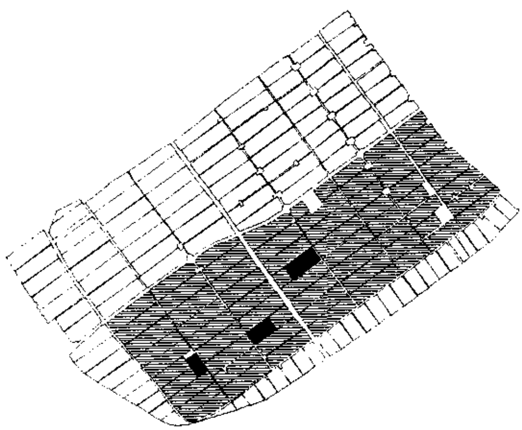


Figure 4.2 *Location of the agricultural fields (cadastral borders)*

4.2.3.2 ROVE campaign (1975-1981)

In the period 1975-1981 radar data and ground truth were collected from experiments at agricultural test farms in Wageningen and Southern Flevoland in The Netherlands (see Table 4.3; Van Kasteren, 1993). Measurements were performed throughout the growing season with a tower-based X-band (9.6 GHz) system. The radar was calibrated by means of a corner reflector; the average accuracy was better than 0.5 dB. Mainly the data sets of 1975, 1979 and 1980 were used for study, which were obtained at test sites with different soil types: sandy soil, alluvial clay and marine clay respectively. In the 1980 data ground measurements included not only crop height, crop cover, biomass, soil moisture and plant dimensions, but also reflectance measurements in the visible and NIR region. From the latter it is possible to assess the *LAI* with a vegetation index like the CLAIR model. The processing of the radar data was performed by Delft University of Technology (TUD) and the Physics and Electronics Laboratory (FEL-TNO). AB-DLO was responsible for the crop experiments and measurements, and the WAU took care of the soil measurements.

Table 4.3 *Radar and optical data from the ROVE period*

Year	*Location*	*Station*	*radar*	*optical*
1975	Wageningen	Droevendaal	+	-
1976	Wageningen	Droevendaal	+	-
1977	Wageningen	Droevendaal	+	-
1978	Wageningen	Droevendaal	+	-
1979	Wageningen	De Bouwing	+	-
1980	Flevoland	De Schreef	+	+
1981	Flevoland	De Schreef	+	+

4.2.3.3 Agriscatt Campaign 1987-1988

In 1987 and 1988 an airborne radar data acquisition campaign was conducted at several agricultural test sites in Europe. Among these sites was the Dutch Flevoland area, which comprises forest and several agricultural crops such as sugar beet, potato, winter wheat. A very extensive data set was obtained with a variety of sensors. Measurements were made throughout the growing season (Table 4.4) and detailed measurements at plant level were performed for studies of backscatter dependencies on crop characteristics (Vissers *et al.*, 1988). The extensive ground truth of 1987 and 1988 performed by AB-DLO and SC-DLO provided a very useful data set for this study and many future studies.

During the growing season of 1988, multi-frequency and multi-temporal radar data were collected with the DUTSCAT system (Delft University of Technology SCATterometer, Snoeij & Swart, 1987) at a test site located in the Southern Flevoland. Province DUTSCAT was operated at six frequency bands: L (1.2 GHz), S (3.2 GHz), C (5.3 GHz), X (9.6 GHz), Ku-1 (13.7) and Ku-2 (17.3 GHz). Radar measurements were carried out in seven sorties in the growing season at vertical (VV) and horizontal (HH) copolarization. The incidence angles were 10° and 15° during the bare soil period and 20, 30, 40, 50 and 60 degrees at the next five successive measurement days. DUTSCAT was externally calibrated for all of the above-mentioned system parameters by means of corner reflectors by TUD (Snoeij *et al.*, 1988). The average radar backscatter for all agricultural fields was computed by the FEL-TNO. The measured backscatter data of 1987 and two data recordings of 1988, however, had been compressed in a dynamic range owing to wrong attenuator settings. Snoeij *et al.* (1988) reconstructed the data by applying a decompression algorithm, which is the reason why the RS data of 1988 were used.

Table 4.4 *Microwave and optical data from the Agriscatt campaign in 1987 en 1988*

Year	*Location*	*Station*	*Microwave* (# measurements)	*Optical*
1987	Flevoland	Farm	6	every week
1988	Flevoland	Farm	7	every week

4.2.3.4 MAC Europe campaign 1991

During the MAC Europe campaign (Table 4.5), initiated by the National Aeronautics and Space Administration (NASA) and the Jet Propulsion Laboratory (JPL), both radar and optical airborne measurements were made above selected test sites during the growing season of 1991. One of the test sites was the Southern Flevoland Province in The Netherlands.

In 1991 radar measurements were performed with the polarimetric JPL-AIRSAR instrument, which operates in the frequency bands P (0.5 GHz), L (1.3 GHz) and C (5.4 GHz). This campaign was carried out in the framework of the SIR-C/X-SAR project. It was planned for a six week period (Table 4.5) on a multi-temporal basis at the Flevoland test site, starting from the end of June to the first week of August.

Ground truth measurements were limited to soil moisture measurements, soil surface roughness (only two sugar beet fields), field reflectance measurements by means of a hand-held radiometer (Cropscan) and visual crop observations like height and cover percentage (Vissers *et al.*, 1992; Büker *et al.*, 1992a). Calibration of the images was performed at the Jet Propulsion Laboratory in Pasadena and at the Wageningen Agricultural University (Büker et al., 1992b).

In the optical RS domain, NASA executed one overflight with the AVIRIS scanner operating from 0.41 to 2.45 μm. The ground resolution is 20 m as the scanner is flown at 20 km altitude (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).

Table 4.5 *Measurement scheme of the MAC Europe 1991 Campaign, Flevoland, The Netherlands, with the day numbers of recording*

Week nr	*22*	*23*	*24*	*25*	*26*	*27*	*28*	*29*	*30*	*31*	*32*	*33*	*34*
SPOT						185							
AIRSAR			166			184	193			209			
AVIRIS						186							
CAESAR						185			204				241
Cropscan	+	+	+	+	+	+	+	+	+	+	+	+	+

Ground data

Crop variables concerning acreage, variety, planting date, emergence date, fertilization, harvest date, yield and occurring anomalies were collected for the main crops (Büker *et al.*, 1992a). During the growing season, additional variables were measured in the field. The selected variables were the estimated soil cover by the canopy, the mean crop height, row distance, plants per m², the soil moisture condition and comments on plant development stage. Due to hailstorms and night-frost damage of the sugar beet in April 1991 some of the sugar beet fields were sown for a second time in late April resulting in some yield differences at the end of the season.

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. The data consisted of daily minimum and maximum temperature, daily global irradiation and daily precipitation.

Leaf optical properties
These were investigated with a LICOR laboratory spectroradiometer at AB-DLO 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
These were obtained during the 1991 growing season with a portable Cropscan radiometer (Büker *et al.*, 1992a). Eight narrow band interference filters with photodiodes were oriented upwards to detect hemispherical incident radiation, and a matched set of interference filters with photodiodes was oriented downwards to detect reflected radiation. Spectral bands were located at 490, 550, 670, 700, 740, 780, 870 and 1090 nm with a band width 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. Its distance from the crop was 2.5 to 1.5 m depending on 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 m^2 to 0.44 m^2.

The CAESAR (CCD Airborne Experimental Scanner for Applications in RS) applies linear CCD arrays as detectors. It has a modular set-up and can combine the options of high spectral resolution with 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 its 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 flights over the test site were carried out on July 4th, July 23rd and August 29th, 1991.

AVIRIS is an imaging spectrometer mounted on the NASA ER-2 aircraft. From the nominal altitude of 20 km, the swath covers 10 km on the ground; the resolution is 20×20 m. The covered spectral domain spans from 0.4 to 2.5 µm with 224 simultaneous images in 10 nm bands. The image width is 614 pixels. The atmospheric correction was performed with the LOWTRAN model at JPL-NASA (Borgeaud & Noll, 1993).

AIRSAR is a synthetic aperture radar operating at three frequencies and four polarizations (fully polarimetric) which is mounted on the NASA DC-8. It provides P, L and C band images at the same time for HH, HV and VV polarizations. The nominal altitude and speed of the aeroplane are 8.7 km and 670 km per hr respectively. The incidence angle ranges from 20° to 60°. The standard product is a multi-look image (16-look compressed Stokes matrix) which is 1280 pixels wide (range) and 1024 pixels long (azimuth). Each pixel represents 6.66 m (range) × 12.1 m (azimuth) in slant range (from 8 m to 12 m in ground range). Also available is a single-look image (1-look compressed scattering matrix). The MAC Europe polarimetric data of 1991 of the Flevoland test site were calibrated at JPL-NASA.

The SPOT satellite image was obtained on the 4th of July 1991 and was of good quality. The SPOT sensor provided the basis for the crop map as a complete overview of the Flevoland test site was obtained. The SPOT sensor has three bands in the visible (green and red) and in the NIR region.

4.2.3.5 ERS-1 1992

ERS-1 images of the Flevoland test site in The Netherlands were obtained during the growing season of 1992. No detailed ground truth is available, only soil moisture measurements were performed (Heidemij, 1992). Reflectances were obtained with the hand-held radiometer (HHR) Cropscan. These were used for the determination of *LAI* values which were used for Cloud model calibration (see Chapter 2). Calibration of the images was performed at the Winand Staring Centre, Wageningen. In Table 4.6 an overview of all recording data of the different campaigns is presented.

Table 4.6 *Recording dates of used radar data sets in day numbers, The Netherlands*

ROVE 1975	*ROVE 1979*	*ROVE 1980*	*Agriscatt 1988*	*MAC 1991*	*ERS-1 1992*
156	248	114	112	184	123
			122	193	132
every 4 days	every 4 days	every 4 days	165	209	158
			186		167
			195		186
			207		193
			228		221
218	272	272			263

4.2.4 Measurements of crop variables in the field relevant to the synergy study

An overview of the measured crop variables during several RS campaigns of the last two decades is presented in Table 4.7. A good deal of fruitful work was carried out by AB-DLO (Uenk *et al.*, 1992). From Table 4.7 it can be concluded that the Agriscatt data acquisition is very detailed compared to that of the other campaigns. From research in the ROVE programme, researchers have come to the conclusion that many crop variables are of great influence to total backscatter in X-band radar data (De Loor, 1982; Bouman, 1991b). External factors like wind or water stress (especially on sandy soils) appeared to have an impact on the radar backscatter signal as well, as these factors change crop variables, such as plant structure or plant moisture content, during the recording time of the radar.

From an RS modelling point of view, we learned that only a few crop variables are worth considering (Chapter 2, Sections 2.3.4 and 2.4.4): *LAI*, plant moisture and plant structure (e.g. leaf angle distribution). Furthermore, it appeared that the temporal resolution is also of great importance. During the exponential growth phase of several crops (potatoes, sugar beet, etc.) validation of the radar models was difficult because no recordings were made at that period during the Agriscatt campaign in 1988 (see Chapter 2, Section 2.4.3).

The detailed ground data acquisition in the Agriscatt 1987 and 1988 period, provides ample input information for the use of development and calibration of microwave models(complex) (see Chapter 2). Crop variables, such as leaf thickness, width in the case of sugar beet or ear length and stem biomass in the case of wheat, were measured. However, the insight into the complex radar modelling changes with time, and each crop needs to be studied thoroughly in terms of its (bio-)physical characteristics. It appeared that the morphology of the different plant constituents and their distribution and location in space can be of great importance. An example is the sugar beet validation with the MIMICS radiative transfer model (Perez *et al.*, 1994), in which the leaf curvature and dimensions could not be sufficiently described theoretically in order to explain the observed radar signal for different frequencies. Hoekman and Bouman (1992) found several shortcomings in the present state of physical modelling when noticing backscatter behaviour of different agricultural crops at different frequencies during the analysis of the Agriscatt data.

The validation of optical models appeared to be quite easy and reproducible over the years for the same growing conditions and test area (Uenk *et al.*, 1992).

A simple semi-empirical microwave model, like the Cloud model, can be calibrated when the temporal resolution of observation is high in the beginning of the growing season and ground data are available at the time of recording. The reproducibility of validated backscatter models over the years is much worse than in the optical domain (Chapter 2, Section 2.4.3). This is probably caused by the fact that crop characteristics, such as plant structure, are not accounted for in the microwave model and because the physical interaction mechanisms are not described well enough by the microwave model. Later on, in the MAC Europe 1991 campaign and during the ERS-1 campaign in 1993 plant structure measurements in the growing season for the sugar beet crop were performed in order to study the latter effects in more detail. In Table 4.7 the relevant crop variables used in this synergy study are given.

The measured variables most important to this study, especially with respect to canopy modelling, are described below. For description of other variables the reader is referred to the Agriscatt 1988 ground data report (Vissers, 1988).

Leaf Area Index (LAI)

The leaf area index was determined for different crop types; it was measured destructively. For sugar beet a field average was obtained by taking 30 to 40 leaves. From several years of measurements it appeared that determination of *LAI* with a hand-held radiometer results in a representative value of *LAI* (Uenk *et al.*, 1992).

Biomass and plant water (W)

Canopy biomass and moisture content (by AB-DLO) were determined by weighing all field samples in the laboratory to determine the fresh biomass. A subsample of the leaf, leaf stems and the tuber of about 0.5 kg fresh weight each was taken for the determination of dry biomass and moisture content. The number of leaves per plant in all field samples was also counted.

Leaf Angle Distribution (LAD)

In 1993 measurements of *LAD* were performed by Rijckenberg & Van Leeuwen (1994). Also during the MAC Europe campaign in 1991 some limited structure measurements were performed in cooperation with the University College of London. For the measurements in 1993 a simple device (De Wit, 1993) was used, which consists of a protractor with a rotatable indicator. This device was placed on the middle of the curved veins. By clasping the indicator, the angle with respect to the vertical can be read from the scale. The reading error is about 5 degrees and the average difference between operators was of the same order, so that the total accuracy is about 10 degrees.

Table 4.7 *Measured crop variables during the campaigns at the Flevoland test site. "opt" = optical reflectance (field) and "+" = available and "+/-"= sometimes available and "-" = not available*

Variable	*ROVE 1980 1981*	*Agriscatt 1987 1988*	*MAC Europe 1991*	*ERS-1 1992*
Species/variety	+	+	+	+
LAI	opt	+	opt	opt
crop cover	+	+	+	+
crop height	+	+	+	+
plant diameter	-	+	+	+
wet biomass leaves	+	+	-	-
wet biomass stems	+	+	-	-
wet biomass roots	-	+	-	-
total wet biomass	+	+	+	-
dry biomass leaves	+	+	-	-
dry biomass stems	+	+	-	-
dry biomass roots	-	+	-	-
total dry biomass	+	+	-	-
moisture leaves	+	+	-	-
moisture stems	+	+	-	-
moisture roots		+	-	-
total plant moisture	+	+	-	-
leaf length	+	+	-	+
leaf width	+	+	-	+
number of leaves/plant	+	+	-	-
upper leaf angle	-	+	-	-
soil roughness	+	+	+	+
volumetric soil moisture	+	+	+	+
gravimetric soil moisture	+	+	+	+
soil moisture class	+	-	-	+
sowing date	+	+	+	+
harvest date	+	+	-	+
yield	+	+/-	+	+
row direction	+	+	-	+
row spacing	+	+	-	-
plant density	+	+	+	-

4.2.5 Conclusions on relevant data sets and data selection for the study

For this study we have chosen the sugar beet as main crop and the crop winter wheat (Criterion 1). For the case study described in Chapter 5 sugar beet was chosen because of the availability of an excellent inititialized crop growth model for the Southern Flevoland Province.

The crop growth of sugar beet has three main periods (corresponding temperature sums are given for each period, Criterion 3):

1 from sowing to emergence: initial growth, T_{sum}~ 100 degree days;

2 from emergence to closure: exponential growth, T_{sum} ~ 500 degree days;

3 from closure to maturity: linear growth, T_{sum}>500 degree days.

From Agriscatt 1987 and 1988 we have the following data on the biomass of the different plant parts of the sugar beet crop (Table 4.8).

Table 4.8 *Information on sugar beet plant parts during the growing season of 1988 for field 322 as an example at the Flevoland test site in kg/m²*

date	*period*	*leaves*	*stems*	*total above ground*	*under ground*	*LAI*
				kg/m²		*m²/m²*
112	1	0	0	0	0	0
122	1	0	0	0	0	0
164	2	0.332	0.605	0.524	0	0.192
185	2	1.311	2.835	2.745	0.892	1.434
194	3	2.106	4.164	5.185	1.833	3.079
206	3	2.109	4.249	6.284	2.568	4.175
226	3	1.966	5.434	7.107	5.561	5.141

For this particular sugar beet field (Table 4.8) and the meteorological data (rain, temperature, etc.) for 1988 in the Southern Flevoland Province, the increase in leaf biomass is particularly important in period 2. However, the biomass of the stems increases during periods 2 and 3. This indicates that for biomass (of leaves) or *LAI* estimation with microwave RS (of a certain wavelength, e.g. C-band) at least four or five measurements in three to four weeks (period 2) are needed to obtain a statistically reliable fit with the RS model. This imposes requirements of the observation frequency (Criterion 3) of the sensor. Saturation of the microwave RS signal occurs after closure of the sugar beet crop (see Chapter 2) and depends on the wavelength that is used (Criterion 4). Large wavelengths, like L or P-band, are expected to penetrate deeper into the canopy (and soil) than C-band. So saturation of the microwave backscatter is likely to occur later in the growing season. However, the microwave modelling for larger wavelenghts will introduce more degrees of freedom which has its consequences for the regression analysis and related to that to the requirements for frequency of observation.

For winter wheat, as a function of time, a somewhat more complex scheme can be outlined in a similar way, as an extra layer in the Cloud model can be introduced representing the ear layer. Other factors, such as plant density, orientation of plant parts, etc. are additional factors which influence the RS signal. For example, winter wheat sometimes shows more effects of soil characteristics, such as soil moisture and soil roughness, in backscatter time-series during the whole growing season than a crop like sugar beet, probably because of the vertical orientation of the plant parts and lower values of the total above-ground fresh biomass (or better plant water) compared to the more leafy sugar beet crop.

With optical sensors the dynamic properties of crop growth cannot be observed for a length of time as clouds and atmosphere frequently disturb the RS signal. However, when a recording is obtained, crop variable retrieval with the available valid optical RS models gives better results than with microwave RS models.

Matching, as much as possible, the selection criteria posed in Section 4.2.2 with the data described in Section 4.2.3, the data selection and the most important variables for this study are presented in Table 4.9. Soil moisture and roughness were measured consistently for all campaigns.

Table 4.9 *Data selected for the synergy study in the growing season of agricultural crops*

Data set	*Microwave Data*	*Optical Data*	*nr samples (Microwave)*	*W* (*kg m*$^{-2}$)	*LAD*	*LAI* (*m*^{2} *m*$^{-2}$)
ROVE 1979	X HH/VV	-	39	+	-	-
ROVE 1980	X HH/VV	+	39	+	-	+
Agriscatt88	L,C HH/VV	+	6	+	+ (qual.)	+
MAC 91	L,C HH/VV	+	3	-	+ (quant.)	+
ERS-1 92	C VV	+	8	-	-	+
ERS-1 93	C VV	+	14	-	+ (quant.)	+
JERS-1 93	L HH	+	4	-	+ (quant.)	+

The ROVE activities of the years 1975 to 1981 are of interest to the synergy study because of the high temporal resolution of the data set. Only the data of 1980 and 1981 also include optical data. The Agriscatt campaign is interesting because of the detailed field measurements and various measurement frequencies, which is very useful for model development and validation.

The MAC Europe 1991 campaign is interesting because of the synergetic value of the data set in combination with the introduction of new sensors (polarimetry and imaging spectroscopy) and because of the plant structure measurements in the field. Owing to hailstorms and night frost damage of the sugar beet in April 1991 some of the sugar beet fields were sown for a second time in late April resulting into some interesting biomass and *LAI* variation at the beginning of the growing season and yield differences at the end of the season, which made the MAC Europe 1991 campaign a very interesting data set for the study. The L-band HH-polarization and C-band VV-polarization were selected from the full polarimetric data set as these are used for spaceborne observations by the JERS-1 and ERS-1/2 satellites respectively.

During the ERS-1 campaigns of 1991 and 1992 (bare soil period) an interesting sequence of soil data was gathered, which formed an interesting basis for the soil modelling for spaceborne applications. The ERS-1 1992 data provided time-series in the growing season. In the ERS-1 1993 campaign also *LAD* was measured in more detail for comparison with the 1991 data.

4.3 Procedure on data handling and analysis

4.3.1 Definition of information

In general, analysis tools can be more effectively utilized when the degree of RS data integration (or cohesion) is higher. Three aspects can be distinguished in relation to the synergy study of combining RS data with crop growth: spatial, thematic and temporal cohesion. These three aspects must be applied in an integrative manner in the proposed combination methodologies described in Chapter 3. Related to this, with respect to the study objectives the following three types of information definitions can be given of the object, the object state and the object state-transition respectively.

Object

The degree of spatial cohesion increases from the level of basic picture elements (pixels), through basic coherent units (segments, polygons, edges, etc.) to the level at which contextual relationships between coherent units are present. In this study the basic coherent units in RS data are clearly defined objects or fields having clear boundaries (spatial) in combination with homogeneous within-field characteristics (spectral). In this study an object is called homogeneous when the amount of independent RS measurements (or pixels) and their variation lead to a statistically sound spectral representation.

Object state

The thematical (or physical) features of an object can be imagined as a collection of RS observables and additional thematic data. The RS observation gives information on the object state at a given time. Through the functional relationships between the RS observables and the additional thematic data described in models (crop growth models, EM interaction models, etc.) a possible synergistic effect can be obtained.

Object state-transition process

The temporal cohesion will increase when more observations of the same object are made. The period of RS observation and time intervals, however, should be chosen carefully. It should be chosen on the basis of the time scales at which object state-transition processes take place (e.g. features in RS time-series linked to the crop growth process).

4.3.2 Processing of object information

In order to meet the objective of this study, the various sources of information from objects, like fields with sugar beet or wheat, must be combined. The information concerning this study consists mainly of models and data. In the combination methods described in Chapter 3 ground data and RS data are used as input for RS models for calibration and validation. Furthermore, RS data extracted from images are used for estimation of crop variables (object state) with the calibrated (inverse) RS models. The crop variables estimated with RS can be compared with the same variables estimated by the crop growth models for calibration of the object. Time series of extracted RS data can be used for the indication of crop development changes (object state-transition process).

The input and output relationships in RS models and crop growth models are described in Figure 1.2. The combination of information is an interaction or exchange between various analysis modules (see Figure 4.3). The following modules can be distinguished in an interpretation process:

I Data acquisition (RS observables and ground data)
- Object identification
- Geometric and radiometric correction
- Data extraction

II Database: structuring, storage, integration and query of information

III Data analysis: modelling of RS interaction and biophysical process

IV Database visualization

The combination approach defines the order of the successive steps in using the various data and models for the crop growth monitoring (see Chapter 3 and Figure 3.7 and Figure 3.10).

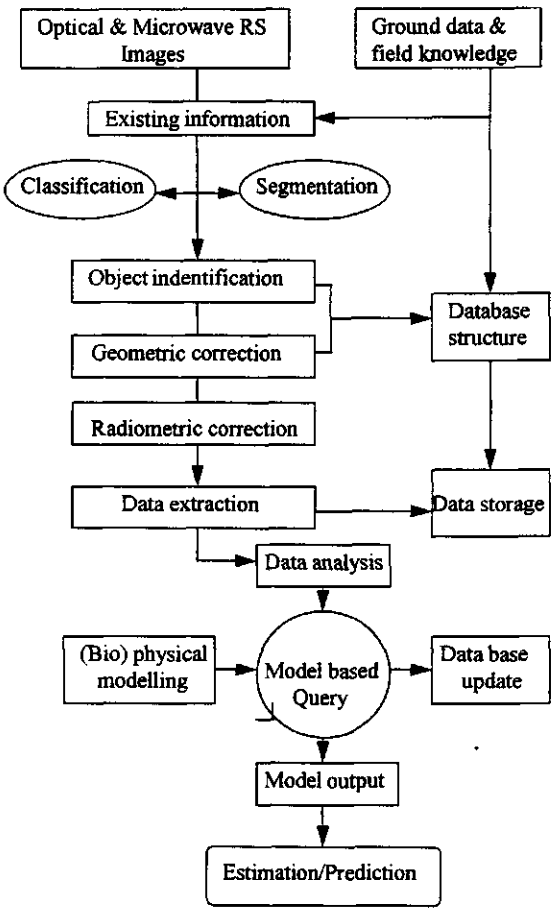


Figure 4.3 *The interaction between the data processing modules is presented*

4.3.2.1 Data acquisition

During the synergy study new measurement techniques for civil purposes were introduced in the RS campaigns, namely airborne radar polarimetry and imaging spectroscopy. This had consequences for the user group in the sense of accessibility of data. Besides the fact that image processing had become an extra activity for the

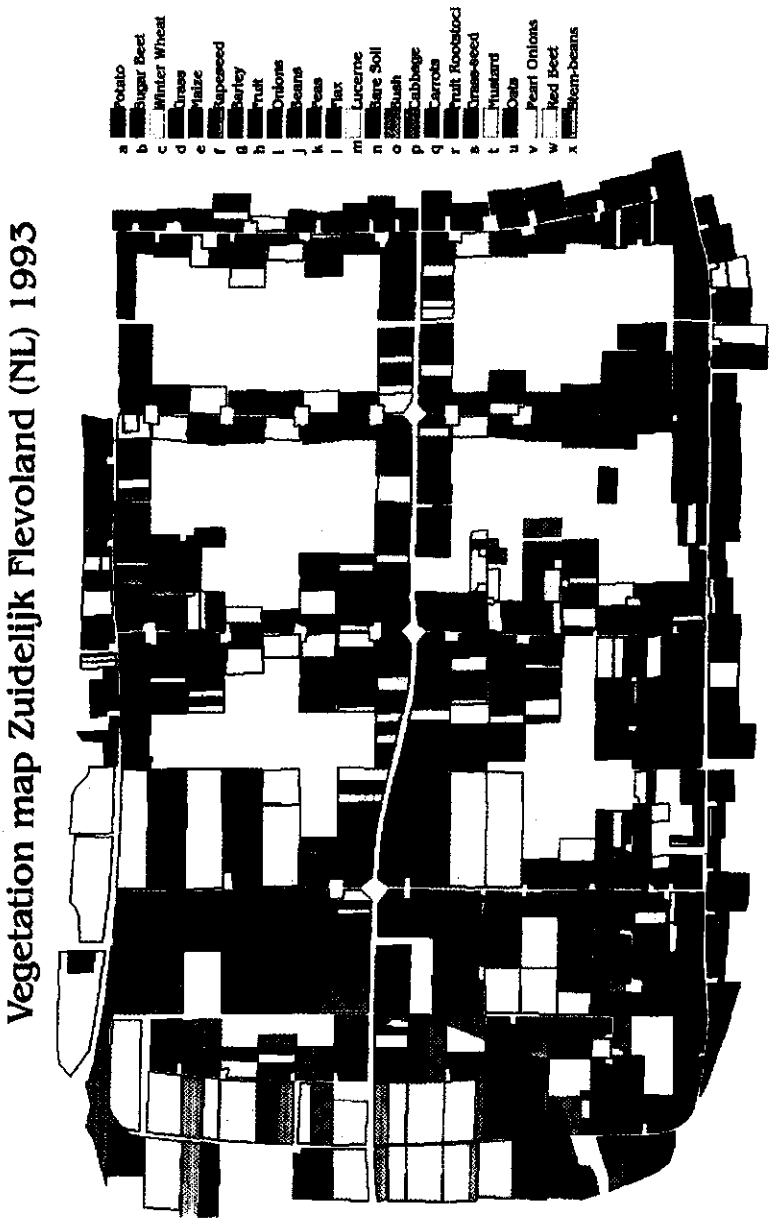


Plate 1 *With the crop map digitized from the SPOT image of 2nd July in 1993, the field boundaries (polygons) can be used as information carrier. In this example the polygon vector map has been transformed to the "Rijksdriehoeks" coordinate system and is used for data extraction and for visualization of the average backscatter of the airborne microwave observations.*

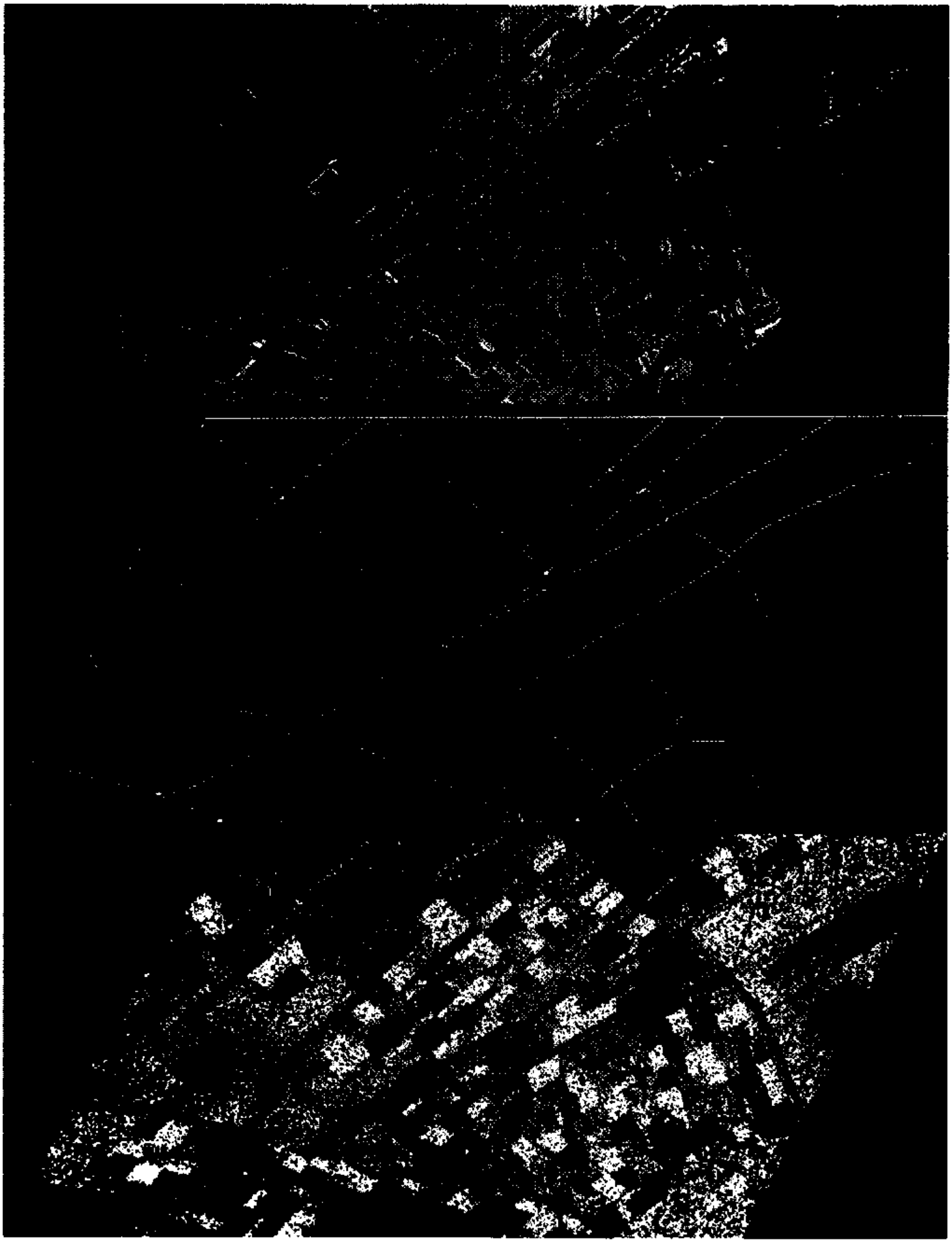


Plate 2 *Data acquisition: object identification (crop map in middle), geometric and radiometric correction of optical (upper image: AVIRIS 3 wavelengths at one date) and microwave (lower image AIRSAR: three dates for 1 wavelength) RS images, and data extraction and visualization of RS and ground data with polygon vector map (middle) as information carrier (Perez et al., 1994).*

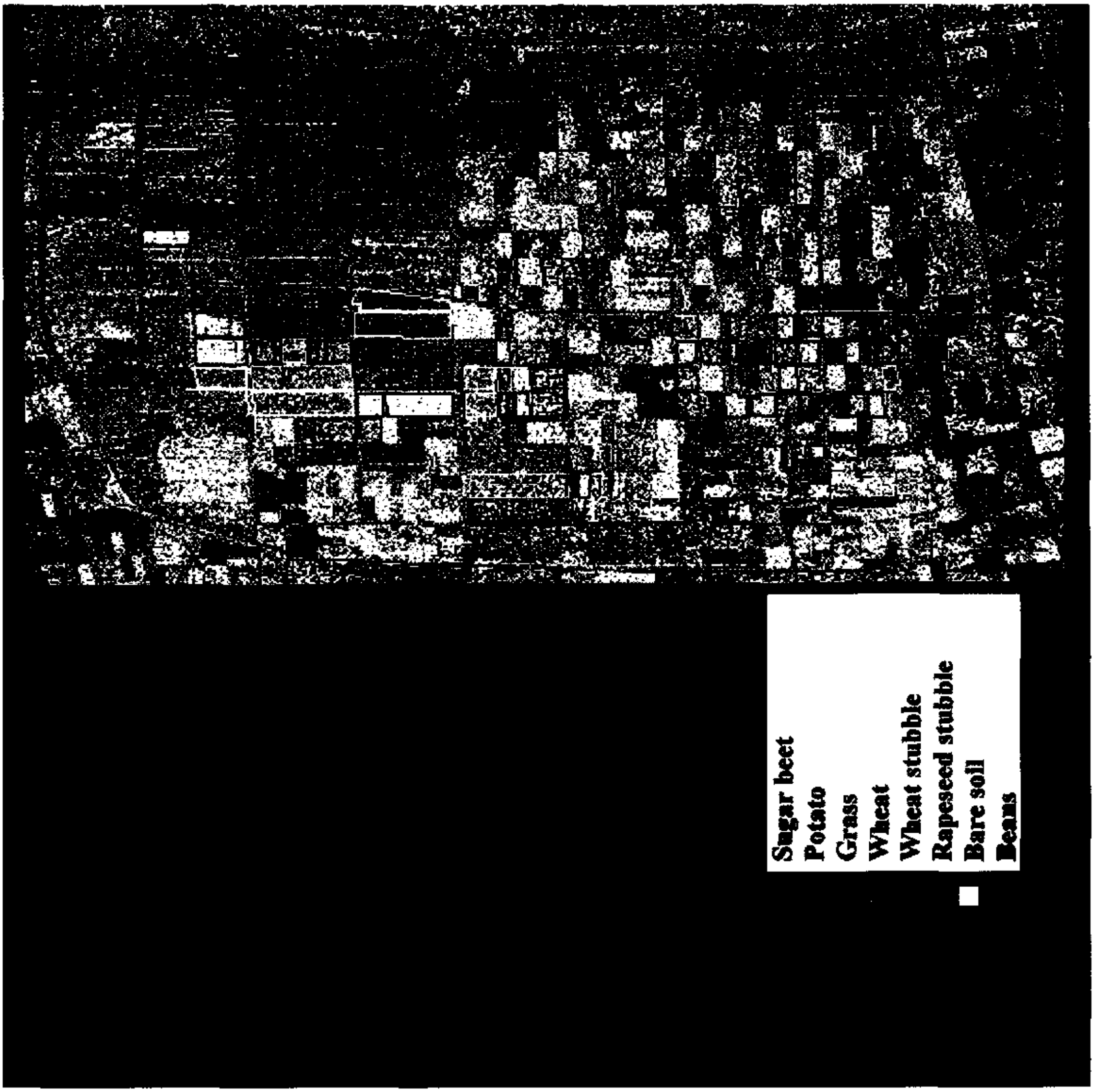


Plate 3 *Integration of a airborne SAR (IRIS; MAESTRO campaign Flevoland, August 1991) image with geographical information presented in a* **local** *(flight) coordinate system; overlay of a vector file (color of the polygons represent crops) presenting crop type information over a remote sensing image (raster file)*

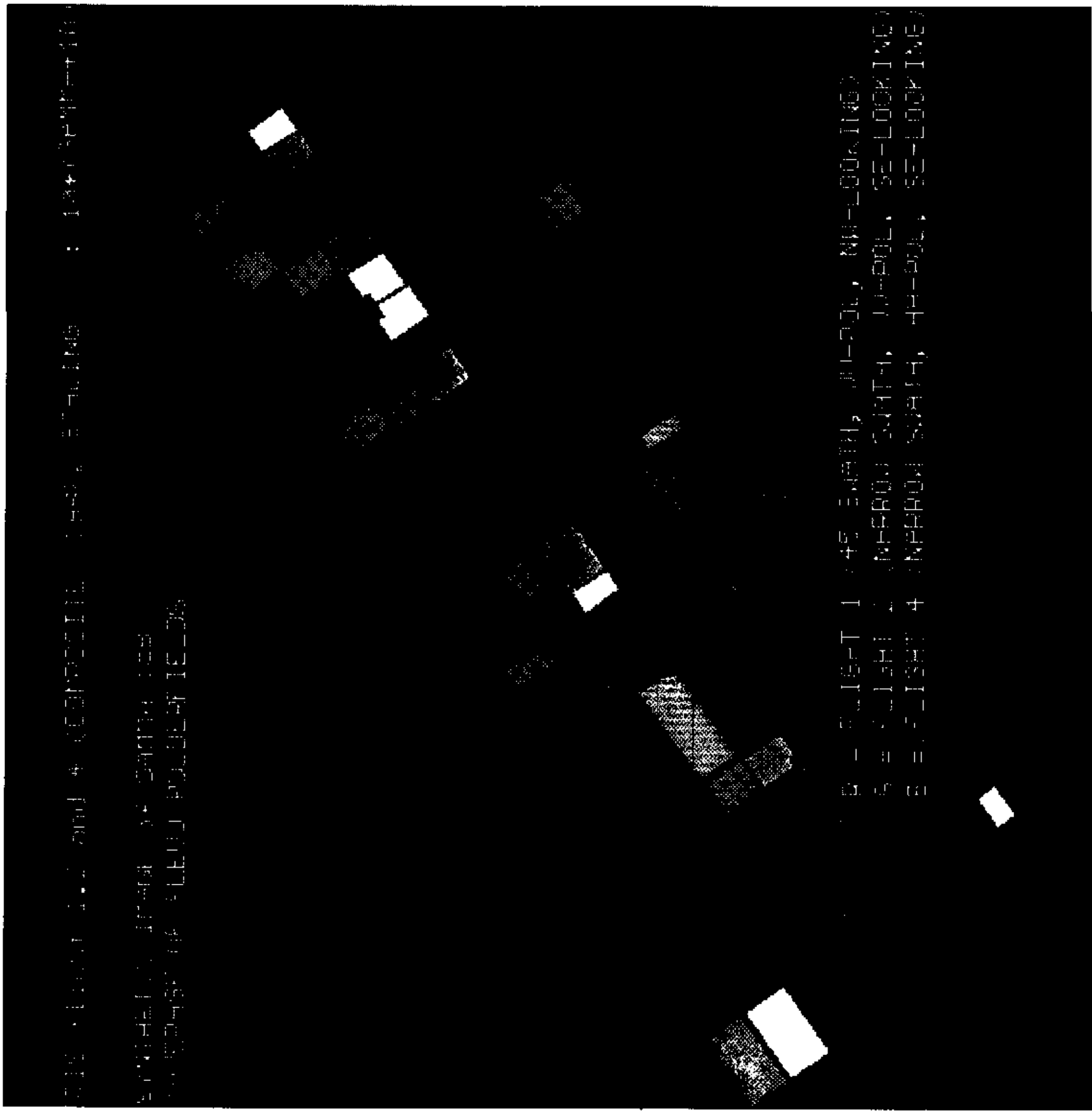


Plate 4 *Part of the airborne radar image of Plate 2 is transformed to the "Rijksdriehoeks" reference coordinate system with the local facet transformation programme FATRAS. The polygons visualize average backscatter data per field of three flights. In this way several airborne observations could be combined.*

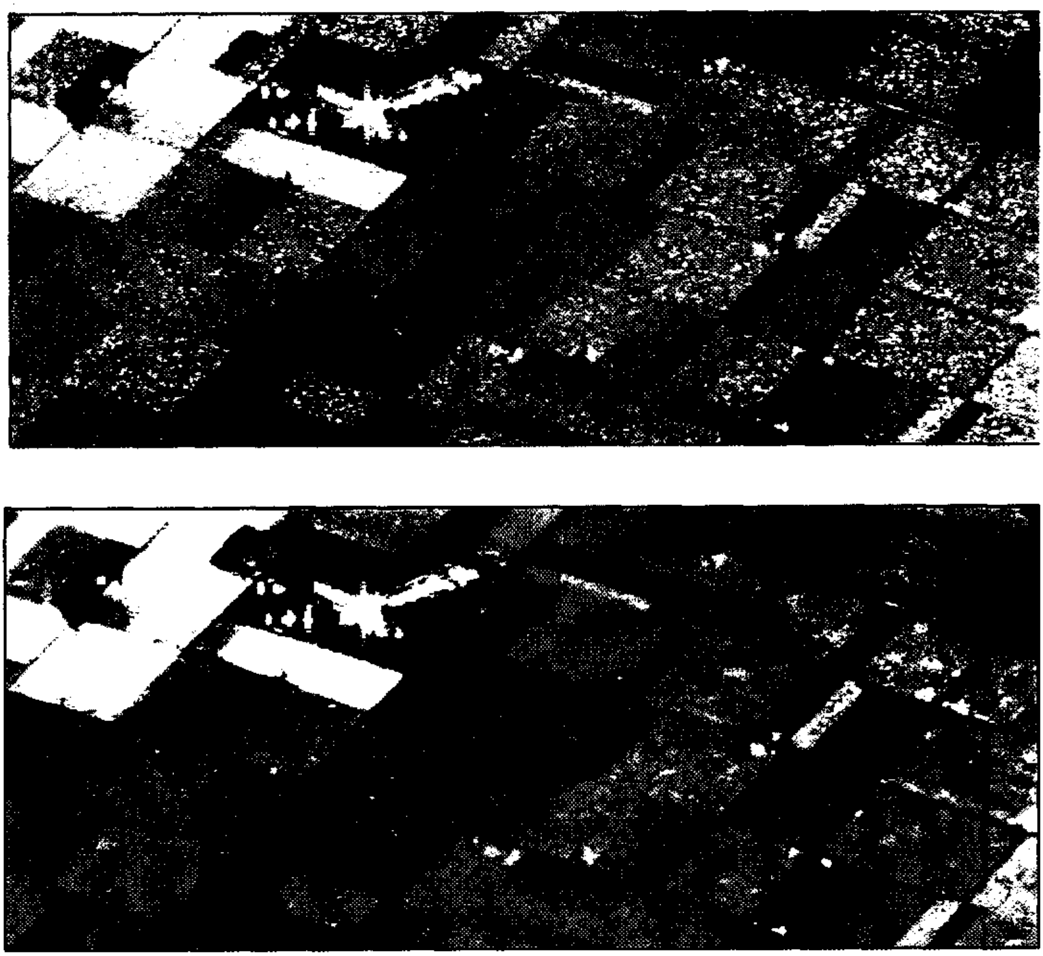


Plate 5 *Determination of fields improves when segmentation of microwave RS data is performed of the Flevoland test site during the MAC Europe 1991 campaign. Raw L-band image (upper), L-band image (lower) filtered with speckle filter and segmented (Source: Schoenmakers et al., 1994).*

CROPMAP FLEVOLAND 1991

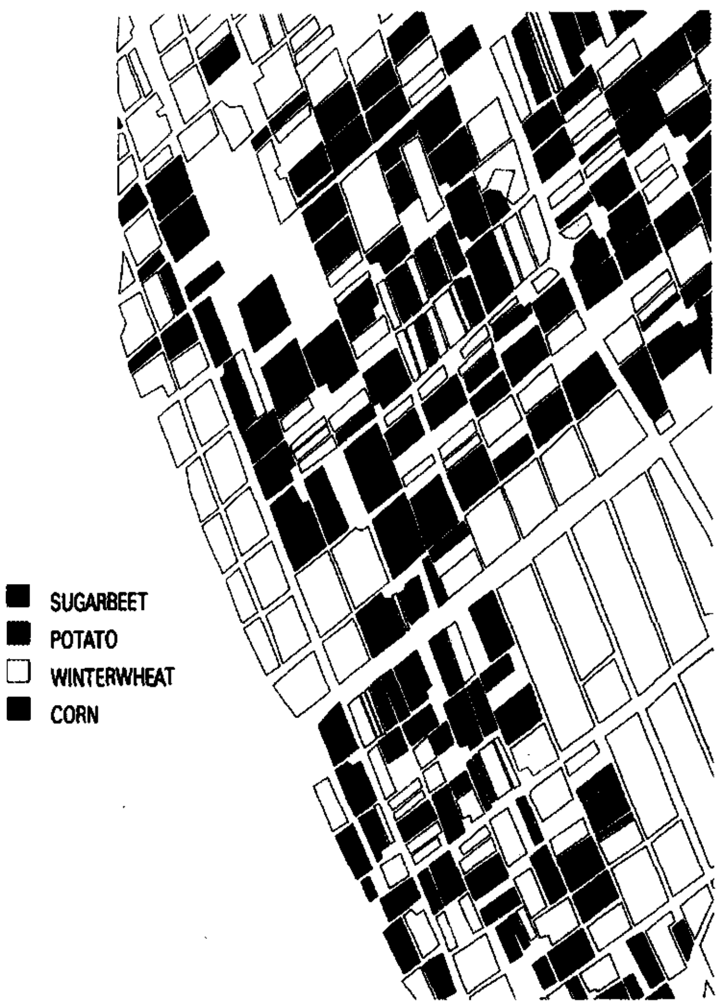


Plate 6 *Crop map of the Flevoland test site of the 1991 growing season (ARC/INFO) using the polygons from the AVIRIS image*

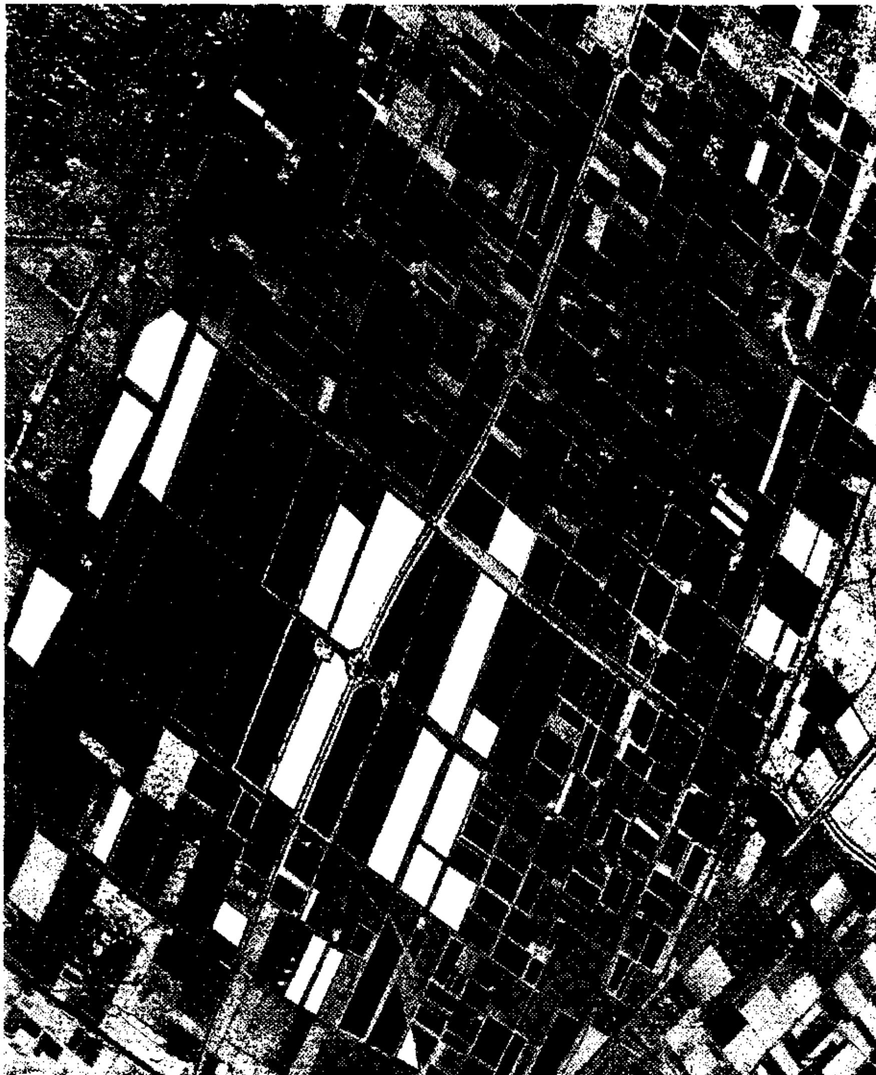


Plate 7 *MAC Europe 1991 campaign: AIRSAR image and field boundaries (polygons) constructed with help of the airborne optical AVIRIS data of the agricultural crops at the Flevoland test site*

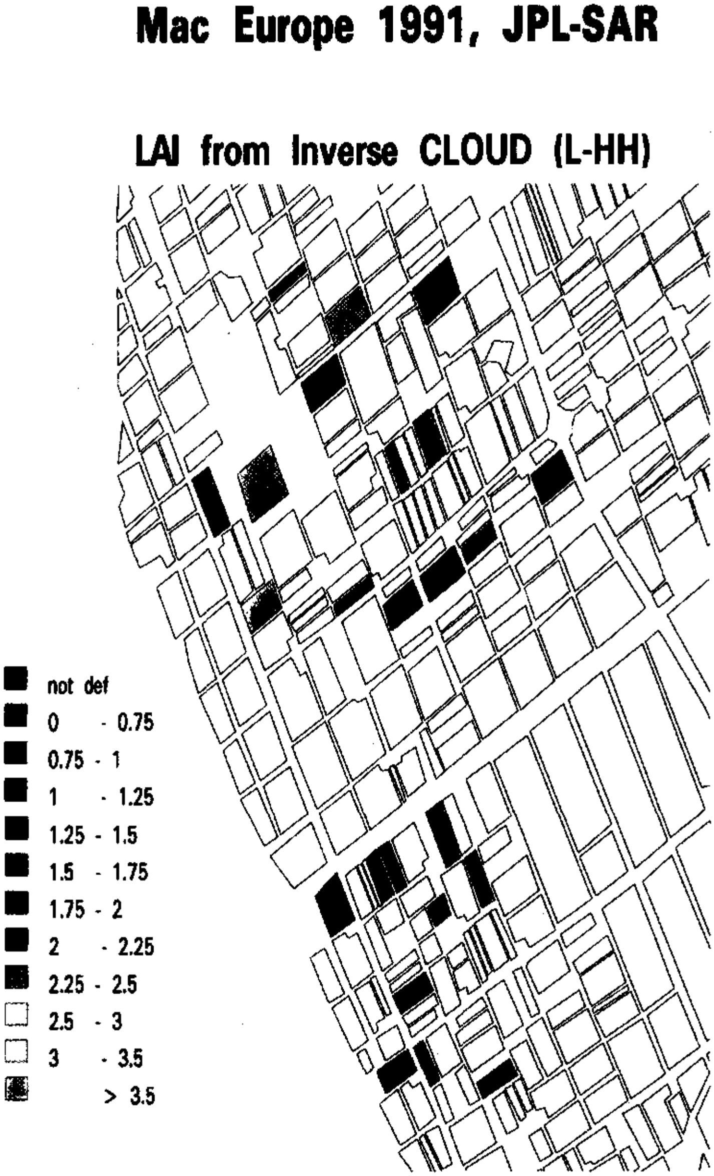


Plate 8 *The same polygons as for Plate 5,6 and 7 used as information carrier for visualization (ARC/INFO) of the inversion results of the Cloud model with MAC Europe 1991 campaign data.*

research group compared to signal processing in the ROVE (FMCW radar) and Agriscatt period where scatterometers were used for conditioned research activities, also data handling became a severe problem in the sense of the amount of gathered data. One day in the MAC Europe 1991 campaign resulted in a few gigabytes of radar polarimetric and optical multi-spectral RS data. Techniques for data reduction needed to be developed. An example of reduction of data is the processing of huge images to field averages of polarimetric radar data by means of vector or polygon maps of the objects of study (Braam *et al.*, 1989; Molenaar & Janssen, 1993). Before this data reduction can take place, object identification is necessary.

Besides RS data, ground data must be acquired as well for calibration and validation of the sensors and the RS models involved in the research. Therefore, data acquisition should be a model-driven activity, which was not always the case in the past (technology push, politics, etc.).

4.3.2.1.1 Object identification

In the case of agricultural applications, crops can be either mapped by field studies (see Plate 1) or with RS image classification or, even better, with both in order to reduce the costs involved in intensive field surveys.

Introduction of prior knowledge on systematically repeating farm management and growing conditions could improve the (semi-) automatic crop identification at field level. An example of prior knowledge in the case of the Southern Flevoland Province is the rotation of crops over the growing seasons, which is a common phenomenon. With this knowledge, (object or per field) classification of crops using optical RS data can be performed as was shown by Janssen (1994). A disturbing factor is the yearly variation in geometry and location of agricultural fields at farm level caused by yearly changing farm management and planning. In turn, with the help of segmentation of optical RS data this may improve the classification (Janssen & Schoenmakers, 1992).

Introduction of (polarimetic) microwave RS may improve the identification of objects (could be subsection of fields with the same crop) as other physical characteristics of the object can be detected compared to optical RS (Lemoine *et al.*, 1991). In the case of the MAC Europe 1991 campaign introduction of both sensors improved the identification of fields. Plate 2 shows that microwave (time-series) and optical (different wavelengths) images could distinguish different fields. Part of the crop map of 1991 is presented with the help of a polygon vector map.

4.3.2.1.2 Geometric and radiometric correction

Geometric correction of RS images can be carried out by the data distributor in the standard processing. However, airborne experimental RS data were mostly supplied uncorrected. For airborne RS recordings, local image distortions by plane movements could be corrected by the FATRAS software developed at the Department of Landsurveying & RS of the Wageningen Agricultural University, for microwave as well as for optical RS data (Braam *et al.*, 1989). In Plate 3, an airborne SAR image in a local coordinate system is presented. Spaceborne RS data could easily be corrected by the available image processing software ERDAS and DISIMP.

Radiometric correction of microwave RS data is normally done by the data distributor according to standard processing procedures (SAR processing, antenna calibration, etc.). The external calibration can be performed by placing corner reflectors or transponders in the field at the time of recording. Local incidence angle effects are also discounted for in the data extraction procedures in the case of RS observations.

The same procedure can be applied to airborne optical RS, where (known) reference fields or artificial plates serve as correction for the radiometry. With the reduced data set these corrections can be done quite efficiently. Atmospheric correction forms a common component of calibration in the case of optical RS data (Buiten & Clevers, 1994; Clevers *et al.*, 1994d). It can be performed either by applying the earlier mentioned reference objects method, as atmospheric influences are assumed to disturb the radiation coming from the observed object linearly for every wavelength in the reflective optical part of the spectrum, or, in case of spaceborne optical remote sensing, by applying an atmospheric correction model such as LOWTRAN, which can account for complex atmospheric interaction mechanisms (like Rayleigh, Mie-scattering, etc.).

4.3.2.1.3 Object-based data extraction

Once the field boundaries are known, polygons (vector data) can be constructed. These vectors can be geometrically transformed to other images of the same study area.. As local geometrical distortions occur in the recorded image caused by the airborne measurement, local (facet) geometrical transformations can be applied (Braam *et al.*, 1989). The image raster data can be sampled and displayed with the help of the transformed polygons (see Plate 4), resulting in files with field average reflectances or backscatter values e.g. according the following data scheme:

Attribute		Attribute value
Image title	:	FLEVOLAND 116-2 (A)
Frequency	:	C-Band
Date of acquisition	:	03-JUL-91
Image dimensions	:	1024 pixels; 1279 lines
Near range (m)	:	10462.76
Slant range pixel (m)	:	6.662100
Radar altitude (m)	:	8245.000
General Scale Factor	:	1.588119
Compressed stokes file	:	/opt/c3jul.dat
DISIMP - file	:	fl0307.dis
Data record	:	
	# Field, Crop, # Polygon, Inc.angle, # Pixels, Sighh, sd Sighh, Sighv, sd Sighv, Sigvv, sd Sigvv, S11, S12, S13, S14, S22, S23, S24, S33, S34, S44	

Coregistration of raster data compared to the vector transformation method described above is not preferable as this will be more time consuming and will affect the radiometry by the accompanying resampling of image data.

4.3.2.2 Database: structuring, storage and integration of information

4.3.2.2.1 Database structure

The structure of the database was determined by the models and data needed for this study. Attribute names from the tables containing data used in the study are:

- Year of campaign
- Crop type (e.g. "SBT" for sugar beet or "WHE" for winter wheat)
- Time of year (expressed in day numbers)
- Location (expressed in polygon numbers related to geocoded vector structures)
- Type of RS data (different sensors and configurations: frequency, polarization, incidence angle)
- RS data (e.g. backscatter data, reflectance data, standard deviations, etc.)
- Ground data (see Table 4.7)
- Weather data (e.g. rainfall, temperature, global radiation, etc.).

Queries for information from these tables can be used for the various models used in the combination methodology:

RS model

input : ground data of object and regression parameters

output : simulated RS data

Inverse RS model

input : measured RS data and regression parameters

output : estimated object data (crop-soil system)

Crop growth model:

input : initialization data, daily weather data

output : daily simulated crop variables.

The structure of the database in a practical sense was built by using ORACLE and SQL commands resulting in tables (see Figure 4.4). The tables and their records are related and joined with each other by using key attributes. The combination methods of Chapter 3 were written in FORTRAN and the data needed for crop growth modelling and RS modelling were queried with SQL commands embedded in FORTRAN source code (in SBFLEVO_OPT, Cloud or CLAIR).

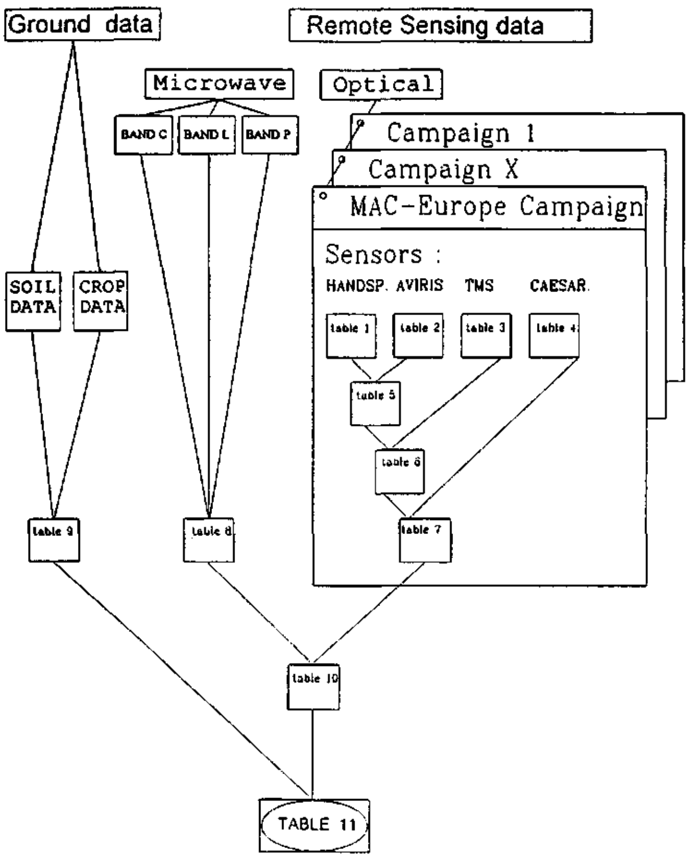


Figure 4.4 *Organization of the RS and ground truth data in several distinct tables and also merged into one overall table for the Mac Europe 1991 campaign (Luimstra, 1994)*

4.3.2.2.2 Data storage

After data processing the MAC Europe 1991 data were stored in a uniform format, suitable for import into, for instance, an ORACLE relational data base. This was already done for the ROVE database by Van Kasteren (1993). In this way all mentioned data sets (see Figure 4.4) for the synergy study were stored in ORACLE tables with the following attributes:

a key attributes for all tables were day number, crop type, field number, sensor type;

b attributes for each record of the tables represented by the ground data and RS variables mentioned in 4.3.2.2.1.

4.3.2.2.3 Data integration

With database SQL commands such as "join" and "union", the various tables for the MAC Europe 1991 campaign were merged into one central table with unique records. For the modelling and analysis the records with RS and ground data can easily be queried by using the key attributes with the "select" SQL command.

4.3.2.3 Database query for modelling

A software programme in FORTRAN can serve as carrier for process information (RS measurement or crop growth process) and can communicate with the ORACLE database by query and update (SQL) commands embedded in the FORTRAN programme source. In this way the combination methodology could be practically elaborated. The database query and update are ruled by the input and output relationships between the model and the information structure.

For the sake of visualization the connection with conventional image processing and GIS systems can be made (ARC/INFO) by relating the geometrical characteristics (polygon vector structures) to the data base structure with the proper identifiers (key attributes). In this way the extracted data of RS campaigns can be directly accessible to the interpretation process. Also, products of modelling can be visualized in a more thematic way with the geometrical characteristics (polygon field structures) as intermediates.

For the MAC Europe 1991 campaign Luimstra (1994) stored data sets in ORACLE tables and visualized the different variables in crop growth or RS models with ARC/INFO (see Chapter 5). The results of the various campaigns are stored in ORACLE (Van Kasteren, 1993; Luimstra, 1994; Van Leeuwen *et al.*, 1995b). RS studies on the basis of the various campaigns can be performed because of the uniform format.

Prototype software has been developed to query the ORACLE database with SQL queries embedded in FORTRAN source code. In this way input for RS models and crop growth models written in FORTRAN can easily be obtained for calibration, validation, inversion, multitemporal analysis, etc. With libraries such as FORTRAN NAG routines or "numerical recipes", the combination method can be extended as well with analysis procedures like optimization or inversion. Visualization of modelling results can be performed by connecting ORACLE tables with the ARC/INFO software which was done for the MAC Europe campaign for plotting *LAI* maps for the Flevoland test site (see Chapter 5). The *LAI* from the tables were visualized by using the field boundaries of the ARC/INFO coverage converted from the ERDAS polygon vector data. With the ARC/INFO “relate” command, information from the tables in ORACLE (like *LAI*, biomass, crop type, etc.) was linked by the polygon (or field) number with the ARC/INFO coverage resulting in for example Plate 1, 6 or 8.. Even evaluation of modelling output by combining thematic maps can be performed in the multipurpose ARC/INFO software related with ORACLE.

Even studies at European level are possible if the data sets are accessible with SQL queries. The EURACS (JRC-EU) data base can be queried with SQL. However, hardly any use has been made of it by European investigators so far, because of unfamiliarity with the presence of this database. The EURACS data are stored in DBASE IV and ORACLE compatible data information systems. The JRC-EU is promoting the CEO (Centre for Earth Observation) concept in which ground data and remote sensing data are available to researchers and particularly to other potential users. Initiatives have been taken to standardize ground data and RS data in order to make them available via the electronic highway or World Wide Web.

4.3.3 Data analysis

RS data and ground data stored in the information structure can be queried (see item II of Section 4.3.2) and processed using different analysis procedures. As shown in Chapter 2, various analysis steps are needed for the combination method of RS and crop growth models. In this study RS model calibration, validation and sensitivity analysis preceded the inversion of RS models resulting in estimations of crop growth variables like *LAI* or biomass. The estimation of crop growth variables by inversion is affected by errors in RS measurements (Table 4.2) and regression procedures. This section only focuses on the methodology of inversion leading to crop growth variables to be used in the combination methodologies of Chapter 3.

4.3.3.1 Inversion

Inversion of RS models can be accomplished in different ways, which will be explained here. In the combination methodologies applied in this study inversion of RS models is a central issue for the reasons mentioned in Chapter 3. Several inversion methods can be used varying from simple to complicated.

1 *Approximated or linearized (or so-called local) model inversion*
  A practical way of inversion is the use of simplified models derived from the complex exact physical representations of the RS measurement process, which are valid within the boundaries supplied by the regression analysis (see Chapter 2);
2 *Graphical inversion*
  The inversion can be performed graphically by constructing nomograms using the variables in study (e.g. see Chapter 2, Section 2.7 Figure 2.8);
3 *Matrix inversion*
  A mathematical (numerical) way of inversion by solving equations of linear combinations of model variables, representing the solution space within the proper ranges of the variable.

The matrix inversion procedure (3) will be outlined below to explain the theory of the relative simple procedures 1 and 2, which were used in this study.

The RS model (complex) and crop growth model can be used for simulations of outputs such as RS signal or daily crop growth variables using the input described in Section 4.3.2.2.1. In this way a multidimensional model space can be simulated by varying the model input variable combinations systematically within the plausible variable ranges.

To describe the multivariable space of the RS model (or even crop growth model) in another but straightforward manner, a matrix A can be constructed from linear combinations of the specific model variables (Equation 4.1). This way of describing the model in a discrete sense, instead of the complex sequences of (bio-)physical relationships (SBFLEVO, SAIL, MIMICS), opens the way to mathematical (numerical) inversion of RS models (or crop growth models).

Enough independent measurements (vector b) are needed in relation to the degrees of freedom (rank of matrix A) of the problem in order to invert these models and to produce solutions numerically (vector x). Independent measurements in the RS observation of the study object could be supplied by introducing different frequencies, incidence angles, etc. of the same field of observation. In general:

$$A \cdot x = b \tag{4.1}$$

From inversion the least squares solution vector x or the RS model variable combination is:

$$x = V \bullet A^T \bullet W \bullet b \tag{4.2}$$

With a general least squares method simulated (linear combinations of input variables resulting in direct simulated output) and measured RS signals can be compared. With the help of numerical techniques the inverse of the matrix A can be constructed ($V \bullet A^T \bullet W$) in which W is a weighting matrix and V an inverse matrix. The weighting factors can be constructed on the basis of the reciprocal of the standard deviation of the RS measurements (error). In the case of RS the matrix A is mostly overdetermined, which means that there are more measurements than unknowns.

In practice, an alternative for inversion can be a simple search procedure by finding the correct measured RS value with a certain range in a look-up table (e.g. in ORACLE) of simulated RS data resulting in a set of related combinations of RS model variables.

Within the scope of the combination methods mentioned in Chapter 3, the Price algorithm was used in the SBFLEVO_OPT prototype (Price, 1979). This optimization method has analogies with the simple matrix inversion (or also searching in Lookup Table 'LUT') described above. The 200 combinations of four crop growth model variables, varying within their biophysically plausible ranges, were selected from 3000 forward crop growth model simulations with a simple minimum of the overall error. In the same way, matrix A may be built by the various combinations between the most important crop model variables (sowing date, light use efficiency, relative growth rate, maximum leaf area) and inverted with the "measured" *LAI* and biomass estimated with RS (b vector).

Compared to RS model inversion, in this case optimization of the crop growth model is done by comparing crop variables (*LAI*, biomass) estimated by RS and simulated by the crop growth model resulting in a vector x with the four crop growth variables. Compared to RS model inversion, in which the reciprocal of the standard deviation of the RS measurement acted as weighting factor, the weighting factor in the crop growth optimization method can be expressed by the reciprocal of the standard deviation in *LAI* or biomass estimated by RS.

4.4 Summary

This chapter comprises a brief overview of data sets from campaigns at the Flevoland test site. For testing the combination methodologies of Chapter 3, the MAC Europe campaign of 1991 was selected on the basis of criteria defined for the synergy study objectives. For RS model calibration and validation as well as for crop growth model initialization the Agriscatt 1987 and 1988 campaigns proved particularly suitable. The ROVE data set contains measurements of high temporal frequency and can be used to understand the crop growth process in relation to microwave X-band measurements in particular, but also to illustrate specific radar features.

A total processing line for RS data interpretation is used and partly developed in the scope of this study. For crop growth monitoring fields were identified with the help of classification and segmentation of RS images. Field delineation by polygon vector data was used for data extraction. The field delineation in ERDAS polygon vector format was converted to an ARC/INFO coverage linked with the ORACLE table to visualize thematic aspects of the combination methodologies. A database was built in ORACLE in which the data from the MAC Europe campaign are stored after data extraction, and geometric and radiometric correction. The RS and ground data were uniquely stored in the ORACLE tables and can be used for several purposes.

The combination methodology of Chapter 3 was evaluated with some considerations on inversion methods.

5 A case study: combination of remote sensing and crop growth information applied to the MAC Europe 1991 campaign

5.1 Introduction

To meet the objective of this study, optical and microwave RS data were selected in Chapter 4. It appeared that the data set of the MAC Europe 1991 campaign at the Flevoland test site was suitable to test the synergism of combining multisource data. This data set consists of multisensor, multitemporal RS data and ground truth data. With the help of the crop map and an optical SPOT satellite image fields (elementary objects) of the whole test site in the Southern Flevoland Province were identified. With this information data could be extracted of all the airborne microwave and optical RS images and stored in a database in a uniform manner (Section 5.2).

In Chapter 2 it was concluded that in contrast to the optical RS model CLAIR, the microwave RS model Cloud was not transferable over the seasons. Section 5.3 describes and discusses calibration and validation of the microwave model Cloud with the RS and ground data of the 1991 growing season in particular.

In Section 5.4 information on RS time-series, which is not accounted for in the RS modelling of Section 5.3, will be extracted for combination methods later in this chapter (Section 5.5).

In Table 5.1 the different combination methods for RS information and the crop growth model are presented schematically. The combination methods of Chapter 3 will be tested with contemporaneous and non-contemporaneous recordings of both optical and microwave remote sensors. Additionally, the combination with structure information from microwave RS data in the process of crop growth model calibration is applied to the MAC Europe 1991 data set.

The results of this case study for the combined use of optical and microwave data using a model-based, feature-based and an integrated combination method will be presented in more detail in Section 5.5.

Table 5.1 shows the set-up of this chapter in order of appearance. First, combination of RS with a crop growth model using direct RS models (Method I) is tested assuming standard growing conditions of the Flevoland test site (Bouman, 1992b). Subsequently, the use of the inverse RS model (Method II) is compared with the direct use of RS information (Method I) linked to crop growth to test the model-based combination method. RS information from time-series, possibly resulting in canopy structure information, will be used in the so-called feature-based method (Method III). An integrated approach using as much information from RS as is available, is tested in Method IV.

Table 5.1 *Approach and set-up of the case study in order to test the combination methodology of Chapter 3 with data of the MAC Europe 1991 campaign. For the results of this case study see Tables 5.7 and 5.11. The C-band VV polarization and L-band HH polarization of the airborne microwave data (AIRSAR) and the Red and NIR of the airborne optical data (AVIRIS) have been chosen for the case study*

Combination method	*Optical*	*Microwave*	*Contemporary*	*Section*	*Casenr*	*Method*
*Calibration	+ (A1)	+ (A1)	+	5.3.1		
Calibration+crop info	+ (A1)	+ (A1)	+	5.3.2		
No RS (std. crop)	-	-	-	5.5.1	1	
*Direct RS model	+ (G10)	-	-	5.5.1	2	I
ROVE	+ (G)	+ (G)	+	5.5.1		I
*Inverse RS model	+ (G10)	-	-	5.5.2.1	3	II
	+ (A2)	-	-	5.5.2.2	4	II
	-	+ (A2)	-	5.5.2.3	5+6	II
	+ (A2)	+ (A2)	-	5.5.2.4	7+8	II
	+ (A1)	+ (A2)	-	5.5.2.4	9+10	II
*Inverse + feature	+ (G10)	-	-	5.5.3		III
	-	+ (A2)	-	5.5.4.2	11+12	IV
	+ (A2)	+ (A2)	-	5.5.4.3	13+14	IV

xx number of ground-based measurements (Gxx)
xx number of airborne measurements (Axx)

5.2 MAC Europe campaign 1991

5.2.1 Identification of objects

A crop map was constructed from field visits during the 1991 growing season. With the help of segmentation using optical RS data this could improve the classification (Janssen, 1994). The introduction of (polarimetric) microwave RS can improve the identification of objects (between and even within variations in fields). This has been shown when studying the separability of agricultural fields by classification using polarimetric and multi-frequency SAR data (Lemoine *et al.*, 1991). In the case of the MAC Europe campaign, introduction of both sensors improved the identification of fields even more when multitemporal RS data were used (Schoenmakers *et al.*, 1994) (see Plate 5). For this study fields and their boundaries were identified and localized by digitizing recent air photographs, AVIRIS data of July 4th and field visits, resulting in the following crop map (Plate 6).

5.2.2 Data extraction with polygon vector data

The data handling procedure of Chapter 4 was applied in the MAC Europe 1991 campaign. The database structure is based on the tables in Chapter 4.

With the knowledge obtained from the object identification the field boundaries were found and polygons (vector data) were constructed by simply screen digitizing on the basis of the multispectral airborne image of the AVIRIS sensor using an image processing system (ERDAS). These vector maps were geometrically transformed to the different images (AIRSAR, CAESAR, AVIRIS images) recorded during the MAC Europe campaign as shown in Plate 7. As local distortions can occur owing to the airborne data recording, a facet transformation with the FATRAS programme was applied (Braam *et al.*, 1989). The image raster data were sampled with the help of the transformed polygons, resulting in field average reflectances or backscatter values with corresponding incidence angle information. For the contemporaneous use of microwave and optical data, radiometric corrections were performed by using the LOWTRAN model in the case of the AVIRIS optical RS data (Borgeaud & Noll, 1993) for atmospheric correction as this optical sensor flew at 20 km height over the test site. The handling of the AVIRIS optical data can be compared to space borne data as the atmospheric disturbances in the visible/NIR domain are mainly caused by the lower part of the atmosphere.

5.2.3 Data storage

After processing the data of the MAC Europe 1991 campaign were stored in a uniform format, suitable for import into the ORACLE relational database (Chapter 4). The calibrated data from the AIRSAR microwave and AVIRIS and CAESAR optical airborne sensors were converted to ASCII files of fixed format. These were then loaded into ORACLE tables, after having created the table structures (attributes and format).

The ground data and the RS data were joined on the basis of the key attributes mentioned in Chapter 4, Section 4.3.2.2.2 in one total table (Luimstra, 1994), which was queried with Standard Query Language commands, embedded in FORTRAN programmes or interactively. Figure 4.4 shows the data merging with the aid of polygon field numbers. Tables 5.2a and 5.2b present the key attributes and attribute values.

Table 5.2a *Key table for joining various field and airborne optical RS data on the basis of sensor wavelength (nm)*

Description	*Cropscan*	*CAESAR*	*AVIRIS*
Green	550	550	548
Red	670	670	667
NIR	870	870	852

Table 5.2b *Key table for joining RS data and ground data of the MAC Europe 1991 campaign on the basis of RS recording date (day number)*

Soil	*Crop*	*Cropscan*	*AIRSAR*	*AVIRIS*	*CAESAR*	*Key day*
	175					175
184	184	184	184	186	185	184
193	191	191	193			191
	203				204	204
209	210	210	209		204	210

On the basis of these key tables it was decided how to join and combine data for the various analysis procedures such as calibration, crop growth modelling, calibration of RS models, sensitivity analysis, inversion with look-up tables, etc. Sometimes key attribute values from different data sets were not exactly the same. For the joining of the data sets the nearest key attribute values were chosen. This is done with the key attribute "day" in Table 5.2.b., and also with the key attribute "wavelength" in Table 5.2a.

5.3 RS model calibration and validation for the MAC Europe 1991 campaign

In Chapter 2 it was concluded that optical RS models for sugar beet (and other crops) with known growing conditions can be used for different seasons. Therefore, the optical RS model CLAIR, calibrated in former campaigns, was used for the MAC Europe 1991 campaign (see Chapter 2).

Unfortunately, the same is not true for microwave RS modelling. Concerning the Cloud model, which is so far the most suitable and practical microwave model, calibration and validation depend on the amount and quality of the data acquired during the campaign itself. Throughout the years when several microwave campaigns were held, variation in Cloud fit parameters was caused by a shortage of ground data and sensor failure. Another reason was (mentioned earlier, in Chapter 3) that crop characteristics, such as leaf (or stem) angle distribution, had not been measured or not been accounted for as a variable in the modelling. For these reasons the Cloud model needed calibration and validation in the growing season of 1991. Because of the lack of ground data (such as *LAI* values or biomass) other sources of information were used like airborne optical RS data. The airborne optical sensor AVIRIS was used to estimate *LAI* assuming that the crop did not change drastically in two days. Another source of information was the crop growth model initialized for the growing conditions at the Flevoland test site, in the case of the sugar beet crop. All together, the prediction of *LAI* or biomass with optical RS and a standard crop growth model provided in fact the additional "ground data" needed for the study.

5.3.1 Calibration of the Cloud model using space-time transformation

The calibration of the Cloud model as presented in Chapter 2, Section 2.4.3, however, was not successful owing to a lack of sufficient ground truth. Chapters 2 and 3 showed that optical RS data can be used for estimating *LAI* with great accuracy. Therefore, it was decided to use the *LAI* estimated by optical RS data. In this section a successful calibration of the Cloud model is presented using data of the MAC Europe 1991 campaign. Ground truth (*LAI*, biomass) is provided by using airborne optical (AVIRIS) RS data from nearly the same date and by using a standard crop growth model. Use is made of the variation in crop growth stages which are the results of different management practices of the various farmers by having different sowing dates at the Flevoland test site. Normally, sowing dates do not differ from each other more than one or two weeks, but in 1991 early frost damage to the young sugar beet plants forced some farmers to resow. This resulted in a range in *LAI* of 2 units ($0<LAI<2$) at the time of contemporaneously recorded airborne microwave (day 184) and optical imagery (day 186). This was a great opportunity to test the proposed methods.

An intersection was made of all sugar beet fields in the AVIRIS image with all sugar beet fields in the AIRSAR image using data from the 1991 MAC Europe campaign at the beginning of July. This resulted in a total of 37 sugar beet fields. From a calibrated NIR spectral band (Nr. 51) and a calibrated green spectral band (Nr. 16) from AVIRIS the *WDVI* of each field was calculated (cf Büker *et al.*, 1992b). Subsequently, *LAI* values were derived from these *WDVI* values using the CLAIR model. The relationship between measured and estimated *LAI* from AVIRIS data is illustrated in figures 5.1 to 5.6 for the C-, L- and P-band of the AIRSAR respectively. It should be noted that the incidence angle varied between fields (the average is about 45°). These figures show that useful calibration of the Cloud model may be expected for L-band HH-polarization and for C-band VV-polarization. These are two very interesting combinations since the ERS-1/2 carries a C-band SAR with VV-polarization and the JERS-1 carries an L-band SAR with HH-polarization (Note that the incidence angles of the microwave sensors for the different sugar beet fields are somewhat different: the incidence angle of the ERS-1/2 is about 23° and that of JERS-1 about 35°).

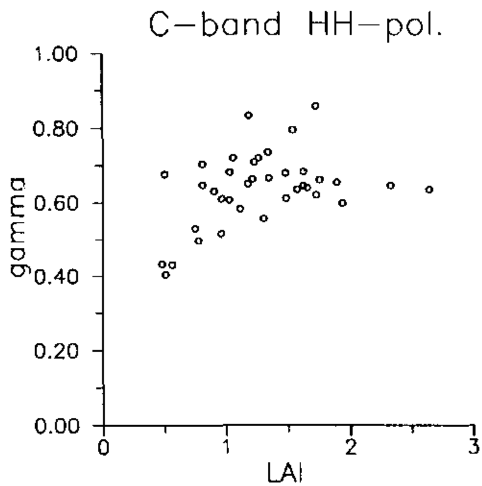


Figure 5.1 *Relationship between measured γ in C-band HH-polarization and estimated LAI from AVIRIS for 37 sugar beet fields (Flevoland, MAC Europe 1991 campaign)*

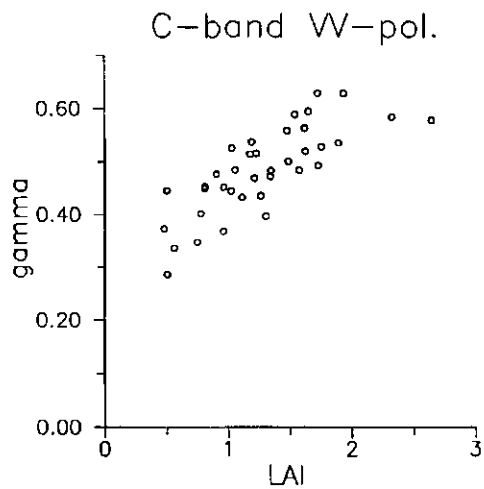


Figure 5.2 *Relationship between measured γ in C-band VV-polarization and estimated LAI from AVIRIS for 37 sugar beet fields (Flevoland, MAC Europe 1991 campaign)*

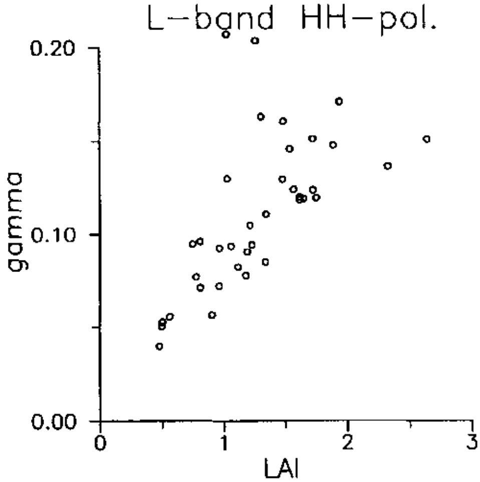


Figure 5.3 *Relationship between measured γ in L-band HH-polarization and estimated LAI from AVIRIS for 37 sugar beet fields (Flevoland, MAC Europe 1991 campaign)*

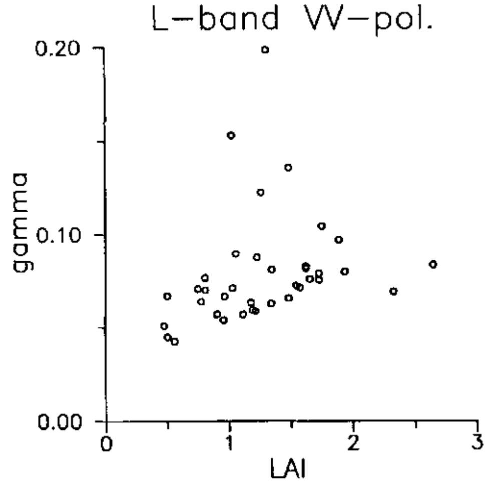


Figure 5.4 *Relationship between measured γ in L-band VV-polarization and estimated LAI from AVIRIS for 37 sugar beet fields (Flevoland, MAC Europe 1991 campaign)*

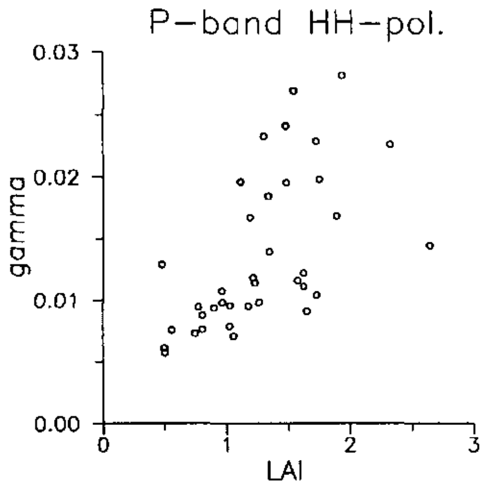


Figure 5.5 *Relationship between measured γ in P-band HH-polarization and estimated LAI from AVIRIS for 37 sugar beet fields (Flevoland, MAC Europe 1991 campaign)*

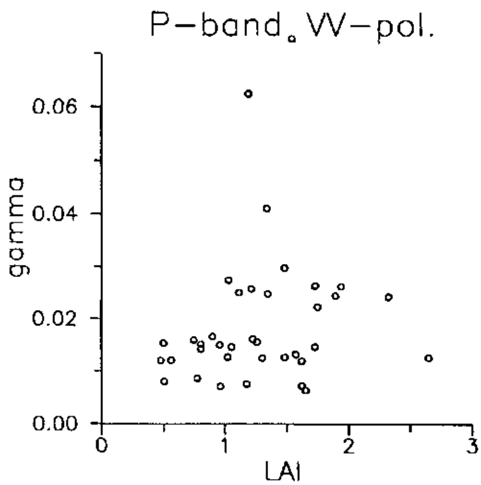


Figure 5.6 *Relationship between measured γ in P-band VV-polarization and estimated LAI from AVIRIS for 37 sugar beet fields (Flevoland, MAC Europe 1991 campaign)*

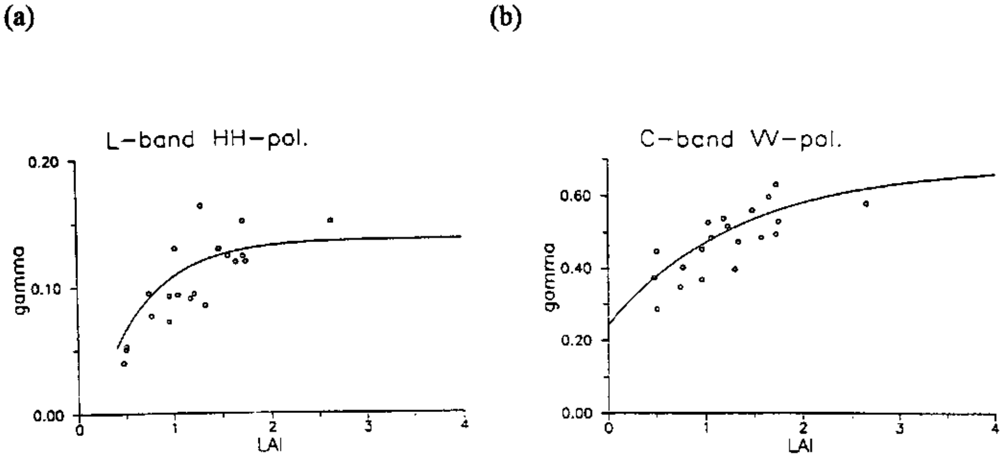


Figure 5.7 *Results of the calibration of the Cloud model at July 3rd for L-band HH-polarization (a) and C-band VV-polarization (b) using a random set of 20 sugar beet fields (Flevoland test site, MAC Europe 1991 campaign)*

To calibrate the Cloud model for L-band HH-polarization and for C-band VV-polarization, a random calibration set of 20 fields was selected from the available fields. Table 5.2 summarizes the main calibration results for these 20 fields by using Equation 3.9. A constant incidence angle of 45° was assumed as this was the average observation angle for most of the fields in the AIRSAR image. Figure 5.7 illustrates the calibration results.

Table 5.3 *Calibration results of the Cloud model for sugar beet using one recording of the AIRSAR (day 184) and one recording of AVIRIS (day 186) airborne sensor from the MAC Europe 1991 campaign at the Flevoland test site*

Parameter	*L-band HH*	*St.dev.*	*C-band VV*	*St.dev.*
D'	0.8967	0.5227	0.3660	0.3725
*D (D'*A)*	0.7411	0.4320	0.3025	0.3079
C	0.1369	0.0191	0.6821	0.2047
K	0.1767	0.0601	0.4394	0.1395
R^2	0.6250		0.6665	
Residual mean square	0.0005		0.0030	
$\sigma[\gamma]$	0.022		0.055	

Comparing this calibration with the calibration procedures in Tables 2.3 and 2.4, the C and D parameters differ from the regression results of other campaigns. The L-band results from Agriscatt 1988 and MAC Europe 1991 match rather well, but nothing can be concluded when the standard deviation is of almost the same magnitude as the regression parameter value itself (see Table 5.3).

Figure 5.8 plots the estimated *LAI* using the Cloud model against the "measured" *LAI* (from AVIRIS) for the calibration set of the MAC Europe 1991 campaign. In addition, the lines exhibiting deviations of +/- twice the standard deviation from the "measured" *LAI* are shown.

(a) (b)

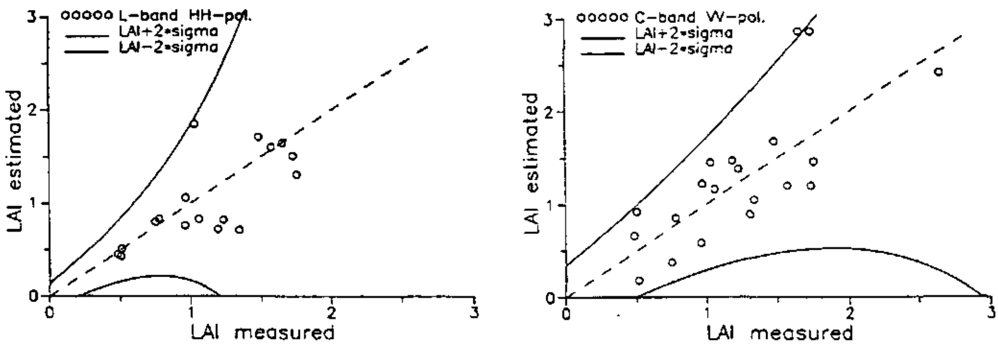


Figure 5.8 *Relationship between estimated LAI using the Cloud model and measured LAI for sugar beet in L-band HH-polarization (a) and C-band VV-polarization (b) (Flevoland test site, 1991 MAC Europe campaign)*

Note that the use of different frequencies and polarizations has implications for the backscatter behaviour as well: this backscattering between canopy layers or within the layer or even with the soil can become dominant. It will also restrict the applicability of the Cloud model. With different frequencies (C, L, P band), simultaneously obtained from the AIRSAR, different behaviour was noticed from the same observed fields featuring in figures 5.1 to 5.6. Probably, when the frequency becomes lower (P-band), the canopy is assumed to become transparent to the microwaves. For P-band, probably the lower canopy layers and the soil will contribute more to total backscatter than in the case of higher frequencies like C-band. Without a proper validated microwave RS model the behaviour of backscatter is difficult to interpret. It is clear that the simple Cloud model does not account for these features at lower frequencies.

5.3.2 Calibration of Cloud model using time-series and a standard crop growth model

When the second SAR recording (12th July) is included in the Cloud model calibration procedure, both optical (no AVIRIS flight) and ground truth data are lacking. Therefore, we have to estimate *LAI* from an other, earlier information source. A standard crop growth model, adjusted for the few available optical data and sowing date (known from the database), can be used to predict the *LAI* nine days later (after the first SAR recording of July 3rd). Table 5.4 shows the calibration results.

Table 5.4 *Calibration results of the Cloud model in Equation 3.9 for sugar beet using data from the 1991 MAC Europe campaign at the Flevoland test site and using a standard crop growth model*

Parameter	*L-band HH*	*St.dev.*	*C-band VV*	*St.dev.*
D'	1.6611	0.5866	0.6730	0.2905
*D (D'*A)*	1.3728	0.4848	0.5562	0.2401
C	0.1357	0.0060	0.6126	0.0420
K	0.3379	0.1692	0.4580	0.1019
R^2	0.5014		0.5406	
Residual mean square	0.0006		0.0044	
$\sigma[\gamma]$	0.025		0.067	

The introduction of crop growth knowledge improved the calibration for C-band VV-polarization, resulting in a lower standard deviation for the estimation of the regression parameters. However, this was not the case for L-band HH-polarization. Probably, in L-band HH-polarization backscatter from the soil causes some additional deviation in the microwave signal relative to the mean. This feature is likely to occur on the first date of recording (day 184 in Table 5.3) and is probably still important nine days later at the second recording, when *LAI* has increased with about one unit. The saturation level of backscatter of C-band VV-polarization is almost the same, for the two calibration experiments parameter C did not differ much (see Figure 5.9).

From Figure 5.9 it can be concluded that the dynamic range in *LAI* from the first recording day (July 3rd) is already sufficient to calibrate the Cloud model for C-band VV-polarization. For L-band HH-polarization we can see that parameter *D* changed significantly by using additional data further in the growing season compared to Table 5.3. Note, that the soil moisture condition of the soil is probably not the same for the two days, which could cause a shift of the points along the *Y*-axis. Secondly, the estimation of *LAI* on the second day with the standard growth model probably also introduces a shift along the *X*-axis. Despite these reasons, it is interesting to consider the use of a growth model for RS model calibration purposes.

(a) (b)

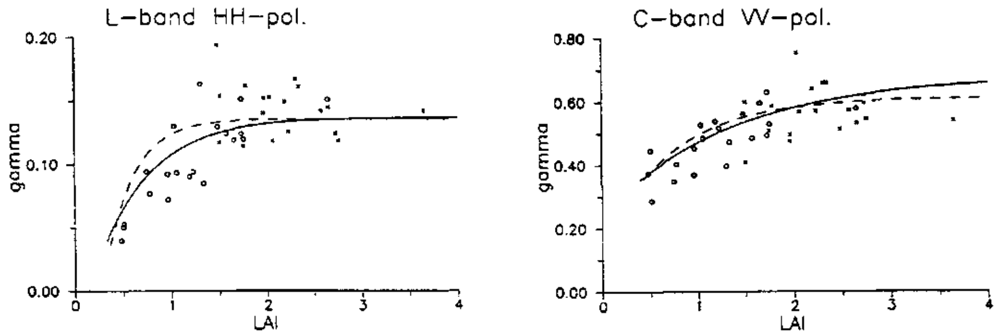


Figure 5.9 *Results of the calibration of the Cloud model on July 3rd (o) and 12th (x) for L-band HH-polarization (a) and C-band VV-polarization (b) using a random set of sugar beet fields. The solid line is the Cloud model as a result of the fit procedure on data from July 3rd only and the dotted line from both days (Flevoland test site, MAC Europe 1991 campaign).*

The regression parameters of Table 5.3 were selected for the combination methods later in this chapter. Note that this Cloud model is valid for further use within the range 0.5 < LAI < 2.5 for C-band VV and L-band HH polarization for the MAC Europe case.

5.3.3 Discussion on calibration

The Cloud model was calibrated with data from the MAC Europe campaign for sugar beet for the 1991 growing season. For C- and L-band HH-polarization reasonable results were obtained. However, for C-band VV-polarization and L-band HH-polarization airborne microwave measurements good results were obtained owing to the fact that enough variation in biomass and *LAI* was present. Soil moisture was assumed to be constant for all fields. It is assumed that the soil contribution plays a minor role for C-band. Modelling of the various backscattering mechanisms introduced by lower frequencies, such as L-band, is difficult. Therefore, the Cloud model with its assumptions for soil backscatter contribution, is probably not suitable. Rijkenberg and Van Leeuwen (1994) discussed the addition of some more terms in the Cloud model equation, for additional backscatter mechanisms like a term for volume scattering of canopy layer(s) or a term for the interaction between canopy and soil. Such an extended Cloud model should be tested in more detail with theoretical models for studying the relative backscatter contributions in order to explain the total backscatter values and the range in backscatter in figures 5.3 - 5.6.

The calibration of the Cloud model in the growing season of 1991 is still of use to the combination methodology, as the estimated *LAI* from the inverse Cloud model will be weighted with the accuracy in *LAI* estimation. When the accuracy in estimating *LAI* is low, which is the case for L-band, microwave observations during cloudy weather could still contribute to crop growth monitoring by providing weighted information.

The use of a crop growth model for simulating *LAI* did not contribute to better calibration of the Cloud model because of a lack of ground data. However, with known sowing dates and daily temperature series, the crop growth model can certainly provide information on *LAI* and biomass which can be used as "ground data" for the calibration of RS models.

New in this calibration procedure is that only one point in time (beginning of July) could represent a significant part of the growing season (dynamic in *LAI* between 0 and 2), leading to the necessary dynamic range in backscatter caused by different management practices by the various farmers (different sowing dates). However, the calibration was possible only because of the fact that the optical (AVIRIS) and microwave (AIRSAR) images were obtained around the same day. This space-time transformation (different biomass levels at various fields at one moment in the growing season) of the sugar beet crop is usually not that obvious (the 1991 growing season suffered from frost damage and therefore resowing was needed).

However, it is interesting to consider the fact that differences in crop growth development stage caused by differences in management and growing conditions (sowing date, fertilization, temperature regimes, etc.) could supply us with the needed dynamics in crop variables for temporal studies with RS.

5.3.4 Validation of optical and microwave models (contemporaneous case)

When using the results of Section 5.3.1 in combination with Equation 3.12, it is striking that the standard deviation of *LAI* estimation using microwave RS data becomes quite large, already at low *LAI* values. This is in contrast with the situation in the optical domain as described in Chapter 3. The comparison between standard deviations of *LAI* estimates from optical and microwave measurements is shown in

Figure 5.10. This figure clearly illustrates that the accuracy of *LAI* estimation from microwave measurements is not as good as from optical measurements, except for very low *LAI* values. So, only little additional value is to be expected from microwave measurements for *LAI* estimation when optical measurements are available.

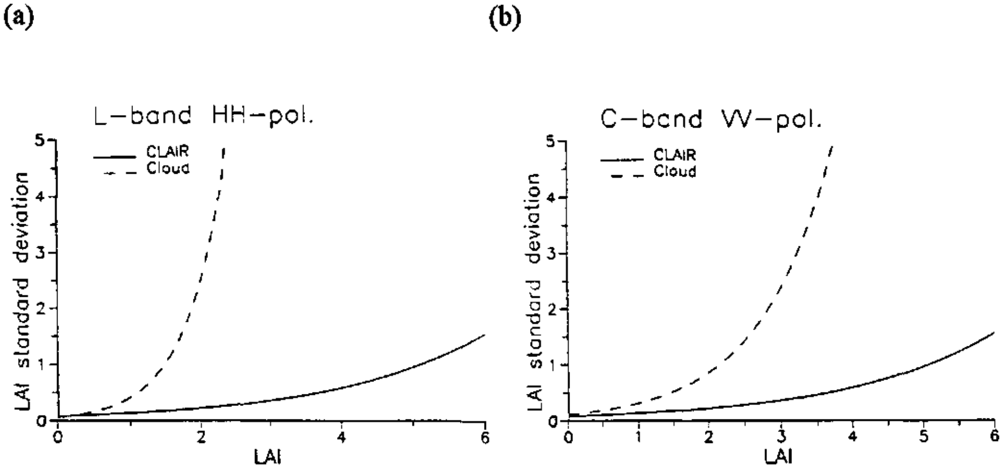


Figure 5.10 *Comparison of standard deviations of LAI estimates from the optical model CLAIR (Agriscatt 1988) and the adapted inverse Cloud microwave model (MAC Europe 1991). (a) L-band HH-polarization; (b) C-band VV-polarization*

The practical use of the calibrated RS models for the model-based combination methods described in Chapter 3, Section 3.4 can be further evaluated using the residual set of 17 sugar beet fields from the original 37 fields that were not used for calibrating the Cloud model. In Table 5.5 *LAI* estimates and standard deviation, based on either optical or microwave measurements, are compared. In a combined approach both optical and microwave measurements are available. No actual field measurements of *LAI* are available for validation of the RS models calibrated for the MAC Europe 1991 campaign. These results can be expected when comparing them with Figure 5.10. The standard deviation of *LAI* estimated by optical RS is lower than that estimated by microwave RS.

The confidence intervals ($\mu \pm 2 \cdot \sigma$) of the *LAI* estimates are given in Table 5.6. This table shows that the confidence interval of the *LAI* estimates from optical RS measurements generally lies within the confidence intervals of *LAI* estimates from microwave measurements with only a few exceptions (fields 188, 144 and 120 for L-band HH-polarization).

Table 5.5 *LAI estimates from optical (WDVI) and microwave (γ) RS measurements from MAC Europe 1991 for 17 sugar beet fields at the Flevoland test site.*
Note: "-" means that the LAI could not be estimated because the Cloud model could not be inverted when the measured γ was larger than the asymptotic value in the Cloud model (γ > parameter C in Table 5.3)

Field	*Optical*		*L-band HH*		*C-band VV*	
Number	*LAI*	*σ[LAI]*	*LAI*	*σ[LAI]*	*LAI*	*σ[LAI]*
136	0.56	0.11	0.53	0.19	0.41	0.27
280	0.81	0.13	0.89	0.33	0.95	0.35
188	0.81	0.13	0.60	0.20	0.98	0.36
144	0.90	0.13	0.53	0.19	1.27	0.45
180	1.03	0.14	-	-	0.99	0.37
120	1.18	0.15	0.80	0.27	1.73	0.59
135	1.11	0.15	0.82	0.28	0.98	0.38
88	1.49	0.18	-	-	1.66	0.57
95	1.62	0.19	1.72	0.95	2.37	0.84
182	1.26	0.16	-	-	0.91	0.35
273	1.21	0.15	1.00	0.40	1.04	0.37
204	1.62	0.19	1.38	0.73	1.49	0.51
113	1.94	0.22	-	-	3.82	1.87
406	1.35	0.16	1.04	0.46	1.06	0.37
310	1.54	0.18	-	-	2.12	0.81
143	2.33	0.26	4.10	32.2	2.56	0.96
412	1.89	0.21	-	-	1.43	0.49

The ranges in estimated *LAI* from optical and microwave RS data in Table 5.6 confirm that, when both optical and microwave measurements are taken at about the same day in the growing season, the microwave measurements give no additional information on the *LAI* estimation of sugar beet (at least following a model-based approach). However, the ranges in *LAI* estimated with microwave RS indicate that the absolute value of *LAI* estimated by microwave RS seem to be within a plausible order of magnitude. This means that the Cloud model for the MAC Europe 1991 campaign can be considered to be valid within the corresponding boundary conditions and ready for use in the combination methods. The boundary conditions are represented by the range in the data (*LAI* and γ) used for the Cloud model calibration. Of course the standard deviation in backscatter must be taken into account when combining the Cloud model with the crop growth model.

In this section no synergy occurred in the estimation of *LAI*. The significance of microwave measurements lies in the possibility of obtaining information about crop growth in periods where optical RS is not possible from a practical point of view (mainly because of bad weather conditions) and in the possibility of obtaining information about plant structure (feature-based approach). Therefore, in the rest of this study the emphasis will be on monitoring the growth of crops in a dynamic way using growth models (non-contemporaneous methods).

Table 5.6 *Confidence interval ($\mu \pm 2 \cdot \sigma$) of LAI estimates from optical (WDVI) and microwave (γ) RS measurements from the MAC Europe 1991 campaign for the remaining 17 sugar beet fields (besides the fields used for calibration) at the Flevoland test site for validation study.*

Field number	*Optical*	*L-band HH*	*C-band VV*
136	0.34-0.78	0.15-0.91	0.00-0.95
280	0.55-1.07	0.23-1.55	0.25-1.65
188	0.55-1.07	0.20-1.00	0.26-1.70
144	0.64-1.16	0.15-0.91	0.37-2.17
180	0.75-1.31	-	0.25-1.73
120	0.88-1.48	0.26-1.38	0.55-2.91
135	0.81-1.41	0.26-1.38	0.22-1.74
88	1.13-1.85	-	0.52-2.80
95	1.24-2.00	0.00-3.62	0.69-4.05
182	0.94-1.58	-	0.21-1.61
273	0.91-1.51	0.20-1.80	0.30-1.78
204	1.24-2.00	0.00-2.84	0.47-2.51
113	1.50-2.38	-	0.08-7.56
406	1.03-1.67	0.12-1.96	0.32-1.80
310	1.18-1.90	-	0.50-3.74
143	1.81-2.85	0.00->8.0	0.64-4.48
412	1.47-2.31	-	0.45-2.41

It must be noted, however, that the above-described contemporaneous approach does yield synergy in so far that optical RS measurements are used for calibrating the microwave model, which would not have been possible without optical data in this study.

5.4 Features in microwave signatures related to crop development?

In 1993 extensive measurements of *LAD* were performed by Rijckenberg and Van Leeuwen (1994) in order to interpret the microwave time-series of the MAC Europe 1991 campaign. The *LADs* of three sugar beet fields were measured on day number 166, 176, 190, 203 and 215 in 1993. Each measurement included about 100 plants per field and three leaves randomly chosen per plant, measured in the morning until the beginning of the afternoon while the crop did not suffer yet from water stress and had recovered from the previous day in cases of high evapotranspiration in hot summer growing conditions.

Some leaf angle measurements were taken in the early afternoon hours in order to identify waterstress caused by hot weather conditions. Leaves were clearly hanging down at these conditions until late in the evening. During the night, the plants were able to recover from these hot days under the favourable growing conditions at the Flevoland test site. The distribution of the leaf angle was assumed to be constant in azimuth direction, which was consistent with visual observations. The processing of the data was performed at WAU.

Figures 5.11 and 5.12 show distributions that were measured in the field in 1991 and 1993 respectively. The similarity between the different *LADs* of both years indicates that a particular sequence of orientations is possibly characteristic during the growing season for sugar beet. Note that owing to relatively high temperatures at the beginning of the 1993 growing season, crop development was 2-3 weeks earlier than in 1991.

Two changes were observed in the *LADs* measured during the growing season in the years 1991 and 1993 at the Flevoland test site (Rijckenberg and Van Leeuwen):

I. In the situation of partial coverage there is an initial leaf angle distribution which is a combination of spherical and erectophile leaves changing into a more pronounced erectophile distribution when the canopy is about to close (*feature 1*). The occurrence of the change in *LAD* depends on crop management (application of nutrients like nitrogen) or plant density, which results in closure of the canopy at different levels of *LAI* or biomass. Leaf width and growth rate are directly related to the amount of nitrogen supplied. The increase in the average leaf angle, caused by competition with the neighbouring plants occurring especially at closure, is therefore biomass related and not clearly related to development. This period of change can be seen in Figure 5.11 (Note the X-axis represents the leaf angle with respect to the vertical, while in Figure 3.9 it is with respect to the horizontal!), where the average leaf angle decreases from day of year 190 to 204 (concave towards convex curve) and in Figure 5.12 from day of year 166 to 176 to 190 (see arrow 1: concave towards convex curve as well). In the case of De Wit's measurements (Chapter 3, Section 3.4.2, Figure 3.9) the change in average leaf angle during the season is much less compared to the recent measurements. This could be explained by the nutrient availability, which was much less at the test area Droevendaal in 1965 at the time when De Wit measured the leaf angles. At Droevendaal the nitrogen level is much lower than at the Flevoland test site where growing conditions are optimal. Therefore the range of average leaf angle is much greater. This indicates that feature 1 is related to a change in biomass level.

II. Secondly, a maximum erectophile distribution will be reached before the moment the leaves tend to droop, changing to a more planophile distribution owing to the increasing weight of the outer leaves (*feature 2*). This change can be noticed, but is somewhat less pronounced, in Figure 5.11 from day of year 204 to 239 (convex towards less convex curve) and more clearly in Figure 5.12 from day of year 190 to 203 to 215 (see arrow 2: also convex to less convex curve). Besides the effect seen in the leaves, this change coincides with the fact that the tuber of the beet is growing. The resulting distribution of planophile and spherical or erectophile leaves will be an extremophile distribution. Since this process has been identified by several independent sources (Ross, 1981; De Wit, 1965), this feature may coincide with certain consistent growth or development stages of the sugar beet crop.

Based on Chapter 2, Section 2.5.2 and Chapter 3, Section 3.4.2 and the *LAD* field measurements from the MAC Europe campaign a cautious interpretation of the (AIRSAR) microwave data can be made.

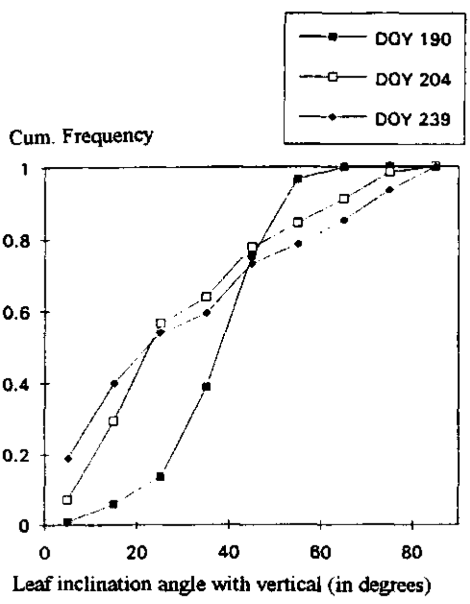


Figure 5.11 *Measured distributions in 1991 for three different calendar days (DOY = Day Of Year) for sugar beet at the Flevoland test site (Source: Rijckenberg and Van Leeuwen 1994; Courtesy J.G.P.W. Clevers and Ph. Lewis)*

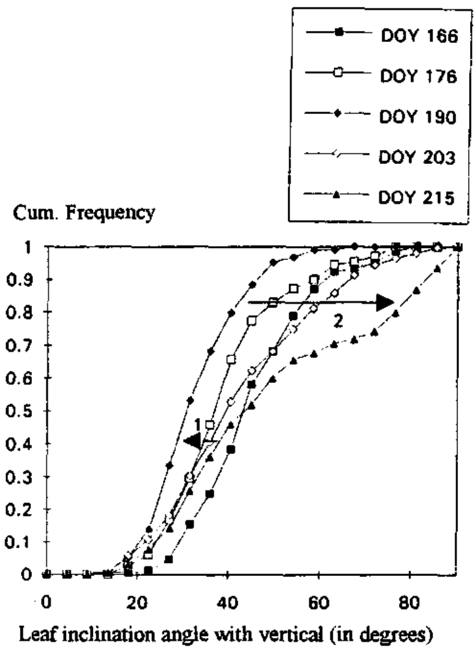


Figure 5.12 *Measured distributions of sugar beet leaf angles in 1993 for five different calendar days and three fields. The distribution is based on about 200 measurements per field (DOY = Day Of Year)(Source: Rijckenberg and Van Leeuwen, 1994)*

Figures 5.13 and 5.14 show sugar beet backscatter behaviour as a function of temperature sum for L- and C-band, respectively.

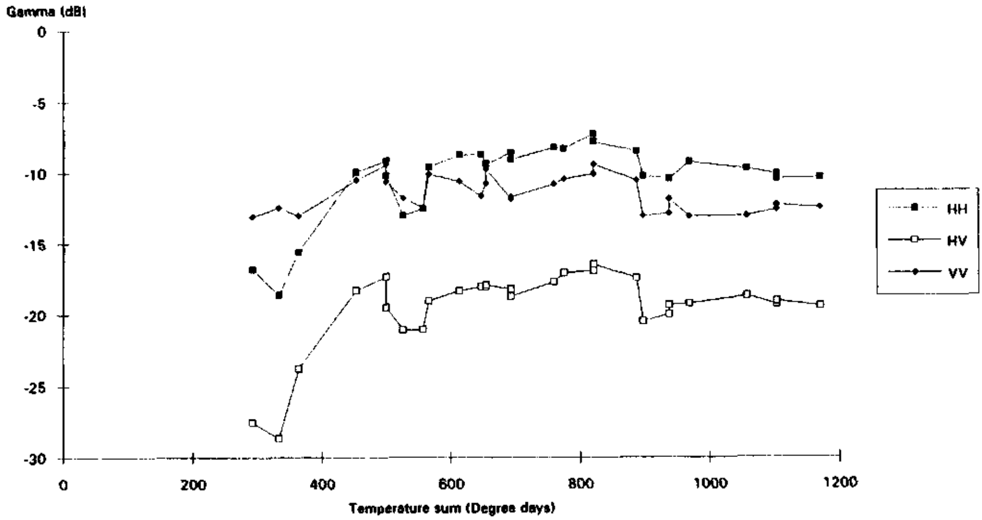


Figure 5.13 *MAC Europe 1991 campaign microwave backscatter at L-band from sugar beet as a function of temperature sum (Source: Rijckenberg and Van Leeuwen, 1994)*

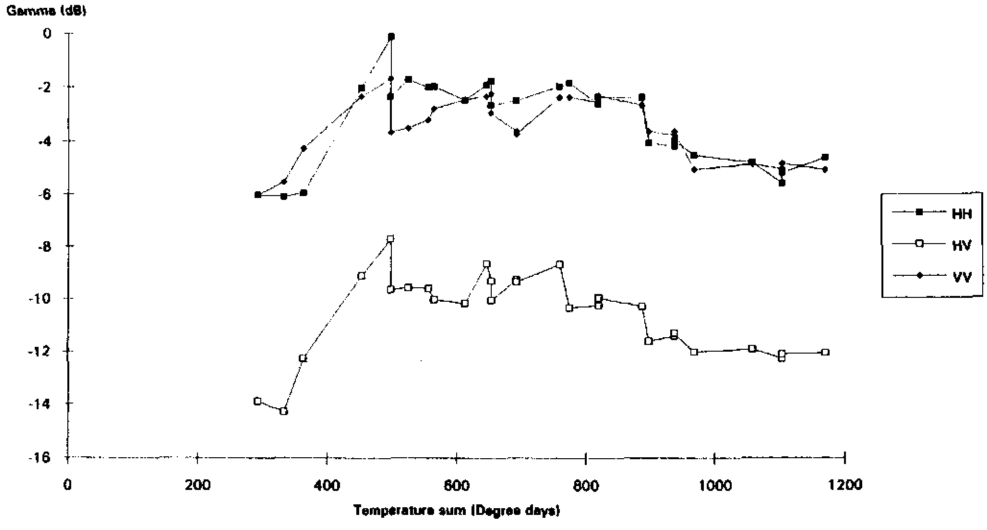


Figure 5.14 *MAC Europe 1991 campaign microwave backscatter at C-band from sugar beet as a function of temperature sum (Source: Rijckenberg and Van Leeuwen, 1994)*

A dip occurs at T_{sum} ~ 500 in Figure 5.13 and somewhat less in Figure 5.14. This could be attributed to the change in leaf orientation caused by canopy closure. This feature (1) is not seen in all series, possibly because of the differences in plant density between the different fields in combination with the sensor configuration.

At this point in the growing season the microwave signal saturates and the influence of the underlying soil will be less from this point on for C-band and even for L-band. A somewhat more pronounced decrease in backscatter can be observed at T_{sum} ~ 900. When the transition to the extremophile distribution begins, the backscatter no longer decreases, because more radiation is scattered back as more leaves are drooping to a planophile distribution.

Figure 5.15 shows the backscatter at P-band. Rijckenberg and Van Leeuwen (1994) noticed a different behaviour, which might have been expected, since at P-band structural effects of the canopy should be less important than at the higher frequencies, for reasons of transparency.

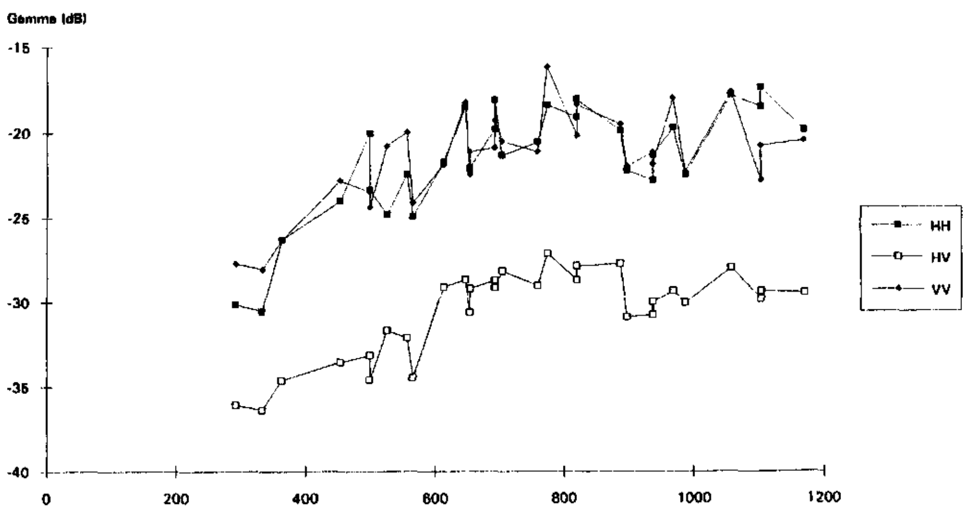


Figure 5.15 *MAC Europe 1991 campaign microwave backscatter at P-band from sugar beet as a function of temperature sum (Source: Rijckenberg and Van Leeuwen, 1994)*

Feature 1 cannot be noticed. Secondly, at T_{sum} ~ 900 no significant decrease in backscatter occurs either. The variations in the backscatter after the dip at T_{sum} ~ 900 are greater than the decrease in backscatter itself. From meteorological records we know that this was a dry day. If we look at Figure 5.16, in which backscatter is illustrated as a function of soil moisture distinguished in two classes (T_{sum} < 800 and T_{sum} > 800), we can see that the backscatter level at low soil moisture is comparable to that at high soil moisture. The main backscatter mechanism at P-band is considered to be of the underlying soil surface, which cannot clearly be seen in the figures. Therefore, P-band is not expected to be useful for detecting changes in canopy structure in contrast with X- and C-band (see Figure 2.6).

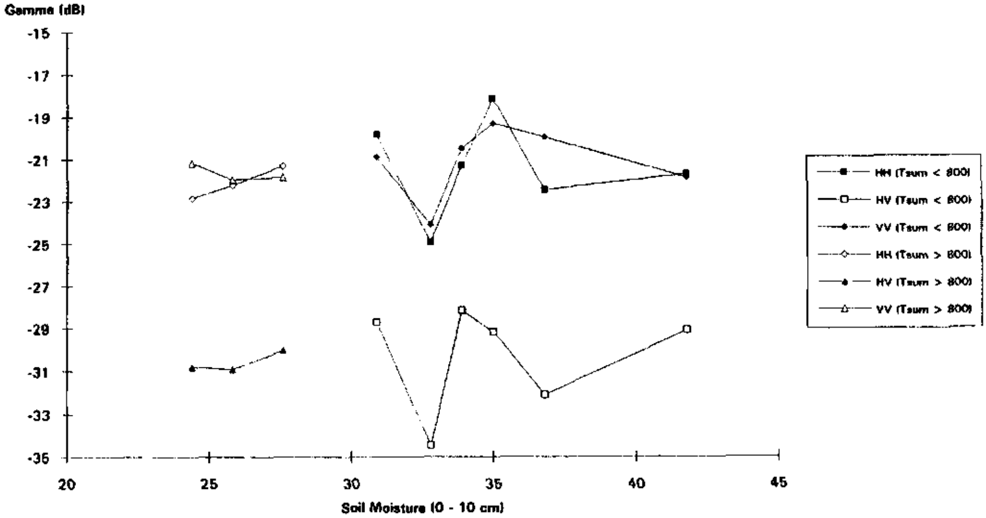


Figure 5.16 *MAC Europe 1991 campaign microwave backscatter at P-band from sugar beet as a function of soil moisture, with two T_{sum} classes (Source: Rijckenberg and Van Leeuwen, 1994)*

5.5 Results of combination methods I, II, III and IV

Central in the approach of this section is the step from ground-based to airborne use of RS for agricultural applications, with sugar beet as test case. Before showing the results of the different combination methods mentioned in Table 5.1 separately, an overview of the results is given in Table 5.7. The order of appearance in this table is characteristic of the approach followed in this section. First the results of the direct modelling approach by Bouman (1992b) are reproduced in Section 5.5.1 for the ten farms of the MAC Europe 1991 campaign test site using the Cropscan field measurements (see Table 5.11 in Section 5.6). In Section 5.5.2, the SBFLEVO prototype adapted for the inverse approach is applied to the same Cropscan measurements. This ideal situation, in which only optical data (ground-based) with a high temporal resolution are used, is meant as a reference for the best possible result with RS. Furthermore less RS data in time are used and instead of ground-based optical data, airborne optical data are used. Subsequently, only airborne microwave data are applied for two measurement configurations (L-HH and C-VV). Furthermore, we combine airborne optical and microwave data. In Section 5.5.3 feature information present in the microwave backscatter signatures is introduced into the combination method. In Chapter 6 special attention is given to the next step towards space-borne applications of RS in agriculture.

Table 5.7 *Optical [O] and microwave [R] RS configurations with high (10 measurement days) and lower temporal resolution, used for the inverse modelling method and the accompanying results, represented by errors in tons per hectare (1 ton =1000 kg)*

RS data source	*Method*	*Category*	*Average error (ton ha^{-1})*	*Error (%)*	*Figure*
1 Without RS (only standard crop growth)	-	[-]	13.4	17.5	5.18
2 CROPSCAN (10)	I	[O]	3.0	4.1	5.18
3 CROPSCAN (6)	II	[O]	3.7	5.1	5.20
4 CAESAR (2)	II	[O]	4.2	5.5	5.21
5 AIRSAR L-HH (2)	II	[R]	9.2	13.0	5.22a
6 AIRSAR C-VV (2)	II	[R]	7.2	9.8	5.22b
7 AIRSAR L-HH (2) + CAESAR (2)	II	[R+O]	3.0	4.2	5.23a
8 AIRSAR C-VV (2) + CAESAR (2)	II	[R+O]	3.5	4.8	5.23b
9 AIRSAR L-HH (2) + CAESAR (1)	II	[R+O]	2.8	3.8	5.24a
10 AIRSAR C-VV (2) + CAESAR (1)	II	[R+O]	6.7	9.3	5.24b
11 AIRSAR L-HH (2) + feature	IV	[R]	2.5	3.6	5.28a
12 AIRSAR C-VV (2) + feature	IV	[R]	6.8	9.3	5.28b
13 AIRSAR L-HH (2) + CAESAR (2) + feature	IV	[R+O]	3.1	4.5	5.29a
14 AIRSAR C-VV (2) + CAESAR (2) + feature	IV	[R+O]	2.9	4.1	5.29b

In general, the results in Table 5.7 indicate improvement in yield prediction by introducing other information sources provided by RS, beside the standard crop growth model. The results are based on ten fields, which is not sufficient to be used at regional scale. Bearing in mind the considerations of the calibration method of the crop growth model in Chapter 4, Section 4.3 these figures on yield and accuracy need to be handled with caution. This table is meant to be a general guide in the evaluation of the combination methods in the next sections.

5.5.1 Results of the direct modelling method (Method I)

The crop growth model SBFLEVO was extended with the CLAIR model to simulate the *WDVI* of the growing crop (Bouman, 1992a). SBFLEVO was used in this section to predict the beet yield for ten selected fields at the Flevoland test area in 1991 (Table 5.8) for the purpose of validation and comparison with the combination methods II, III and IV in the following sections.

Table 5.8 *Information on sugar beet fields from ten sugar beet fields at the Flevoland test site in 1991. The dates are in days of the year (DOY, starting from the 1st of January)*

Farmer	*Sowing date (DOY)*	*Emergence date (DOY)*	*Harvest date (DOY)*	*Actual yield ton/ha*	*Remarks*
1	85	100-104	277/298	87.0	frost
2	86	100	284/303	79.0	frost
3	74	91	288	75.0	frost
4	85	104	293	77.0	frost
5	116	127	305	69.5	2nd seed
6	116	130	304	68.0	2nd seed
7	116	135	319	70.0	2nd seed
8	119	130	280	61.0	hail damage
9	116	121	305	70.0	hail damage
10	88	103	296/313	77.0	frost

Input for the model were the location parameters, weather data for the 1991 growing season and crop-specific model parameters. Simulating growth of a sugar beet crop using a "standard" crop growth model (initialized for growth conditions at the Flevoland test site) with an average sowing date of April 15th (day of year 105) and an average harvest date of October 22nd (day of year 295) resulted in a simulated beet yield of 60.0 ton ha^{-1} for every field. This means an average simulation error of (fresh) beet yield of 13.4 ton ha^{-1} (17.5% error).

We can think of two measures for judging the performance of the calibration and for comparing different calibration procedures:

1 The correspondence between simulated and estimated or measured data as a result of the optimization procedure. The results were judged by making graphical presentations.

2 Looking at the simulated yield at the end of the growing season and comparing it with the measured yield. This is an extrapolation of the results obtained under 1. Moreover, in the case of sugar beet, this measure refers to the yield of the beet root

whereas with RS mainly information on the above-ground plant parts is obtained. The relationship between e.g. *LAI* and beet yield may not be that direct.

Next, SBFLEVO was calibrated such that the simulated *WDVI* during the growing season matched the WDVI measured with the Cropscan as closely as possible for all ten fields individually. "Optimum crop parameter values" are given in Table 5.9. The optimum crop parameter combination of sowing date, relative growth rate, light use efficiency and maximum leaf area is the result of the calibration procedure and is selected from the minimum total deviation between measured and simulated WDVI. The optimum parameter combination does not necessarily represent the correct realistic combination as this is a local solution of the 4-dimensional variable space (*DAYSOW, RGRL, EFF, LSHA*) of the crop growth model (see Chapter 4).

Table 5.9 *Parameter values that resulted in the best correspondence between simulated and measured WDVI time series for ten fields in Flevoland in the 1991 growing season using the direct modelling method of the SBFLEVO crop growth model (Bouman, 1992a)*

Field	*DAYSOW*	*RGRL*	*EFF*	*LSHA*	*YIELD*
1	96	0.0169	0.0150	5.118	80.0
2	92	0.0150	0.0150	4.649	76.7
3	102	0.0168	0.0149	5.021	74.3
4	104	0.0169	0.0142	3.907	71.5
5	122	0.0170	0.0147	4.844	70.5
6	124	0.0149	0.0145	5.372	65.3
7	119	0.0166	0.0150	5.130	69.9
8	124	0.0167	0.0146	5.489	68.1
9	105	0.0166	0.0148	5.181	72.2
10	98	0.0163	0.0148	5.426	75.7

DAYSOW = sowing date (days);
RGRL = relative growth rate;
EFF = light use efficiency;
LSHA = maximum leaf area (shading);
YIELD = simulated yield after model calibration (harvest date = 295) (ton ha^{-1}).

Since in operational yield estimations, information on exact sowing and harvest dates are not readily available, SBFLEVO was also initialized on the *WDVI* measurements (i.e. the sowing date was also one of the calibration parameters). The day of harvest was taken as day number 295. Figure 5.17 shows the simulated beet yields after model calibration versus actually obtained yields. For all fields except one, the yield simulated after calibration was nearer to the actually obtained yield than the yield simulated before calibration. On average, the simulation error of beet yield decreased from 13.4 ton ha^{-1} (17.5% error) using "standard" SBFLEVO, to 3.0 ton ha^{-1} (see Table 5.7 line 2; 4.1% error) with SBFLEVO calibrated to time-series of *WDVI*.

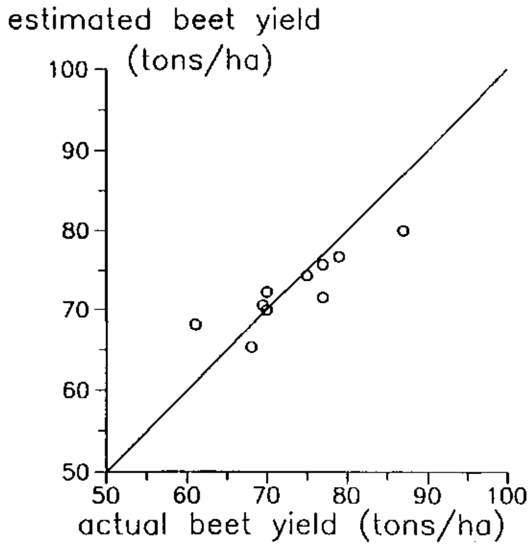


Figure 5.17 *Simulated beet yield using SBFLEVO, calibrated to measured WDVI (direct modelling method) versus actually obtained beet yields at ten fields in 1991 at the Flevoland test site*

An example of such a calibration result for one of the farmers is given in Figure 5.18.

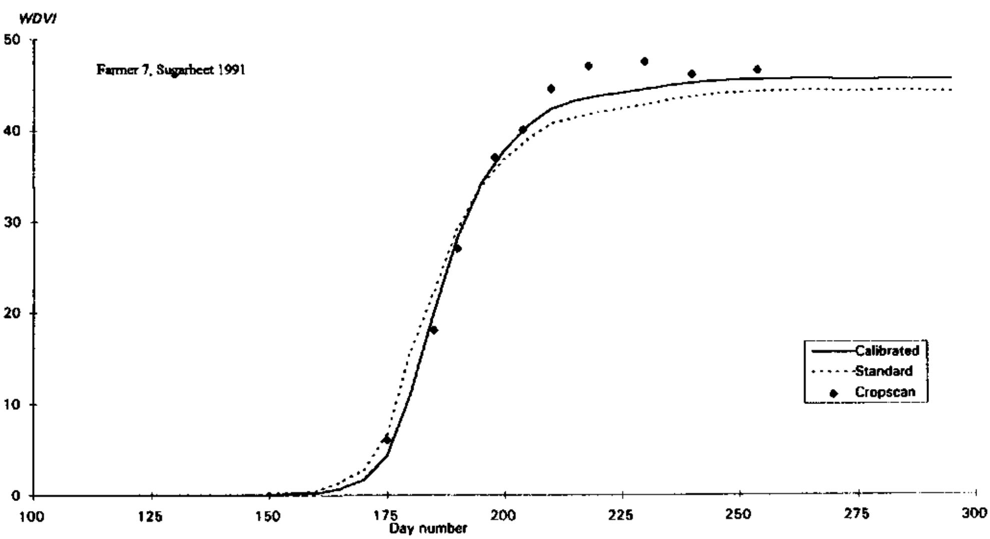


Figure 5.18 *Example of the result of calibrating the crop growth model to a time-series of Cropscan reflectance measurements (WDVI) using the direct modelling method (drawn line). As a comparison the result for the "standard" crop growth model without using RS data is shown as well (dotted line)*

This figure shows that simulated *WDVI* values match the measured ones quite well. As a comparison, also the simulated *WDVI* using "standard" SBFLEVO is shown in Figure 5.18.

Figure 5.19 illustrates the comparison between simulated *LAI* using the calibrated SBFLEVO model and the *LAI* estimated directly from *WDVI* using the CLAIR model. In this figure the estimated *LAI* values which superseded an *LAI* of 5 are left out (cf Figure 5.18). At these high *LAI* levels estimations with the CLAIR model are inaccurate. From optical RS data a much higher maximum *LAI* is estimated than from simulation with the crop growth model. One may query the correctness of such high *LAI* values. The influence of the *LAD* was proven to be significant in the sensitivity analysis of optical RS models in Section 2.3.4 of Chapter 2. The observations of *LAD* presented in Figures 5.11 and 5.12 showed that the *LAD* for sugar beet changes during the growing season. If that is so, other regression parameter values must be used in the CLAIR model, resulting in other *LAI* estimates. During the Agriscatt campaigns (the data set used for calibrating the CLAIR model for sugar beet in Chapter 2, Section 2.3.3) the maximum measured *LAI* was about 5.0. However, it should be noted that during the Agriscatt campaigns most *LAI* measurements were performed before the beginning of August.

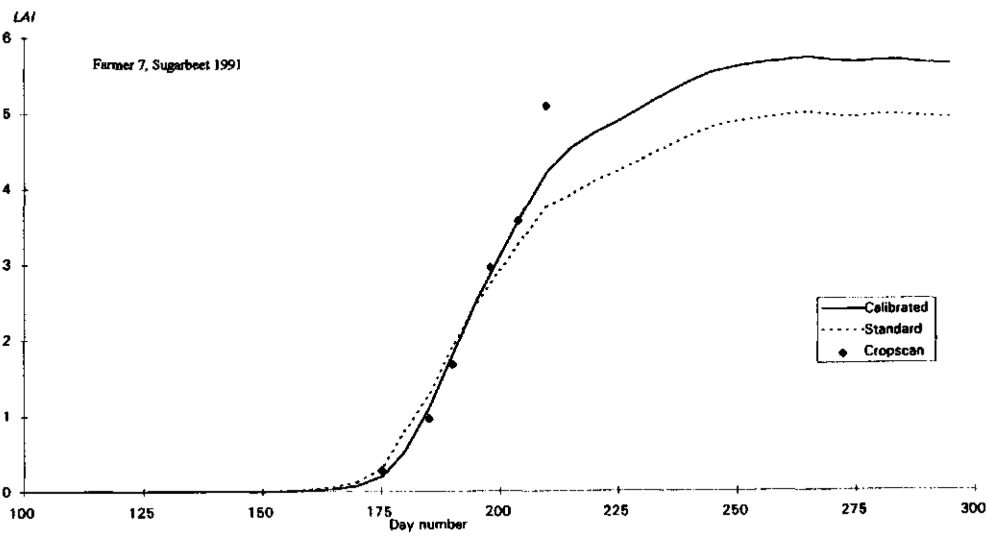


Figure 5.19 *Comparison between simulated LAI and LAI estimated from WDVI using the CLAIR model (Cropscan measurements; direct modelling method)*

The direct modelling method compares simulated RS data with measured RS data. In this method the input parameters, plant moisture and *LAI* of the RS models (Cloud and CLAIR), are produced by the crop growth model. This was done for every crop growth simulation day, assuming that the validity of the RS models is such that their application is possible. It is the validity (and with that the applicability), which could help in weighting the various contributions from the RS measurements in the crop growth calibration process with inverse RS modelling. In Chapter 3 reasons were given for using inverse modelling in the combination methods.

In the next sections higher values than *LAI* = 5 estimated from optical measurements are not used and presented in the figures, for reasons of model validity.

5.5.2 Results of the inverse modelling method (Method II and III)

5.5.2.1 Results of combination method II using only ground-based optical data

The crop growth model SBFLEVO was calibrated for sugar beet for ten selected fields in the Flevoland test area of the MAC Europe 1991 campaign using the inverse modelling method (cf Chapter 3, Section 3.4.2). SBFLEVO was calibrated so that simulated *LAI* during the growing season matched *LAI* values estimated from ground-based Cropscan *WDVI* measurements using the CLAIR model as closely as possible.

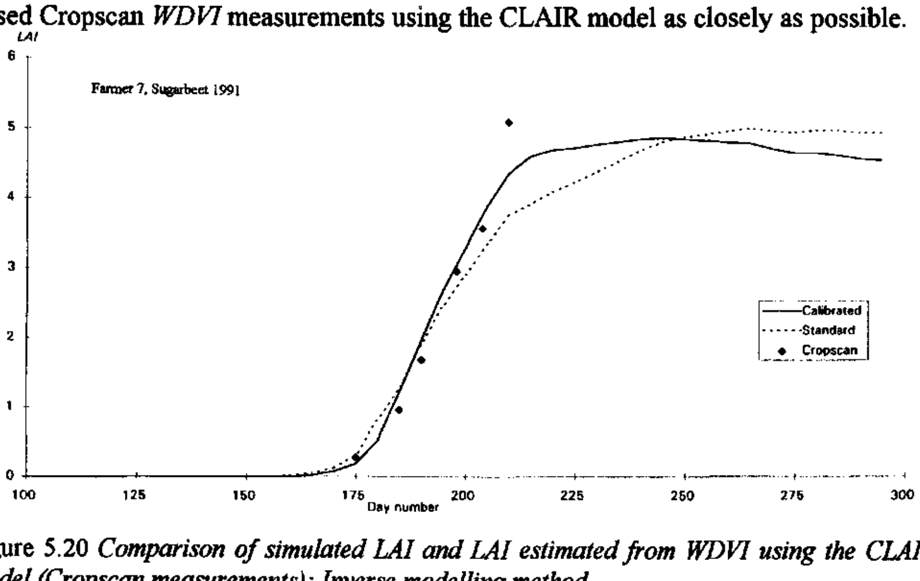


Figure 5.20 *Comparison of simulated LAI and LAI estimated from WDVI using the CLAIR model (Cropscan measurements); Inverse modelling method*

Yield figures are given in Table 5.11, Case 3. Here too, the sowing date was one of the calibration parameters and the harvest date was taken as day number 295. Figure 5.20 illustrates the comparison between simulated *LAI* using the calibrated SBFLEVO model, and the *LAI* estimated from *WDVI* using the CLAIR model. In general, no large differences were observed between the inverse modelling method and the direct modelling method. On average, the simulation error of (fresh) beet yield was 3.7 ton ha^{-1} (5.1% error) with SBFLEVO calibrated on time-series of *LAI* using the inverse modelling method (see Table 5.7).

5.5.2.2 Results of combination method II using airborne optical data only

With respect to calibration of SBFLEVO presented thus far, time-series of 8 to 12 dates with optical RS measurements were used. Of course, this is not a very realistic situation. Generally, fewer dates will be available for calibrating such a crop growth model. In order to get some idea of the calibration results one would obtain with fewer recording dates, the measurements obtained from the two CAESAR recordings (July 4th and July 23rd; cf Chapter 4, Section 4.2.3) during the MAC Europe 1991 campaign above the Flevoland test area were used.

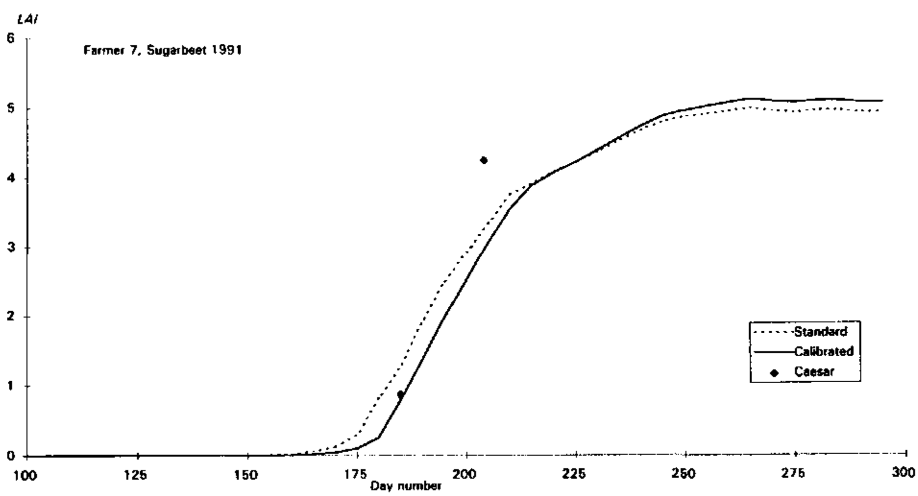


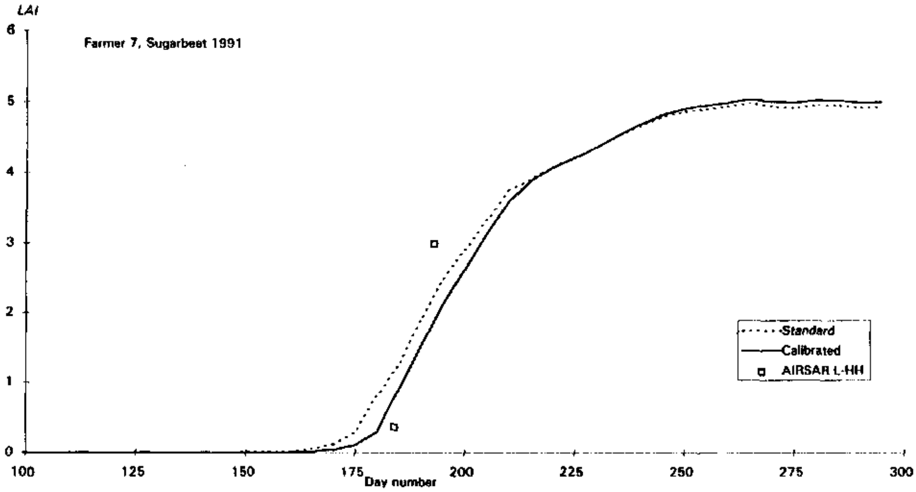
Figure 5.21 *Comparison between simulated LAI and LAI estimated from WDVI using the CLAIR model for two CAESAR recording dates (inverse modelling method)*

For each date the *LAI* values for sugar beet of the same ten farmers, were estimated from the CAESAR recordings. Subsequently, SBFLEVO was calibrated on these two *LAI* estimates, using the reciprocal of the standard deviation of *LAI* estimate as weighting factor. The yield results can be found in Table 5.11, Case 4. The comparison between simulated and estimated *LAI* for one of the fields is illustrated in Figure 5.21. Results from only two dates during the growing season in the calibration procedure still seem to be quite satisfactory. However, of three CAESAR observations in time only one was correctly simulated as one of them was lying outside the validity region and the third could not correctly be simulated. One may question such yield results that are based on so few data. On average, for all fields the simulation error of (fresh) beet yield was 4.2 ton ha^{-1} (5.5% error) with SBFLEVO calibrated on two CAESAR dates using the inverse modelling method (see Table 5.7).

5.5.2.3 Results of combination method II using only airborne microwave data

Two data points were used during the growing season for a model-based approach from the airborne microwave recording in the MAC Europe 1991 campaign. By applying Equation 3.10 with the appropriate Cloud regression parameter estimates from Table 5.3, the *LAI* was estimated for all sugar beet fields present in both AIRSAR images. Equation 3.12 offered an estimate of the accuracy (standard deviation) of these *LAI* estimates. Subsequently, SBFLEVO was calibrated on these *LAI* estimates from the AIRSAR recordings of July 3rd and July 12th 1991 for the fields used before, as far as the corresponding fields were present on both AIRSAR images. The reciprocal of the standard deviation was used as a weighting factor for both dates in the optimization procedure. The yield results are presented in Table 5.11, Cases 5 and 6 for L-band HH-polarization and C-band VV-polarization respectively. The comparison between simulated and estimated (from γ) *LAI* for one of the fields is illustrated in Figure 5.22. Since we have two recording dates rather early in the growing season, parameters such as light use efficiency (*EFF*) and maximum leaf area (*LSHA*) cannot be calibrated accurately and are therefore excluded in the optimization procedure. As a result, accurate yield estimates cannot be expected. On average, the simulation error of (fresh) beet yield was 9.2 ton ha^{-1} (13.0% error) for L-band HH-polarization and 7.2 ton ha^{-1} (9.8% error) for C-band VV-polarization respectively, with SBFLEVO calibrated on two AIRSAR dates using the inverse modelling method (see Table 5.7).

(a)



(b)

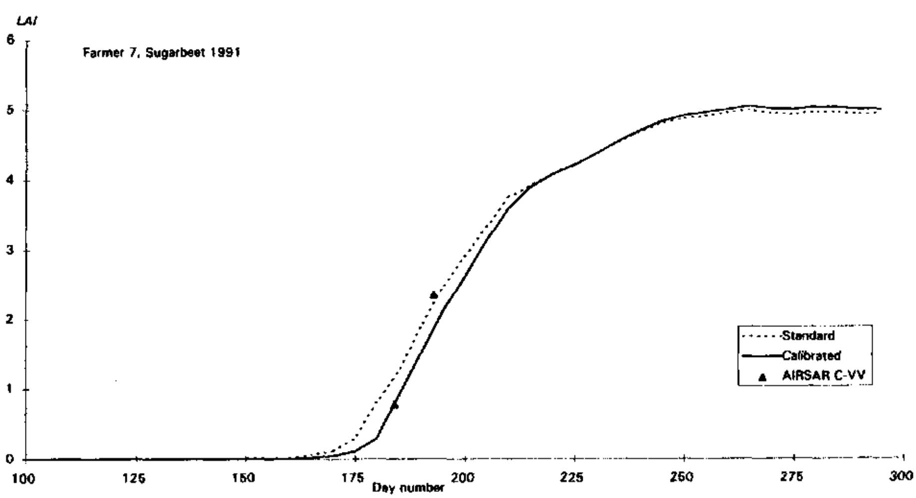


Figure 5.22 *Comparison between simulated LAI and LAI estimated from γ using the Cloud model for two AIRSAR recordings in L-band HH-polarization (a) and C-band VV-polarization (b); Inverse modelling method*

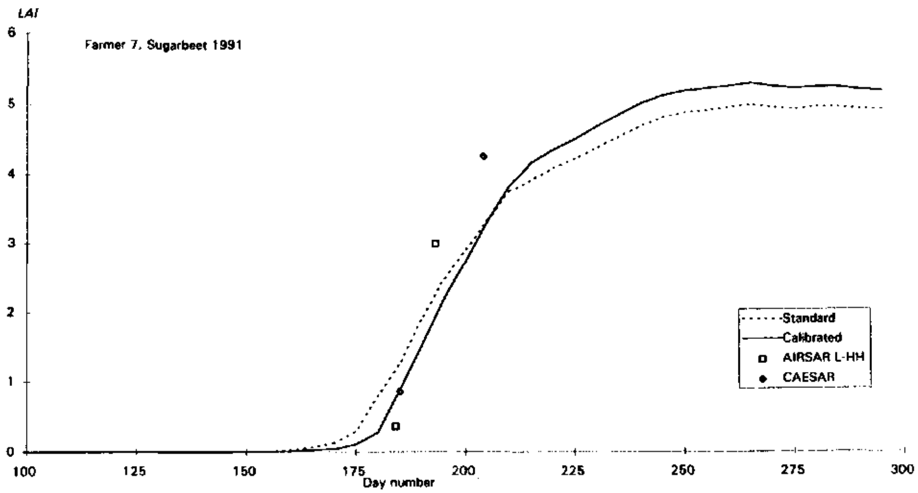
This result is better than the one obtained with "standard" SBFLEVO without RS information (which gave an average simulation error of 13.4 ton ha^{-1}, see also Table 5.7). Moreover, in this case C-band VV-polarization offers better results than L-band HH-polarization. For sugar beet this is about the best we can expect using only the model-based approach for microwave data, since after mid-July (in 1991) the Cloud model could not be applied anymore. A (combined) model-based and feature-based approach may result in further improvements in terms of simulating crop growth during the entire growing season. This is further elucidated in Section 5.5.4.

5.5.2.4 Results of combination method II using airborne optical and microwave data

In Section 5.5.2.2 the results of calibration of SBFLEVO using optical data only were presented, in which two CAESAR recordings from the MAC Europe campaign in 1991 were used. In Section 5.5.2.3 the results of calibration of SBFLEVO using microwave data only were presented. Two AIRSAR recordings from the same campaign were used. In both cases the so-called model-based approach was applied, meaning that the CLAIR and Cloud model were used for deriving *LAI* estimates on the dates of recording. Subsequently, these *LAI* estimates were used for calibrating the crop growth model SBFLEVO.

In this section, *LAI* estimates from the two CAESAR recordings and the two AIRSAR recordings are integrated and, with their appropriate weighting factors, used for calibrating SBFLEVO. This calibration is performed for the same fields as used in Section 5.5.2.3. Yield results are given in Table 5.11, Cases 7 and 8 for the two CAESAR recordings in combination with L-band HH-polarization and C-band VV-polarization microwave data respectively. The comparison between simulated and estimated (from either *WDVI* or γ) *LAI* for one of the fields is illustrated in Figure 5.23. On average, the simulation error of (fresh) beet yield was 3.0 ton ha^{-1} (4.2% error) for L-band HH-polarization and 3.5 ton ha^{-1} (4.8% error) for C-band VV-polarization respectively. This error is evidently smaller than the one obtained for the two CAESAR recording dates only (cf Section 5.2.2) and of the same magnitude as the errors obtained using time-series of Cropscan (optical) measurements during the whole growing season. These results indicate a synergistic effect (see Table 5.7) when using both optical and microwave data for crop growth monitoring. However, under practical conditions only very few optical data will be available during the growing season. For instance, when no optical data from July 4th would be available it is to be expected that microwave data from the beginning of July offer a significant improvement to the monitoring of crop growth, particularly at the beginning of the growing season.

(a)



(b)

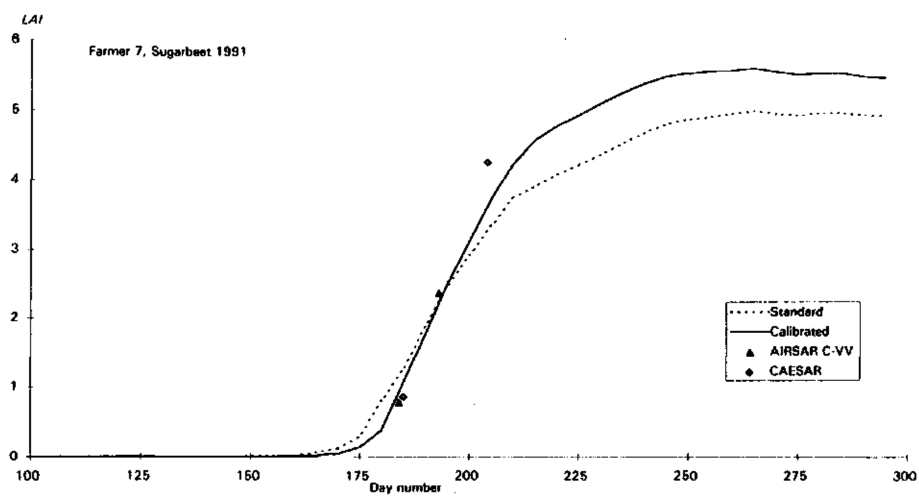
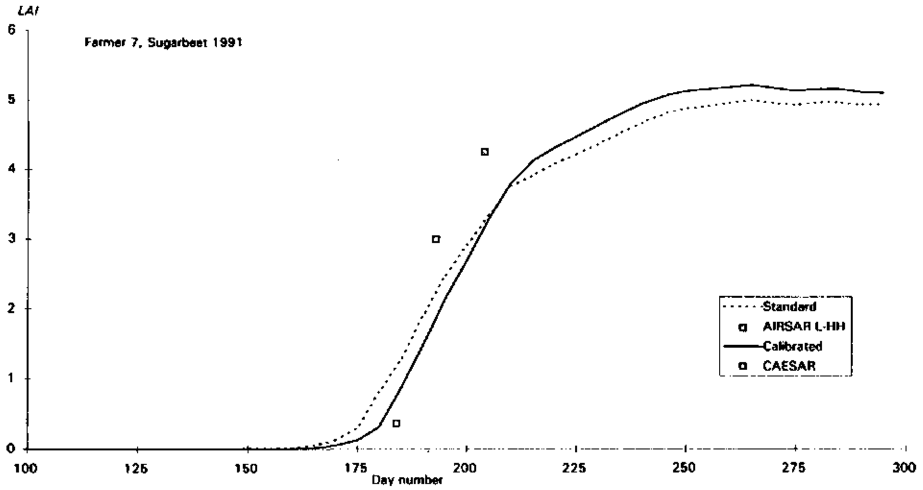


Figure 5.23 *Comparison between simulated LAI and LAI estimated from WDVI using the CLAIR model for two CAESAR recording dates and from γ using the Cloud model for two AIRSAR recordings in L-band HH-polarization (a) and C-band VV-polarization (b) (inverse modelling method)*

It is interesting to leave out some optical data from CAESAR at times when microwave data are already available. In this way one can find out whether microwave data can replace optical data, still leading to acceptable results.

(a)



(b)

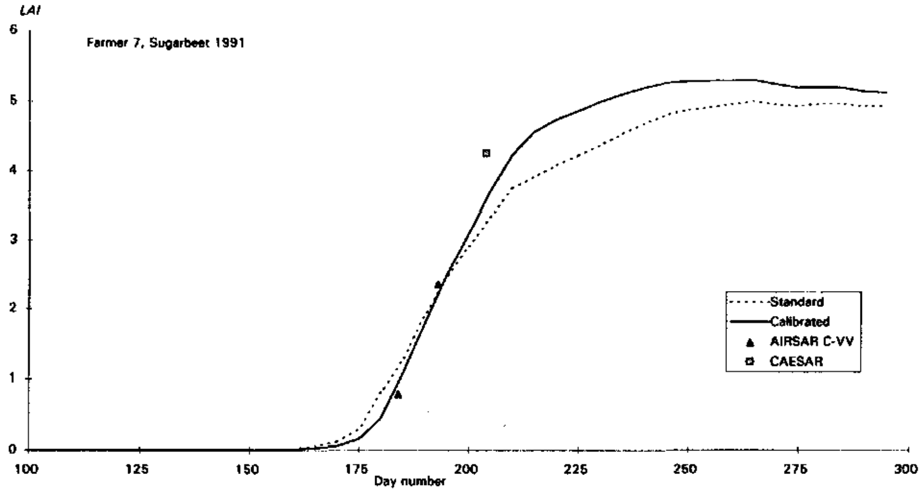


Figure 5.24 *Comparison between simulated LAI and LAI estimated from WDVI using the CLAIR model for one CAESAR recording date and from γ using the Cloud model for two AIRSAR recordings in L-band HH-polarization (a) and C-band VV-polarization (b) (inverse modelling method)*

One CAESAR date was left out (day 185) and the remainder (day 204) was combined with the same two microwave observations we used in former combinations (day 184 and day 193). For L-band HH-polarization this led to comparable results as in combination with two optical observations (Table 5.11 case 9). On average, the simulation error of (fresh) beet yield was 2.8 ton ha^{-1} (3.8% error). However, for C-band VV-polarization the results were significantly poorer. Here the error was 6.7 ton ha^{-1} (9.3% error). These results should be compared with the results in Table 5.11, Cases 5 and 6, where only two microwave observations in time were used. Striking is the fact that with only one optical observation the results for L-band improve so much. When comparing the results with Table 5.11, Case 7 and Table 5.11, Case 8, we notice that leaving out one optical date in the C-band configuration leads to less satisfactory results. This could mean that the estimation of *LAI* by L-band is better. (See the calibration results in Table 5.3 where the standard deviation for L-band HH-polarization is about 2.5 times smaller than for C-band VV-polarization, meaning that the weight factor is 2.5 times greater for L-band HH-polarization in the calibration procedure.) The comparison between simulated and estimated *LAI* for one of the farms is illustrated in Figure 5.24.

As mentioned before, another potential advantage of microwave measurements lies in the possibility of obtaining information about crop structure changes. The latter may be related to important transitions in the phenological development stage. This will be addressed in the next section.

5.5.3 Crop growth optimization (Method III) using feature information from RS only

Time-series of microwave backscatter signatures of agricultural crops exhibit crop specific patterns. These patterns could lead to crop classification in the first place (De Loor, 1984). However, when the crop type is already known to the investigator, these patterns could in fact also lead to determination of the actual processes (hydrology, crop growth).

Since a transition in leaf angle distribution of sugar beet halfway the growing season, as was shown in Section 5.4, also affects the parameters of the CLAIR model, the *LAI* values estimated from optical RS data after the occurrence of feature 2 must be adapted before they enter the optimization procedure for the crop growth model. The significance of this adaptation will be illustrated in Section 5.5.4.1. Subsequently, in Section 5.5.4.2 the results will be presented using microwave data only in the optimization procedure, but now integrating the model-based and feature-based approach. Finally, in Section 5.5.4.3 the results of the integration of microwave data (model-based and feature-based approach) with optical data will be presented.

When studying the time-series of microwave backscatter for the various sugar beet fields, it may be concluded that the dip (feature 2) will occur between day numbers 193 (July 12th) and 209 (July 28th). This is illustrated in Figure 5.25 and is true for all sugar beet fields. In the feature-based approach this is all the information we can obtain from the microwave data. Firstly, using meteorological data from 1991, a T_{sum} of 900 (with a window of 10 degree days) on day 193 (with one day time window) results in a sowing date range between day numbers 70 and 75. This can be used as input for the calibration procedure of the crop growth model. Secondly, an *LAI* of 4.0 at day 193 is the one calibration point in the calibration procedure. A T_{sum} of 900 (with a window of 10 degree days) at day 209 (with one day time window) results in a sowing date range between day number 104 and 118. This again can be used as input for the calibration procedure of the crop growth model. $LAI = 4.0$ at day 209 is the only calibration point in the calibration procedure. Results for the optimum parameter values for the two dates (day number 193 and 209) are given in Table 5.10.

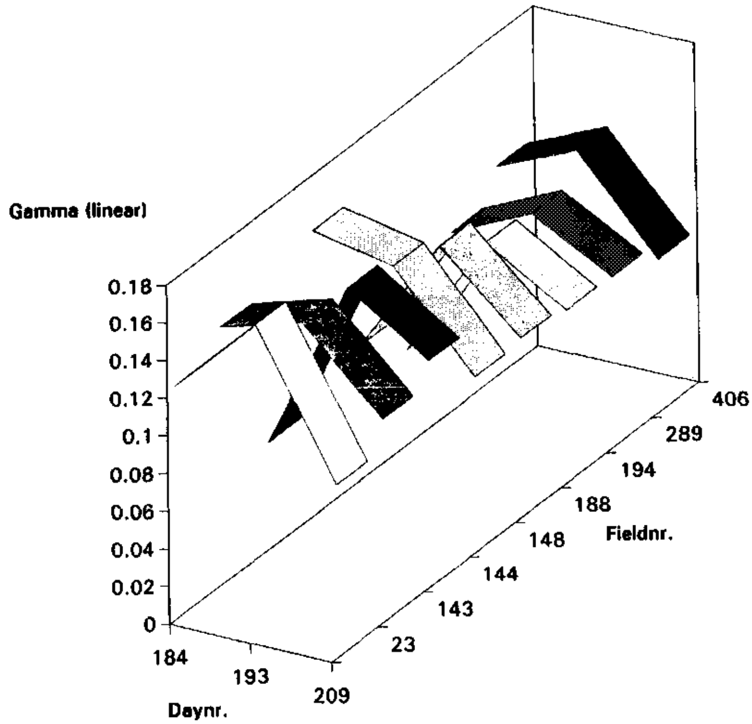


Figure 5.25 *Time-series of microwave backscatter in L-band HH-polarization for individual sugar beet fields. Flevoland test site, 1991 MAC Europe campaign*

Table 5.10 *Parameter values that resulted in a simulated LAI = 4.0 at day numbers 193 and 209, using the feature-based approach only and the inverse calibration method of the SBFLEVO model*

	DAYSOW	*RGRL*	*EFF*	*LSHA*	*YIELD*
Lower limit (day 193)	74	0.0168	0.0124	4.077	72.5
Upper limit (day 209)	108	0.0162	0.0134	4.316	65.8

The resulting two "extreme" growth curves using the values of the parametrization (Table 5.10) are shown in Figure 5.26. These curves are valid for all sugar beet fields in the test area. When Figure 5.26 is compared with, for example, Figure 5.20, it appears that in the curve on the right in Figure 5.26 *LAI* is 4.0 on day number 209 agrees quite well with Figure 5.20. This would indicate that feature 2 occurs at about day 209. Also the rest of the growth curve for the upper limit (day 209), particularly between emergence and day 209, matches quite well with the earlier curves, at least for field 7. As a result, a reasonable estimate of final beet yield is already obtained using only the feature-based approach. This estimate is much better than the one obtained without RS information which predicted a yield of 60.0 ton ha^{-1}.

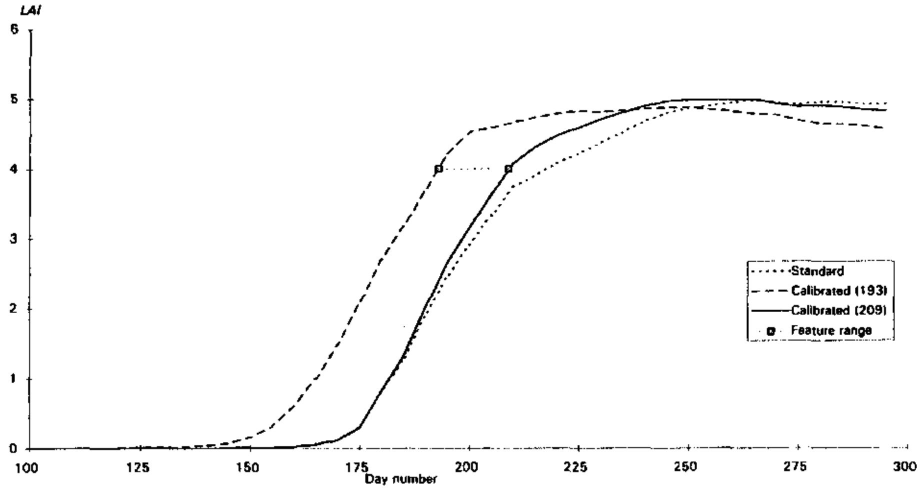


Figure 5.26 *Results of calibrating the growth model using only a feature-based approach (inverse modelling method), yielding a simulated LAI of 4.0 at either day number 193 (left curve) or day number 209 (right curve)*

5.5.4 Crop growth optimization using all information from RS (Method IV)

In the previous sections three sources of information were distinguished leading to an estimation of *LAI* and subsequently to calibration of a crop growth model. These three sources of information are optical RS data (using the CLAIR model), microwave RS data used in a model-based approach (using the Cloud model) and microwave RS data used in a feature-based approach.

To obtain the best possible estimation of crop growth, one needs all possible information there is. However, not all information contributes to this estimation in the same way. In fact, each contribution is weighted in its own way in the optimization procedure. Combination of the different sources of information has been accounted for in previous sections.

5.5.4.1 Results of combination Method IV using optical data and feature information

In Section 5.4 we found a changing *LAD* of the sugar beet crop during the growing season as a function of T_{sum}. Up to the second feature, at the onset of tuber filling (T_{sum} 900-1000), a spherical/erectophile *LAD* is applicable. After that stage the *LAD* is more extremophile. Dividing the growing season of sugar beet into these two phases, *LAI* values can be estimated from *WDVI* measurements using the CLAIR model.

Using the new CLAIR regression parameter estimates of Chapter 2, Section 2.3.5 in the second part of the growing season of the sugar beet crop for each field in the Flevoland test area in 1991, SBFLEVO was calibrated so that the simulated *LAI* matched these newly estimated *LAI* values. *LAI* was estimated with the Cropscan measurements (cf results in Section 5.5.2.1). Figure 5.27 illustrates the comparison between simulated *LAI* and estimated *LAI* using the adaptation of canopy structure after feature 2 for the same field as pointed out before. It can be seen that the maximum *LAI* during the second half of the growing season is much lower than that obtained in previous sections. Moreover, the correspondence between simulated and estimated *LAI* is much better, particularly during the second half of the growing season (cf Figure 5.20).

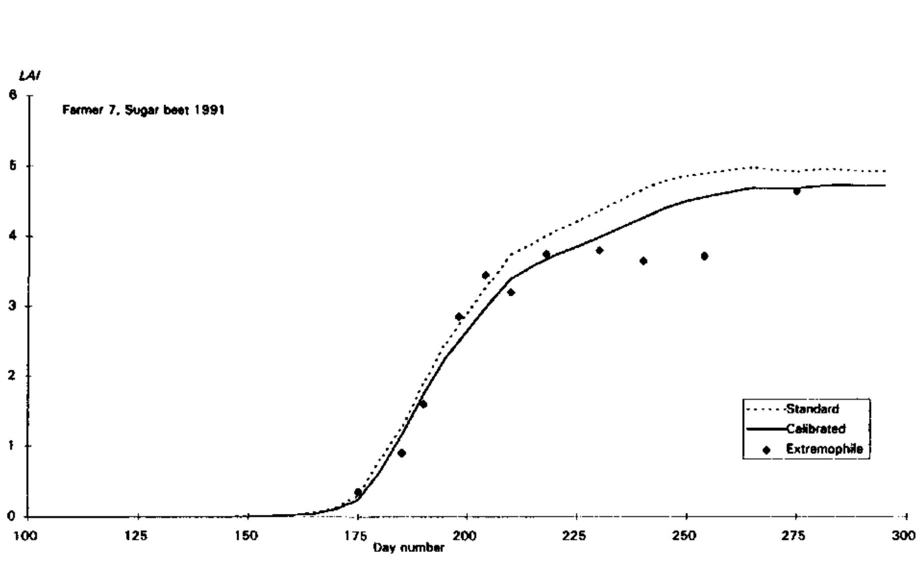
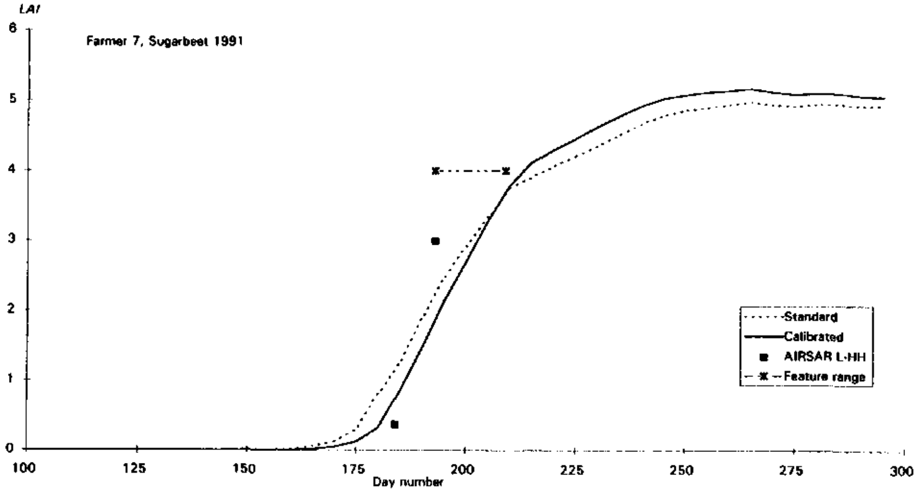


Figure 5.27 *Comparison between simulated LAI and LAI estimated from WDVI using the CLAIR model including an extremophile LAD during the second part of the growing season (after feature 2), based on Cropscan measurements. (inverse modelling method)*

5.5.4.2 Results of combination Method IV using airborne microwave data and feature information

In this section *LAI* estimates for July 3rd and July 12th, obtained from AIRSAR recordings in L-band HH-polarization and C-band VV-polarization, with their appropriate weighting factors (cf Section 5.5.2.3) are combined with the feature-based information, described in Section 5.4, for calibrating the crop growth model. In the calibration 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 (see Table 5.10). In the optimization procedure *LAI*=4.0 was given a weight of 1.0 as a first approximation. Yield results are given in Table 5.11 in lines 11 and 12 for L-band HH-polarization and C-band VV-polarization respectively. The comparison between simulated and estimated (from γ and feature) *LAI* for one of the farms is illustrated in Figure 5.28. On average, the simulation error of (fresh) beet yield was 2.5 ton ha^{-1} (3.6% error) for L-band HH-polarization and 6.8 ton ha^{-1} (9.3% error) for C-band VV-polarization respectively (see Table 5.7).

(a)



(b)

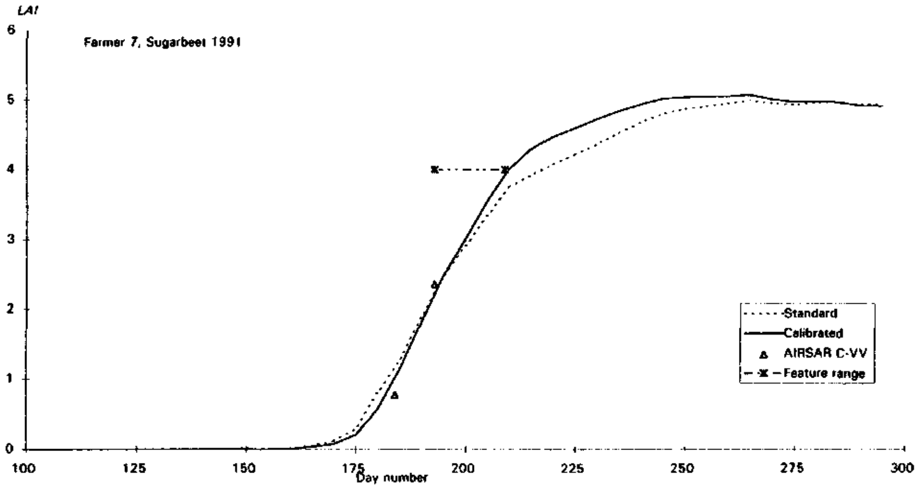


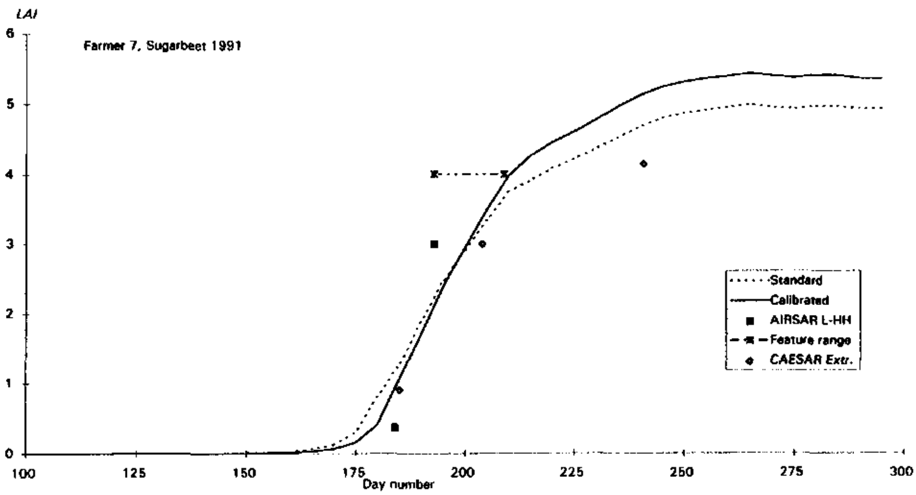
Figure 5.28 *Comparison between simulated LAI and LAI estimated with the Cloud model for two AIRSAR recordings in L-band HH-polarization (a) and C-band VV-polarization (b) in combination with the feature-based information. (inverse modelling method)*

This is better than the result obtained with "standard" SBFLEVO without RS information (which gave an average simulation error of 13.4 ton ha^{-1}, and better than the results obtained with microwave data using only the model-based approach (Section 5.5.2.3).

5.5.4.3 Results of combination Method IV using all RS data and feature information

In this section *LAI* estimates from the two CAESAR recordings and the two AIRSAR recordings in L-band HH-polarization and C-band VV-polarization respectively, with their appropriate weighting factors (Chapter 2), are combined with the feature-based information, for calibration of the crop growth model. The feature-based information is used in the same way as mentioned before. Yield results are shown in Table 5.11, Cases 13 and 14 for L-band HH-polarization and C-band VV-polarization respectively. The comparison between simulated and estimated *LAI* (from *WDVI*, γ and feature) for one of the fields is illustrated in Figure 5.29.

(a)



(b)

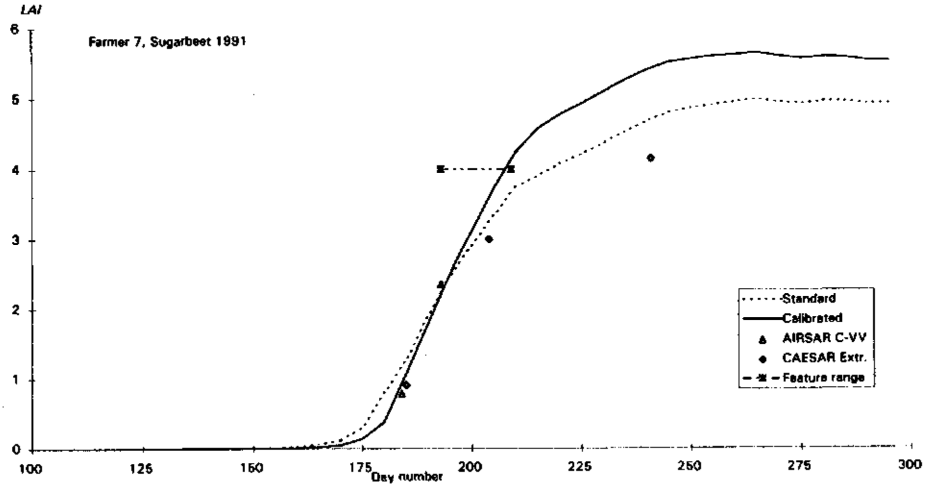


Figure 5.29 *Comparison between simulated LAI and LAI estimated from WDVI using the CLAIR model (including an extremophile LAD during the second part of the growing season, after feature 2) for two CAESAR recording dates and from γ using the Cloud model, for two AIRSAR recordings in L-band HH-polarization (a) and C-band VV-polarization (b) in combination with the feature-based information (inverse modelling method)*

On average, the simulation error of (fresh) beet yield was 2.9 ton ha^{-1} (4.1% error) for C-band VV-polarization and 3.1 ton ha^{-1} (4.5% error) for L-band HH-polarization respectively (see Table 5.7). These results are somewhat poorer for L-band HH-polarization and better for C-band VV-polarization in comparison to the results obtained with optical and microwave data using only the model-based approach (Section 5.5.2.4).

As a result, the additional value of the feature-based approach has not been proven yet. The results indicate that this approach may be valuable when no optical data are available. So, different scenarios with various combinations of optical and microwave data at various dates during the growing season will show quite different results in terms of significance of microwave data (in a model-based and feature-based approach) for crop growth monitoring.

5.6 Summary and discussion

To study the synergetic properties of optical and microwave data sets a distinction was made between contemporaneous and non-contemporaneous observations and between a model-based approach and a feature-based approach.

In this study, the Cloud model was calibrated for sugar beet using L-band HH-polarization and C-band VV-polarization data from the MAC Europe 1991 campaign at the Flevoland test site for only one day. The space-time transformation of information on sugar beet allowed us to produce a calibrated Cloud model to be used in a contemporaneous model-based manner.

For the beginning of the growing season, optical remote sensing data were used for estimating the *LAI* for a large number of sugar beet fields because destructive field measurements were missing. Subsequently, these *LAI* estimates were used for calibrating the Cloud model. This procedure appeared to yield quite satisfactory results. The Cloud model appeared to be validated when applied to other fields. In principle, this already is synergy in the way that optical remote sensing measurements are used for calibrating the Cloud model, which in this study would not have been possible without optical data.

However, for simultaneous (contemporaneous) observations no real synergy occurred in the estimation of *LAI* using the model-based approach. The contemporaneous data set of the beginning of July from the 1991 MAC Europe campaign was used to test the combined use of optical and microwave data. *LAI* was used as an index for crop growth and it was estimated from reflective optical data (AVIRIS) using the CLAIR model and from microwave data (AIRSAR) using the inverted Cloud model. The accuracy of the estimation of *LAI* from microwave data was so poor that it yielded no improvement on the *LAI* estimation from optical data only.

For operational applications the assumption of non-simultaneous observations is more realistic. Therefore, for studying synergy, crop growth should be monitored in a dynamical way using growth models (non-contemporaneous approach). For sugar beet a model-based approach can be applied early in the growing season (before crop closure) while an integrated approach, i.e. model-based for optical information and feature-based for microwave information, is applicable to the remaining period. The significance of microwave information lies in the possibility of acquiring data on a repetitive basis, unimpeded by atmospheric conditions, and obtaining data related to changing plant structure.

Table 5.11 *Total yield results (in ton ha^{-1}) of various combination methods (case numbers are related to Tables 5.7 and 5.1) used in the study. Missing data is (--.-).*

	Yield of each particular farmer per case										Statistics		result
Case	1	2	3	4	5	6	7	8	9	10	Av.	std.	error
0	87.0	79.0	75.0	77.0	69.5	68.0	70.0	61.0	70.0	77.0	71.2	5.7	
1	60.0	60.0	60.0	60.0	60.0	60.0	60.0	60.0	60.0	60.0	60.0	0.0	13.4
2	80.0	76.7	74.3	71.5	70.5	65.3	69.9	68.1	72.2	75.7	71.0	3.0	3.0
3	77.0	74.3	73.6	74.9	69.5	64.3	70.8	70.5	71.4	72.8	71.2	3.7	3.7
4	76.4	73.9	74.7	71.6	67.1	62.7	66.4	61.9	67.5	71.5	68.2	4.8	4.2
5	--.-	70.7	66.6	64.6	55.6	64.1	63.1	48.7	62.7	--.-	62.0	6.8	9.2
6	--.-	68.2	66.4	60.7	71.3	69.4	67.8	62.4	54.6	--.-	65.1	5.5	7.2
7	--.-	74.1	72.9	72.9	67.4	65.7	67.5	62.9	65.9	--.-	68.7	4.1	3.0
8	--.-	74.0	71.6	70.2	70.8	66.3	69.5	64.2	64.1	--.-	68.8	3.6	3.5
9	--.-	77.1	67.2	81.0	69.3	68.1	68.4	63.5	65.8	--.-	70.1	5.9	2.8
10	--.-	70.1	61.5	77.4	62.4	64.3	69.7	65.7	54.6	--.-	65.7	6.8	6.7
11	--.-	75.9	74.1	74.5	67.9	67.0	68.5	67.5	67.1	--.-	70.3	3.8	2.5
12	--.-	68.0	63.4	64.2	64.1	68.8	66.7	68.0	67.9	--.-	66.4	2.1	6.8
13	--.-	77.1	71.0	72.7	65.7	65.2	68.2	65.8	68.4	--.-	69.3	4.1	3.1
14	--.-	75.9	74.0	70.8	65.8	66.1	69.5	66.1	68.5	--.-	69.6	3.8	2.9

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 the calibrated crop growth model. The results obtained this way were much better than the simulation results of a standard growth model without using remote sensing information (see Tables 5.7 and 5.11).

The results obtained from using only two recording dates with an optical sensor (CAESAR) during the growing season were not much poorer than those obtained with a complete time-series (Tables 5.7 and 5.11). Of course, it should be noted that the distribution of the recording dates over the growing season will greatly influence the expected results. So, these results should be handled with care. However, they do show that optical recording dates in the order of two per growing season at well-chosen periods can yield very satisfactory results for monitoring crop growth and yield estimation.

The results from only two recording dates with a microwave sensor (AIRSAR) during the beginning of the growing season were better than the results of the yield estimates not using any remote sensing information. However, these results were significantly poorer than those obtained with the optical sensors (Table 5.7). It should be noted that only two recording dates with the AIRSAR could be used in a model-based approach.

When combining the two CAESAR recordings and the two AIRSAR recordings in the calibration procedure of the crop growth model, good results were obtained (Table 5.7). The resulting errors in yield estimation were smaller than those obtained with CAESAR data or AIRSAR data individually. The results were even better than those obtained with a complete time-series of optical measurements. This already is a synergistic effect of combining both optical and microwave data. Moreover, it clearly indicates the possibilities of using microwave data in addition to optical data when only very few recording dates with an optical sensor are available. For instance, when no optical data are available from the beginning of the growing season it is to be expected that microwave data from the beginning of the growing season offer a significant improvement in crop growth monitoring.

In order to test the additional value of microwave measurements when only very few optical recordings are available, the two AIRSAR recordings were combined with one CAESAR recording date (of end of July 1991) in order to calibrate the growth model. The results show that particularly the L-band HH-polarization data offer very good results with yield errors that are even slightly smaller than those of the combination of two CAESAR dates with two AIRSAR dates (Tables 5.7 and 5.11). This confirms the statement that the main advantage of microwaves lies in the possibility to acquire information on crop growth when other techniques (in particular optical techniques) fail.

The temporal backscatter signature of sugar beet appeared to exhibit a clear dip at a temperature sum of about 900, which is related to a change in leaf orientation from spherical/erectophile to extremophile. This feature coincides with a transition in development stage from leaf formation to tuber filling and occurs at *LAI* of about 4.0. This transition is very important for crop growth monitoring and yield prediction. This information was also introduced in the calibration procedure of the crop growth model.

When only microwave data were available, the results showed that the feature-based information, added to the model-based information from two AIRSAR dates, gave a better estimate of the final beet yield (Tables 5.7 and 5.11). The improvement was even quite pronounced for L-band HH-polarization. When the feature-based information was added to the model-based information from two AIRSAR dates combined with two CAESAR dates there was no clear improvement. So, at this stage of research, it must be concluded that the additional value of the feature-based approach has not been proven yet. The results indicate that this approach may become significant when no optical data are available.

PART III CONCLUDING DISCUSSION

6 Application of the developed methodology: a discussion

6.1 Introduction

This chapter deals with the questions posed in Section 1.4 of Chapter 1. The case study of Chapter 5 focused on the use of airborne remote sensing in crop growth monitoring. The research questions in Section 1.4 will be answered here with respect to airborne remote sensing and their potential for crop growth monitoring. Also, an attempt will be made to study the potential of spaceborne remote sensing for crop growth monitoring in particular. The questions were:

- Which information on biophysical properties of agricultural crops estimated with airborne remote sensing is useful for crop growth monitoring and yield prediction?
- How can this information be integrated in the methodology for combining crop growth and remote sensing?
- Can the developed combination methodology be applied for operational crop growth monitoring and yield prediction and are the present spaceborne sensors appropriate?

Whether remote sensing techniques can be applied in an operational context requires a thorough inventory of the user's requirements. The requested accuracy of information and the scale at which the information is needed are important aspects to be considered. Up till now, remote sensing has been mostly used at field level for agricultural applications. The generalization of remote sensing information from field to regional level provides information which can possibly be used in a regional context of crop growth monitoring and yield prediction.

6.2 Estimation of biophysical properties with airborne RS for crop growth monitoring

Crop growth can be monitored on a daily basis by using crop growth models. However, estimates of crop growth are often inaccurate in the case of non-optimal growing conditions. The crop growth models used in this study predict the potential yield and serve mainly as research tools. During this study, the growth model for sugar beet appeared suitable for the research objective.

So far, airborne and ground-based RS have provided information on the actual status of agricultural crops at field level, thus calibrating the growth model for actual growing conditions. Good results have already been obtained by using (reflective) optical RS data (e.g. some vegetation index) in regular estimation of *LAI* during the growing season and subsequent calibration of the growth model on time-series of estimated *LAIs*. However, the regular acquisition of airborne optical RS data is hampered by frequent cloud cover or variable light conditions. Microwave RS data may offer a solution in acquiring RS information with a high temporal resolution owing to its all-weather capability. Microwave RS could give information on biomass and structure of the canopy.

In this study optical and microwave RS data are combined with crop growth models through *LAI* as essential link. The *LAI* is estimated with the derived inverse RS models and introduced to the calibration procedure of the crop growth model with its appropriate weight factor. Furthermore, features in microwave time-series were found during periods in the growing season that the canopy structure had changed. These features provide means to determine development stages of the crop.

In this section a brief overview of the findings of previous chapters (with special reference to the first research question, see also Section 1.4) with respect to airborne RS is made in order to prepare the discussion for potential application of spaceborne RS with respect to crop growth monitoring.

6.2.1 Estimation of *LAI* and *LAD* with airborne optical RS

Information from airborne optical RS observations can easily be corrected and transferred to physically meaningful reflectance values by using calibration targets in the field such as reference plates. These plates or smaller versions were also used to calibrate the field reflectance measurements. The contribution in reflectance by the atmosphere in relation to the total measured reflectance by airborne optical sensors is mostly linear for each wavelength band in the optical region, unless there are hazy and unstable weather conditions. The observed surface, however, is larger than the field of view of a handheld radiometer. When assuming that within one field the surface is homogeneous and that there are enough independent measurements available, ground-based and airborne optical measurements can be compared with each other. Therefore, the step from ground-based to airborne optical RS is easy to make.

Physical modelling of a vegetated surface at field level in the optical region of the EM spectrum has as main aim the understanding of the interaction between solar radiation and vegetation and soil elements within the same field. Complicated physical reflectance models, like radiative transfer models, (such as the SAIL canopy and the PROSPECT leaf reflectance models) are very useful for sensitivity analyses in order to investigate the influence of crop characteristics and external variables on reflectances or simple vegetation indices. Moreover, they appeared to be of great value to the investigation of boundary conditions for the application of certain simplified relationships. However, these multivariable models are difficult to invert and therefore not really suitable for practical applications.

Therefore, in this study a simple semi-empirical reflectance model for estimating the *LAI* of a green canopy was used (CLAIR model). This model is based on the weighted difference vegetation index (*WDVI*). A sensitivity analysis with a combined SAIL-PROSPECT model shows that *WDVI* is mainly determined by *LAI* and *LAD*. Other leaf and canopy variables and additional factors as soil background could have an impact on the optical RS signal. However, in general, the CLAIR model has proven to be a very useful concept for estimating the *LAI* of various agricultural crops in practical conditions. It was calibrated for several agricultural crops by using historical field reflectance data of various seasons, e.g. for sugar beet. The regression parameters of the CLAIR model appeared to be stable and thus transferable over the various growing seasons. Moreover, the CLAIR model is already an inverted model and as such directly useful for estimating *LAI*. In this way the CLAIR model forms an important link in the synergy approach. The drawbacks in estimating *LAI* and *LAD* with optical RS models are:

- estimation of *LAI* and *LAD* is not possible in cloudy or unstable weather conditions;
- for inversion of the multivariable SAIL-PROSPECT model more than one measurement in several bands (green or red and near infrared) and/or viewing angles are needed, not necessarily resulting in a unique determination of *LAI* and *LAD*;
- the CLAIR model only provides an estimation of *LAI*, other factors affecting the RS signal are included in the regression parameters. The inaccuracy in estimating *LAI*

with the CLAIR model is therefore caused by the other variables, such as *LAD*, leaf colour, soil background, etc.

As *LAI* and *LAD* are the main factors influencing the RS signal, it is important to estimate both of them by using at least two independent measurements of the same field at the same moment. In airborne applications observations can be made at two different viewing angles or by using different wavelengths. Additional information, like crop status, from standard growth models also help in finding the proper solution for inversion of the remote sensing model.

Summarizing, airborne optical RS provides well calibrated optical reflectance measurements at various resolutions resulting in reliable information on crop and soil characteristics when enough independent measurements are available.

6.2.2 Estimation of biomass and canopy structure with airborne microwave RS

Information from airborne microwave observations can be corrected to provide physically meaningful backscattering coefficients by using reference targets, such as corner reflectors. Microwave RS is sensitive to structure and row effects of the canopy and tends to observe the "canopy-soil" medium. Optical RS (visible and near infrared part of the spectrum) tends to observe the upper part of the canopy mainly, due to the fact that the optical wavelengths are much smaller relative to the canopy elements. The canopy elements are in the order of the size of microwave wavelengths or smaller, resulting in larger contributions in backscatter of the lower parts of the canopy and the soil. When the sensors are calibrated properly, ground-based and airborne RS measurements can be related quite well.

The development of complicated physical models in the microwave region has not progressed as far as that in the optical region. Application of these RS models to agricultural crops is not straightforward. Besides development, also calibration and validation of complicated physical RS models for agricultural crops is hampered by the lack of understanding of the physical processes and interaction mechanisms involved in the microwave backscatter measurement. However, these complicated RS models might provide insight into the relative importance of the crop variables affecting the microwave backscatter measurement.

The most promising results were obtained with both reflective optical RS and microwave RS data by using more simple semi-empirical models. One of the first microwave models that was calibrated for agricultural crops was the Cloud model. It is a simple semi-empirical model, in which the vegetation is represented as a collection of water droplets, which are held in place by the vegetative matter. Also included is a ground term, which represents direct backscatter from the underlying soil with a certain soil moisture and surface roughness, attenuated by the vegetation layer. Besides plant water also plant structure determines the microwave backscatter signal. There are indications that soil moisture still has its influence on total backscatter at full closure of the crop. Therefore, for calibration of the Cloud model, reliable soil moisture figures need to be used as input for each field. In contrast to optical models, however, consistent and stable regression parameters from calibration of the Cloud model over the years for the same crop, are not yet available. This has consequences for the estimation of biomass and canopy structure.

Using average backscatter time-series and average ground data (such as soil moisture, etc.) over several fields in a particular region might improve the stability of the regression parameters of the Cloud model. However, the standard deviation of the average signatures remains large in general, which still complicates the estimation of biomass. This is for further study, when numerous time-series are available over several years.

6.2.2.1 Biomass

The backscatter of leafy crops such as sugar beet exhibited a convex signature as a function of time at the beginning of the growing season, when biomass (leaves and stems) increases. When the sugar beet crop started to close, a constant backscatter level was reached (saturation of the backscatter). This is in agreement with the theory that the backscatter is related to the amount of plant moisture or, indirectly, to the *LAI* (due to a link between plant moisture and *LAI*). This means that at the beginning of the growing season of the sugar beet crop a model-based approach (Section 3.4.2.2) can be applied for estimating *LAI* from microwave backscatter data.

Crops like cereals have more pronounced features in time-backscatter signatures related to changes in crop morphology. Microwave models for cereals like winter wheat appeared difficult to calibrate and validate between different seasons. A two-layer Cloud model (Hoekman *et al.*, 1982; Van Leeuwen, 1992b) was calibrated, modelling one layer for the leaves and stems and one for the ears. However, too many variables and regression parameters make calibration and the inversion of the model difficult.

6.2.2.2 Canopy structure

Halfway the growing season in summer time, a drop in backscatter was observed for sugar beet at the Flevoland test site. This could be explained as a structure effect related to a certain crop growth development stage of the sugar beet crop, because it occurred consistently in many airborne data sets for sugar beet (Agriscatt 1987 and 1988, MAC Europe 1991). The sugar beet average leaf angle will drop as well due to water shortage of the plant during hot days. Changes in canopy structure may have a large impact on the microwave backscatter. Such features in microwave time-series could be of use for crop growth modelling only when the frequency of satellite overpass matches the dynamics of changes in canopy structure of a specific crop. Specific development-stage related features may provide clear calibration points in order to adjust the crop growth model simulation with the feature based approach (Section 3.4.2.3).

For cereals like winter wheat specific microwave time-series or signatures were found for C-band VV. The decrease in *LAI* and the development of the ears exhibit clear effects in the winter wheat microwave time-series. Good time-series can be obtained from airborne microwave measurements as well, provided that the density of the recordings in time is high during the growing season.

The drawbacks of estimating biomass or canopy structure with microwave RS are:

- calibration and validation of the RS models at field level is difficult, which hampers the estimation of crop variables like biomass or structure (*LAD*);
- the standard deviation in total backscatter is very large, which troubles the inversion of RS models;
- the uncertainty of estimation of variables and the low frequency of observations mostly troubles the interpretation of time-series at field level.

Concluding, airborne microwave RS can provide good backscatter measurements when proper calibration has been performed. However, the interpretation of instantaneous measurements or time-series is difficult owing to the complex backscatter behaviour of the observed crops which is not yet well understood. Besides this, the standard deviation of the measurements is mostly very large. Of course, the system configuration (frequency, polarization, etc.) is important as well. The ground-based X-band measurements of ROVE resulted in somewhat better modelling results than the C- and L-band airborne configuration of the Agriscatt 1988 and MAC Europe 1991 campaign. Application of simple semi-empirical models to airborne microwave RS measurements is therefore not as obvious as it is for airborne optical RS.

6.3 Integration of RS information in developed combination methodology

In Section 1.4 the following research question (b) was posed: 'How well can information derived from RS be integrated in the developed combination methodology?' In this section this question will be answered based on findings from previous chapters.

In Chapter 3 four relevant methods of crop growth model calibration with remote sensing were explained, and in Chapter 5 these were applied to airborne RS. The four relevant combination methods:

I Direct modelling method;
II Inverse modelling method;
III Feature-based method;
IV Combination of methods II and III.

To study synergetic properties of optical and microwave data sets in Chapter 5 a distinction was made between contemporaneous and non-contemporaneous airborne observations and between a model-based approach (I and II) and a feature-based approach (III).

For contemporaneous observations no synergy occurred in the estimation of *LAI* using the model-based approach. The contemporaneous data set of the beginning of July from MAC Europe 1991 was used to test the combined use of optical and microwave data for airborne observations. *LAI* was estimated from reflective optical data (AVIRIS) using the CLAIR model and indirectly from microwave data (AIRSAR) using the inverted Cloud model and a relationship between *LAI* and plant water for sugar beet. The estimation of *LAI* from microwave data was so inaccurate that it yielded no improvement on the *LAI* estimation from optical data only. Optical field observations using a hand-held radiometer were found to be useful for obtaining ground data and consequently for the interpretation and calibration of the airborne microwave data.

In the dynamical crop growth monitoring applied in this study, the SBFLEVO model is initialized and calibrated to fit simulated *LAI* values to estimated *LAI* values obtained from RS measurements. Thus, first the CLAIR and/or inverted Cloud model were applied for obtaining *LAI* estimates from the RS measurements. Subsequently, the SBFLEVO model was calibrated on these *LAI* estimates. Since it was found that the accuracy of the *LAI* estimates depends on the absolute value of *LAI*, the reciprocal of the standard deviation of *LAI* estimation is used as a weighting factor for each individual *LAI* estimate used in the crop growth model calibration procedure. This approach yields at the same time a proper mutual weighting between optical and microwave data when data from both windows are used together in this optimization procedure. Moreover, it is obvious that for the methodology it is not relevant whether one has optical and microwave data from the same date or not.

When a time-series of optical recordings is available, *LAI* can be estimated quite well, and with that a proper prediction of sugar beet yield at the end of the season is possible by calibration of the crop growth model. The results in the MAC Europe 1991 campaign were much better than simulation results of a standard growth model without using RS information (see Table 5.7). As was shown in the calibration procedures of the crop growth model in Chapter 5, the variable sowing date proved to be one of the most important variables to be optimized. Therefore, it is expected that when the sowing date is known, the standard crop growth model for sugar beet initialized for the Southern Flevoland Province combined with weather information is already going to predict the yield quite well.

The combination of information from optical and microwave RS will be successful when the estimation of variables with RS models or time-series is sufficiently accurate. When the variation in RS measurements at a certain moment is very large, the inversion of simple RS models gives very poor results. A variable like *LAI* or biomass with a large standard error of the estimate is not likely to yield good results when combining with a crop growth model. However, a dense series of measurements in the growing season is likely to provide better information on crop development when related to changes in canopy structure.

6.4 Potential of spaceborne RS in crop growth monitoring

In Section 1.4 the following research question was posed: 'Can the developed combination methodology be applied for operational crop growth monitoring and yield prediction and are the present spaceborne sensors appropriate?' This research question will be addressed here using the conclusions from previous chapters.

In the previous sections of this chapter and in Chapter 5, airborne remote sensing provided useful information for crop growth monitoring. For example, in the MAC Europe 1991 campaign the optical airborne sensors operated only when the atmospheric conditions were favourable. In turn, the optical airborne sensors provided useful information like *LAI* to interpret the airborne microwave sensor.

With its pre-programmed time intervals and recording tracks the use of satellite remote sensing is of course more or less restricted. It was shown that remote sensing information for the benefit of crop growth monitoring needs to be acquired with certain conditions imposed by crop growth. It is therefore interesting to discuss whether the developed methodology, which was successful for the airborne campaigns, can be applied to operational crop growth monitoring using satellite remote sensing. This is the reason, why in this section an optical and a microwave satellite sensor will be discussed. The geometrical resolution of the satellite images is sufficient to have enough independent measurements within a field to produce statistically sound reflectance or backscatter values. The methodology so far has been tested at field level.

6.4.1 Information from an optical RS satellite

Spaceborne observations in the optical domain of the EM spectrum performed e.g. by the SPOT satellite allow retrieval of crop characteristics, such as *LAI* and *LAD*, only when atmospheric correction is done properly. However, satellite observations need to be corrected for a much longer path through the atmosphere compared to airborne observations. In this respect complicated atmospheric correction models have been developed, which will not be described here in detail. Several simple methods are also available to correct for the atmosphere. An example of a simple correction is the so-called "darkest pixel correction", which corrects for atmosphere in a linear way by using "black" targets as reference. Also other available (natural) surfaces with known reflectance can serve as reference fields. The reference plates used in ground-based or airborne campaigns are too small for satellite observation as the geometric resolution of the satellite is too low.

As an example of using optical satellite information some results of an experiment for the Dutch sugar beet industry (Verhoef *et al.*, 1996) will be discussed here briefly.

Relationship LAI - yield

One SPOT image of July 2nd was available in the growing season of 1993 for yield prediction in the Flevoland Province (South and North East region). The SPOT image of July 2nd had been radiometrically calibrated by using optical recordings with the Cropscan radiometer in the field. In this way *LAI* values from the satellite image could be estimated with the CLAIR model for many sugar beet fields.

The use of optical satellite data estimating *LAI* for crop growth monitoring is discussed in Figures 6.1a-c. Unfortunately, only one optical satellite recording was obtained and which was relatively late in the growing season (cf. Figure 6.2), resulting in high *LAI* values of about 2.5 to 4. It is therefore important to have at least one optical satellite observation in the period from emergence to closure (*LAI* between 0 and 2). This was luckily the case for the airborne campaign in Chapter 5. Therefore, the following 3 figures need to be interpreted carefully with respect to the potential of satellite RS for crop growth monitoring. As the sowing date is an important variable for crop growth modelling, it is presented with *LAI* in Figure 6.1a.

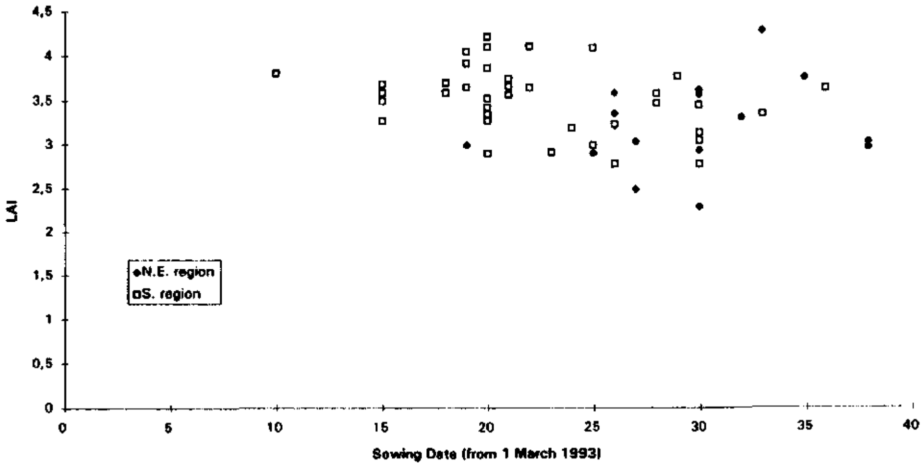


Figure 6.1a *LAI derived from SPOT of July 2nd (1993) for sugar beet in the Flevoland Province versus sowing date for the South and the North east Flevoland Province*

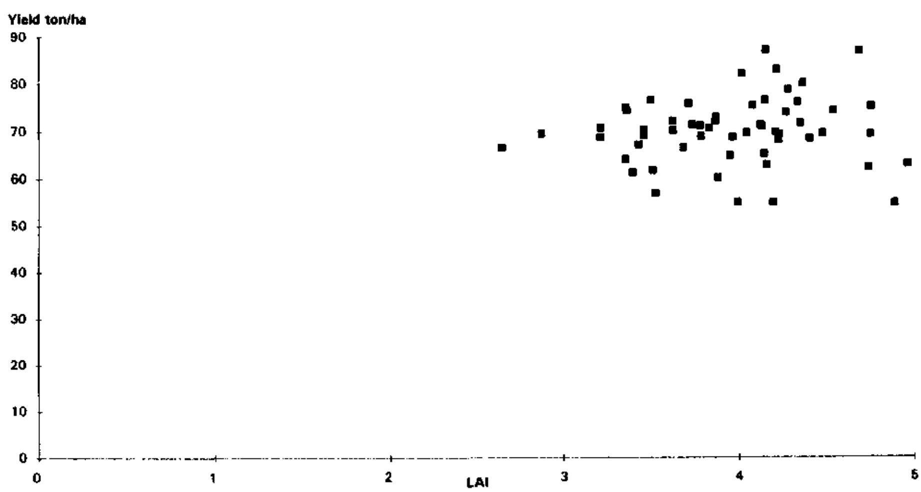


Figure 6.1b *The LAI derived from SPOT of July 2nd (1993) is plotted against the yield (tuber weight) acquired by the Dutch sugar industry for both the South and the North east Flevoland Province (not distinguished here).*

Probably because of the fact that the observation by SPOT is relatively late in the growing season, no direct relationship can be found between sowing date and *LAI* in Figure 6.1a. Other factors, such as local atmospheric effects, soil type, canopy structure and not in the least the sugar beet cultivar could also result in errors of estimation of *LAI* (Verhoef *et al.*, 1996). A slight but not pronounced shift in sowing date between the two regions does not result in a change in *LAI*.

In Figure 6.1b the two regions are not distinguished, therefore. In this figure apparently no clear relationship exists between the above-ground (*LAI*) and underground (tuber weight) parts of the sugar beet crop. Probably this is caused by too many inaccuracies in the estimation of *LAI* from optical satellite RS in this study and by the late recording date in the growing season (after crop closure) resulting in a larger standard deviation of *LAI* estimation (cf. Equation (3.6)).

From measurements of the Dutch sugar beet industry it is shown in Figure 6.1c that a difference of the average sowing dates between the growing seasons of 1993 and 1994 can be clearly noticed. However, the latter does not have consequences for difference in yield in the two successive years.

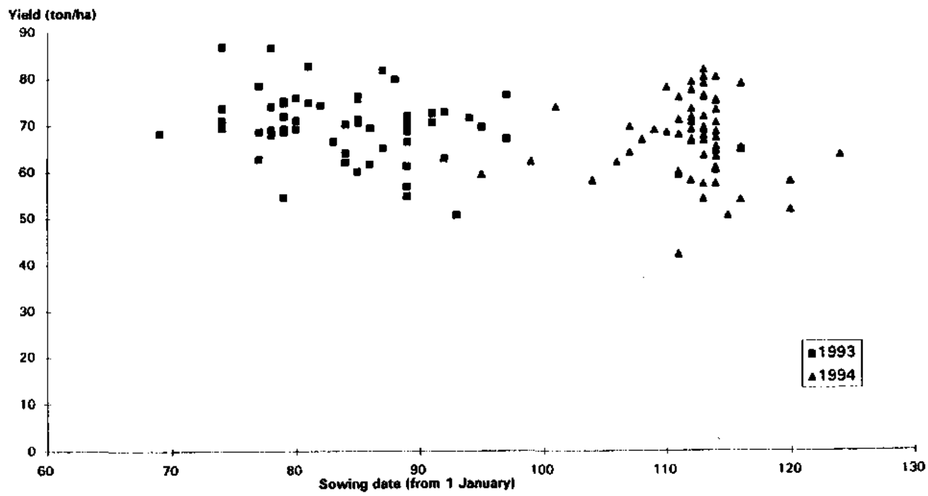


Figure 6.1c *The yield (tuber weight) and sowing date acquired by the Dutch sugar industry for both the South and the North east Flevoland Province (not distinguished here) for the growing seasons of 1993 and 1994*

Apparently *LAI* is not directly related to yield in this example, but *LAI* can be used to calibrate the crop growth model in order to predict yield as outlined earlier in this thesis. This indirect relationship between *LAI* and yield is driven by other factors like growing conditions (temperature sum, incoming radiation, soil conditions, etc.) which are accounted for in the crop growth modelling. Therefore, differences between seasons (Figure 6.1c) and possibly between regions are expected to be noticed with RS in combination with a crop growth model. Certainly, this is true for the present generation of crop growth models which can be initialized for growing conditions in the Flevoland Province very well. In order to have a good calibration of the crop growth model with optical RS, accurate estimation of *LAI* is required. These conditions are best met with optical RS when data are acquired in the beginning of the growing season.

As an example, the crop growth model was calibrated at field level for a certain farm in the southern part of the Flevoland Province with measured Cropscan time-series in 1993. The results are presented in Figure 6.2 using combination method II. The SPOT image was recorded on July 2nd or day number 183, which is rather late in the growing season (see arrow in Figure 6.2). As a result from Figure 6.2, it can be concluded that at the time of the SPOT recording and later on in the growing season it is difficult to estimate *LAI* very accurately from optical RS data without additional field information. This is one of the reasons why the former figures do not show clear relationships between yield and sowing date and *LAI*.

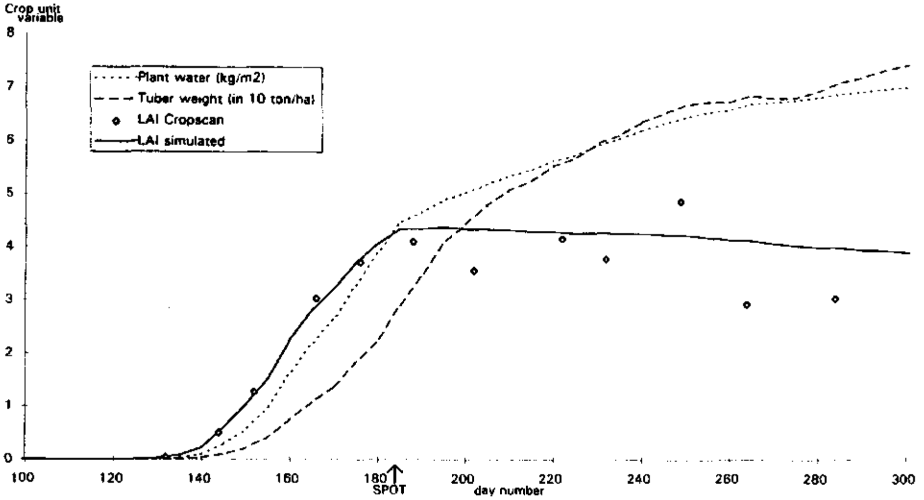


Figure 6.2 *Crop growth model calibrated by LAI using Cropscan field measurements (Method II) for the discussion on the application of optical satellite information at field level. Plant water, Tuber weight and LAI are simulated by the crop growth model SBFLEVO.*

The *LAI* estimated with the SPOT satellite can be well compared with the *LAI* supplied by the initialized crop growth model SBFLEVO for the Flevoland Province. This means that crop growth information such as sowing date, harvest date, yield and weather data from the 1993 campaign, might serve as a welcome independent source of information to calibrate the SPOT image radiometrically. For example in Figure 6.3 *LAI* is provided respectively by a standard crop growth model, a crop growth model with known yield only and one with known sowing date and yield. These *LAI* time-series can be well compared with the *LAI* time-series measured with optical RS (in this case the Cropscan).

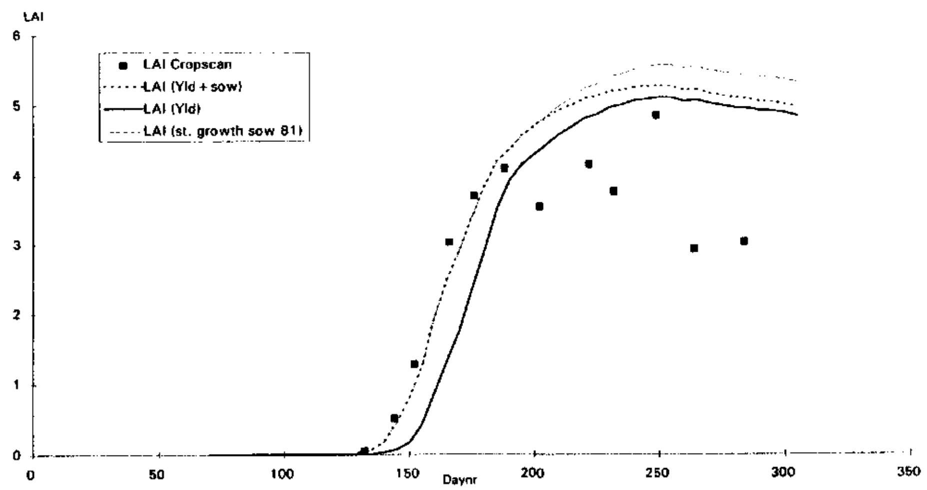


Figure 6.3 *A well initialized crop growth model could even calibrate an RS satellite image like SPOT, when compared with Cropscan measurements. Note that the calibration will be performed best when LAI values are below 4 (validity CLAIR model) and when the sowing date is known (here day 81)*

Timing

In general, for sugar beet crop monitoring it is important to have optical satellite recordings in the first part of the growing season. The estimation of *LAI* for a specific field derived from satellite measurements is influenced by the factors mentioned in Section 6.2.1 (drawbacks of optical RS modelling).

Because of cloudy weather situations in the Netherlands, the amount of spaceborne optical images is not likely to be sufficient for crop growth monitoring. When there is only one optical image, but several microwave images, in the period between emergence and closure of sugar beet and other leafy crops like potato, the same methodology (space-time transformation in Section 5.3.1) as for the MAC Europe 1991 campaign might be used. In this methodology use is made of the differences in crop growth (range in *LAI*) over the various fields at a certain *moment* representing a certain *period* in the growing season (see range in *LAI* in Figure 6.1a). An important conclusion of Chapter 5 in this respect was that a radar image did not give synergy when having also one optical image contemporaneously. However, with this method a calibrated Cloud model can provide additional information on biomass or *LAI* later in the growing season when no optical data might be available, but only microwave data.

Furthermore, optical satellite images have proven to be helpfull for identifying fields (location and crop type) by means of classification methods. In this way vector maps can be made which can be used for data extraction from other RS images, such as microwave satellite images.

6.4.2 Information from a microwave RS satellite

When calibrated properly (Laur, 1992), the ERS-1 microwave measurements can be performed with an accuracy of about 1 dB. This calibration accuracy is quite comparable with that of airborne microwave measurements. The geometric resolution of the ERS-1 images is of the same order as that of the conventional imaging airborne SAR systems (e.g. AIRSAR system).

An important advantage of the ERS-1 microwave satellite observations to crop growth monitoring is that despite the fact that there are cloudy days during the growing season, measurements are available frequently and with constant time interval. A common observation frequency is the 35-days recording cycle.

Interesting to discuss is the impact of recording frequency on crop growth monitoring taking the growing season of one field into consideration. A time-series with a high recording frequency is the ROVE X-band ground-based microwave data (VV 20 degrees incidence angle, see Figure 6.4). The elimination of backscatter measurements resulting in series with less frequent observations has an impact on the characteristic curve of the sugar beet crop. Especially in the period during closure, when biomass increases rapidly, a dense series of measurements is needed. This has also consequences for the calibration of the RS model (like the Cloud model) at field level. One can imagine that the Cloud model regression parameter D, describing the curve when biomass increases significantly, will change with the density of recording in time.

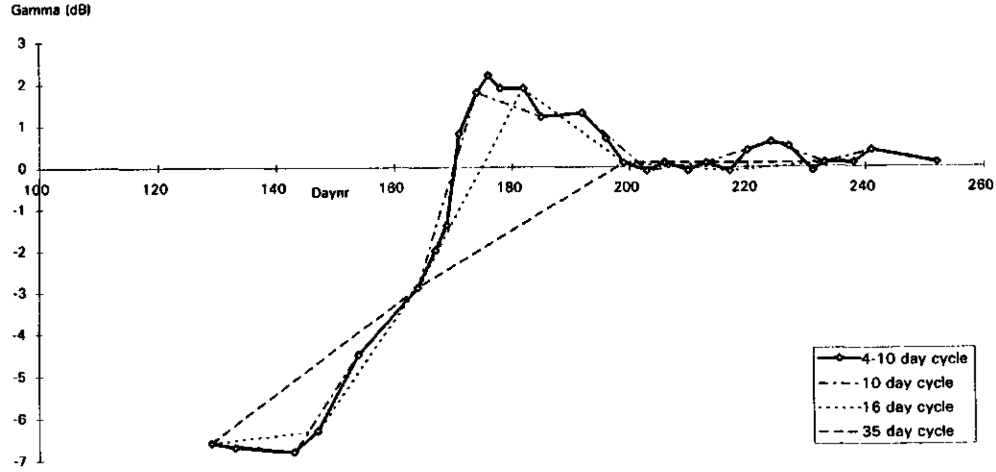


Figure 6.4 *The impact of frequency of observation on the curvature from the sugar beet crop of the microwave X-band time series of one field (ROVE X-band, De Schreef 1980, VV polarization and 20° incidence angle)*

In Figure 6.4 it is obvious that less measurements (35-day cycle) result in a more even curvature of the time-series than a curvature of a high-frequency time-series (4-10 day cycle). For this X-band experiment for sugar beet a 16-day cycle seems to be appropriate for modelling still. For other frequencies like C-band for the ERS-1 the required density of recordings will probably be different. The regression parameter C at different densities of recording will probably remain the same as the saturation level of backscatter is constant during the closed situation of the sugar beet crop. Cloud model calibration results of single fields (or small groups of fields) in the various campaigns over different growing seasons were not consistent as was already concluded in Chapter 2. Apart from this, information from the ERS-1 microwave satellite at the time between emergence and closure is difficult to use for estimating biomass with RS modelling without field information such as soil moisture, biomass and leaf or stem angle distributions, crop geometry, etc. on each specific field. Differences in management practices like sowing and fertilizing enhance the difficulty in interpretation and comparison between the fields even more.

In other words, variation in many variables of the crop soil system can have consequences for the total backscatter for each field. The potential use of microwave satellite RS information at field level for crop growth modelling with respect to sugar beet is probably therefore not very promising. Only when enough ground data and validated models are available, combination Methods II, III and IV can have success in yield prediction. This probably accounts for other crops as well.

6.5 Recommendations and suggestions for application of the developed combination methodology

Operational use of RS in crop growth monitoring procedures depends on the type of information, the scale level of information, the accuracy of the particular information to be retrieved from RS and not to forget, the potential cost reduction. On the other hand, this information must match the requirements of the conventional crop yield prediction. A good example is the Dutch sugar industry, which developed a conventional method for yield prediction based on historical experiments and crop growth models for eleven distinguished regions in the Netherlands. For logistic reasons, yield prediction before the middle of August is important for the industry.

This section comprises some discussion on possible use of RS in the conventional method used by the sugar industry. For operational application, RS information should lead to improvements in yield prediction at regional level as the industry works at this scale level of information to organize and manage the logistics of processing and storage of the harvested products. Information at regional level can be acquired by using RS satellites. One RS image comprises a few hundreds of square kilometres, which is comparable to the size of regions distinguished by e.g. the Dutch sugar industry. The information acquired by RS on separate sugar beet fields is not representative for the distinguished region, because of all kinds of factors, which will be described in Section 6.5.1.

A side step is made to other crops, like for instance cereals, which have a completely different structure compared to the leafy crops like sugar beet and potato. In Section 6.5.2, a suggestion is made to upscale the information estimated by satellite RS from field level to regional level. Besides that, airborne microwave RS compared to satellite RS measurements usually involves much labour (more flights to cover the same area, fieldwork, processing, etc.) and is mostly too capital intensive for operational use.

6.5.1 Crop growth monitoring at field level with satellites

In Section 6.4 we have seen which information can be supplied by optical and microwave satellite images at field level. This section discusses the potential and drawbacks of crop growth monitoring at field level by using satellite information.

In estimating *LAI* from optical satellite images, like SPOT or Landsat, the following considerations can be made:

- Atmospheric correction probably does not result in a totally correct reflectance value;
- The identification of fields (thematically and geometrically) with different crops is expected to be good only when additional field data are used in the classification procedure of optical satellite images;
- The inversion of optical models like SAIL is difficult because only few independent measurements (nadir viewing angle for the available wavelength band) are available. Too many unknowns lead to several solutions;
- The inversion with relatively simple models like CLAIR or other vegetation indices leading to an *LAI* estimation is troubled by the influence of many other crop and soil variables;
- Within one crop type several cultivars exist, each with its morphological and physiological characteristics. This is not accounted for in the previous study for calibration of the RS model.

It is easy to understand that a variable like canopy structure (*LAD*) will be even more difficult to estimate by inversion of optical models using satellite information. Newly developed sensors like the SPOT-VEGETATION satellite, to be launched in 1997, with multiple view angles, are expected to give better results. Another problem is that so far it is assumed that the reflection of crops is uniformely (Lambert) distributed over the hemisphere. Bi-directional reflectance models could improve the optical modelling by considering the reflection behaviour of the crop in several viewing directions.

In the combination methodology *LAI* is the key variable, which is used for the calibration of the crop growth model at field level. It is therefore expected that inaccuracy in estimation of *LAI* with RS will affect the calibration of the crop growth model. Another important factor is the time of availability of RS data. In temperate climate regions, cloud cover hampers the acquisition of optical images. Besides this, the time of availability of optical RS data at a specific growth stage of the crop is also of importance. In Chapter 3, it was found that the optical RS signal saturates at about an *LAI* of 4, i.e. later in the growing season. It is therefore recommended to have optical RS satellite images before this stage in the growing season in order to have accurate *LAI* estimations.

The same can be concluded for microwave satellite RS, resulting in information on biomass and canopy structure and eventually soil moisture with (simplified) RS models. In contrast to optical RS, the calibration for microwave RS models probably needs to be performed for every new season. Furthermore, additional factors (like wind, etc.) influence the total backscatter of the crop-soil system with microwave observations which is not the case for optical observations. This hampers the inversion of RS models. Another fact is that the present ERS-1 configuration provides us with only one wavelength per image pixel per recording session (C-Band, VV-polarization, 23° incidence angle), while the optical satellites provide several wavelength bands per pixel. This has consequences for the inversion of RS models as well.

In Section 6.4.2 it was concluded that the information from microwave satellite observations is probably more successful for crop growth monitoring when using time-series with a high frequency of measurements. In this way, characteristic features can lead to interpretation of development stages and, with that, to a calibration of the crop growth. This will be more successful for cereals because probably a better relationship between changes in canopy structure during the growing season and development of the crop exists.

For operational applications the assumption of non-contemporaneous observations is realistic. The non-contemporaneous combination of airborne RS information with crop growth models at field level was studied in Chapter 5. It appeared that for sugar beet a model-based approach is applicable early in the growing season (before crop closure) and an integrated approach, i.e. model-based for optical and feature-based for microwave, for the remaining period. The significance of microwave RS lies in the possibility of acquiring data on a repetitive basis, unimpeded by atmospheric conditions, and in obtaining data related to changing plant structure and crop development.

For crops like winter wheat and other cereals, however, changes in crop structure can be related to changes in development stage and can be recognized in microwave time-series. The number of measurements in time determines the detectability of these morphological changes and, with that, the applicability of information. This needs to be validated with accurate measurements of leaf, ear and stem orientations of the above-ground part of winter wheat in the field.

The applicability of the yield prediction procedure for sugar beet at field level appeared to be promising (Chapter 5) for airborne RS. For operational application it seems more obvious to monitor crop growth at a higher aggregation level than field level for reasons of variability and efficiency of interpretation. In Section 6.5.2, a proposition for crop growth monitoring at regional level will be discussed in order to study the potential application of satellite information.

6.5.2 Crop growth monitoring with satellites at regional level

In this section, the discussion on regional yield prediction with RS is illustrated by using the experience from the former chapters as well as a recent study on operational use of RS in sugar beet yield prediction (Verhoef *et al.*, 1996). In this section a proposition for regional yield prediction is presented using the same concept of the combination methods developed in this thesis. Application of the method is presented for the Southern Flevoland Province for sugar beet for the growing season of 1993. The RS information is extracted at field level, still, but is generalized for use at regional level by averaging of all field information.

6.5.2.1 Information from optical satellite on regional level

The information extracted from the optical SPOT image in July 1993 (day 183) is used again in this example. *LAI* is estimated for each sugar beet field by using the simple semi-empirical CLAIR model. The sugar beet industry has divided the Netherlands into eleven regions. In this example the southern and the northeastern region of the Flevoland Province coincide with two regions distinguished by the industry. For the two regions an average *LAI* can be calculated, weighted by the errors of inversion and radiometric calibration per field. The resulting regional *LAI* and the corresponding regional variation is then used in the combination methodology.

Secondly, the crop growth model initialized for the specific region, is calibrated by optimizing the estimated regional *LAI* and the simulated *LAI* of the crop growth model. Analogous to combination method II described in Chapter 3, the *LAI* used for calibration is weighted by the calculated regional standard deviation in the *LAI* estimate at each RS recording time. It is preferred to have more than one optical satellite observation in the first half of the growing season. Therefore, when having only one regional *LAI* estimation, the most important calibration variables for the crop growth model are varied during the calibration exercise. They are the average regional sowing date (*DAYSOW*) and the average relative growth rate (*RGRL*). The other two variables (*LSHAD, EFF*) are set to a constant average value (standard crop growth).

The regional average *LAI* estimated with the SPOT satellite image from July 2nd, 1993 (see also Figure 6.1) is presented in Table 6.1 for the South and Northeast region of the Flevoland Province. Note that the calculation of a regional *LAI* from optical measurements is based on the assumption that the relationship of *WDVI* and *LAI* is linear in the range of *LAI* 3-4 of the CLAIR model.

Table 6.1 *Regional estimated WDVI and LAI and standard deviations σ from the SPOT image of July 2nd 1993 and root weight (ton ha^{-1})estimated by the conventional procedure of the Dutch sugar beet industry of the northeastern and the southern region of the Flevoland Province (from: Verhoef et al., 1996)*

Region	*WDVI*	σ*WDVI*	*LAI*	σ*LAI*	Yield
N.E. Region	46.74	2.42	3.72	0.53	78.0
S. Region	48.41	1.77	4.10	0.49	79.0

The lower and higher boundary of the range in regional *LAI*, calculated from the standard deviation in *LAI* from Table 6.1, is used as input for the SBFLEVO crop growth model. This forces the model to produce simulated yield at the end of the growing season at day 295 with a range of roughly 10 ton ha^{-1} (see Figure 6.5).

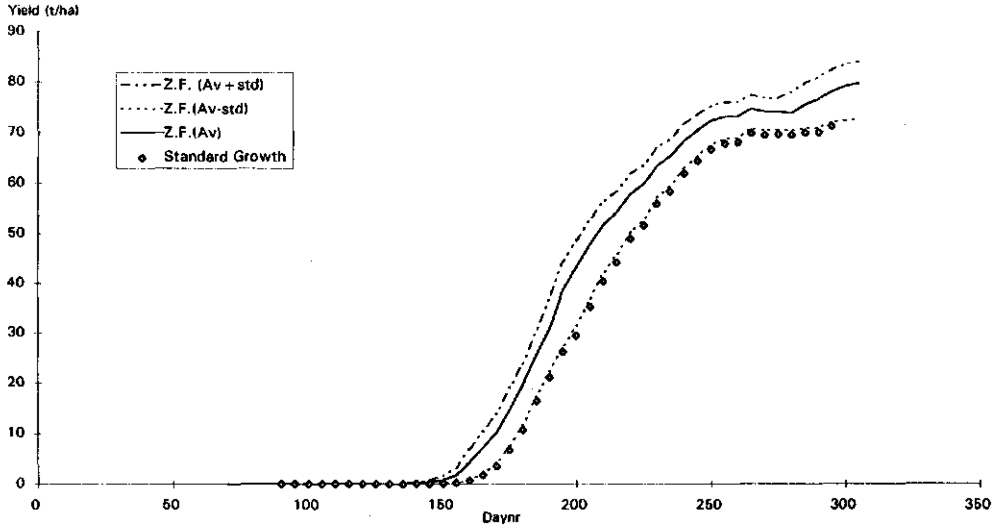


Figure 6.5 *Results of crop growth calibration at regional level of the southern region of the Flevoland Province based on a SPOT satellite observation on the 2nd of July in 1993 for sugar beet*

From the calibration of the crop growth model the yield in the southern region was 70.9 ton ha^{-1} on day 295. This is about 10 ton ha^{-1} below the regional estimates by the sugar beet industry (Table 6.1). The results of this exercise are not as good as the field approach in Chapter 5, mainly caused by the late moment of recording during the growing season. At regional level many factors play a role in the yield prediction. Apart from reliable acreage estimation and location of the sugar beet field (Janssen, 1994), reliable yield figures per hectare from the industry are necessary to validate this methodology. Another limitation was that the harvest date was not known. In stead of one average date for harvesting probably several weeks or months are needed to harvest the sugar beet fields in the whole region. During the harvest period of the sugar beet crop in a certain region (from about September till December) tuber growth depends also on unpredictable factors such as rain, temperature, etc., which can have great impact on the final yield.

Knowing the sowing date and the harvest date, a standard crop growth model already provides a good indication of the yield at the end of the growing season. Figure 6.6 illustrates the impact of different sowing and harvest dates on yield prediction.

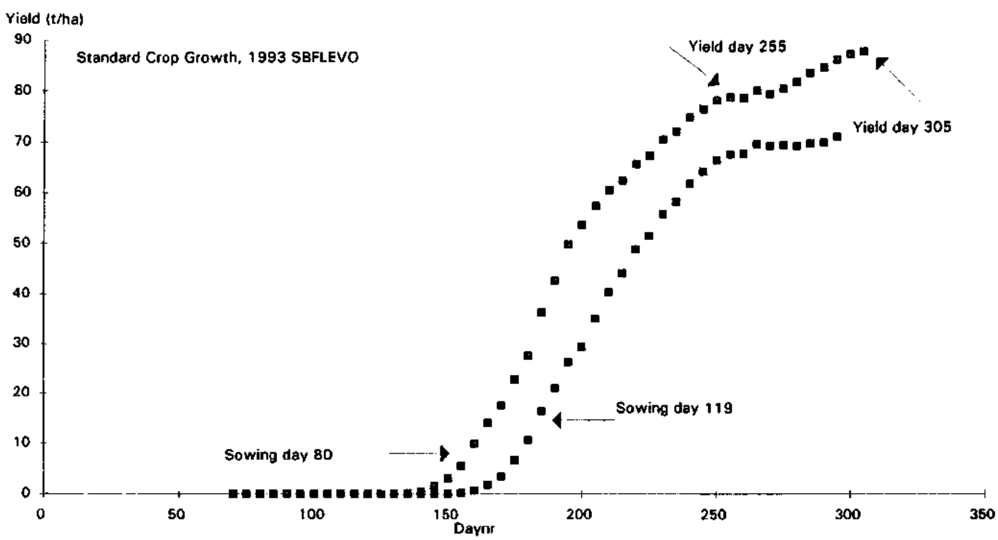


Figure 6.6 *Impact of different sowing and harvest dates on a standard crop growth model with the 1993 meteorological data*

Section 6.4.1 showed that with the estimation of *LAI* from optical RS some factors could lead to errors. A distinction must be made between field level and regional level. The various factors are probably averaged out considering many fields in a certain region in stead of just one field. Of course this has consequences for the yield prediction as *LAI* is the key factor in the calibration of the crop growth model. The variation in *LAI* on regional level is caused by different factors as mentioned before. The calibration of the SUCROS type crop growth model on field level is therefore recommended rather than on average data on regional level.

6.5.2.2 Information from microwave satellites on regional level

In Section 6.2.2 and 6.4.2, it was shown that microwave information at field level is restricted to estimation of biomass (or *LAI*) values with high inaccuracy, owing to the poor calibration of the Cloud model and strong variation in backscatter per field and between the fields. However, time-series with a high observation frequency showed to have greater potential for detecting changes in canopy structure during the growing season, without using an RS model.

Knowing this, it is interesting to discuss the potential of microwave RS information averaged over many fields in stead of only one field. The averaging over all fields in a particular region leads to a general backscatter signature with a certain standard deviation. In contrast with field signatures, regional signatures are expected to behave more stable as all the sources of errors mentioned in Section 6.2.2 are averaged as well. Major changes in crop status at regional level can provide other, additional useful information for crop growth monitoring.

To illustrate this, the microwave satellite observations of the same region as in Section 6.5.1 will be discussed for the 1993 growing season of the sugar beet crop. In Figure 6.7 the average backscatter signature is plotted (drawn line) for 79 sugar beet fields at the Flevoland test site. From the field survey it is known that the sugar beet crop closed roughly at day 150. In Figure 6.1 the average sowing date for sugar beet in the southern region was at the end of March (about day 90). A few weeks later the sugar beet plants emerged and within two to three weeks from then the crop closed entirely. Figure 6.7 shows that the increase in biomass caused a clear increase of backscatter in this period of closure. Note that the effects of soil moisture and roughness probably still play an important role in this period of partial closure of the sugar beet crop.

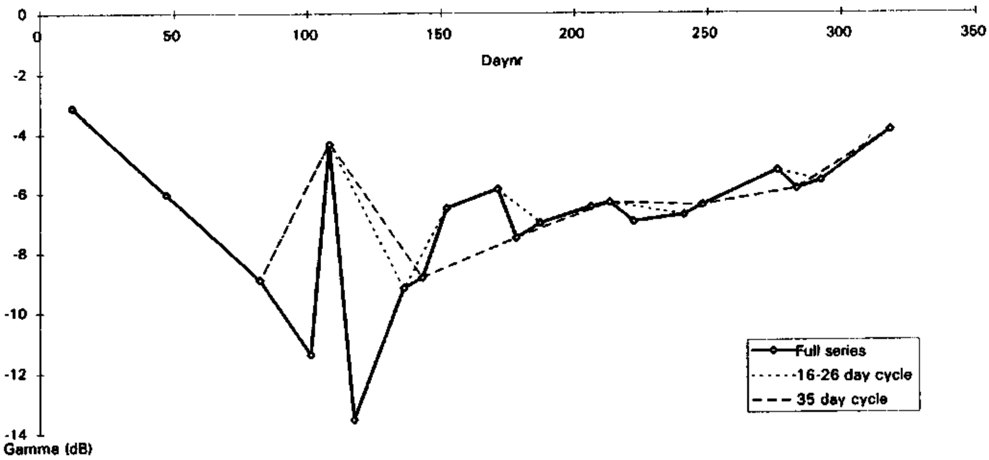


Figure 6.7 *An average time series of the ERS-1 of the southern region of the Flevoland Province for sugar beet. The impact of different measurement intervals of varying recording cycles is simulated*

The peak at day 110 is probably caused by heavy rainfall during the recording. Note also that the impact of less frequent observations results in a totally different time-series of backscatter in time.

The dynamic range and curvature of the time-series in Figure 6.7 shows potential for fitting a Cloud model at regional level. However, to do so at least information on average soil moisture and biomass is needed. This would require a huge campaign to provide all the information. This would not be very practical for operational purposes. In Chapter 5, an optical airborne image of the same recording day as the microwave recording in the period of partial closure provided *LAI* values without much supporting ground truth collection. A problem remains that no reliable estimations of soil moisture are available. A well calibrated hydrological model fed by meteorological data might provide an average soil moisture profile in space and time for the region as well.

It is interesting to study the regional standard deviation of ERS-1 time-series in two different growing seasons in the Southern Flevoland Province presented in Figure 6.8, including the 1993 season. The reduction in standard deviation coincides with the closure of the sugar beet crop. If the moment of closure can be indicated precisely (see range indicated by dotted arrows), valuable information for crop growth monitoring can be provided by microwave satellites.

Again, the recording frequency determines the accuracy of estimation of this date of closure. It is striking that all years show a similar behaviour in backscatter variation and not in backscatter level as was shown in earlier campaigns mentioned in Chapters 2, 3 and 5.

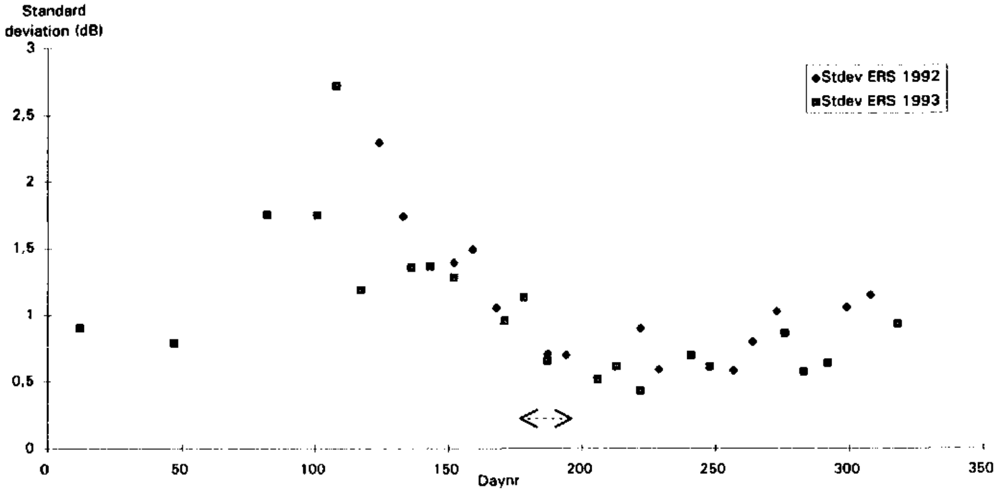


Figure 6.8. *Standard deviation in two growing seasons (1992 and 1993) of the sugar beet in the Southern Flevoland Province. The range in time (arrows) indicates the inaccuracy of determining the moment of closure of the sugar beet.*

It seems that crop closure can be determined at regional scale better than at field level. The effect of closure in microwave time-series might be explained as feature 1 mentioned in Chapter 3, Section 3.4.2.3. At field level various factors like wind, water stress, etc. could result in different time-series of backscatter. This troubles the interpretation of radar backscatter with respect to structure. These factors will probably average out when studying regional time-series of backscatter. Closure of sugar beet probably exhibits such a regional observable change in structure. However, the drooping of the leaves at the end of the growing season is probably less easy to detect at regional level.

Each crop has its own backscatter behaviour and will have different microwave signatures during the growing season. For example the average backscatter signature of the winter wheat crop of the 1993 growing season of the Southern Flevoland Province is given in Figure 6.9.

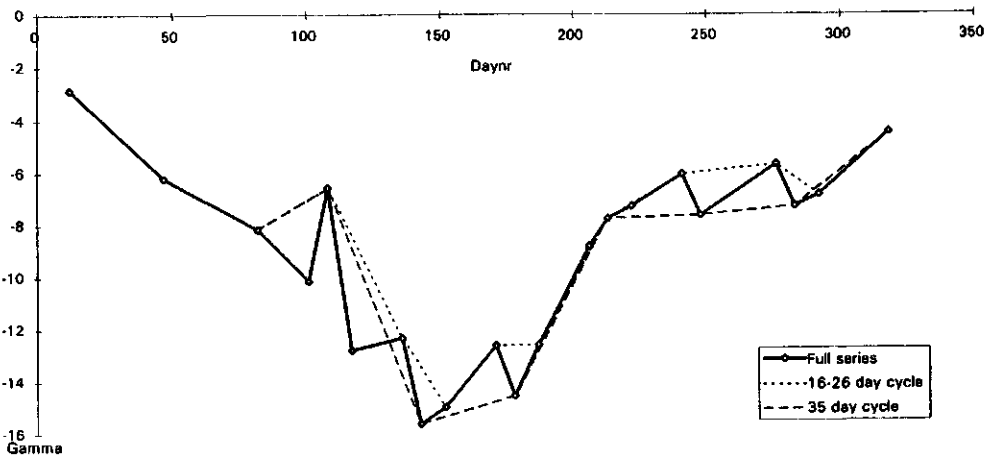


Figure 6.9 *An average time series of the ERS-1 of the southern region of the Flevoland Province for winter wheat. The impact of different measurement intervals of varying recording cycles is simulated*

The characteristic time curve for winter wheat remains, also when a lower frequent time-series is available. Opposite to the sugar beet crop, winter wheat has clear changes in canopy structure (elongating of stems and ear formation) during the growing season and these changes occur during a longer and thus better observable period by ERS-1. However, the start of these changes in structure is again not easy to identify in time, when the regional backscatter signal has a large standard deviation and when the frequency of recording is too low. In Figure 6.9 a shift between different ERS-1 recording scenarios can be noticed during the vegetative phase (decrease of backscatter). However, for the different scenarios, the increase in backscatter in the generative phase (ear formation and filling) later in the growing season seems to be more in line with each other. More study over different growing seasons needs to be done to work this out.

6.5.2.3 Integrated use of optical and microwave information at regional level

This section briefly discusses the potential of an integrated use of optical and microwave satellite information for crop growth monitoring, with sugar beet as an example. When simultaneous observations by optical and microwave satellites of the same area of study and additional average information on soil moisture, crop growth conditions and management (sowing, harvest time, etc.) are available, a combined model-based approach may be feasible (method I or II). The method will yield better results, when more optical and microwave recordings in time during the closure of the crop are available. Even the feature-based approach in Method III and IV could work when the moment of closure is treated as a regional feature in the average regional backscatter time-series. In all cases, the accuracy of the information from the microwave (and optical) observations will probably not be high enough to calibrate the sugar beet crop growth model. The standard crop growth model is already very well initialized for the crop growth conditions in the southern region of the Flevoland Province (see Figure 6.3) when general information, such as sowing date and daily temperature, is available. The inversion of an RS model and the detection of closure on microwave time-series will result in regional information with low accuracy (high standard deviation), leading to a high range in yield figures (see Figures 6.5 and 6.6).

It is of interest to discuss how this low accuracy information may still be of value to the industry with its conventional strategy for yield prediction. The sugar beet industries in the Netherlands (and in Europe) predict yield on the basis of experience. Generally, historical statistics like figures or (crop growth) curves are used for the insight and understanding each year. The intensity of (destructive) field sampling during the growing season has become less and less throughout the last decade. Figure 6.10 is an example of historical knowledge of yield prediction used by the sugar beet industry. In this figure yield is plotted against the moment of closure (from 1 June) which is the so-called growth point (X-axis). In the past, field surveys were carried out to determine the point in growth where the tuber of the sugar beet started to grow and fill itself with sugar. This growth point in the growing season appeared to correlate in general with canopy closure of the sugar beet in the region. Apparently, in general a correlation exists between a certain development stage and the physical closure. Of course, due to different crop management (plant density, soil type, and other growth conditions, etc.) crop closure is not easy to define exactly.

By fitting a line through the data points a certain linear relationship could be found between the growth point and yield. With a confidence interval of 95% a range in the two regression parameters of the linear relationship is expressed in an interval expressed by the dotted lines in figure 6.10. In general, when the growth point is early in the season a higher yield can be expected for the region. In order to predict yield at a certain moment at the end of the growing season, the average date of closure (regional indication of the growth point) results in a range of possible yields.

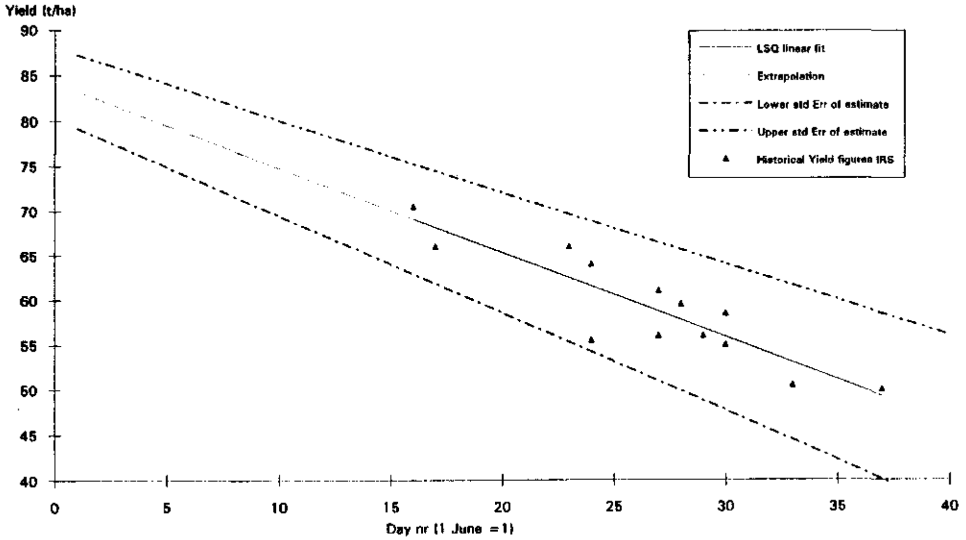


Figure 6.10 *An example of historical knowledge of yield prediction at regional level by the sugar beet industry. Data points are replotted and refitted by the author (Courtesy, Instituut voor Rationele Suikerproduktie, The Netherlands)*

It is also interesting to study the potential use of RS in the conventional procedure when the accuracy of yield prediction can be improved by reducing this range. When using the information from microwave and optical satellites before a certain moment in the growing season (e.g. August 15th is of interest to the industry for logistic reasons), the yield range might be reduced by using:

- Time-series of microwave information (RS model) for finding the growth point, coinciding with general crop closure in the region with a certain range of error in time (X-axis of Figure 6.10);
- Instantaneous optical and/or microwave information (RS feature) for calibrating an average regional crop growth model yielding a range in simulated yield figures (Y-axis of Figure 6.10).

When the error in time and yield information provided by RS is smaller than the error of yield estimation using the conventional procedure, RS can contribute to the yield prediction in a positive way. Another matter is whether this will be interesting for the industry from a financial point of view. The discussion in this chapter and Verhoef *et al.* (1996) have shown that numerous questions with respect to the sugar beet crop still need to be answered and that more interaction with the industry is needed to find out whether it is feasible to incorporate RS into the conventional yield prediction procedure in general.

The latter can be concluded for each other agricultural crop. A thorough knowledge of the practical (yield) procedures of the potential user (industry) is inevitable in order to bring RS nearer to its operational and commercial application. In Chapter 7 the results of this discussion are summarized in the conclusions and recommendations of this study.

7 Conclusions and recommendations

The objective of this thesis was to develop and test a methodology which could be used to monitor crop growth and predict yield with help of existing knowledge or actual knowledge acquired with remote sensing (RS) techniques and to understand how optical and microwave RS could be used in a synergetic way in this methodology.

The information extracted from RS observations (Chapter 2) and the information on crop growth (Chapter 3) were combined in several steps in order to study the synergism in relation to yield prediction and crop growth monitoring. This chapter concludes on the methods used in combining different sources of information in order to predict crop growth (Chapter 5). Evaluation of the applicability (Chapter 6) and recommendations for improvement of the methods used in the study will follow subsequently.

7.1 The main conclusions in this study

1. In this thesis the use of semi-empirical RS models describing the observation of agricultural crops, like sugar beet and winter wheat, especially in the microwave region appeared to be more suitable than the use of the theoretical and more complex (e.g. radiative transfer) RS models. The physical process of observation in the microwave region is not yet fully understood. These RS models have too many variables. Therefore, simple RS models like Cloud and CLAIR with few variables were used for calibration, validation and inversion with RS campaign data. The complex RS models like MIMICS and SAIL were used for sensitivity analysis.

2. The semi-empirical microwave RS model 'Cloud' for sugar beet and winter wheat, appeared to be difficult to calibrate at field level for the different campaigns used in the study. In the optical region the simple RS model CLAIR has been calibrated with good results and showed consistent results over the years. Roughly, the calibration for optical models occurred to be twice as good compared with the calibration of microwave models, when considering the standard error of estimate of the regression parameters of the Cloud and CLAIR model. The calibration of the Cloud model has the most success when enough independent measurements are available in the period from emergence till

crop closure. The calibrated CLAIR model is applicable over a larger period in the growing season than the Cloud model. The CLAIR model is valid until the leaf area index reaches the value of 4 to 5.

3. The applicability of the RS models for estimation of crop variables at field level during a certain campaign depends mainly on the validity of the model itself. The Cloud model needed to be recalibrated and revalidated for each year. Temporal analysis of series of microwave observations during growing seasons of several years showed more consistency. It appeared that certain features in backscatter time signatures co-occurred with changes in canopy structure. These features appeared to be easier to detect for winter wheat than for sugar beet.

4. For crop growth monitoring, a new combination method was developed using the inverse of the simple RS models, the features in RS time-series and a detailed crop growth model. This resulted in a model-based (method II) and a feature-based method (method III). The SBFLEVO crop growth model was particularly suitable for the study and offers several links with variables of direct RS models (method I). The inverse use of RS provided the possibility of integrating optical and microwave RS in a weighted manner in the combination method (method II). The inverse use of the optical and microwave RS model supplied the crop variables leaf area index and biomass, respectively, and their error of estimation. These weights provided a well balanced use of optical and microwave information in the combination method. This also indicates the applicabillity of RS modelling with respect to crop growth monitoring. Besides this, the microwave time-series provided additional information (features) for a total combination method (method IV) indicating changes in canopy structure. Changes in canopy structure often are linked to development of the crop in the case of winter wheat and less obvious in the case of sugar beet.

5. New in crop growth monitoring with RS is the step from ground-based towards airborne RS techniques. The MAC Europe 1991 campaign was selected as test case for the combination methodology for the synergy study because of the availability of different airborne sensors (optical and microwave) in a simultaneous and a multi-temporal format. The large variation in *LAI* of the various sugar beet fields owing to resowing activities offered several stages in growth during one observation moment (space-time transformation). Airborne optical RS data provided the *LAI* for a large number of sugar beet fields. The soil moisture condition for all fields was assumed to be constant at this particular day. Subsequently, these *LAI* estimates were used for calibrating the Cloud model using AIRSAR microwave RS data simultaneously with the

AVIRIS optical RS data. This procedure resulted into a well calibrated Cloud model for sugar beet for the 1991 growing season.

6. Results of method II using only two recording dates with an optical airborne sensor (CAESAR) during the growing season were almost as good as those obtained with a complete time-series with a field radiometer.

Results using only two recording dates with a microwave sensor (AIRSAR) during the beginning of the growing season were better than the results of the yield estimates without using any RS information. However, results were by far not as good as those obtained with the optical sensors. This was due to the high inaccuracy of estimation with the inverse Cloud model.

When combining the two CAESAR recording dates and the two AIRSAR recording dates in the calibration procedure of the crop growth model, good results were obtained. The resulting errors in yield estimation were smaller than those obtained with CAESAR data or AIRSAR data only. Results were even better than results obtained with a complete time-series of optical measurements. This already is a synergistic effect of combining both optical and microwave data.

In order to test the additional value of microwave measurements when only very few optical recording dates are available, the two AIRSAR recording dates were combined with one CAESAR recording date (of end of July 1991) in order to calibrate the growth model. Results show that particularly the L-band HH-polarization data offered very good results with yield errors that were even slightly smaller than those of the combination of two CAESAR dates with two AIRSAR dates.

This confirms the statement that the main advantage of radar lies in the possibility to acquire information on crop growth when other techniques (in particular optical techniques) fail.

7. Knowing the time of occurrence of the microwave RS feature from the AIRSAR observations of sugar beet, the sowing date could be reconstructed and also a calibration point related to a change in plant structure was used in addition to method III. Using only two AIRSAR microwave observations method III gave promising results compared to the situation having no information at all.

When the feature-based information from two microwave observations was added to the model-based information (method IV) combined with two optical observations a slight improvement could be noticed.

8. One step further in using RS information for crop growth monitoring is the use of satellite RS. Indications on the potential of satellite RS for crop growth monitoring so far have been found and discussed.

Information from optical satellite RS when well calibrated and not hampered by unclear weather conditions may provide *LAI* values on field level. This can be achieved only when enough additional information is available such as crop type (and cultivar), soil information, calibration information as reference surfaces and curves, etc.

Time series of microwave RS backscatter data of the ERS-1/2 on a regional scale indicated that average RS data for specific crops result into a more consistent behaviour than for individual fields. Especially for winter wheat average backscatter behaviour of fields in the Southern Flevoland Province resulted into a unique signature. Furthermore, it appeared that at the same time of crop closure for sugar beet a minimum of standard deviation in backscatter was reached.

The success of having unique signatures of either average backscatter or standard deviation in backscatter is related to the various factors involved in the physical backscatter process for each crop and how they average out on regional level. Another important factor is the observation frequency and the moment of observation in the growing season. The determination of calibration points or features in time series can not be determined precisely in time because of these factors.

There exists an indication that average information from RS at a regional scale could improve the average estimation of crop growth variables. For practical use of RS by the industry in crop growth and yield prediction, RS could improve the actual yield estimation for a certain region when recorded at the proper time during the growing season. This is crop type dependent. Field visits remain inevitable in order to check the estimations with space borne sensors.

7.2 Recommendations

1. Knowledge on the most significant periods for monitoring growth of the crop to be studied should impose requirements onto satellite RS data acquisition. Since optical RS data are well suited for growth estimation but the monitoring aspect is limited due to frequent cloud cover, it is expected that the significance of radar mainly lies in the possibility of acquiring data on a repetitive basis, unimpeded by atmospheric conditions. More scenarios with various combinations of optical and microwave data at various dates during the growing season should be evaluated in order to obtain an accurate picture of the significance of microwave data for crop growth monitoring.

2. Moreover, the date at which the yield estimate figures must be available, for instance to the sugar beet industry, must be taken into account. In order to plan all the logistics around the harvesting campaign, the estimates often must be available at some preliminary point in the growing season (e.g. beginning of August in the case of sugar beet).

3. The technique to calibrate a crop growth model with RS data was developed for sugar beet in Flevoland. The behaviour of other crops (other cultivars, other locations) can be quite different. The developed techniques, therefore, have to be evaluated for other cases (crops, regions, etc.) as well, which eventually may result in a more generalized approach.

4. Microwave data with higher temporal resolution (seasonal, diurnal) are needed to understand the physics of the backscatter process. The relation between plant structure and microwave backscatter needs more study. For fundamental research and development of better microwave RS models a systematic and conditioned experiment with ground-based (polarimetric, multi-frequency) scatterometers and optical spectrometers should be performed and is preferred to airborne campaigns.

5. Complicated crop growth models as used in this study are basically meant for detailed studies at field level. For practical applications they are in fact much too complicated and computationally tedious. In this study this was solved by optimizing the growth model for just four parameters that are most significant to the temporal *LAI* signature of a crop. For operational application, simple semi-empirical growth models may be more feasible.

6. In the calibration procedure of the crop growth model the *LAI* was used as key variable. One may doubt whether this really is a good variable for calibration of the crop growth model. From an agronomical point of view the *APAR* is more important, because this really determines the growth that is possible. In Clevers *et al.* (1994) it was concluded that the *APAR* is determined by the incoming *PAR* and the fraction of *PAR* absorption by the vegetation (*FPAR*). This *FPAR* can also be determined from optical RS data. The *FPAR* can be estimated by simply multiplying the *WDVI* with a crop specific factor. The *LAD* of the crop is the main factor influencing this multiplication factor. A simple approach based on the *FPAR* has been presented for crop growth monitoring and yield estimation by Clevers *et al.* (1994) and should be considered for yield prediction at regional level.

7. Furthermore it is important to notify that the crop growth model SBFLEVO is recently extended with a hydrological component. It might be interesting to study soil moisture in the top layer of the soil as a means to calibrate the hydrological model and indirectly the crop growth model. E.g. growth limitation can occur due to water stress.

8. Based on the findings of this study a proposition is done for a methodology for regional yield prediction in chapter 6. Information from RS at a higher aggregation level, in this case regional level, might be used in a similar manner in combination with the crop growth model initialized for the specific regional growing conditions. Besides aggregated information from RS models like an average *LAI* or biomass with a standard deviation representing the variation in the region, also information like crop closure or crop identification could be derived from airborne or even spaceborne observations. The inaccuracy of estimated variables on regional level with RS can be used as weights as was done in the combination methods developed for field level.

9. The differences in crop characteristics and growing conditions are probably averaged out in these aggregated representations of *LAI* or biomass. Factors as water stress, layering of wheat, wind, heavy rain, management, etc. affect the dynamic range of the RS signal of the region. The extent of this determines the possibility whether *LAI* can be estimated properly with simple RS models like Cloud or CLAIR.

10. In the combination methods of this study simple semi-empirical models were used. These models do have some physical basis but concentrate more on the crop variables which are important in relation to the RS signal (biomass, structure). New research should be focused on improving these simple semi-empirical relations. A first attempt was made in this study where canopy structure had been introduced to the

optical model CLAIR in a semi-empirically manner. This could be considered for microwave models as well.

11. Probably more reliable information can be expected from regional microwave time series resulting in e.g. an estimation of crop closure of sugar beet for a certain region. This needs further study.

12. For operational applications of the combined use of optical and microwave measurements for yield prediction, the use of spaceborne data must be studied in more detail. The role of optical satellites like NOAA-AVHRR, Landsat-TM and SPOT must be evaluated in relation to the role of microwave satellites like ERS-1 and JERS-1. This is precisely the goal of present studies carried on to specify the various EOS platforms (instruments, timing, orbit selection, etc.).

Abstract

Van Leeuwen, H.J.C, 1996, Synergy of optical and microwave remote sensing in agricultural crop monitoring; with special reference to sugar beet. PhD thesis, Wageningen Agricultural University, Wageningen, the Netherlands.

This thesis presents several methods for combining optical and microwave RS data for the purpose of crop growth monitoring. The objective is to understand how optical and microwave remote sensing may be used in a synergetic way in order to elaborate a methodology, that can be used to monitor crop growth and predict crop yield with the help of existing knowledge and with actual knowledge acquired from remote sensing observations.

To monitor growth and production of agricultural crops with RS techniques, an inventory of the information estimated with RS was done. A review of the state of the art in modelling in the reflective optical and microwave region of the electromagnetic (EM) spectrum is required since a major objective of this study is the investigation of the possibilities of a synergistic use of both optical and microwave RS data (Chapter 2). Furthermore, the most suitable models are selected and validated with actual realistic measurement situations as well as possible.

The underlying physiological processes of crop growth are studied in order to link them with RS information. The knowledge concerning these processes can be summarized in crop growth models. For growth monitoring or yield prediction of a certain crop in a growing season, the crop growth model is calibrated to the actual growing conditions. This calibration is performed by using actual information from the field or information supplied by remote sensors from airborne or space borne platforms. In Chapter 3, a methodology for combining the information (RS data, field data and models) of different sources is proposed in order to meet the research objective. The ultimate goal is to monitor crop growth and to predict the yield. In this respect research questions are formulated: Can RS provide relevant biophysical parameters and with what accuracy can these be estimated for linking RS with crop growth models? RS models are inventarized and selected for the study. Information valuable for crop growth monitoring is provided by inversion of the selected RS models. Additional knowledge is needed to condition the inversion of RS models. Simplified RS models proved to be helpfull in providing the main crop variables. Leaf area index and biomass were estimated from optical and microwave RS data, respectively. New is the use of structure information from crops (especially winter wheat) inferred from microwave RS time series. Subsequently, the growth model can be calibrated with the actual estimates of these variables derived from RS observations.

In order to meet the research objectives, Chapter 4 deals with data gathering and data analysis in order to work out and test the combination methodology applied in Chapter 5. Mostly, information has been gathered by several campaigns held in the past in the Southern Flevoland Province in the Netherlands, stimulated by the introduction of new sensors (spectroscopy, polarimetry, interferometry) and strategic funding. In order to study the effect of synergism of optical and microwave RS data, conditioned data sets are required. A theoretical RS model or interaction model needs to be calibrated with experimental data and validated with other experimental data sets. This has certain consequences for the quality and the quantity of data. Criteria are defined to do this properly.

With the analysis of RS data by image processing and information extraction in Chapter 4 a thorough data preparation and data fusion of several campaigns is accomplished. A synergetic data set is selected and tested. It appeared that the MAC Europe data set of 1991 from the test site in Southern Flevoland Province was suitable to test the synergism of combining multisource data in Chapter 5. The combination methods of Chapter 3 are tested with contemporaneous (simultaneous) and non-contemporaneous recordings of optical and microwave airborne sensors. A new methodology to introduce structure information from microwave data into the procedure of crop growth model calibration is applied on the MAC Europe data set of 1991.

In Chapter 6 the potential of application of the methodology and the potential of present satellites with respect to crop growth monitoring and yield prediction is discussed. A cautious attempt is made in order to study RS information at regional level in stead of field level as in the former chapters. A more regional approach seems to meet the practical applications of the method in conventional prediction strategies of the present (food) processing industry somewhat better.

Keywords: microwave, optical, remote sensing, synergy, crop growth, modelling, monitoring, sugar beet, inversion, calibration, agriculture.

Summary

Methodology for combining optical and microwave remote sensing in agricultural crop growth monitoring

Accurate and up-to-date information on agricultural production is a vital component in running present market economies. In Europe considerable differences between countries in their agricultural production have led to a complex system of rules and subsidies which all rely on a certain level of accuracy regarding agricultural statistics (such as acreage and yield). At national level and regional level, such statistics have been collected so far by using conventional methods, which are mostly based on knowledge and experience from the past. Before using this information on a European level, there is a growing need for combining new information techniques and present knowledge to provide realistic estimates of crop yield and production on a lower scale level.

Yield prediction is an important tool for industry, farmers and policy makers, facilitating logistic planning of transportation and production, storage and sale at national level and planning at farm level. In this thesis, the study is concentrated on the application of observation or remote sensing (RS) techniques to crop growth monitoring of agricultural crops in the Netherlands. A common crop in the Netherlands is the sugar beet crop and this crop served as a perfect illustration for validation of the developed methodology in this study. The objective of this study is to understand how optical and microwave remote sensing may be used in a synergetic way in order to develop a methodology, that can be used to monitor crop growth and predict crop yield together with existing knowledge.

More specifically, the study presented in this thesis aims to reveal (1) how useful information on biophysical properties of agricultural crops estimated with airborne remote sensing is for crop growth monitoring and yield prediction, (2) how successful this information can be utilized in the developed methodology for combining crop growth and remote sensing and (3) whether there are possibilities to apply this methodology for operational crop growth monitoring and yield prediction procedures by using airborne and to some lesser extent the current available spaceborne sensors.

The thesis work is subdivided in three parts. Part I outlines the theory and background supporting the thesis methodology and the combination methodology itself. In Part II, the test data are presented and, for the case study, the synergy of the combination of information is studied, especially for the multi-sensor airborne campaign MAC Europe 1991. Here the research questions 1 and 2 are being studied. The application of the methodology (research question 3) described in this thesis is evaluated in Part III, accompanied by concluding remarks and recommendations.

In Chapter 2, an inventory of the information estimated with RS is made in order to prepare the development of a methodology to monitor growth and production of agricultural crops with RS techniques. The major objective of this study is the investigation of the possibilities of a synergistic use of both optical and microwave RS data. Therefore, a review of the state of the art in modelling in the reflective optical and microwave region of the electromagnetic (EM) spectrum is performed. Furthermore, the most suitable models are selected and validated with the data from campaigns held in the Flevoland Province of the Netherlands as good as possible. It appeared that semi-empirical RS models, describing the observation of crops in a simplified physical way, could be calibrated and validated better than the complex radiative transfer models. The CLAIR model in the optical region has proven to be applicable over the different growing seasons, while the semi-empirical Cloud model in the microwave region revealed an unstable behaviour. Both models are calibrated with campaign data and were applied under strict conditions in this study in order to supply actual crop status information on respectively leaf area index (LAI) from the optical and biomass in the microwave model by inversion. From sensitivity analysis of the more complex radiative transfer (RS) models canopy structure appeared to be another important factor in the observation of crops as well in the optical as in the microwave region. Canopy structure information is not clearly incorporated in the semi-empirical RS models and therefore difficult to estimate. Changes in canopy structure have been recognised as specific features in time series of RS observation of the crop during the growing season, especially in microwave RS observations. The sugar beet crop revealed some characteristic features during the growing season, but not as clear as the vertically structured cereal crops, like winter wheat. Crop development related to changes in canopy structure in the case of winter wheat showed more potential for detection in RS time series as for sugar beet.

In Chapter 3, a general methodology is proposed for combining the information (RS data, field data and models) of different sources in order to monitor crop growth

and predict the yield. The underlying physiological processes of crop growth are studied for linkage of crop growth models with RS information. The SUCROS-type of crop growth model for the sugar beet crop from the School of de Wit from Wageningen appeared to be very suitable for this study, because of its detailed description of crop growth modelling and its status of being well initialised for crop growth conditions for sugar beet in the Flevoland Province. In this chapter, different methods were developed to calibrate the crop growth model with the actual information estimated by RS. The combination methods are:

- Direct modelling method: Calibration of crop growth model with a forward RS model. By comparing the simulated RS signal with the observed RS data optimization of the most important variables of the crop growth model is performed.
- Inverse modelling method: Calibration of crop growth model with an inverse RS model. In this method crop variables estimated with an inverse RS model are compared with crop variables of the crop growth model and used for optimization of the most important crop growth variables of the crop growth model.
- Feature modelling method: Calibration of crop growth model by using characteristic information from RS time-series, which is mostly related to a change in structure of the canopy owing to changes in development stage of the crop.

The direct model-based approach is only used for reference for the other methods and is developed in former research.

The inverse model-based approach combines LAI and biomass estimated by optical and microwave RS model inversion with the crop growth model. The crop growth model was calibrated with this information and their estimation accuracies by using the reciproke of the standard deviation, which reflects the 'state of the art' in the RS modelling.

The feature-based approach completes the methodology by detection of features in RS time series information on changes in canopy structure possibly related to crop development stages, which provide another source of information to calibrate the crop growth model as well. The overall methodology comprises the combination of the two approaches.

Chapter 4 comprises a brief overview of data sets from campaigns at the Flevoland test site held in the past. In order to study the effect of synergism of optical and microwave RS data, conditioned data sets were required and aspects of quality and quantity of data in campaigns were discussed. The criteria for the synergy study were best met by the data set of the MAC Europe 1991 campaign compared to the other available data sets. For testing the combination methodologies of Chapter 3, the data from the airborne MAC Europe 1991campaign were selected for the synergy study. This campaign was held at the time of the thesis study, so specific additional measurements could be collected like measurements on canopy structure. For RS model calibration and validation as well as for crop growth model initialization the Agriscatt 1987 and 1988 campaigns proved particularly suitable, because of the highly detailed information on field measurements. The ROVE data set from the late seventies provided measurements of high temporal frequency and were used for study of the impact of canopy structure on microwave backscatter and with that to illustrate specific radar features. The spaceborne ERS-1 time series from 1992 and 1993 were selected in order to discuss the potential of microwave satellite RS for operational crop growth monitoring in the last chapter and were not explicitly used in the study. A total processing line and a database for RS data interpretation was set up to prepare the study.

In Chapter 5, the proposed combination methods of Chapter 3 were applied with contemporaneous (simultaneous) and non-contemporaneous recordings of airborne optical and microwave sensors of the MAC Europe 1991 campaign. The configuration of the airborne RS data was selected for this study on basis of the current optical (SPOT and Landsat) and microwave (ERS-1/2 and JERS-1) satellite configurations. The performance of the methods was measured by comparing the simulated yield as a result of the calibrated crop growth model and the actual measured yield figures at a specific harvest date.

The inverse method is tested on the selected data set. The inverse RS model estimates LAI and biomass with a certain accuracy. The accuracy depends on the success of calibration of the (direct) RS model. It appeared that estimation of LAI from the optical model 'CLAIR' is at least twice as good as estimation of LAI from microwave model 'Cloud'. The combination of the crop growth model with optical data only gave good results. The added value of microwave data to this is present when no optical data are available (e.g. bad weather conditions). Using the information from both the airborne optical and microwave sensors weighted with the reciproke of the standard deviations the combination methods yielded success especially when the RS data was acquired in the beginning of the growing season. In this period the LAI can be well estimated, especially with optical RS models. Later in the growing season other information was found in RS time-series. With special attention to microwave

time-series information on changes in canopy structure has been found and validated with field measurements of leaf angle distributions with respect to sugar beet. In the case of sugar beet these changes in structure are not clearly related to development of the crop. However, this is more pronounced in the case of cereals (e.g. winter wheat). This is information is also a source of calibration of the crop growth model. However, the accuracy of the feature found in the time-series is not high enough to calibrate the already well initialized crop growth model. When the observation frequency is high enough (weekly) then this information could be used for estimating the moment of sowing by using the meteorological information during the growing season.

Chapter 6 discusses the practical application of the methodology. An important aspect is that the level of study is translated from field to regional level in order to find practical use for the method in conventional prediction strategies of the present (food) processing industry. The generalization step appeared to give new information. An example is that e.g. the minimum in standard deviation in backscatter time-series from ERS-1 for all sugar beet fields in the Southern part of the Flevoland Province appeared to be related to a regional crop closure of the sugar beet for two different years (1992 and 1993). It is obvious that information estimated with RS models for each specific crop is valuable for crop growth monitoring when the moment and density of the RS measurement is well chosen during the growing season. This imposes high requirements to the present available satellite systems (ERS-1/2, JERS-1, Radarsat, SPOT, Landsat, etc.)

Chapter 7 presents the main conclusions and recommendations for further research. More research is needed to calibrate and validate RS models for application in crop growth monitoring. The present generation crop growth models evolve towards reliable tools for yield forecasting and impose high requirements on quality of the RS information in order to be valuable for operational purposes. The methods used in this study gave good results in the case for airborne RS data on field level. Airborne optical and microwave RS information appeared to give synergetic results when combining with a crop growth model. The step towards a more operational monitoring method is expected to be difficult. The latter should be studied into more detail by using a more simple crop growth model and regional information from RS.

Samenvatting (summary in Dutch)

Van Leeuwen, H.J.C, 1996, Synergie van optische en microgolf remote sensing t.b.v. gewasgroeimonitoring; met speciale aandacht voor suikerbieten. Dissertatie. Landbouwuniversiteit Wageningen.

Remote sensing (RS) is een observatietechniek, waarmee processen en actuele status van een object van interesse, zoals landbouwgewassen, kunnen worden bestudeerd. Het volgen van de gewasgroei en het voorspellen van de opbrengst aan het einde van het groeiseizoen is van belang voor zowel de boeren enerzijds als de industrie anderzijds. Het bijhouden van actuele informatie over de produktie van landbouwgewassen is tevens belangrijk voor de huidige markteconomie. Door de vele verschillen in gewasproduktie tussen de Europese landen is er een ingewikkelde regelgeving en subsidieregeling ontstaan. Deze Europese regelingen dienen ondersteund te worden door betrouwbare en nauwkeurige informatie over landbouwstatistieken zoals opbrengst en areaalschatting.

In dit proefschrift is de aandacht geconcentreerd op de toepassing van verschillende RS technieken ten behoeve van het volgen van de gewasgroei in Nederlandse groeiomstandigheden. Omdat de suikerbiet een veel bestudeerd en voorkomend gewas is in Nederland, is dit gewas gekozen als voorbeeld in deze studie. Het doel van deze studie is gericht op de ontwikkeling van een combinatiemethode van informatie van optische RS, microgolf RS en tevens gewasgroeimodellen, zodanig dat op een synergetische wijze het gewasgroeiproces gevolgd kan worden en de gewasopbrengst geschat. Op nationaal en regionaal nivo worden landbouwstatistieken en ervaringen aangewend van het heden en verleden voor het schatten van de gewasopbrengst door de industrie. In deze studie is een combinatiemethode ontwikkeld en gevalideerd op veldnivo. Een vertaalslag van deze methode naar de praktijk zal echter een opschaling van veld naar hoger nivo vereisen. Het gebruik van RS technieken op dit schaalnivo zal zich dan meer concentreren op satelliet beelden dan op vliegtuig RS, daar een beter overzicht verkregen wordt en tegen minder kosten.

In dit proefschrift worden de volgende onderzoeksvragen gesteld:

1. Is de informatie over fysiologische eigenschappen van het gewas geschat uit vliegtuig RS waarnemingen bruikbaar voor gewasgroeimonitoring en opbrengst schatting?
2. Is deze informatie met succes bruikbaar in een methode waarin gewasgroeimodellen en RS data gecombineerd worden?
3. Bestaat de mogelijkheid een combinatiemethode toe te passen voor het volgen van gewasgroei en het voorspellen van de oogst in de praktijk door het gebruik van de huidig beschikbare satellietsensoren?

Dit proefschrift is verdeeld in 3 delen. In deel I wordt de achterliggende theorie van de verschillende combinatiemethoden m.b.t. RS en gewasgroeimodellen uiteengezet. In deel II worden de methoden toegepast op een aantal gegevenssets van vroegere RS campagnes voor het beantwoorden van de onderzoeksvragen 1 en 2. In deel III wordt onderzoeksvraag 3 onder de loep genomen waar de ervaring met vliegtuig RS van deel II wordt aangewend in de discussie m.b.t. toepassing van satelliet RS in het volgen van gewasgroei en het schatten van gewasopbrengst. Als afsluiting worden de conclusies en aanbevelingen op basis van voorgaande gepresenteerd.

In dit proefschrift zijn een aantal combinatiemethoden te onderscheiden op basis van de informatie die aanwezig is:

- "Direct modelling" methode; Calibratie van gewasgroeimodel met een *voorwaarts* RS model. M.b.v optimalisatie van de belangrijkste gewasgroeivariabelen wordt het voorspelde RS signaal vergeleken met het gemeten RS signaal;
- "Inverse modelling" methode; Calibratie van gewasgroeimodel met een *invers* RS model. M.b.v optimalisatie van de belangrijkste gewasgroeivariabelen worden geschatte RS modelvariabelen vergeleken met de overeenkomstige gewasgroeimodelvariabelen;
- "Feature modelling" methode; Calibratie van gewasgroeimodel met karakteristieke informatie afkomstig uit RS tijdseries, veelal gerelateerd aan veranderingen in de structuur van het gewas als gevolg van veranderingen in de gewasontwikkeling;
- Een combinatie van de laatste 2 voorgaande methoden.

De methoden zijn getest met gegevenssets van verschillende RS campagnes in Zuidelijk Flevoland. De MAC Europe campagne in 1991 bleek het meest geschikt voor de studie. De aanwezigheid van optische en microgolf vliegtuiggegevens op 3 tijdstippen in het groeiseizoen en de vele veldwaarnemingen vormden de basis voor de studie. In deze studie zijn de ingewikkelde theoretische RS modellen voornamelijk gebruikt voor gevoeligheidsanalyse. Semi-empirische RS modellen zijn om praktische redenen ingezet in de hierna volgende combinatiemethoden.

"Direct modelling" methode

In alle genoemde methoden staat de filosofie van het modeleren van het gewasgroeiproces van de school van C.T. de Wit en zijn collega's van de vakgroep Theoretische Produktie Ecologie van de Landbouwuniversiteit en van DLO onderzoeksinstituut voor Agrobiologie en Bodemvruchtbaarheid te Wageningen centraal. Specifiek aan deze combinatiemethode is dat een voorwaarts simulerend RS model (zowel optisch als microgolf) wordt gebruikt. Deze methode is in deze studie alleen gebruikt ter vergelijking van de volgende ontwikkelde methoden.

"Inverse modelling" methode

Deze methode maakt gebruik van het inverse RS model. Het model voorspelt met een zekere nauwkeurigheid de gewasvariabelen leaf area index (*LAI*) en biomassa van de bovengrondse delen van het gewas. De nauwkeurigheid van het schatten van deze variabelen uit RS wordt bepaald door de mate van succes van calibratie en validatie van de optische en microgolf RS modellen met verzamelde veldgegevens. Het blijkt dat het schatten van variabelen uit optische beelden minstens twee keer zo goed plaats vindt in het begin van het groeiseizoen van de suikerbiet als met microgolf beelden.

De combinatie van het gewasgroeimodel met informatie geschat uit optische vliegtuigbeelden alleen geeft reeds goede resultaten. De toevoeging van informatie geschat uit microgolf vliegtuigbeelden heeft alleen meerwaarde wanneer door slechte weersomstandigheden geen optische beelden aanwezig zijn. De verschillende bijdragen van RS informatie in de combinatiemethode worden gewogen met de reciproke waarde van de standaard afwijking verkregen uit de hiervoor vermelde RS modelcalibratie. Dit laatste geeft een verantwoorde wijze van combineren van informatie verkregen uit twee totaal verschillende waarnemingsbronnen en het geeft tevens de laatste stand van kennis weer in de RS modelontwikkeling. Verder gebeurt de optimalisatie op basis van variabelenivo in plaats van op RS-signaalnivo en tevens binnen de geldigheidsgrenzen van het gewasgroeimodel en het gevalideerde RS model. Hieraan gerelateerd is het dus van belang dat de informatie uit RS geschat wordt op momenten dat het RS model geldig is en het meest gevoelig voor de betreffende variable.

In het geval van het suikerbietgewas bleek dat *LAI* het best geschat werd door optische RS in het eerste deel van groeiseizoen tot ver na gewassluiting (LAI van 4 to 5). Het microgolf RS model (C-band VV-polarisatie en L-band HH-polarisatie) echter, schatte biomassa (gerelateerd aan LAI) het beste tot aan de gewassluiting en minder nauwkeurig dan in het geval van het optische RS model.

Een overeenkomst met "direct modelling" methode is dat combinatie van gegevens op een zeker *tijdstip* in het groeiseizoen gebeurt. De volgende methode is gebaseerd op een verandering van het gewas en daarmee ook het RS signaal gedurende een zekere *periode* in het groeiseizoen.

"Feature modelling" methode

In deze methode is een extra meerwaarde vanuit de microgolf RS geïntroduceerd door karakteristieke informatie uit tijdseries te gebruiken die niet goed door de toegepaste semi-empirische RS modellen beschreven konden worden. Het microgolfsignaal blijkt naast biomassa ook gevoelig te zijn voor struktuurveranderingen in het gewas. Deze struktuurverandering is in geval van suikerbieten gerelateerd aan voornamelijk de bladstandverdeling aangezien het blad het meest dominant aanwezig is. In tegen stelling tot de graangewassen zijn de struktuurveranderingen bij de suikerbiet niet gerelateerd aan veranderingen in gewasgroeiontwikkeling, maar meer aan plantdichtheden, niet optimale groeiomstandigheden, rasverschillen, etc. In het geval van wintertarwe zijn duidelijke veranderingen in microgolftijdseries gerelateerd aan struktuurverandering als gevolg van bepaalde gewasontwikkelingsstadia. Deze informatie wordt gebruikt om het gewasgroeimodel te calibreren, waarbij voornamelijk de zaaidatumbepaling van belang zal zijn. De nauwkeurigheid van het vaststellen van het optreden van een bepaald ontwikkelingsstadium hangt met name van de dichtheid van de RS waarnemingen in de tijd af.

Het zal duidelijk zijn dat de informatie geschat uit RS waarnemingen voor elk specifiek gewas op het juiste moment en met de juiste dichtheid in de tijd aangeboden dient te worden. Dit stelt zeer hoge eisen aan de beschikbaarheid van RS informatie. In de praktijk zullen de huidige RS satellietsystemen (ERS-1/2, Landsat en SPOT) op hun bruikbaarheid voor gewasgroeimonitoring nader onderzocht moeten worden. Uit deel III van deze studie blijkt dat er indicaties zijn dat gebruik van RS op een hoger schaalnivo dan tot nu toe (veldnivo) beter kan aansluiten op de praktijk. Een voorbeeld is het moment van sluiten van het suikerbietgewas in het Zuidelijke deel van Flevoland, hetgeen duidelijk te herkennen is in de standaard afwijking van ERS-1 metingen van vele suikerbiet velden in deze regio in 1992. Tevens blijkt voorgaande consistent te zijn voor twee verschillende jaren achtereen (1992 en 1993). Een ander voorbeeld is het verschil in geldigheid van het microgolf RS model tussen verschillende jaren bepaald op basis van enkele velden.

Meer studies van calibratie en validatie van RS modellen op basis van gemiddelde waarnemingen op regionaal nivo is daarom aanbevolen. Een praktisch probleem is dat er op dit schaalnivo moeilijk aan de benodigde hoeveelheid veldgegevens te komen is. Gedeeltelijk kan dit probleem opgelost worden door andere informatie in te brengen uit de nauwkeurigere optische metingen of uit voorinformatie uit de steeds beter wordende gewasgroeimodellen.

De methoden en ervaringen die in dit proefschrift gepresenteerd zijn moeten worden beschouwd als een stap verder in de richting van het volgen van de gewasgroei en het opbrengstschatten m.b.v. RS in de praktijk.

REFERENCES

Allen, W.A. and A.J. Richardson, 1968. Interaction of light with a plant canopy. J. Opt. Soc. Am. 58: 1023-1028.

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

Asrar, G., M. Fuchs, E.T. Kanemasu and J.L. Hatfield, 1984. Estimating absorbed photosynthetic radiation and leaf area index from spectral reflectance in wheat. Agron. J. 76: 300-306.

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

Attema, E.P.W. and F.T. Ulaby, 1978. Vegetation modelled as a water cloud, Radio Science 13(2), pp. 357-364.

Attema, E.P.W., P.J. van Kats and L. Krul, 1982. A radarsignature model for partially coherent scattering from irregular surfaces. Telecommunication and Remote Sensing Laboratory, Delft University, The Netherlands.

Baret, F. and G. Guyot, 1991. Potentials and limits of vegetation indices for LAI and APAR assessment. Rem. Sens. Envir. 35: 161-174.

Beaudoin A., T. Le Toan and Q.H.J. Gwyn, 1990. SAR observations and modelling of the C-band backscatter variability due to multiscale geometry and soil moisture, IEEE Trans. Geosc. Remote Sensing, GE-28, 886-894.

Borgeaud. M and J. Noll, 1993. Comparisons of active microwave and optical remote sensing data over agricultural terrains. Proceedings of the IAPR TC-7 International workshop, september 7-9 1992, edited by M. Molenaar, L.F.F. Janssen and H.J.C. Van Leeuwen. Delft, The Netherlands.pp.141-146.

Bouman, B.A.M., and J. Goudriaan, 1989. Estimation of crop growth from optical and microwave soil cover. Int. J. Remote Sensing, Vol. 10, no. 12, pp. 1843-1855.

Bouman, B.A.M., and H.W.J. van Kasteren, 1990a. Ground-Based X-Band (3-cm Wave) Radar Backscattering of Agricultural Crops. I. Sugar beet and potato;backscattering and crop growth. Remote Sens. Environ. 34: pp. 93-105.

Bouman, B.A.M., and H.W.J. van Kasteren, 1990b. Ground-Based X-Band (3-cm Wave) Radar Backscattering of Agricultural Crops. II. Wheat, Barley and Oats; the Impact of Canopy Structure. Remote Sens. Environ. 34: pp. 107-118.

Bouman, B.A.M., 1991a. The linking of crop growth models and multi-sensor remote sensing data. Proceedings of the 5th International Colloquium on Physical

Measurements and Signatures in Remote sensing, held in Courchevel, France, on 14-19 January 1991, ESA.

Bouman, B.A.M., 1991b. Crop Parameter Estimation from Ground-Based X-Band (3 cm Wave) Radar Backscattering Data. Remote Sens. Environ. 37: pp. 193-205.

Bouman, B.A.M., 1991c. Linking X-band radar backscattering and optical reflectance with crop growth models. Thesis Agricultural University Wageningen, The Netherlands, 169 pp.

Bouman, B.A.M., 1992a. SBFLEVO and WWFLEVO, Growth models to simulate crop growth, optical reflectance and radar backscatter of sugar beet and winterwheat, calibrated for Flevoland. CABO-DLO report 163, Wageningen, The Netherlands, 61 pp plus appendices.

Bouman, B.A.M., 1992b. SBFLEVO_OPT, A program to calibrate the crop growth model SBFLEVO for sugar beet in Flevoland on optical reflectance and/or radar backscatter data. CABO-DLO report 164, Wageningen, The Netherlands, 32 pp plus appendices.

Bouman, B.A.M. and D.H. Hoekman, 1992c. Agriscatt-88 Flevoland; Analysis of DUTSCAT radar data over an agricultural test site. Maestro-Agriscatt workshop.

Bouman, B.A.M., 1992d. Linking physical RS models with crop growth simulation models, applied for sugar beet. Int. J. Rem. Sensing13:2565-2581.

Bouman, B.A.M., D. Uenk and A.J. Haverkort, 1992e. The estimation of proportion ground cover of potato by reflectance measurements. Potato research 35: 111-125.

Bouman, B.A.M., H.W.J. van Kasteren and D. Uenk, 1992f. Standard relations to estimate ground cover and LAI of agricultural crops from reflectance measurements. Eur. J. Agron. 4:249-262.

Braam, B.M., H.J. Buiten, D.H. Hoekman and H.J.C. Van Leeuwen, 1989. Analyse VARAN-S en IRIS radarbeelden. Geautomatiseerde geometrische verwerking en data-extractie. BCRS-report 89-37, 135 pp.

Buiten H.J. and J.G.P.W. Clevers, 1994. Land observation by remote sensing; Theory and applications. Current Topics in remote sensing volume 3. Gordon and Breach publishers.

Büker, C., J.G.P.W. Clevers, H.J.C. Van Leeuwen, B.A.M. Bouman and D. Uenk, 1992a. Optical component MAC Europe, Ground truth report, Flevoland 1991. BCRS report 92-27, 55 pp.

Büker, C., J.G.P.W. Clevers and H.J.C. Van Leeuwen, 1992b. Optical component MAC Europe, Optical data report, Flevoland 1991. BCRS report 92-28, 49 pp.

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.

Bunnik, N.J.J, 1984. Review of models and measurements of multispectral reflectance by plant canopies; recommendeations for future research. NLR report MP 84039 U, National Aerospace laboratory NLR, The netherlands.

Causton, D.R. and J.C. Venus, 1981. The biometry of plant growth. Edward Arnold, London: 307 pp.

Clevers, J.G.P.W., 1986. Application of remote sensing to agricultural field trials. Thesis, Agricultural University Wageningen Papers 86-4, 227 pp.

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. and D.H. Hoekman, 1989a. Modelvorming en synergie optische en microgolf remote sensing. Deelrapport 1; voorstudie. Delft (BCRS, Netherlands Remote Sensing Board), BCRS report no. 89-23, 82 pp.

Clevers, J.G.P.W., 1989b. 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. and W. Verhoef, 1990. Modelling and synergetic use of optical and microwave RS. Report 2: LAI estimation from canopy reflectance and WDVI: a sensitivity analysis with the SAIL model. BCRS report 90-39, 70 pp.

Clevers, J.G.P.W., 1992a. Modelling and synergetic use of optical and microwave RS. Report 4: Influence of leaf properties on the relationship between WDVI and LAI: a sensitivity analysis with the SAIL and the PROSPECT model. BCRS report 92-14, 36 pp.

Clevers, J.G.P.W., B.A.M. Bouman, C. Büker and H.J.C. van Leeuwen, 1992b. A conceptual framework for estimating crop growth using RS data. International Archives of Photogrammetry and RS Vol. XXIX, Part B7, Comm. VII, XVIIth ISPRS Congress, Washington D.C., 1992, pp. 189-196.

Clevers, J.G.P.W., H.J.C. van Leeuwen and W. Verhoef, 1993. Modelling and synergetic use of optical and microwave remote sensing. Report 5: APAR estimation by means of the WDVI: A sensitivity analysis with a combined PROSPECT-SAIL model. BCRS report 93-02, 40 pp.

Clevers, J.G.P.W., H.J.C. van Leeuwen and W. Verhoef, 1994a. Estimating the fraction APAR by means of vegetation indices: a sensitivity analysis with a combined PROSPECT-SAIL model. Remote Sensing Reviews 9: 203-220.

Clevers, J.G.P.W., C. Büker, H.J.C. van Leeuwen and B.A.M. Bouman, 1994b. A framework for monitoring crop growth by combining directional and spectral remote sensing information. Rem Sens. Envir. no. 50:161-170.

Clevers, J.G.P.W. and H.J.C. van Leeuwen, 1994c. Combining directional and high spectral resolution information from optical remote sensing data for crop growth monitoring. Sixth International Symposium Physical Measurements and Signatures in Remote Sensing, Val d'Isère, France, 17-21 January 1994.

Clevers J.G.P.W., H.J.Buiten and H.J.C. van Leeuwen, 1994d. Modelling and synergetic use of optical and microwave remote sensing. Report 8 Application of optical remote sensing for crop growth monitoring. BCRS report no. 94-16.

Daughtry, C.S.T., K.P. Gallo, S.N. Goward, S.D. Prince and W.P. Kustas, 1992. Spectral estimates of absorbed radiation and phytomass production in corn and soybean canopies. Rem. Sens. Envir. 39: 141-152.

Delécolle, R., S.J. Maas, M. Guérif and F. Baret, 1992. Remote sensing and crop production models: present trends. ISPRS J. Photogramm. Rem. Sensing 47: 145-161.

Den Dulk, J.A., 1989. The interpretation of remote sensing: a feasibility study. PhD thesis, Wageningen Agricultural University, 173 pp.

De Loor, G.P., 1982. The Dutch ROVE program. IEEE Transactions on Geoscience and Remote Sensing, Vol.GE-20,pp.3-7.

De Loor, G.P., 1984. Variation of the radar backscatter throughout the growing season. Proc. EARSel Workshop Microwave RS applied to vegetation, ESA SP-227, pp. 63-67.

De Loor, G.P., 1987. Moisture determinations in and under vegetation canopies: part II:results after parametrization of the Cloud model. TNO-FEL, The Netherlands. pp.17.

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

De Wit, C.T., 1993. Personal communication, Wageningen.

Dobson, M.C., F.T.Ulaby, M.T. Hallikainen and M.A.El-Rayes, 1985. Microwave Dielectric Behaviour of Wet Soil-Part II, Dielectric Mixing models. IEEE Trans. Geosci.Remote Sens., GE-23, 35-46.

Duntley, S.Q., 1942. The optical properties of diffusing materials. J. Opt. Soc. Am. 32: 61-70.

Ernst, H. and G Fischbeek, 1984. X- and L-band backscatter analysis of agricultural crops in West Germany. Proc. IGARSS'84 Symposium, Strasbourg 27-30 Aug. 1984, Vol. 1, pp. 137-140.

Eom, H.J. and A.K. Fung, 1984. A Scatter model for Vegetation up to Ku-Band. Remote Sensing of Environment, vol 15, pp 185-200.

Fung, A.K. and G.W. Pan, 1987. A scattering model for perfectly conducting random surfaces I. Model development. Int. J. Remote Sensing, vol. 8, no. 11, pp. 1579-1593.

Goel, N.S. and T. Grier, 1986. Estimation of canopy parameters for inhomogeneous vegetation canopies from reflectance data. I. Two- dimensional row canopy. Int. J. Rem. Sensing 7: 665-681.

Goudriaan, J., 1977. Crop micrometeorology: a simulation study. Thesis Landbouwhogeschool, Wageningen, 249 pp.

Goudriaan, J., 1988. The bare bones of leaf-angle distribution in radiation models for canopy photosysnthesis and energy balance. Agricultural and forest meteorology, 43. pp. 155-169.

Heidemij, 1992. Ground data collection ERS-1 campaign, report no. 635/21084, Heidemij, Lelystad, the Netherlands.

Hoekman, D.H., Krul, L. and E.P.W. Attema, 1982. A multilayer model for radar backscatter from vegetation canopies. Proceedings of IGARSS'82 Symposium, Munich, pp. 4.1-4.7.

Hoekman, D.H., 1990. The Agriscatt campaign; Radar data acquisition at agricultural sites in five West-European countries during the 1987 and 1988 growing seasons. LUW-LMK 199002, 92 pages.

Hoekman, D.H., and B.A.M. Bouman, 1993. Interpretation of C- and X-band radar images over an agricultural area, The Flevoland test site in the Agriscatt-87 campaign. International Journal of Remote sening 14:1577-1594.

Idso, S.B. and C.T. De Wit, 1970. Light relations in plant canopies. Appl. Opt. 9: pp.177-184.

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

Jacquemoud, S. and F. Baret, 1991. Prospect: a model of leaf optical properties spectra. Rem. Sens. Envir. 33.

Jacquemoud, S. S. Flasse, J. Verdebout and G. Schmuck, 1994. Comparison of several optimization methods to extract canopy biophysical parameters - application to CAESAR data. Proc. Sixth International Symposium Physical Measurements and Signatures in Remote Sensing, Val d'Isere, France.

Janse, A.R.P., 1993. radar backscatter of soils. In: Landobservations of Remote Sensing, Theory and applications, pp. 237-254, edited by H.J.Buiten and J.G.P.W. Clevers. Current Topics in remote sensing volume 3. Gordon and Breach publishers..

Janssen, L.L.F. and R.P.H.M. Schoenmakers, 1992. Integrated segmentation and clasification of high resolution satellite images. Proceedings Workshop, IAPR TC-7, 1992, Delft , The Netherlands pp 65 - 84.

Janssen, L.L.F., 1994. Methodology for updating terrain object data from remote sensing data. Thesis Landbouw Universiteit Wageningen.

Kanemasu, E.T., G. Asrar and 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).

Karam, M.A., Fung,A.K., Lang, R.H., Chauhan, N.S., 1992. A microwave scattering model for layered vegetation, IEEE trans. Geosc. Remote Sensing, vol. 30, no. 4, pp 767-784.

Karam, M.A. and A.K. Fung, 1992. Leaf-shape effects in electromagnetic wave scattering from vegetation. IEEE Trans. Geosc. RS 27(6): 687-697.

Kubelka, P. and P. Munk, 1931. Ein Beitrag zur Optik der Farbanstriche. A. Techn. Physik 11: 593-601.

Kuusk, A., 1985. The hot spot effect of a uniform vegetative cover. Sov. J. Rem. Sensing 3: 645-658.

Laur. H., 1992. ERS-1 SAR calibration; derivation of backscattering coefficient in ERS-1 PRI products. ESA, Internal Report, Noordwijk, The Netherlands, 16pp.

Lemoine G.G., D.H. Hoekman and H.J.C. van Leeuwen, 1991. Separability of agricultural fields and forest stands using multi-frequency polarimetric SAR data of the Flevoland site. Proceeding of the IGARSS '91 Symposium, Helsinki Finland, 3-6 June, pp. 681-684.

Lemoine, G.G., H.J.C. van Leeuwen and J. Bakker, 1994. Monitoring agricultural land preparation activities with ERS-1 SAR data. Internal study report SYNOPTICS, september 1994. Also published in NRSP-1 BCRS, ERS-1 study: Applications of ERS-1 SAR data in agriculture and forestry edited by G.J.A Nieuwenhuis and W.W.L van Rooij, 1995, SC-DLO report no. 101.

Le Toan, T., A. Lopes and M. Huet, 1984. On the relationships between back-scattering coefficient and vegetation canopy characteristics. Proc. IGARSS'84 Symposium, Strasbourg 27-30 Aug. 1984, Vol. 1, pp. 155-160.

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

Luimstra, O., 1994. From survey to model output: an integrated remote sensing process. MsC Dept. of Landsurveying and Remote Sensing. Thesis Wageningen Agricultural University. Scriptie nr 1993-3.

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

Maas, S.J., 1993. Agroclimatology and modelling. Parameterized Model of Gramineous Crop Growth: I. Leaf Area and Dry Mass Simulation. Agron. J. 85:348-353.

Molenaar, M. and L.L.F. Janssen, 1993. Terrain objects, their dynamics and the integrated processing of remote sensing data. Proceedings of the IAPR TC-7 International workshop, september 7-9 1992, edited by Molenaar M., L.F.F.Janssen and H.J.C. van Leeuwen. Delft, The Netherlands.pp.113-134.

Perez, Ph., H.J.C van Leeuwen, J.G.P.W. Clevers, B.A.M. Bouman, G.J.Rijckenberg B.v.d. Broek and. Taconet, 1994. Synergy in the modelling of microwave with optical remote sensing data. ESA study contract no.9837/92/NL/GS, Noordwijk, The Netherlands.

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

Price, W.L., 1979. A controlled random search procedure for global optimisation. The computer Journal 20:367-370.

Ross J., 1981. The radiation regime and architecture of plant stands. Tasks for vegetation sciences 3, Dr W. Junk Publishers, The Hague-Boston-London, 391 pp.

Rouse, D.I., W. Stol and O. Klepper, 1991. A fortran program for calibration and uncertainty analysis of crop growth models: description with users guide and program listing. CABO report, Wageningen, The Netherlands.

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

Rijckenberg, G.J. and H.J.C. van Leeuwen, 1994. Modelling and synergetic use of optical and microwave remote sensing. Report 6: Radar backscatter modelling for synergistic use with optical remote sensing in the application to agricultural crops. BCRS report no 94-12, 104 pp.

Schnute, J., 1981. A versatile growth model with statistically stable parameter. Can.J.Fish. Aquat. Sci. 38: 1128-1140.

Schoenmakers, R.P.M.H., H.J.C. van Leeuwen, G.G. Lemoine and E. Nezry., 1994. Segmentation of combined high resolution optical and radar imagery for the determination of field inhomogeneities. Proc. IGARSS '94 Symposium, Pasadena, California, Volume IV:2137-2139.

Sellers P.J., 1985. Canopy reflectance, photosynthesis and transpiration. Int. J. Remote Sensing, vol. 6, no. 8, 1335-1372.

Seligman, N.G., 1990. The crop model record: promise or poor show? In: Rabbinge, J. Goudriaan, H. van Keulen, F.W.T. Penning de Vries and H.H. van Laar (Eds.), Theoretical production ecology: reflections and prospects. Simulation monographs, PUDOC, Wageningen, pp 249-262.

Snoeij, P. and P.J.F.Swart, 1987. The DUT airborne scatterometer. International Journal of Remote Sensing, vol8 n011, pp:1709,1716.

Snoeij, P., P.J.F. Swart and R. Verhoeven, 1988. ESA Agriscatt-88 campaign, processing of the DUTSCAT data. Dept. of Telecommunication and Remote Sensing Technology, Technical University Delft, The Netherlands, pp 35.

Spitters, C.J.T., 1987. An analysis of variation in yield among potato cultivars in terms of light absorption, light utilization and dry matter partitioning. Acta Horticulturae 214: 71-84.

Spitters, C.J.T., 1988. Modelling crop growth and tuber yield in Helianthus tuberosus. Proceedings Jerusalem artichoke EEC Workshop 1987, Madrid. Commission of the European Communities, Luxembourg, report EUR 11855: pp 29-35.

Spitters, C.J.T., H. van Keulen and 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 and H.H. van Laar. Simulation Monographs 32. Wageningen: Pudoc, 420 pp.

Spitters, C.J.T., 1990. Crop growth models: their usefulness and limitations. Acta Horticultura 267: Timing of vegetable production. pp. 345 - 363, Symp. Wageningen, Aug. 1989.

Steven M.D., P.V. Biscoe and 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.

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

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

Tsang, L., J.A. Kong and R.T. Shin, 1985. Theory of Microwave Remote Sensing, Wiley-Interscience, New-York.

Uenk D., B.A.M. Bouman and H.W.J. Kasteren, 1992. Reflectie aan landbouwgewassen. Handleiding voor het meten van gewasreflectie, Standaardlijnen voor de bepaling van bodembedekking en LAI. AB-DLO (former CABO), verslag 156.

Ulaby, F.T., R.K. Moore and A.K. Fung, 1982. Microwave remote sensing, Vol II. Addison-Wesley, Reading Masssachusettes, United States of America.

Ulaby, F.T., R.K. Moore and A.K. Fung, 1986. Microwave remote sensing, Vol III. Artech House, Washington, United States of America.

Ulaby, F.T. and M.A. El-Rayes, 1987. Microwave Dielectric Spectrum of Vegetation-Part II: Dual Dispersion Model. IEEE Trans. Geosc. Remote Sensing, vol. GE-25, no. 5, pp. 550-557.

Ulaby, F.T., K. Sarabandi, K. McDonald, M. Whitt and M.C. Dobson, 1990. Michigan microwave canopy scattering model. Int.J. Remote Sensing, vol.11, no.7, pp.1223-1253.

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

Van Kasteren, H.W.J., 1993. Description of the ROVE database. CABO report no. 176, Wageningen, The Netherlands, 53 pp.

Van Keulen, H., F.W.T. Penning de Vries and E.M. Drees, 1982. A summary model for crop growth. In: Simulation of plant growth and crop production (1982), edited by F.W.T. Penning de Vries and H.H.van Laar, PUDOC, Wageningen, The Netherlands.

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

Van Leeuwen, H.J.C., 1991. Multifrequency backscatter modelling of bare soil: Attema, Kats and Krul model (AKK model) applied on Agriscatt 1987 data. BCRS report nr 91-43. MsC Thesis Agricultural University Wageningen 1988. (Internal nr Fac. Electrotechniek, Teleobservatie en -communicatie, TU-Delft, 64- 220-88-A-2LU), The Netherlands.

Van Leeuwen, H.J.C., G.G. Lemoine,. and D.H. Hoekman, 1992a. Model-based Derivation of Vegetation and Soil Parameters In Multi-frequency Radar Data Sets. Proc. Int. Geosci. Rem. Sens. Symp. (IGARSS'92), pp 54-56, Houston, Texas, USA.

Van Leeuwen H.J.C., 1992b. Multifrequency and multitemporal analysis of scatterometer radar data with respect to agricultural crops using the cloud model Proceedings IGARSS'91, Helsinki, Finland, June 3-6, 1991, Volume IV, 1893-1897.Also presented Final workshop 6-7 March 1992, Maestro-1/Agriscatt report.ESA wpp-31, may 1992, ESTEC, Noordwijk, the Netherlands.

Van Leeuwen H.J.C., and J.G.P.W. Clevers, 1994a. Synergy between optical and microwave remote sensing for crop growth monitoring. Proc. Sixth International Symposium Physical Measurements and Signatures in Remote Sensing, Val d'Isere, France, pp. 1175-1182.

Van Leeuwen H.J.C., Clevers, J.G.P.W. and Rijckenberg, G.J., 1994b. Synergetic use of optical and microwave remote sensing data using models and specific features with respect to the sugar beet crop. Proc. IGARSS '94 Symposium, Pasadena, California, Volume II:827-831.

Van Leeuwen H.J.C and J.G.P.W. Clevers, B.A.M.Bouman, G.J.Rijckenberg and B. v.d. Broek, M. Borgeaud and J.Noll, 1995a. Comparisons of crop yield prediction using both microwave and optical data. MAC Europe 1991 Workshop Lenggries, 4-6 October, 1994, Germany. pp 131-137.

Van Leeuwen, H.J.C., G.G. Lemoine, M.A.M. Vissers, 1995b. Ground data archives for remote sensing calibration and validation in the Netherlands. Proc. CEO workshop 24-25 april 1995, Brussels, Belgium, JRC-EU workshop.

Verhoef, W. and 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.

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., 1985a. Earth observation modeling based on layer scattering matrices. Rem. Sens. Envir. 17: 165-178.

Verhoef, W., 1985b. A scene radiation model based on four stream radiative transfer theory. Proc. 3rd Int. Coll. Spectral Signatures Objects Rem. Sensing, Les Arcs, France, ESA SP-247, pp. 143-150.

Verhoef, W., 1990. Informatie-extractie uit multispectrale beelden met behulp van stralingsinteractiemodellen. Report NLR TP 90243 L, 48 pp.

Verhoef. W, H.J.C. van Leeuwen and J.G.P.W. Clevers, 1996. Remote sensing assisted sugar beet yield forecasting. BCRS report, NRSP-2, nr 95-24.

Vissers, M.A.M., D.Uenk and B.A.M. Bouman, 1988. Agriscatt 88 ground data collection Flevoland (NL). CABO report 108, Wageningen, The Netherlands. pp. 46 + annexes.

APPENDIX A

Relationship canopy moisture with LAI

The relationship between LAI and canopy moisture is interesting for the synergy study as it could provide a link between optical and microwave RS models. For contemporaneous observations by a microwave and an optical sensor, the LAI could be derived from optical images far better for reasons of model validity in the optical region. The optical LAI could then be used for microwave image interpretation with use of the empirical relationship between canopy moisture (W·d in the Cloud model) and LAI.

From the field measurements in the Agriscatt 1987 en 1988 campaign the relationship between W·d and LAI was found (Equation 3.7). However, LAI represents the leaves and not all above ground biomass, which includes stems as well. When there exists a relationship between the total above ground canopy moisture and the leaf moisture only, then differentiation in layers could be made in the microwave modelling. For sugar beet one could distinguish a stem and a leaf layer. The sugar beet leaf layer is supposed to be dominant as the distribution and packing of the leaves is rather dense at the Flevoland Province.

The relationship between volume fraction *V* of wet leaves per unit soil area with leaf thickness *D*, crop height *d* and *LAI* can be represented by the following simple equation (Ulaby *et al.*, 1986):

$$V = LAI \bullet D / d \qquad \text{(A.1)}$$

This relationship provides, in volumetric terms, information about the amount of scatterers involved in the observation of the crop-soil system per unit volume vegetation material in the canopy layer. The amount of leaves will simply be assumed to be the amount of scatterers, based on the assumption mentioned above. This relationship can be validated by field measurements from the Agriscatt '88 campaign. The number of scatterers (or so-called number of constituents in the canopy layer) *Nrc* can be calculated as the measured amount of plants per unit area *Nrp* and the amount of leaves per plant *Nrlpp*. Absolute volume fraction fresh material per 1 m^2 (V_{fmeas}) then equals:

$$V_{fmeas} = Nrc * *R^2 *D/d = Nrp* Nrlpp* Vl/d \qquad \text{(A.2)}$$

With a given bulk density ρ_d of dry leaf material, the total content of water G_v of leaves in the canopy medium (in kg.m^{-3} per soil area) with leaf water fraction M_w can be estimated as:

$$G_v = \frac{M_w}{\left(\frac{1-M_w}{\rho_d} + \frac{M_w}{\rho_w}\right)} \cdot d \qquad \text{(A.3)}$$

with ρ_w=1000 kg.m^{-3}

The absolute weight of water G_w (in kg) per unit soil area (1 m^2) can be estimated as:

$$G_w = V_f * G_v \qquad \text{(A.4)}$$

This value may be compared with G_{wmeas} measured in the field as the difference of leaf fresh weight G_{lfw} with leaf dry weight G_{ldw}:

$$G_{wmeas} = G_{lfw} - G_{ldw} \qquad \text{(A.5)}$$

G_{wmeas} is leaf moisture W_l*d (kg.m^{-2}), which is used in the microwave Cloud model when a distinction of layers is made. In this study the Cloud model for one layer is modelled and therefore the relationship between LAI and total canopy moisture has been used in this study. The relationship between total canopy moisture W·d and leaf moisture W_l·d is presented in Figure A.1.

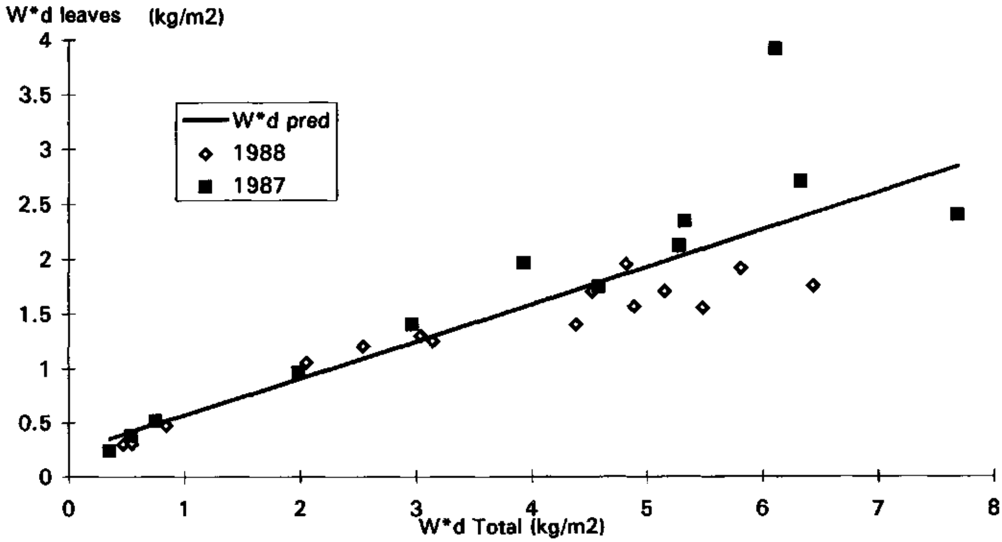


Figure A.1 *Relationship between total canopy moisture $W{\cdot}d$ and leaf moisture $W_l{\cdot}d$ derived from field measurements of the Agriscatt 1987 and 1988 campaign.*

The relationship in Figure A.1 can be found as:

$$W_l{\cdot}d = 0.34 \cdot W{\cdot}d + 0.23 \qquad \text{(A.6)}$$

with correlation coefficient 0.87 and an R^2 of 0.76.

with Equation 3.7 moisture of the leaf layer is:

$$W_l\, d = 0.41 \cdot LAI + 0.23$$

This relationship is expected to be valid especially in the beginning of the growing season.

APPENDIX B

Calibration results for winter wheat: Agriscatt '88 campaign.

The calibration results using a multi-layer Cloud model (Hoekman *et al.*, 1982) applied to the winter wheat of the Agriscatt '88 campaign (Van Leeuwen, 1992b) is presented in Table B1. Note that no standard deviation of the regression parameters is given in Table B.1. The figures in Table B.1 give some indications.

Table B.1. *Fit results of radar data for winter wheat in the Agriscatt 1988 campaign; airborne scatterometer with multi-frequency and incidence angle (20. 30. 40. 50. 60. degrees; HH and VV polarization)(Source Van Leeuwen, 1992).Regression parameters Cloud model: G, C1 & D1(vegetative matter), C2 & D2 (ear-layer) and K (K= 0.1*ln 10 * B, where B is sensitivity to soil moisture (dB/vol%))*

	G					
θ	*L*	*S*	*C*	*X*	*Ku-1*	*Ku-2*
20.	.0061	.0255	.020	.04000	.110	.080
30.	.0047	.0150	.019	.02500	.070	.085
40.	.0022	.0080	.009	.01042	.075	.098
50.	.0012	.0067	.011	.00050	.090	.090
60.	.0016	.0090	.011	.04000	.060	.060
	C2					
θ	*L*	*S*	*C*	*X*	*Ku-1*	*Ku-2*
20.	.0556	.4861	.2249	.1230	.3919	.2661
30.	.0698	.2771	.2086	.1331	.4379	.2975
40.	.0676	.2203	.1302	.1191	.4188	.2954
50.	.0868	.1996	.1547	.1001	.4843	.3103
60.	.1150	.3009	.2795	.2298	.3302	.3623
C1	.0486	.1566	.1727	.2099	.1904	.1813
D2	2.0789	1.9799	.0717	.0009	.1491	.4810
D1	2678	.0047	.0033	.5568	.5568	.5847
k	.100	.069	.058	.048	.044	.041

Curriculum Vitae

Hans Jacob Charles van Leeuwen was born in Abbekerk (Noorder Koggenland, Noord Holland), the Netherlands, at 22 January 1964. In 1982 he finished secondary education at the Laurens College in Rotterdam and started his study at the Wageningen Agricultural University (WAU). He graduated in 1988 majoring in soil science and remote sensing. This study was partly done in Costa Rica with respect to landsurveying. The other part of this study was an internship at the Teleobservation and Telecommunication Laboratory of the Faculty of Electrical Engineering of the Delft University of Technology.

In 1989 he worked on a project of the Dutch Remote Sensing Board (BCRS) on automization of data extraction of microwave images at the Department of Landsurveying and Remote sensing of the WAU. From 1990 till mid 1995 he worked as a research assistant and lecturer at the WAU on his PhD research on combining RS and crop growth information for crop growth monitoring and yield prediction. He participated in several RS campaigns of the BCRS, ESA and NASA at the Flevoland test site in the Netherlands. During this period he studied related topics with funding from the BCRS and ESA.

Since 1995 he holds the position of remote sensing consultant in the company Synoptics B.V. of which he is cofounder.