SAR FOR AGRICULTURE: ADVANCES, PROBLEMS AND PROSPECTS

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ABSTRACT

The aim of this paper is to illustrate the state of the art in SAR data use for agricultural applications, discuss the main problems and give suggestions for future work.

The paper is introduced with some short historical notes about the evolution of ground based, airborne and spaceborne radar observations, as well as about the advances in scattering modeling.

Then, the paper considers three aspects of the retrieval problem, corresponding to three fundamental steps: i) identification of a convenient radar configuration; ii) development of reliable relationships between backscatter coefficient and agricultural variables (direct problem); iii) retrieval in the strict sense (inverse problem). For each of the three topics, the important recent advances are summarized and the author's point of view about the state of the art is given.

1. INTRODUCTION

The objective of this paper is to illustrate and discuss the state of the art in SAR data use for agricultural applications. This topic has been the object of many investigations, in the last decades.

A first extensive experimental data base was provided by several ground-based measurements carried out in the 70's and early 80's, mainly in the US, using calibrated scatterometers. Single fields of various crop types, e.g corn, soybeans, alfalfa, wheat, grass, etc., were monitored during their growth cycle. Observations over vegetated fields were mainly carried out in a frequency range between 4 and 18 GHz and in a linear copolar configuration (i.e. at VV and HH polarizations). Extensive results were published in several papers, e.g. Ulaby (1980), and summarized in important books (Ulaby et al., 1986; Ulaby & Dobson, 1989). In general, experimental results indicated that the radar backscatter coefficient σ° is sensitive to vegetation parameters. Over some specific fields, a very nice correlation versus important vegetation variables was observed, e.g. in Figure 21.53 of Ulaby et al. (1986) This first activity gave a fundamental stimulus to microwave remote sensing for agricultural applications.

In the late 80's, some airborne campaigns made radar signatures available to a wide community of users (Hoekman, 1992; Churchill & Attema, 1992). The instruments, in this case, observed large agricultural areas including several fields. In order to monitor fields developments, the areas were observed 3-4 times during the Summer season. However, the temporal extension of the observations was more limited than in the case of ground based observations. The correlation between σ° and ground parameters was investigated considering several fields observed simultaneously during limited time intervals. In general, correlations versus vegetation variables were not as good as with multitemporal single-field ground based observations. Soil properties and plant structure were different among the various fields. Therefore, σ° was not simply correlated to a single variable, but was influenced by complex interactions among soil scattering, vegetation attenuation and vegetation scattering, as well as differences in geometry and permittivity of vegetation components (stem, leaf, petiole, ear, etc.). Moreover, the calibration problems were not yet completely solved, especially for airborne observations.

In the late 80's and in the 90's important advances were achieved, opening prospects of a full future utilization of SAR data for agricultural applications. First of all, significant improvements in calibration techniques were obtained using corner reflectors, extended targets and active calibrators (Van Zyl, 1990; Zebker & Lou, 1990; Freeman et al., 1990). Moreover, fully polarimetric instruments were realized. A lot of sites worldwide were overflown by AIRSAR (Held et al., 1988) and SIR-C (Stofan et al., 1995), thus allowing several scientists to get an insight into the problem of interaction between waves and natural media. Important activities were also carried out by means of EMISAR (Christensen et al., 1998). The launches of ERS-1, ERS-2, JERS-1 and RADARSAT made spaceborne multitemporal signatures available to many users for the first time. Finally, in parallel with the quantitative and qualitative improvements of experimental data bases, very important progresses were achieved in modeling, leading to a significant expansion of our capabilities in interpreting radar signatures. A simple "cloud" model gave a first key to understand σ° dependence on main soil and vegetation variables (Ulaby & Attema, 1978). Important studies led to simulate σ° using a discrete Radiative Transfer (RT) model, with vegetation elements represented as discs and cylinders (Eom &

Fung, 1984), (Karam & Fung, 1988). Further studies, aimed at refining the models in order to include leaf curvature and/or coherent effects, are in progress.

To summarize, tremendous efforts have been carried out, leading both to a significant expansion of experimental data bases available to us and to an important improvement of our capability to interpret the data. From the application point of view, the main objective is the retrieval of important agricultural variables such as Water Content (WC, kg/m^2) and Leaf Area Index (LAI, m^2/m^2). The work aimed at solving this problem may be subdived into three main steps. The first step consists in identifying a convenient radar configuration, i.e. one or more combinations of frequency, incidence angle and polarization for which σ° is sensitive to the variable to be retrieved. As a second step, a relationship between σ° and all soil and vegetation variables by which it is influenced has to be established. The relationship must be reliable, in the sense that must be valid in different sites and under different operational conditions. Finding this relationship, which is constituted by a model, solves the direct problem. Finally, the inverse problem has to be solved, i.e. retrieving the variables of interest using data collected in a convenient radar configuration and with the aid of a reliable direct model.

The three steps will be the objects of Sections 2, 3 and 4, respectively. For each of them, some important recent advances will be summarized and the author's point of view about the state of the art and the main present problems will be illustrated. Suggestions about future research directions will be given.

2. STUDIES ON RADAR SENSITIVITY

In order to retrieve a variable, the remote sensing system must be sensitive to the variable itself. In case of agricultural crops, since we are generally interested on variables associated to crop growing and crop senescence (i.e. WC and LAI), we need to identify combinations of frequency, incidence angle and polarization for which the σ° value is significantly influenced by the crop cycle. This is ensured by a high σ° dynamic range between full growth and early stage and a gradual transition between the extreme values. Since the various crop types show different geometries, the convenient radar configuration is not the same for all crops, but must be considered for any specific type, as it will be evident in Section 2.2.

2.1. Recent advances

As stated in the Introduction, the problem of radar sensitivity to vegetation variables has been investigated since the 70's using experimental data and models of various complexity. Some important papers, published during the last three years, are shortly summarized below.

Skriver et al. (1999) have illustrated polarimetric multitemporal signatures collected by EMISAR at L and C band over several crop types in Denmark. Main features have been discussed in comparison with previous works.

Saich & Borgeaud (2000) have analyzed ERS SAR signatures collected at Flevoland (NL) site in 93, 94, 95 and 96 over potato, sugarbeet, wheat, barley and grass fields. Crop typical temporal patterns and year-to-year variabilities have been analyzed, also using a second order RT model.

Macelloni et al. (2001) have investigated the different relationships between σ° and biomass of narrow and broad leaf crops. Critical comparisons with previous works have been shown. Radar signatures collected by various airborne and spaceborne instruments, as well as a first order RT model, have been used.

De Roo et al. (2001) have investigated the radar sensitivity to soil moisture and vegetation water content of soybeans fields. L and C band signatures and a semiempirical model have been used.

Important advances have been achieved in studies on rice cycle monitoring. Ribbes & Le Toan (1999) have investigated the performance of RADARSAT SAR, also in comparison with ERS SAR. Rosenquist (1999) has studied the temporal and spatial characteristics of JERS-1 SAR signatures.

2.2. Survey

Considerations about convenient radar configurations, based on studies carried out till now, are shown in this Section. For sake of concreteness, a set of 7 crop types, i.e. potato, corn, sugarbeet, rape, wheat, barley and rice, has been selected. This set is limited, but statistically significant, in that covers a high fraction of world crop area. For each of the seven crop types, diagrams or references to the literature are used to identify convenient radar configurations, on the basis of multitemporal trends or comparisons vs. σ°'s of bare soils and other crops. Most of the diagrams are plotted using σ° data made available in the framework of the ERA-ORA Project, founded by ECC. Results are interpreted by means of electromagnetic considerations.

2.2.1. Potato crop

At L band, HV polarization, higher angles, σ°'s of developed potato fields are clearly higher than σ°'s of other crops and bare soils. This configuration appears to be convenient since produces a high dynamic range. Figure 1 shows results, obtained by AIRSAR over Flevoland site in 1991, made available by University of Wageningen. Signatures collected in other experiments, shown by Ferrazzoli et al. (1998) and by Skriver et al. (1999), are in agreement with data of Figure 1. Stem density of potato is low (10-15 m^{-2}). Crop structure is ramified with large twigs (diameter > 4 mm). The feature of Fig. 1 may be explained by the crosspolar scattering of twigs.

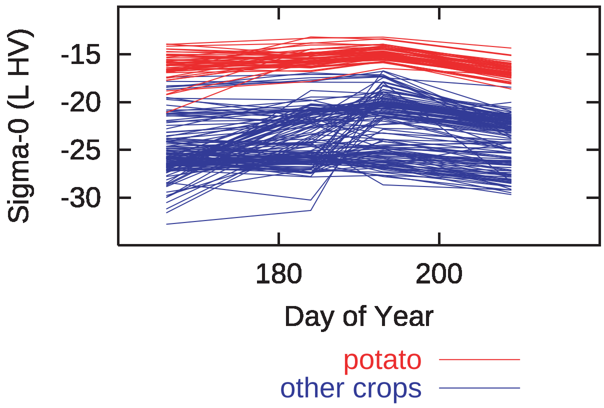

Figure 1. Multitemporal signatures collected at Flevoland in 1991. L band, HV polarization. Comparison between potato and other crops

2.2.2. Corn crop

At L (S) band, HV polarization, high angles, an appreciable $\sigma°$ increase is observed in corn fields during the time interval of plant growth. This property is observed in Figure 2, showing again L band AIRSAR data collected at Flevoland in 1991. Results shown by Ferrazzoli et al. (1997) and Macelloni et al. (2001) confirm this increasing trend. Experimental data collected by the RASAM multifrequency scatterometer at the Central Plain site in Switzerland (Wegmüller, 1993) show a similar trend also at S band. Stem density of corn is low (7-10 m^{-2}). The crop shows broad leaves with large ribs and petioles. The feature of Fig. 2 may be explained by the crosspolar scattering of ribs and petioles.

2.2.3. Sugarbeet crop

For sugarbeet, a clearly convenient configuration is not easy to be identified. A good contrast with respect to bare soil is generally achieved at HV polarization, high angles. Moreover, $\sigma°$ increase vs. frequency is more evident than in other crops or in bare soils. These properties may be observed in Figure 3, showing crop averaged $\sigma°$'s measured by RASAM and made available by GAMMA. Stems are sparse (7-10 m^{-2}) and low. Scattering is dominated by the wide and thick leaves, particularly at the higher frequencies.

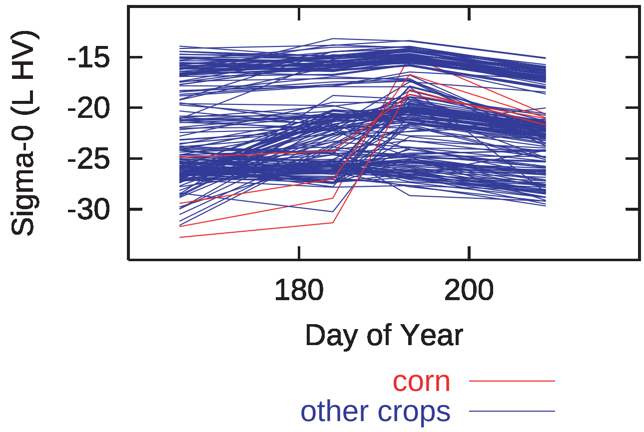

Figure 2. Multitemporal signatures collected at Flevoland in 1991. L band, HV polarization. Comparison between corn and other crops

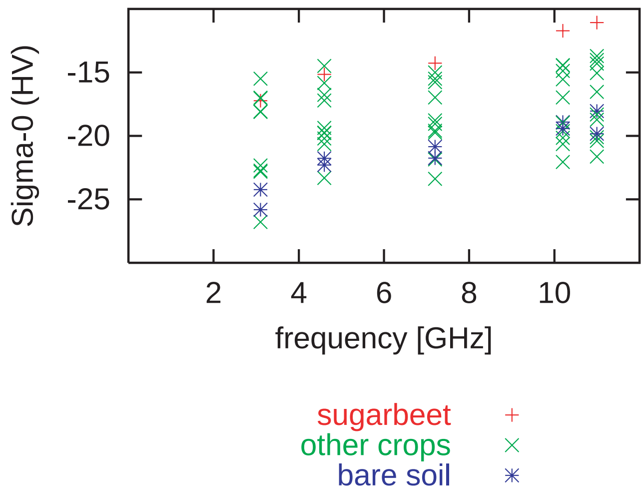

Figure 3. Multifrequency signatures collected by RASAM at Central Plain. HV polarization. Comparison between sugarbeet, bare soil and other crops

2.2.4. Rape crop

At C band, HV polarization, high angles, $\sigma°$'s of developed rape crops are clearly higher than $\sigma°$'s of other crops and bare soils. Therefore, this radar configuration is convenient for rape. Figure 4 compares C band HV signatures collected by AIRSAR at Flevoland. The high rape backscatter before harvest is evident. Signatures collected in Italy (Ferrazzoli et al., 1997) and in Denmark (Skriver et al., 1999) agree with these statements. Stem density of rape is typically 70-80 m^{-2}. Plants are ramified, with several small twigs (< 2 mm diameter) and pods. The feature of Fig. 4 finds explanation in the crosspolar scattering of twigs and pods.

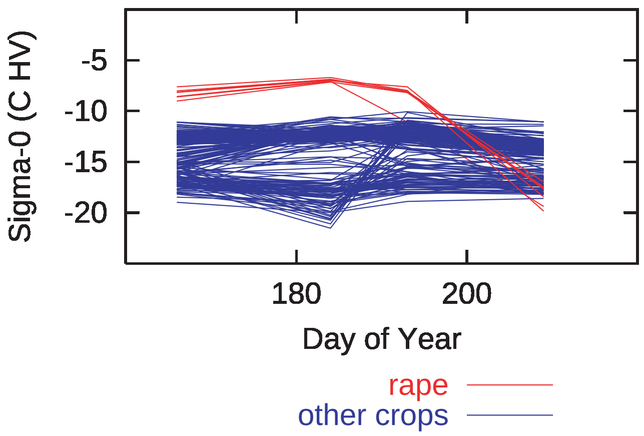

Figure 4. Multitemporal signatures collected at Flevoland in 1991. C band, HV polarization. Comparison between rape and other crops

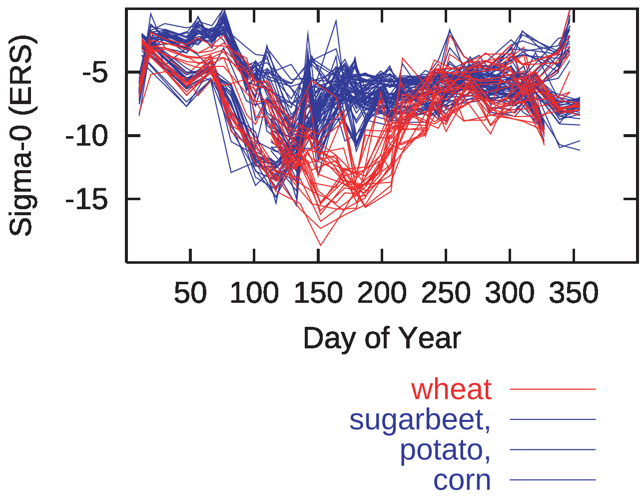

Figure 5. Multitemporal ERS signatures collected at Flevoland. Comparison between wheat and other crops

2.2.5. Wheat crop

At C, VV polarization, low angles (20°-30°) wheat $\sigma°$'s show and evident lowering during crop growth. This is clearly observed in Figure 5, where multitemporal ERS SAR $\sigma°$'s of wheat fields are compared against the ones of potato, corn and sugarbeet fields. Data were collected at the Flevoland site in a 4-years period, from 93 to 96, and have been made available by ESA/ESTEC. This wheat behavior is observed and discussed also by Saich & Borgeaud (2000), Cookmartin et al. (2000) and Macelloni et al. (2001). The ERS SAR configuration appears to be convenient for cycle monitoring. According with the results published by Del Frate et al. (2001), VV polarization contains useful information also at S and X band. Wheat stems are thin and dense (500-1000 m^{-2}) with narrow leaves. Ears are present on top in the mature stage. The feature of Fig. 5 finds explanation in the increasing attenuation suffered by VV soil backscattering due to growth of vertical stems and ears.

At HV polarization, wheat $\sigma°$ is mostly related to ear bending; therefore, this polarization does not appear to be reliable for crop monitoring. As far as L band is concerned, useful information could be added by its availability, in that the sensitivity to crop density is improved. However, L band signatures are heavily influence by azimuth orientation, as demonstrated by Stiles et al. (2000).

2.2.6. Barley crop

The general behavior of barley signatures is similar to the one observed for wheat. This may be explained by the general similarity between the two crop structures. Figure 6 compares multitemporal ERS signatures of barley with the ones measured over potato and sugarbeet. Considerations similar to the ones of Fig. 5 may be applied. In the mature stage, barley ear bending is more enhanced than wheat ear bending. Therefore, the use of HV polarization for growth monitoring is not appropriate, and may be even misleading.

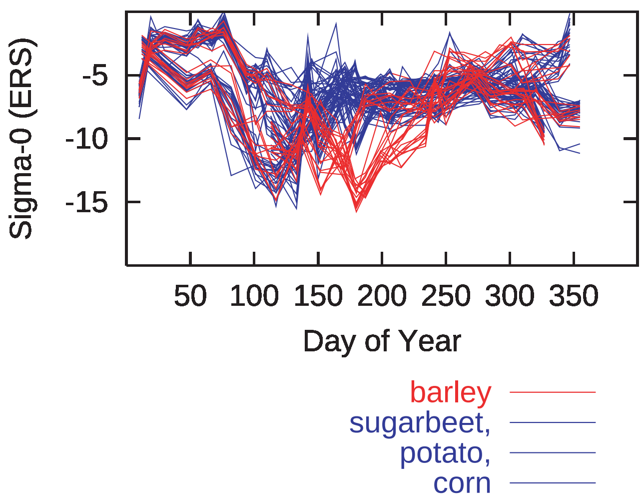

Figure 6. Multitemporal ERS signatures collected at Flevoland. Comparison between barley and other crops

2.2.7. Rice crop

Rice crop backscatter has been the object of several experimental and modeling studies, in the recent years. Measurements carried out over various sites indicate ERS SAR configuration to be convenient. An evident σ° increase is observed during crop growth, with limited variability. Model simulations give a theoretical basis to this result (Le Toan et al., 1997). Rice stem density is relatively high ($\sim$ 200 m^{-2}). Stems are grouped in bounches. The soil is flooded during the growing phase. At early stage σ° is low, since the flooded soil is smooth. Crop growth is associated with a soil/stem double bounce effect, producing a gradual σ° increase. The direct vegetation backscatter dominates in full growth.

Also RADARSAT and JERS-1 rice signatures have been analyzed. The σ° contrast between full growth and early stage is lower in RADARSAT than in ERS signatures. This is explained by the lower interaction of stem with HH polarization, with respect to VV polarization (Ribbes & Le Toan, 1999). Investigations carried out by Rosenquist (1999) indicate that, for manual planting, also L band signatures (JERS-1 configuration) are well correlated with crop growth. The situation is more complex in case of mechanical planting, since a significant dependence on azimuth angle is observed, due to coherent interactions.

Studies about rice are at an advanced stage. Some applications, such as classification and crop monitoring, are preoperational (Ribbes & Le Toan, 1999). Unfortunately, few data in HV polarization are available.

2.3. Considerations about coherence

The considerations of Section 2.2 are relevant to σ° amplitude. In the recent years, the application potential of interferometric coherence data collected by using SAR tandem overpasses has been investigated. This research has been stimulated by the availability of tandem images obtained by ERS-1 and ERS-2 with 1 day time delay. Some works indicate that the coherence contains useful information about vegetation type and vegetation status (Wegmüller & Werber, 1997). In order to get an insight into this problem, some coherence data made available by GAMMA have been analyzed. Figure 7 shows some multitemporal trends, obtained over the Flevoland site in 1995, relevant to wheat, potato and sugarbeet fields. For most of potato and sugarbeet fields, coherence is low in full growth and increases during drying. However, there are some anomalous samples of difficult interpretation. Coherence of wheat fields is high: this property could be due to a more advanced drying, with respect to other crops, or to the differences in geometrical characteristics. According to the data of Fig. 7, coherence confirms to have a good potential for agricultural applications, but its dependence on canopy and soil properties needs further investigations.

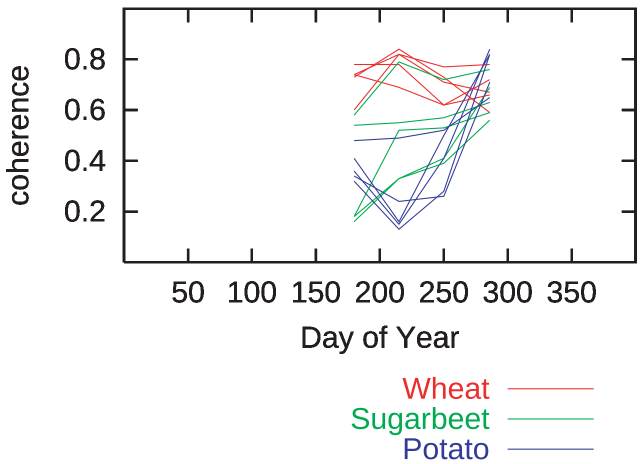

Figure 7. Multitemporal coherence data collected at Flevoland by ERS tandem overpasses. Comparison between potato, sugarbeet and wheat

2.4. Summarizing considerations

The analysis of section 2.2 indicates that general conclusions, valid for all crop types, cannot be drawn, since the radar sensitivity is affected by single crop properties. However, two observations of general validity may be done.

- An increase in stem density, generally associated to a decrease in stem diameter, leads to an increase of the convenient frequency. For wheat, barley, rice, rape (higher stem density, lower stem diameter) a high interaction with C (X) band waves is observed, making high frequencies interesting for monitoring. For corn and potato (higher stem diameter, lower stem density) lower frequencies (L and S band) appear to be more convenient.
- HV polarization is particularly useful when crops are well ramified, i.e. the relative weight of twigs, pods, petioles and leaf ribs becomes important. It is the case of potato, corn and rape. For crops dominated by vertical structures, such as wheat and barley, the most significant information is contained in the attenuation and/or double bounce effects produced at VV polarization.

It must be remembered that L band, HV polarization, has proved to be a convenient configuration also for sunflower (Ferrazzoli et al., 1997) and soybeans (De Roo et al., 2001).

The above considerations are valid when scattering is dominated by cylindrical elements. Their applicability to sugarbeet, characterized by large leaves and very low stems, is not straightforward.

¿From a system point of view, the forthcoming considerations apply.

- The configurations of present spaceborne SAR's, particularly ERS SAR, are interesting for some crops, such as rice, wheat and barley.
- ENVISAT ASAR signatures, provided ground resolution will be sufficient, will produce a significant improvement in monitoring, in that may contain HV polarization.
- A general good potential in monitoring of the main crops could be achieved in the future by simultaneous availability of L and C band observations.

The analysis has been limited to linear polarizations. However, previous studies indicate that the availability of fully polarimetric data is very useful for classification (Ferrazzoli et al., 1998; Skriver et al., 1999) and, to a lesser extent, for crop monitoring (Ferrazzoli et al., 1997; Skriver et al., 1999).

3. MODELING

It is well recognized that σ° of crops depends on several soil and vegetation variables. The latter may show simultaneous variations. As an example, crop growth and soil drying processes, both influencing σ°, generally occur simultaneously in springtime and early summertime. In order to correctly describe the scattering process, it is necessary to single out vegetation effects from soil effects and to distinguish among the influences of the various vegetation variables. To this aim, a model is required. A model is a relationship linking σ° to the observation parameters (i.e. frequency, incidence angle, polarization) and to N surface variables:

$$\sigma^\circ = F(f, \theta, \psi_r, \chi_r, \psi_t, \chi_t; a_1, a_2, ...a_N)$$

where f is the frequency, θ is the incidence angle ψ_r and χ_r are the rotation and ellipticity angles in reception, ψ_t and χ_t are the rotation and ellipticity angles in transmission (Ulaby & Elachi, 1990). The N variables $(a_1, a_2, ...a_N)$ include the objectives of the observation, useful for applications, as well as other variables less useful for applications but influencing σ° anyhow. The complexity of the model ranges from a simple empirical relationship, linking σ° with few general vegetation and soil variables, to complex physical models taking the canopy geometry and the complex interactions among scatterers into account.

3.1. Recent advances

A fully phase-coherent model has been proposed, including coherent interactions among single plant elements and among different plants (Stiles & Sarabandi, 2000; Stiles et al., 2000). Leaf and stem curvature effects have been also considered. The model has been tested over scatterometer data collected over a wheat canopy. It has been found that L band signatures are severely affected by coherent effects, depending on azimuth direction and radar resolution. At C band, single scatterer geometry is important. Soil direct backscatter is low.

Chauhan & Lang (1999) have modeled alfalfa canopies as conical clumps of stems that are clustered with leaflets. Coherent effects are considered within each clump. The model is able to explain some high σ° values measured over alfalfa canopies at L band.

Chiu & Sarabandi (2000) have developed a coherent model and tested it against experimental soybeans signatures, collected at L and C band. Coherent effects result to be appreciable at L band.

Cookmartin et al. (2000) have tested a second order RT model against multitemporal ERS signatures collected over wheat fields. The agreement is good in the growing season, but crop attenuation is overestimated in the drying season. Laboratory studies are in progress to investigate the problem (Brown et al., 2001)

3.2. The state of the art

A lot of models have been proposed till now to represent σ°'s of agricultural fields. Models may be classified in increasing order of complexity, as indicated below.

- The simples approach may consist in an empirical formula relating σ° to soil moisture and crop WC (or LAI) with 2 regression coefficients. The latter may be computed by fitting over a statistically significant amount of experimental data at a given frequency, angle and polarization.
- The "Water Cloud" approach (Ulaby & Attema, 1978) is physically based, in that considers soil scattering, vegetation attenuation and vegetation scattering. For each frequency, angle and polarization σ° is related to WC (or LAI) and soil moisture by 4 coefficients to be computed by statistical fitting over experimental data.
- A significant progress in physical representation is achieved using discrete RT models, representing soil as a homogeneous half-space with rough interfaces, and vegetation elements, i.e. stem, leaf, twig, ear, etc. as lossy dielectric scatterers. In general, stems, twigs, ears, etc. are represented as cylinders, while leaves are represented as circular or elliptic discs (Eom & Fung, 1984; Karam & Fung, 1988). The various scattering contributions may be combined by a simple single scattering model or by a more complex

multiple scattering model. The number of variables is higher than in the case of empirical and semiempirical models. As a minimum, the following inputs are requested: soil permittivity; soil hstd. and correlation length; permittivity of stem, ear and leaf; height and diameter of stem and ear; length, width and thickness of leaf; distribution of Eulerian angles describing leaf orientation.

- Refinements of RT models include near field interactions among scatterers (Fung et al., 1987) and/or leaf curvature (Stiles & Sarabandi, 2000). New input variables are required: the average distance among scatterers in the first case, curvature parameters (typically 3) in the second case.
- The models indicated above are based on an incoherent approach, i.e. the contributions of the different scattering sources are summed incoherently within each pixel. Of course, this is an approximation. As pointed out in Section 3.1, several works are in progress, aimed at considering coherent interactions. In coherent models the number of variables is even larger, since geometrical locations of several kinds of scatterers must be correctly characterized.

In order to be useful for remote sensing applications, models must be reliable, i.e. must save their validity under different operational and environmental contexts. From this point of view, empirical models suffer the disadvantage of depending on coefficients fitted over limited data sets. Physical models have an intrinsic more general validity. Moreover, they allow us to understand scattering processes more deeply and compute scattering effects more accurately. However, while increasing model complexity, the input variables characterization becomes more and more critical. In fact, the influence on σ° played by some variables (e.g. scatterer orientation and/or location) is smoothed by something like an averaging process in simple models, while is explicitly considered in physical models. Therefore, the latter lead to a real accuracy improvement only if the input variables characterization is accurate as well.

Model reliability is ensured by comparisons with calibrated experimental data. This leads to: "fitting" for (semi)empirical models, "validation" for physical models. In the reality, some parameters are sometimes defined as "equivalent" and "fitted" also in physical models.

In spite of the important progresses recently achieved, some discrepancies with experimental data are observed and recognized in some papers, see e.g. (Cookmartin et al., 2000; Del Frate et al., 2001). Discrepancies may be due to various reasons, as indicated below.

- Interactions among scatterers are not correctly considered by incoherent models. Coherent models may be more accurate with this respect, provided vegetation elements locations are described with high precision.
- The vegetation canopy is often subdivided into various layers. Some unavoidable arbitrary decisions are taken in this process.
- The single scatterer characterization is not yet a solved problem. Leaves are neither plane nor regularly bent. Stems are hollow cylinders. Ears are not homogeneous cylinders, but have a complex internal geometry and are partially empty. Moreover, presently used permittivity models have not received so many new validations, in the recent years.

Studies aimed at solving the above mentioned problems are recommended. Moreover, if the physical model has to be used to train a retrieval algorithm (see next Section) it could be appropriate to define some variables as equivalent and fit their values over experimental data, provided the model represents well the basic physics of the scattering process and fitting is carried out over mutifrequency and multitemporal data sets, and over various fields of the same crop type.

4. RETRIEVAL

As observed in Section 3, modeling studies are still in progress and refinements are under way. Nevertheless, what has been learned till now by experimental and modeling investigations may be used to develop preliminary retrieval algorithms. Future refinements in the direct problem will produce parallel refinements in the retrieval techniques as well.

4.1. Recent advances

Wigneron et al. (1999) have retrieved crop biomass of a soybeans field using a multitemporal set of σ° data, collected by a C band scatterometer, using a simple "cloud" model calibrated by a discrete RT model.

Prévot et al. (2001) have retrieved the temporal evolution of wheat variables using the STICS crop model in addition to RT models. An assimilation technique has been adopted. Results obtained using only optical data have been compared with the ones obtained by using both optical and SAR data.

Bouman et al. (1999) have tested a composite model including crop growth (SUCROS), water balance (SAHEL) and radar backscatter (CLOUD). ERS signatures collected at Flevoland site over potato, sugarbeet and wheat fields have been used. The paper contains information useful to develop retrieval algorithms.

4.2. State of the art

Among the several variables influencing $\sigma°$, WC and LAI are considered particularly important for applications, and studies are mainly aimed at retrieving them. A list of possible approaches to the problem is given below.

- Direct inversion of simple empirical models. This is a straightforward method. However, empirical relationships are validated over restricted data sets and do not prove to be accurate when used in different operational or environmental contexts.
- Inverting simple models after calibration by physical models. This approach shows a more general validity with respect to the previous one. However, also this procedure has been tested over limited data sets, till now. Therefore, further checks are required.
- Multi-variable inversion of physical models. As stated in Section 3, physical models represent a scattering process in which $\sigma°$ is dependent on several soil and vegetation variables. From a purely mathematical point of view, the inverse problem may be solved, provided the site is observed in several radar configurations, in such a way as to achieve a number of $\sigma°$ data at least equal to the number of unknowns. The mathematical complexity of the problem could be overcome, due to the tremendous advances recently achieved in computational systems and in retrieval techniques (e. g. neural networks). However, even limited inaccuracies of the direct model may produce severe effects.
- Using multitemporal radar data, eventually associated with optical data, and assimilation of a-priori information provided by crop models. This technique appears to be promising, although requires further work.

In the author's opinion, due to the high number of variables influencing $\sigma°$, a feasible and reliable algorithm should take the maximum benefit from: i) multitemporal observations, ii) available a-priori information. The vegetation variables are not independent from each other, but evolve following some rules, for a given crop type and crop variety. Moreover, the temporal evolution is different from field to field, but shows some common aspects which may be assumed as a-priori known.

In order to clarify these concepts, the temporal evolutions of WC measured at different sites have been compared. Ground measurements were carried out over wheat fields at Avignon (F) in 93 and 96 and at Central Plain (CH) in 88 and 89. Central Plain data have been provided by GAMMA in the framework of ERA-ORA Project, while Avignon data have been made available by INRA. The various trends are shown in Figure 8.

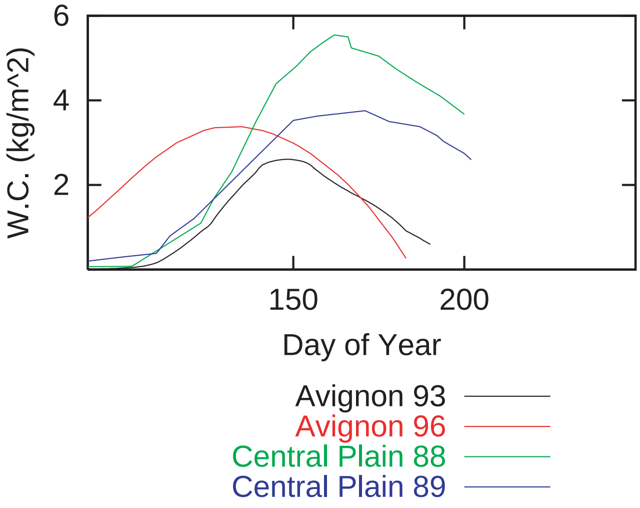

Figure 8. Examples of multitemporal WC trends of wheat fields

All trends show a typical "bell" shape, but there are large differences in maximum WC value (full growth value) as well as in temporal location and temporal duration of the cycles. By applying a simple normalization as:

$$WCn(t) = K \cdot WC(at + b)$$

(where t is the time) and optimizing the a, b and K parameters for each cycle, the trends of Figure 9 are obtained. The latter appear to be well close to each other.

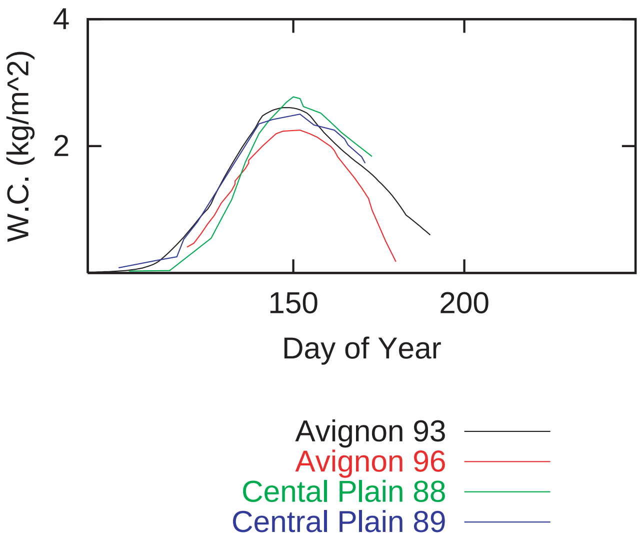

Figure 9. Multitemporal WC trends of wheat fields after normalization

Therefore, a possible retrieval technique could assume a reference "bell" function as a priori known and use remote sensing data to find the a, b and K parameters, which are specific of the observed field. This could be done using: i) a crop model and a simple model relating $\sigma°$ to WC with coefficients fitted over data collected in previous experiments, possibly over fields of the same variety and in the same environment; ii) multitemporal ground truth previously collected over fields of the same crop type and a physical model. An attempt to retrieve the cycle of a wheat field using the second approach is shown by Del Frate et al. (2001). The inaccuracy of the results is mainly due to the direct model, while the algorithm works well. Figure 2 of the same paper indicates that, for 3 fields of the same site, geometrical variables are different from field to field, but evolve following similar trends.

5. CONCLUSIONS

In the work aimed at retrieving crop variables, three main phases have been considered: i) identification of a convenient radar configuration, ii) modeling and iii) solution of the inverse problem. According with the results obtained till now, a future satellite radar system, operating at L and C band, at linear co- and cross-polarization and at an intermediate θ range ($30°$ - $40°$), should acquire most of the potential information for crop monitoring. Advances in modeling have been important, but further refinements are needed to correctly describe single scatterers and understand the importance of coherent interactions. Retrieval techniques based on multitemporal data and assimilation of crop models appear to be promising.

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REFERENCES

Bouman B.A.M., van Kraalingen D.W.G., Stol W., van Leeuwen H.J.C., 1999, "An acroecological modeling approach to explain ERS SAR radar backscatter of agricultural crops", Remote Sens. Environ., vol. 67, 137-146

Brown S.C.M., Quegan S., Bennett J.C., 2001, "High resolution measurements of scattering in wheat canopies - Implications for crop canopy retrieval", This issue

Chauhan N.S., Lang R.H., 1999, "Radar backscattering from alfalfa canopy: a clump modelling approach", Int. J. Remote Sensing, vol. 20, 2203-2220

Chiu T., Sarabandi K., 2000, "Electromagnetic scattering from short branching vegetation", IEEE Trans. Geosci. Remote Sensing, vol. 38, 911-925

Christensen E.L., Skou N., Dall J., et al., 1998, "EMISAR: an absolutely calibrated polarimetric L- and C-band SAR", IEEE Trans. Geosci. Remote Sensing, vol. 36, 1852-1865

Churchill P.N., Attema E.P.W., 1992,"The MAESTRO-1 European airborne polarimetric Synthetic Aperture Radar campaign", MAESTRO-1/AGRISCATT Final Workshop Proceedings, ESA wpp-31, 1-11

Cookmartin G., Saich P., Quegan S., et al., 2000, "Modeling microwave interactions with crops and comparison with ERS-2 SAR observations", IEEE Trans. Geosci. Remote Sensing, 658-670.

Del Frate F., Ferrazzoli F, Guerriero L., et al., 2001, "Monitoring crop cycles by SAR using a neural network trained by a model", This issue

De Roo R.D., Du Y., Ulaby F.T., et al., 2001, "A semiempirical backscattering model at L-band and C-band for a soybean canopy with soil moisture inversion", IEEE Trans. Geosci. Remote Sensing, vol. 39, 864-872

Eom H.J., Fung A.K., 1984, "A scatter model for vegetation up to Ku-band", Remote Sens. Environ., vol. 19, 139-149

Ferrazzoli P., Schiavon G., Solimini D., et al., 1997, "The potential of multifrequency polarimetric SAR in assessing agricultural and arboreous biomass", IEEE Trans. Geosci. Remote Sensing, vol. 35, pp. 5-17

Ferrazzoli P., Guerriero L., Schiavon G., 1998, "Experimental and model investigation on RADAR classification capability", IEEE Trans. Geosci. Remote Sensing, vol. 37, pp. 960-968

Freeman A., Shen Y., Werner C.L., 1990, "Polarimetric SAR calibration experiment using active radar calibrators", IEEE Trans. Geosci. Remote Sensing, vol. 28, 224-240

Fung A.K., Chen M.F., Lee K.K., 1984, "Fresnel field interaction applied to scattering from a vegetation layer", Remote Sens. Environ, vol. 23, 35-50

Held D.H., Brown W.E., Freeman A., et al., 1988, "The NASA/JPL multifrequency multipolarization airborne SAR system", IGARSS'88 Proceedings, 345-349

Hoekman D. H., 1992,"Introduction to the Agriscatt'87 and '88 campaigns", MAESTRO-1/AGRISCATT Final Workshop Proceedings, ESA wpp-31, 13-21

Karam M.A., Fung A.K., 1988, “Electromagnetic scattering from a layer of finite length, randomly oriented, dielectric, circular cylinders over a rough interface with application to vegetation”, Int. J. Remote Sens., vol. 9, 1109-1134

Le Toan T., Ribbes F., Wang L.-F., et al, 1997, “Rice crop mapping and monitoring using ERS-1 data based on experiment and modeling results”, IEEE Trans. Geosci. Remote Sensing, vol. 35, 41-56.

Macelloni G., Paloscia S., Pampaloni P., et al., 2001, “The relationship between the backscattering coefficient and the biomass of narrow and broad leaf crops”, IEEE Trans. Geosci. Remote Sensing, vol. 39, 873-884

Prévot L., Chauki H., Troufleau D., et al, 2001, “Assimilating optical and radar data into the STICS crop model for wheat”, 8th ISPRS Proceedings, 753-758.

Ribbes F., Le Toan T., 1999, “Rice field mapping and monitoring with RADARSAT data”, Int. J. Remote Sensing, vol. 20, 745-765

Rosenquist A., 1999, “Temporal and spatial characteristics of irrigated rice in JERS-1 L-band SAR data”, Int. J. Remote sensing, vol. 20, 1567-1587

Saich P., Borgeaud M., 2000, “Interpreting ERS SAR signatures of agricultural crops in Flevoland, 1993-1996”, IEEE Trans. Geosci. Remote Sensing, vol. 38, 651-657

Skriver H., Svendsen M.T., Thomsen A.G., 1999, “Multitemporal C- and L-band polarimetric signatures of crops”, IEEE Trans. Geosci. Remote Sensing, vol. 37, 2413-2429

Stiles J.M., Sarabandi K., 2000, “Electromagnetic scattering from grassland - part I: a fully phase-coherent scattering model”, IEEE Trans. Geosci. Remote Sensing, vol. 38, 339-348

Stiles J.M., Sarabandi K., Ulaby F.T., 2000, “Electromagnetic scattering from grassland - part II: measurement and modeling results”, IEEE Trans. Geosci. Remote Sensing, vol. 38, 349-356

Stofan E.R., Evans D.L., Schmullius C., et al., 1995, “Overview of results of spaceborne imaging radar-C, X-band Synthetic Aperture Radar (SIR-c/X-SAR)”, IEEE Trans. Geosci. Remote Sensing, vol. 33, 817-828

Ulaby F.T., Attema E.P.W., 1978, “Vegetation modeled as a water cloud”, Radio Science, vol. 13, 357-364

Ulaby F.T., 1980, “Vegetation clutter model”, IEEE Trans. Antennas Propagat., vol. 28, 538-545

Ulaby F.T., Moore R.K., Fung A.K., 1986, Microwave Remote Sensing. Active and Passive. Vol III, Artech House

Ulaby F.T., Dobson M.C., 1989, Handbook of Radar Scattering Statistics from Terrain, Artech House

Ulaby F.T., Elachi C., eds., 1990, Radar Polarimetry for Geoscience Applications, Artech House

van Zyl J.J., 1990, “Calibration of polarimetric radar images using only image parameters and trihedral corner reflectors responses”, IEEE Trans. Geosci. Remote Sensing, vol. 28, 337-347

Wegmüller U., 1993, “Signature research for crop classification by active and passive microwaves”, Int. J. Remote Sensing, vol. 14, 871-883.

Wegmüller U., Werner C., 1997, “Retrieval of vegetation parameters with SAR interferometry”, IEEE Trans. Geosci. Remote Sensing, vol. 35, 18-24

Wigneron J.-P., Ferrazzoli P., Olioso A., et al., 1999, “A simple approach to monitor crop biomass from C-band radar data”, Remote Sensing Environ., vol. 69, 179-188.

Zebker H., Lou Y., 1990, “Phase calibration of imaging radar polarimeter Stokes matrices”, IEEE Trans. Geosci. Remote Sensing, vol. 28, 246-252