

Microwave remote sensing applied to vegetation

Proceedings of an EARSeL Workshop organised by Working Group 4 and held at NLR, Amsterdam, The Netherlands on 10–12 December 1984



GEN107



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INTRODUCTION

J.W. Trevett

HUNTING TECHNICAL SERVICES LIMITED Chairman EARSeL Working Group 4

The Working Group had, over the past four years, been totally committed to the European SAR-580 Campaign. All of the members had been involved in various aspects of research on these data and the workshops connected with that campaign had been seen as workshops of the Working Group.

In a similar manner the reports of the campaign were regarded as reports of the Working Group also, since the reports were contributions by the members. At the same time the group has held other meetings, and produced reports that have also been issued as ESA publications.

With the completion of the SAR-580 Campaign it was necessary for the Working Group to reconsider its future activities. In order to do this it was thought advisable to take stock of the current researches related to microwave technology and vegetation in order to better evaluate the future actions that should be taken.

It was against this background that this workshop was convened and took place in Amsterdam.

The workshop was considered most successful, there was attendance of up to forty members overall, with a very high standard of presentation as can be evidenced by this final report. More important perhaps was the considerable discussions that took place both during the meeting and in the social events.

The workshop was particularly fortunate in obtaining the attendance of Dr C. Elachi from the Jet Propulsion Laboratory in Pasadena, his final major keynote address, coming as it did so soon after the flight of SIR-B, was greatly appreciated by all who attended.

The workshop was also fortunate in having Dr Cihlar attending from Canada. Canada are members of EARSeL so this was seen as a positive example of involvement as well as presenting a valuable insight into Canadian activities.

The workshop ended with a discussion meeting of the Working Group. This meeting was attended by Dr J. Bodechtel who as EARSeL Chairman was able to present members with the changing and improved role of EARSeL and the expectations for the future

Following from these new objectives of EARSeL and arising out of the papers and discussion presented at the workshop, the Working Group drew up the following policy

points setting out the future activities and objectives of the group. These objectives were discussed at length and unanimously agreed by all present.

This Working Group Makes the Following Proposals

 That the next long term objective of the group is the successful use of the ERS series for land applications. Firstly the use of data from ERS 1 and associated research and experiments. Secondly ERS 2. And thirdly the possible ERS 3 with its concentration on

land applications. To this end the group should become the coordinating body within EARSeL and linked to ESA for research and planning projects connected with land use and vegetation

Studies.
 That in connection with 1 above this group should cooperate with the Working Group on microwaves and geology which should play a comparable role.

- 3. It is considered that for a successful ERS campaign that there is a fundamental need for more real SAR data from airborne campaigns preferably C-band and with multitemporal, multi-look capability.
- 4. This Working Group should seek to identify a group of representative test sites for future campaigns and should set up a method of cooperative studies for these test sites including interchange of data.
- 5. That recognising the need for some standard methods of data collection and mindful of the problems previously encountered, this group never the less believes the objective to be worthy of consideration and as a first step constituent laboratories be asked to outline their own methods and these replies to be compiled into a reference and discussion document.
- 6. That further meetings and workshops are desirable and the next workshop is proposed for Freiburg in October 1985 with a principal objective to include a one day field trip in the Freiburg test area. To make a comparative on-the-spot study of SAR-580 1 and 2 data, SIR-B data and field conditions and methods used.
- 7. That regular meetings of the group are essential to meet

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these objectives and that the Council of Ministers should be requested to approve funding to ensure that such meetings can take place.

Unless such funding is available it will be difficult to meet these objectives.

Acknowledgements

The Working Group would like to record their thanks for the considerable help, the use of premises and the provision of facilities given so generously by the Netherlands National Aerospace Laboratory. Thanks also go to the local committee who undertook so much of the local arrangements particularly Pieter Binnenkade who took on the brunt of this local work.

The contributions of ESA in preparing the announcements, the programme, the book of abstracts, this final report and the services of their editor Mr Burke is also gratefully acknowledged.

From the chairman's viewpoint the main thanks is to all those who supported the workshop by attending and by presenting papers. The attendance and the level of interest clearly shows that there is a need and willingness for cooperation in microwave research for vegetation studies in Europe. AGRICULTURAL INTEREST IN REMOTE SENSING

Th.A. de Boer

Member of the RS-board in the Netherlands for the Min. of Agriculture and Fishery

INTRODUCTION

It is an honour to me to give this address as a representative of the Ministry of Agriculture and Fishery in the Remote Sensing Board in the Netherlands (BCRS).

First, I like to give some general ideas about the importance of information gathering.

To manage agriculture in a socio-political and technical sense as a national activity, a lot of information is necessary. The same applies and even more so to agriculture in an international scope, like in the European Common Market.

One has only to look at the importance of statistics in the political struggle between industry, agriculture and the environment.

Many national and European measures are based on studies of statistical information. I agree that statistics in itself are not sufficient to take measures. We also have to know the processes behind the statistical data and the impact on the society as a whole, of the measures taken.

So one can state that statistical patterns are a result of processes. This is a rule we can also apply to ecological and soil patterns.

It means that people with scientific disciplines needed for the above-mentioned subjects can give an interpretation of the processes by studying the patterns.

If we agree with the above-stated argument, we cannot deny that remote sensing techniques, besides the already existing techniques of data gathering, are of importance.

Still, this does not mean that administrators (for example in the Dutch Ministry of Agriculture and Fishery) are convinced of the need of remote sensing. Some of them argue that the information collection system at this moment is good. But sometimes when, because of unfavourable weather conditions, such as too high rainfall, drought and of a negative impact on the environment of agricultural activities, there is an interest in remote sensing. The same applies to RS as a monitoring instrument to control the execution of legal obligations in agriculture (crop rotation) and landscape protection.

As remote sensing community we had to find arguments for the adminstrators and politicians,

why remote sensing techniques are sometimes better in quality, speed or cost-benefit. We also have to realize that at this moment most of the techniques are still at a research and developing stage. Remote sensing systems that give data with sufficient frequency in time, connected with a high speed data handling system and automatically working up to the information ready for specific application, are not yet existing.

I am convinced that those systems can be produced in the future. But even then it will be difficult to convince the administrators in countries with existing dense information situations. An exception could be common markets and other international interests, where the classical systems of agricultural data collection work too slow for adequate measures.

I see a faster introduction into developing countries with a low information level and a geographically poor infrastructure. Already to day we see application of satellite information of various windows for pattern information use in plan developing projects. I am thinking of large scale soil and vegetation (grassland, crops and forests) maps, water resources inventory for irrigation and so on. It is also used in planning roads and habours, which is of interest in developing agricultural activities.

RADAR AND AGRICULTURE

For a long time aerial photographs have already been used as a technique for field inventories as a tool in agricultural development plans and for monitoring purposes.

This means that the importance of remote sensing techniques was already recognized in the world of agricultural research and administration. So when I, as an agriculturist, first came into contact with a physicist specialized in radar techniques, I understood that this could be an important remote sensing technique for agriculture. But I also understood that the only possible way to research and develop this radar technique for remote sensing application, was and is to work in an interdisciplinary group. The physicist, Paul de Loor, was of the same opinion and so the first step was taken towards the Dutch ROVE-team. The meaning of the first letters in English is Radar Observation of Vegetation.

The Dutch researchers who will present their papers in this Earsal Workshop have done their research in

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the framework of ROVE.

We learn from each other continuously in the interdisciplinary project teams, which are arranged around the subjects soil, crop classification, forest, modeling, etc.

The interest of agricultural research in radar as a remote sensing technique is based on the different properties of microwaves.

Among others, I mention the possibility of producing information under a wide range of atmospheric conditions by day and by night. This is an important possibility, because agriculturists are interested in dynamic processes, such as the growth of crops, the development of diseases, the course of water availability in the soil. etc.

This means that the time solution of the used remote sensing technique is very important. In many parts of the world the atmospheric conditions are such that in other remote sensing windows the frequency of information is insufficient to study processes in agriculture. Up to now, this is worse still with satellite remote sensing.

For some large scale vegetations, such as savannah's in semi-arid regions the geo-stationary weather satellites give a defective possibility. The time frequency is very high, but the space resolution very low and mostly too low. However, in the last years information about the biomass increase during the growing season for cattle management problems has been gathered with these satellites in the visible red and near infrared bands.

Another interesting property of radar is the wide areas that can be imaged simultaneously from planes. If the sensor is carried in a spacecraft the swath-wide advantage is lost.

A third value of radar is that polarization of the illumination may be controlled and at the same time also the illumination angle.

With longer wavelengths, in theory, vegetation covers (even in forests?) may be penetrated. Until now, we do not have enough facts about this phenomenon and about the interaction between the type of vegetation cover and radar backscatter in relation to the soil backscatter.

In the thermal infrared window, of course with the drawbacks of sensitivity to atmospheric conditions, we can already estimate the water availability to crops.

A very hopeful result with longer wavelengths was shown by the SIRA mission. In the desert in Egypt an old alluvial system of the Nile underneath meters of sand was imaged. With geological knowledge, estimation of the place of ground water sources were possible in this arid region. However, first more systematic research has to be done on those longer wavelengths, before something can be said about the application possibilities for monitoring of water availability to crops.

With the results from the ground-based pulseradar experiments and SLAR flights based on these experiments, we obtained for the short wavelengths insight into some possibilities concerning information gathering for agriculture.

With two flights at selected moments of the growing season most of the crops in the Netherlands can be recognized for 80-100%. Estimation of crop type areas is important to market planning. However, more information about the crops is needed to make a yield forcast per crop. In the first place the increase in area of leaf per ground area (leaf area index) during the growing season. This, together with weather characteristics with a growth simulation model, gives an assessment of the yield. Information is also needed about the health situation, if not connected to the leaf area index.

The relation of radar backscatter and leaf area index in the studied short wavelengths is not clear until now. The impression is that the influence on the backscatter rate stops already at low values of this index. Influences of the wind velocity and direction on the backscatter also disturb this relation.

Important features of the bare soil during and after sowing are the water content of the topsoil and the roughness. Soils with a special texture are slicked after rainfall. This means a poor condition for sowing, germination and emergence of the germ plant. Information about these soil features is important to get insight in the starting period of crops.

Radar backscatter can give this information, but there are many interactions between the features on the backscatter. By using different illumination angles and polarization it seems possible to get information about the features. But until now, no procedure for application is ready.

Very important is a good callibration of the system, so that a comparison can be made of the amount of backscatter at different moments. Otherwise training samples on the ground are needed each time in the sequence, and so we are in the same situation as with the so-called passive techniques.

With visual interpretation of radar images we also use the texture in the image areas with an average difference in density, so that we can distinguish coniferous and deciduous forests and sometimes crop types. In automatic classification this image texture phenomenon should also be studied. Undoubtedly, the roughness differences of the forest parcels (crown shape) and the crop fields are involved.

CONCLUSION

My conclusion is that radar is a promising technique for information gathering from crops and vegetations important to the management of agriculture.

However, more insight is needed into the backscatter mechanism with the objects and the interaction of different features of the objects. Especially, more knowledge is needed about the longer wavelengths in relation to the mentioned mechanism. The image texture also has to be worked out for application.

For some plant physiological features, such as leaf colour and leaf temperature other electro-magnetic windows are needed. The same applies when higher spacial resolution is necessary.

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KEYNOTE PAPER



MICROWAVE REMOTE SENSING AND VEGETATION; PROBLEMS, PROGRESS AND SOLUTIONS, A REVIEW.

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ABSTRACT

Traditionally radar is used as an instrument for position and/or velocity measurements. These measurements can be performed in a rather straightforward way since there exists a direct physical relationship between the unknown quantities and the measured ones. In radar-based remote sensing however the object information is contained in the radarsignal in a rather complex way.

As for as the approach to this problem is concerned the remote sensing community seems to be divided in two groups. The first group considers the microwave region as just another window to be used in combination with the ones already existing in other wavelength regions. The second part of the community on the contrary is trying to solve the problem by fundamental investigations in the interaction between microwaves and remote sensing objects.

Although both view points are quite understandable it should be recognized that each one has its own limitations. Therefore we can not expect that each approach by itself will lead to operational remote sensing applications. The answer is to be found by combining both approaches.

1. INTRODUCTION

Agriculture and forestry are areas of great economic inportance both within the European Community and throughout the world. Therefore an everlasting effort exists to develop tools that can support activities in these fields. It therefore seems logical that since quite a long time people have pursued the use of remote sensing in this respect. It is clear that the era of space technology offers greater possibilities in this respect then there have ever been before.

A common aspect of all remote sensing systems is that they depend on the use of electromagnetic waves to cover the distance between the sensor and the object to be observed. Consequently, in microwave remote sensing, the physical and/or biological quantities have to be extracted from the electromagnetic wave parameters.

Traditionally radar is used as an instrument for position and/or velocity measurements. These

measurements can be performed in a rather straightforward way: position follows from time delay and antenna resolution whereas velocity is found by measuring Doppler shift. The unknown quantities are related to the measured ones by elementary physical relationships, no complicated transformations are necessary.

The application of radar in remote sensing however presents a completely different situation since in this case the radar signal is the combined result of spectral, structural and material influences. Therefore the way in which the object information is contained in the radar signal **is** of a rather complex nature. Measurements of this type are often called "indirect" in contradistinction to those characterized by a "direct" relation between the quantity to be measured and the signal.

As will be 'explained in section 2 indirect measurements ask for the solution of a complicated calibration problem. Calibration is not only a technological problem but it also demonstrates a need to develop suitable models that can describe the interaction between the electromagnetic waves and the objects.

The radar technological aspects such as linearity and stability are beyond the scope of this review. The interaction modelling however will be discussed quite extensively in section 2. Models can be developed in several ways. Our choice here is in favour of the semi-empirical models i.e. models based on simplified descriptions of the phenomena supplemented by physical parameters which are determined experimentally.

In general the physical parameters, necessary for the development of the interaction models, are measured by means of groundbased or airborne scatterometers [Refs 1,2]. At the same time however these small scale remote sensing measurements can be seen as the origin of new stimuli to bring remote sensing into an operational state. In section 3 several examples of such measurements including their consequences will be given.

Calibration will raise the technological standards in radar. At the same time however new possibilties are created. As an example we mention the possibility to provide radar systems with a memory function.

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For conventional radars such a memory function could imply that the traject ory of a target can be extracted from successive position measurements. In relation to remote sensing, as we will see, it is useful to interpret the trajectory as the description of a proces: change of position

2. MODELLING ASPECTS

As was pointed out already in the introduction the scattered or reflected radar signal has to be considered as a multivariable function, say $S(\xi_1, \xi_2, \ldots, \xi_n)$. Although one may feel inclined to consider the complete knowledge of the function S as a main objective such knowledge will not be of great help in solving the measuring problem of remote sensing. For this the inverted relations would have to be known and such inversions can only be performed for one variable at a time.

The theoretical quantification of the influence of the different parameters of biological objects on the radar signal turns out to be extremely difficult. One of the major complications is that some of the variables are described by measures that are only meaningful in a statistical sense.

A rigorous theoretical description being impossible in general a semi-empirical approach is followed instead. This type of approach is based on simplified description of the interaction between microwaves and targets. Then, as a next step, the relations arrived at in this way are verified and calibrated by experiments.

In order to proceed with this approach consider S to be a function of one variable only supposing that the remaining set of variables can be kept constant. Under these assumptions the function $S(\xi)$, after calibration, is easily inverted to find $\xi(S)$.

In most cases however there will exist additional (unknown)relations between ξ and some other variable. Examples are that biomass can be related to plant structure and soil moisture can be dependent on vegetation cover. Such relations mean that the assumed conditions do not hold and consequently the calibration of S against ξ will depend on e.g. crop type.

For this reason the calibration problem is subdivided into two parts. As a first step we calibrate the power relations by means of technically well defined objects. To this end passive point targets such as corner reflectors [ref. 3] or distributed targets like the Death Valley in California

[ref. 4] can be used. Also proposals for, so-called, active calibration have been considered [ref. 5]. Having performed the power calibration in this way suitable interaction models have to be introduced to link the actual objects to the targets used for calibration and to the relate the radar signal to the quantity to be measured.

One of the basic assumptions in modelling is that the radar return of a resolution cell can be replaced by that of a collection of N scatterers. Within this concept it is conceivable that each scatterer is a representation of a number of neighbouring surface elements, that in a given direction add more or less coherently; the remaining surface area becomes non-reflecting. Since a coherent addition means that the phase distribution is narrow and the one-dimensional phase shift being inversely proportional to λ , the surface covered by one single scatterer is, at least in the quasi-optics approximation, proportional to λ^2 . In connection with the statistical averaging, to be introduced later, it is important that N is sufficiently large. This requires that the resolution cell dimensions increase with λ .

The approach described here results in a discrete distribution of scatterers. In general the density of scatterers will not be uniform since their distribution is determined by the surface characteristics.

With the kth scatterer giving rise to a contribution U_k=u exp ($j\phi_k$) at the receiver, the total voltage U^k for N scatterers will become:

$$U = \sum_{k=1}^{N} u_{k} \exp(j\phi_{k})$$
(1)

For the sake of simplicity we will take all u_k independent of look angle (isotropic scattering) and equal to one.



Fig. 1: Resolution cell to be considered

The configuration to be considered is presented in figure 1. The resolution cell is supposed to be a square whereas the scatterers are positioned in a regular grid. In a vertical plane through a row of scatterers we find φ_k to be composed of two terms (back scattering situation)

$$\phi_{k} = -\frac{4\pi}{\lambda} \{ kp \sin \theta - h_{k} \cos \theta \}$$
(2)

The first term (figure 2^{a}) represents the phase shift along the resolution cell, the second term (figure 2^{b}) gives the phase difference of the scatterer with height h_{k} with respect to that of a scatterer with zero height.

The total received power can be written as

$$UU* = \sum_{l}^{N} \exp (j\phi_{k}) \sum_{l}^{N} \exp (-j\phi_{l})$$
(3)

It is instructive to start with a calculation of received power for the simple limiting case where all heights are equal to zero:







In fig. 3^a as an example $F(\theta)$ is given for a square of 10 λ x 10 λ with 625 scatterers. With the number of scatterers in combination with area of the resolution cell the distances between the scatterers are too small for the scatterers to behave independently. The resulting coupling effects have been taken into account by applying the energy conservation theorem [ref.6]. In fig. 3^D we have the same resolution cell and the same N but the scatterers have heights h_{k} (eq.2) taken randomly from the Gaussian distribution

$$p(h/\lambda) = \frac{1}{\sigma\sqrt{2\pi}} \exp\{-h/\lambda\}^2 / 2\sigma^2\}$$
(5)

with $\sigma = \sqrt{\langle (h/\lambda)^2 \rangle} = 0,3$. The characteristic difference between fig. 3^a and 3^b is that, as a result of the introduction of random heights, the main lobe (θ =0) becomes much smaller where as, outside the main lobe, the regular interference pattern is replaced by a random amplitude structure.

Obviously the calculation of UU* will give a different answer for each resolution cell since each cell will have its own collection of heights.





Fig. 3: a)Coherent scattering of a square 10 λ x 10 λ with 625 scatterers, b)same resolution cell but scatterers have random heights (Gaussian distribution with σ = 0,3).

Therefore, it only makes sense to consider the ensemble average $\langle UU^* \rangle$. Although not impossible it is rather time consuming to arrive at a reasonable estimate for $\langle UU^* \rangle$ averaging the results for a large enough number of realizations based on different series of height samples. It has been demonstrated before that it is advantageous to introduce statistics in a different way resulting in {Refs. 7,8]

 $< UU^* > = F(\theta) \exp(-s^2) + 2\{1 - \exp(-s^2)\}$ (6)

where the distribution given by eq. (5) is used, $s{=}4\pi\sigma$ cos θ and $F(\theta)$ corresponds to eq. (4).

From eq. (6) it is concluded that \leq UU*> consists of two terms, the ratio of which is determined by the parameter S. The first term of the right handside of eq. (6) is the coherent term that, with s=o, corresponds with eq. (4). The second term is the one that remains for large σ -values. This term corresponds with the, so-called, incoherent addition of the scattered contributions. Note the cross-over point at $\theta=\theta$ where \leq UU*> is independent of surface roughness. The corresponding incidence angle follows from the equation F(θ) = 2. With large enough σ only the incoherent term remains and

$$< UU* > = < \sum_{1}^{N} u_{k}^{2} > = N < u_{k}^{2} >$$

Consequently the radar cross section rcs of the resolution cell under consideration in formed by the sum of the radar cross sections of the N scatterers. From a physical point of view the rcs with number k is expected to depend on the size a_k of the area

which it is representing. Therefore we write

$$\operatorname{rcs} = \sum_{1}^{N} < \frac{(\operatorname{rcs})k}{a_{k}} > a_{k}$$
$$= \sigma^{\circ} \qquad \sum_{1}^{N} a_{k}$$

where σ° is called the differential radar cross section or the radar cross section per unit area. Often, instead of σ° , the scattering coefficient $\gamma = \sigma^{\circ}/\cos\theta$ is used. The model described by eq.(6) was used quite successfully to fit bare soil measurements [8], as demonstrated in fig. 4.



Fig. 4: The complete model for bare soil scattering, the dotted points represent a series of measurements.

A second example of the semi-empirical approach that was proved to be very useful is the so-called, cloud model. In the cloud model, as it is formulated by Attema and Ulaby [Ref.9], soil moisture and plant moisture per unit area are the dominant object parameters. The underlying ideas are that the microwave dielectric constant of dry vegetative matter is much smaller than the dielectric constant of water; a vegetation canopy is usually composed of more than 99% air by volume. Therefore, the canopy can be modelled as a water cloud, the droplets of which are held in place by the vegetative matter. As a first step, it is assumed that this cloud consists of small spherical droplets with the same radius and with a uniform random spatial distribution (fig. 5).



Fig. 5: Cloud model geometry.

The radarbackscattering properties of such a low density cloud can be calculated by using the radar equation for distributed targets. After a few derivations and the introduction of the usual approximations finally we may write the scattering coefficient as:

$$\gamma_{\text{veg}} = \frac{\text{rcs}}{2Q} \left\{ 1 - \exp\left(-\frac{2NQh}{\sin\theta}\right) \right\}$$
(7)

where

rcs	is	the	radar cross section of one droplet
Q	is	the	so-called attenuation cross section
	of	one	droplet
N	is	the	number of the droplets per unit vol-

 ${\tt N}$ is the number of the droplets per unit volume h, θ are as indicated in figure 5

It is convenient to simplify this formulation a bit further. Since all water particles are assumed to be identical in shape and size we may replace the ratio rcs/2Q by a parameter C. If we define W as the watercontent of the cloud per unit volume (kg/\dot{m}^3) , N is proportional to W and therefore 2NQ can be replaced by DW, where D is the second modelparameter. Eq.(7) becomes:

$$Y veg = C \left[1 - \exp(-DWh/\sin\theta) \right]$$
(8)

In eq.(8) there is one single crop parameter Wh representing the amount of water per unit surface. This quantity Wh is equal to the biomass per unit area times the volumetric moisture content of the plant. Since the equivalent dropsize is unknown the model parameters C and D must be determined for each crop by non-linear regression analysis.

Because the vegetation layer is partially transparent for microwave radiation the return from the underlying soil myst be taken into account. Assuming that the soilscattering adds incoherently to the vegetation scattering γ can simply be added to γ , taking into account the attenuation by the vegetation layer. In this way we arrive at the cloudmodel equation

$$\gamma_{\text{veg}} = C \left[1 - \exp\left(-\frac{DWh}{\sin\theta}\right) \right] + \gamma_{\text{soil}} \exp\left(-\frac{DWh}{\sin\theta}\right)$$
(9)

For the radar backscattering coefficient $\gamma_{\mbox{soil}}$ we may use eq(6).

In the development of the model described by (eq.9), using radar backscattering measurements of 8 different crops, at X-band throughout the growing season, it turned out that the attenuation parameter D is rather insensitive to the incidence angle. For crops with relatively large leaves (sugarbeets, potatoes and peas) the scattering parameter C is angle dependent.

The analysis showed further that the appearance of so-called ears in the cereals has a dramatic effect on the geometry and consequently on γ . After this stage of growth the assumption of vegetation homogeneity does not apply any longer and the model must be extended to a two-layer model with separate values for C and D, (Hoekman et al.[Ref 10]) Recently it was suggested to improve the cloud model further by the introduction of 'polarization dependence (Allen et al. [Ref.11])

3. EXPERIMENTAL ASPECTS

The modelling work just described can only exist when it is supported by measurement programs. Such measurement programs consist of two parts: the scatterometer measurements and the physical or biological measurements. Especially the development of models for the radar scattering of forests suffers from a lack of suitable measurement data. This seems the more important since the knowledge obtained by the work on other vegetation types cannot be extrapolated in the direction of forests. The main reason for this is that the majority of agricultural crops have a life cycle of one or two years where trees can reach ages of hundreds of years.

Apart from supporting the modelling work scatterometry can also help, in a practical way, to bring microwave remote sensing in the operational state. Interaction models are describing physical laws and call for(measured) parameter values in an actual situation at a given point of time. For the study of operational applications however information over large area's and time periods will be required.

The way in which scatterometry can be useful in this respect is illustrated by the well-known simulations of crop classification by using radar imagery [Ref.12]. The set-up for this investigation can be outlined as follows: First a set of SLR-images is simulated numerically using scatterometer data collected earlier. The data covers the same region but is taken at different times. Next this image is offered to a classifier which has been trained using the same statistics as used for simulating the data.

Having selected a target region, a description of the radar scattering of the relevant crop-types will be needed. Such a description can be composed of a deterministic and a stochastic part. One of the more important results of this study was that classification results are improved by the introduction of multi-temporal analysis. Consequently the radar system has to be a calibrated one in order to make classification successful. Further down other examples of scatterometer data use will be given

Speaking in general terms the practical approach starts from the idea that each extra observation will add some information and in this way will help to meet the remote sensing objectives. Such a statement however can only be maintained when the extra-observation can be considered as statistically or physically independent. Before an appropriate choice can be made we therefore have to consider the potentialities very carefully.

Since the use of electromagnetic waves is a common factor in all remote sensing systems any observed radiation originating from the surface of the earth will have to do with at least one of the characteristic wave parameters frequency (or the equivalent wavelength), phase angle, polarization or look angle. The first aspect is probably the most actual one and therefore will be discussed below in some detail. Whereas polarization and phase angle are random variables in the optical regions they are well defined for microwaves. Since the phase information is used already in synthetic aperture radars to improve resolution only the use of polarization remains, its potentialities will be reviewed later on. Although there seems to be a lot of information in the way radar scattering depends on the look angle it is not realistic to assume that in the near future this look angle can be scanned over on appreciable interval.

The existing experience is that, at given incidence angle, the scattered energy will depend on wavelength (colour). In this context the concept "spectral signature" is used to describe, in the frequency domain, a pattern of features whose shapes, locations and relative intensities are uniquely characterizing a particular material or object. Up to the present each wavelength window is considered to have its own signature. There seems however to exist a growing interest to combine the different windows in order to improve remote sensing results. Such combinations however can only be successful if the information gathered in the different windows is complementary.

Basically the spectral signature is the result of the interaction between waves and objects. This interaction can take place on two levels: the material and the structural interaction levels. Material interaction means that some energy of the incident wave is absorbed by the object material. This absorption can be either of a resonant or a continuous nature. Fine examples of the first category are shown by minerals in the infrared region [ref. 13]. From the electromagnetic point of view absorbing materials can be characterized by a complex dielectric constant $\varepsilon = \varepsilon' - i\varepsilon''$. Structural interaction effects are divided in frequency regions which have to do with dimensional scales relative to wavelength. We distinguish three different regions: the Rayleigh region where the scale length is small compared to wavelength, the Mie region where the scale is comparable with wavelength and finally the optical region where the dimensional scale is large with respect to wavelength. The structural effects of course are superimposed on the material ones.

With reference to the cloud model mentioned in the previous section it may be interesting to use the signature of a water drop for illustration. As a first order approximation a water drop can be considered as a small dielectric sphere. The scattering by such spheres was studied by Mie as early as 1908, a summary of his theory is given by Kerr [Ref.14].

The scattering cross section $Q_{\rm S}$ (which is equivalent to the radar cross section when scattering is isotropic) of a small sphere of diameter 2a at a wavelength λ , long enough for the Rayleigh approximation to be valid, is found to follow from:

$$p_{s}/(\pi a^{2}) = 2c_{3}\rho^{4}$$

where $\rho=2\pi a/\lambda$ and c₃ is a rather complicated function of only ε' and ε'' . In fig. 6 Q is presented, normalized to the geometric cross section of the sphere as a function of ρ for a water sphere with a temperature of 20⁰ C (ε' and ε'' are temperature dependent).

Where the Rayleigh approximation shows a λ^{-4} dependence for Q_s, the Mie region is characterized by an oscillating pattern caused by interference and diffraction phenomena. The amplitude of this oscillation is decreasing gradually towards the optical region. Complex targets like vegetation canopies cannot be described by one dimension only.



Fig. 6: Scattering cross section of a spherical water drop at 20° C as a function of $\rho=2\pi a/\lambda$ where 2a is the diameter of the sphere.

In fact such targets have to be characterized by a statistically distributed range of dimensions. Unfortunately most dimensions are likely to be of the same order as the wavelengths in the microwave region i.e. 1-30 cm which means that the complicated Mie interaction is dominant.



Fig. 7: Growing curves for oats at 10 and 35 GHz, measured at 30° incidence angle.

In fig.7 a set of two growing curves for oats is presented. These curves are the result of groundbased measurements at 10 and 35 GHz. Two such samples however are not sufficient to derive the spectral signature for oats and the same will hold for other crop types. Since these signatures in fact are quite essential in selecting optimum frequencies for multiband systems more measurements have to be made and the development of interaction models, incorporating the wavelength dependence, has to be pursued. As long as such supporting knowledge is not available the best approach seems to be to make the frequency separation as large as possible. The aspect that remains to be discussed is the influence of polarization on scattering. Obviously polarization effects have to do with structure: A structure that is conducting in the direction of the electric field component of the wave will have an intenser interaction than a conducting structure perpendicular to the electric field. Combinations of polarization are named after the electric field orientation for transmitted and received waves: V(ertical) or H(orizonta). Basically there are three possible combinations VV, HH and VH (or HV). The last two combinations will not be attainable in the near future since the level of the so-called cross polar component is 10 - 20 dB lower than the direct components which would require an equivalent increase of transmitted power.



Fig. 8: Growing curves for oats and sugarbeets at 10 GHz, incidence angle 30⁰ and two polarization states VV and HH.

Fig. 8 shows two examples of the influence of polarization on growing curves, measured at 10 GHz. Sugarbeets practically do not show any difference between both polarization states. This means that there exists, at least on the average, no preferential conductivity direction. This conclusion is conformable to the structure and orientation of the large (with respect to wavelength) leaves. Oats is a crop type with stems and the scattered power is larger for vertical than for horizontal polarization.

In addition to multiband or multipolarization applications there are other options to be considered during the next few years. One example in the agricultural field may illustrate this.

The memory function of the radar that becomes available after calibration of the system offers the possibility for a meaningful comparison between measurements of different years and over large area's eg. on a European or even on a worldwide scale; in this respect radar is unparallelled. Up to now biomass is considered to be a key factor in yield prediction. High repeatability, in combination with the memory function can offer an alternative by monitoring the grey tone development as a function of time. Yield can be predicted by averaging the grey tone over a large area and by comparing the result with corresponding curves of other years of wich the yield is known.

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SESSION A



THE STRUCTURE OF PLANTS AND THE BIOMASS RELATED TO MICROWAVE STUDIES

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One of the most important objectives of the research on remote sensing of vegetation canopies is to be able to estimate vegetation growth stage and the stress level.

Toward the goal of estimating parameters related to vegetation biomass and structure, considered as indicators of the vegetation growth condition, studies have been carried out in the past few years in the area of microwave remote sensing.

This paper will present the state_of_the_art concerning agricultural crops. Results obtained from systematic scatterometer experiments and from SAR data interpretation will be summarized.

It will be pointed out that the arrangement of plants and their components in space effects the relative contribution of plant elements, the angular variation and the polarisation dependence of the radar responses.

Relationships between radar backscatter coefficient σ° and some plant parameters (LAI, water content...) will be discussed.

Finally, the conclusions will show the need for further investigations both in conducting experiments and developing models in view of the diversity of vegetation and environmental conditions. 1 ×

ACTIVE MICROWAVE MAPPING OF VEGETATION

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ABSTRACT

A comparison is made between the use of per pixel and per field sampling methodologies for land cover mapping. As a result of the changing viewing geometry land cover map accuracy was found to be low and spatially variable. In an area of flat terrain land cover map accuracy could be increased by making allowance for the variations in viewing geometry. This was achieved by dividing the image into sectors defined by range distance and treating each sector independently. In this study, using SAR 580 data, it was found that the use of tonal and textural information collected on a per field basis for a sectored image gave the highest land cover map accuracy. However, land cover map accuracy was still spatially variable.

Keywords: Sectoring, per field, texture, per pixel.

1. INTRODUCTION

To accurately map vegetation with remotely sensed data it is necessary for the spectral responses of the vegetation classes to be separable from each other and from non-vegetated scene components. However, the spectral response of a cover type is usually a function of the viewing geometry (Refs 1, 2). Since the relationship between the spectral response and viewing geometry is different for each cover type class separability will vary with viewing geometry, which for SAR can be represented by the incidence angle (Figure 1). For flat terrain, which is assumed throughout, class separability will therefore vary with the range distance.

This spatial variation of separability has several implications. (1) Two cover types separable at one viewing geometry (θ) may be inseparable at another, for instance the industrial and commercial classes (Figure 1). (2) Two classes separable across the whole range of viewing geometries can still be confused. This can orcur with the heavy vegetation and arid desert sand classes. If viewed at the same or similar geometry the two are clearly separable. However, the spectral response from these cover types will be within a broad range of back-scatter and so image grey levels (DN). As indicated



Figure 1. Variations in the backscattering coefficient with incidence angle for several terrain classes at 9.375 GH₂. A and B represent the ranges of σ° covered by the arid desert sand and heavy vegetation classes respectively. (Modified from Ref 1's adaption from Ref 3).

on Figure 1 these overlap for the two classes and so would be misclassified unless the effect of the viewing geometry is accounted for. Thus a backscattering coefficient of -15 dB could be either the arid desert sand measured at around 30° incidence angle or vegetation at 70° incidence angle. (3) From the two factors already discussed the location of the training sites for a supervised classification will affect the overall inter-class separability. Locating training sites within a narrow range of geometries will not provide a high degree of overall separability because the spectral response of the targets will change with the

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viewing geometry. Distributing the training sites across the entire range of geometries will also be inappropriate because of (2) above.

For SAR 580 data further complexity is added through the effects of the antenna pattern and gain. For flat terrain both are related to the incidence angle and so can be considered as part of the viewing geometry effect, the overall effect of which is to introduce a systematic spatial variation in image tone (respresented here by DN) across the swath (Figure 2).



Figure 2. X band HH SAR 580 image of part of the test area illustrating the tonal variation across swath. (Near range at the top).

This must be allowed for before a classification is attempted. The aim of this paper is to investigate what effect the spatial dependency of DN has on land cover accuracy and to relative efficiency of different methodologies for classifying land cover.

2. SECTORING

A result of the varying viewing geometry was to introduce a spatial dependency of DN. The measured spectral response of a target is therefore in part determed by its spatial position relative to the radar. This has been found to be a problem with SAR data for land cover mapping (Ref 4).

Short of calibration a simple radiometric balancing technique could be applied to the radar data to reduce the viewing geometry effects. Although these methods have been shown to be of value (eg Refs 5, 6) there are problems with their use (Refs 7, 8). Therefore another approach, that of sectoring, will be used.

For flat terrain the effect of viewing geometry is to cause a systematic variation in tone across imaged swath (Figure 2). Since the factors responsible for this are related to the incidence angle it is possible to divide the image up into subimages defined by incidence angle or range distance. Each sub-image or sector can then be treated independently from the rest of the image and classified separately before recombining the sectors to produce the overall classified image (Ref 7). This assumes that within each sector the variations in incidence angle, antenna pattern and gain present are small enough to be ignored. The method therefore makes allowance for the spatial dependency of DN present in the SAR data.

3. DATA AND METHODS

The study area was the flat floodplain of the River Thames near Dorchester, UK. Optically processed parallel polarised (HH) X-band SAR data were collected for this area on 13 July 1981 as part of the European SAR 580 campaign. Near the time of the overflight land cover information for a 100 km² area was recorded by fieldworkers and oblique colour aerial photography acquired to produce a five class (water, grass, arable, forest and urban) land cover map which was used as ground data.

A 1:25,000 scale topographic map of the area showing field boundaries along which the SAR data were digitised for the analysis. It was therefore possible to digitally overlay the map on the SAR data, which was an aid to sampling on a per field basis. This method was advantageous since sampling on a per pixel basis is an unreliable method of estimating the backscatter from an areally extensive target (Refs 9, 10). Per field sampling not only gives a more reliable estimate of image tone but also allows the inclusion of textural information into the classification. Such procedures have been shown to be of benefit to land cover mapping with SAR 580 data (Refs 11, 12). For comparison both per pixel and per field sampling structures were used.

The image was divided into four sectors of equal size in the ground range direction. For both the per pixel and per field sampling structures stratified random samples were taken for training and testing the classification. These samples were stratified by sector and land cover type. In this way each sector could be treated independently of the others or combined with them. It was therefore possible to train a classifier with the training statistics derived from any one sector and test its accuracy in that or any other sector. With the former situation the sector is treated independently of the rest of the data for both training and testing the classification. When all four sectors are treated in this way and the results later grouped, the image will be referred to as having been 'sectored'. If, however, the sectors are not considered independently and the image as a whole is treated as a single unit it will be referred to as 'pooled'.

For the per pixel sample a total of 847 pixels were used to train a parallelpiped classifier. A further 963 pixels were used to assess the accuracy of the resulting classification. With the per field sampling structure the tonal and textural variables (Table 1) were derived from 65 random pixels sampled from the fields. Training statistics were derived from a total of 112 fields and an additional 130 fields were used to assess the classification accuracy. In this case discriminant analysis was used as the classifier.

Mean	DN	Х	н	$\frac{\Sigma \chi}{n}$

Standard Deviation

Minimum DN

Maximum DN

Third Moment about the Mean $\frac{\sum (\chi - \overline{\chi})^3}{n}$

Σ (χ

X min





Fourth Moment about the Mean

Kurtosis



Σχ

- χ _{min}

X max

.100

Coefficient of Variation (%)

DN Range

Table 1 Variables used in per field classifications (χ = individual sample value; n = number of samples)

Although this is different to the per pixel sample the class boundaries for the parallelpiped classification were determined by probaility assessments as they are in discriminant analysis

With both the per pixel and per field samples the land cover classification accuracy was assessed by the method of 13. The confidence limits at the 95% level were determined from the binominal expansion.

4. RESULTS AND DISCUSSION (1) - PER PIXEL

The classification accuracies obtained from this sampling methodology were low (Table 2), However, three points can be noted. Firstly, the accuracy from the sectored data set is higher than that from the pooled data set. Secondly, each sector is generally classified with a higher accuracy when the training statistics were derived from its own area (Figure 3). Thirdly, when the training statistics were derived from a central sector (2 or 3) the other central sector was classified with a higher accuracy than the edge sectors and \underline{vica} versa.

Land cover map accuracy (%)			
Sectored	Pooled		
31.9 (29-35)	23.5 (21-26)		

Table 2 Comparison of the results from the per pixel sample for the sectored and pooled data sets. 95% confidence limits in brackets.



Indicates the sector from which the training statistics were developed

Figure 3. Effect of training site location and sectoring on land cover map accuracy from the per pixel sample. Mosaicked refers to the sectored data (sector 1 = near range, 4 = far range). From Figure 3 it is evident that care is needed in determining from where in the image the training statistics are derived. If the training statistics are derived from one sector then not only does the overall classification accuracy vary but so too does the spatial distribution of the accuracy. The effect does not disappear if training statistics are derived across the whole image since the two central sectors are still classified with a higher accuracy than are the edges, which are the near and far ranges.

However, sampling on a per pixel basis appears inappropriate. The low classification accuracies are in part related to the narrow bandwidth and the coherent nature of the sensor, which gives rise to speckle. This can result in two pixels from a homogeneous cover type exhibiting considerably different DN. As a result of this the spectral responses of the land cover types are broad and overlap giving rise to errors of classification. Attempts to reduce the effect by low pass spatial filtering has little effect with the pooled data (Figure 4).



Figure 4. The influence of low pass median filters of various sizes on land cover map accuracy from the per pixel sample with the pooled data.

A further problem with this sampling technique is that only tonal information has been used. A classification employing tonal and textural information with a different sampling structure to the per pixel one used could be expected to increase the classification accuracy.

5. TEXTURE

Image texture is a difficult phenomenon to measure. It is closely related to tone (Ref 14) but it allows two areas which have the same overall tone to be distinguished on the basis of microtonal patterns (Ref 15). Texture can therefore be thought of as being the systematic variations of DN within an area.

Various approaches exist for quantifying texture for use in a digital classification. Perhaps the most commonly used methods are those based around the use of grey level co-occurence matrices (Refs 16-18). With these texture, is considered to be represented by the spatial distribution and spatial dependence of DN inside the small local area making up the matrix. However, the textural variables derived from the matrices can be difficult to interpret and depending on the number of grey levels, computational problems may arise during their calculation (Refs 10, 17, 18).

Another approach to texture analysis is to use the frequency distribution of DN. Probability density distributions could be used to discriminate between the cover types (Refs 19, 20). Simple statistical measures can be determined to quantify these distributions, and so be used as textural variables (Table 1). These variables can also be calculated on a per field basis. This may be preferable if field boundaries are known and it is reasonable to assume a homogeneous cover type within each field. Sampling on a per field basis also conforms to standard fieldwork methods of land cover data collection and presentation (Refs 21, 22).

6. RESULTS AND DISCUSSION (2) - PER FIELD

It was noted in section 4 that sampling on a per pixel basis was not suitable for SAR data. However, there is no significant change in classification accuracy if a per field sampling structure is adopted with only tonal information (mean DN) employed in the classification of the pooled data set (Table 3).

Variables used in	Land cover map accuracy (%)		
classification	Sectored	Pooled	
All Variables, Direct	54.6(45-63)	52.3(43-61)	
All Variables, Step- wise	56.1(47-65)	48.5(39-57)	
Mean and Standard Deviation	61.5(51-70)	35.4(27-45)	
Mean DN	53.1(44-62)	23.1(16-32)	
Standard Deviation	41.5(33-50)	35.4(27-45)	
Minimum DN	47.7(39-57)	25.4(18-34)	
Maximum DN	51.5(42-60)	25.4(18-34)	
Third Moment about the Mean	33.1(25-42)	17.7(11-26)	
Skewness	29.2(22-39)	19.2(13-27)	
Fourth Moment about the Mean	41.5(33-50)	26.9(19-36)	
Kurtosis	26.1(19-35)	23.8(17-32)	
Coefficient of Variation	24.6(18-32)	16.1(10-24)	
DN Range	36.9(29-46)	33.0(25-42)	

Table 3. Summary of classification accuracies from the per field samples . 95% confidence limits in brackets.

Since both classifications use only tone it can be concluded that for the pooled data set there is no benefit to be gained by changing the sampling methodology alone. This indicates that either tonal information is of little value in the classification or that other factors, such as the tonal imbalance across the swath, are of more importante than the effect of the sensor coherence in causing low land cover map accuracies. The latter is more likely since there is a much larger difference in the accuracy between the sampling methodologies when the image is sectored. It also indicates why low pass spatial filtering of the data had little effect (Ref 8) (Figure 4).

For both the pooled and sectored data sets the inclusion of textural information resulted in increased classification accuracy. In all cases the accuracy was higher when the image was sectored (Table 3). The advantage of sectoring the image over treating it as one unit is shown graphically in Figure 5. The pattern is similar to that found with the per pixel sample, with the highest accuracies being obtained for the data derived from the central sectors. Whilst the accuracies obtained from the data derived from the far range may be acceptable, those from the near range may not. In nearly every case the lowest accuracy was obtained from the data derived from the near range. For some studies this may be a justifiable reason for ignoring this part of the data, but it will be included here.

Although spatial filtering was found to have little effect on land cover map accuracy for the pooled data it may have for individual sectors. The SAR data for sector 2 was spatially filtered with a low pass median filter with a 3 x 3 pixel filter window size (Ref 23). The data were then classified using the same fields for the training and testing stages of the classification. Whilst the accuracy with which the data could be classified increased for some of the variables it decreased for others (Table 4).

3x3 Filtered (%)	Unfiltered (%)	
48.1	40.7	All Variables Direct
59.3	51.8	All Variables Step- wise
55.6	55.6	Mean and Standard Deviation
55.6	55.6	Mean DN
59.3	51.9	Standard Deviation
44.4	40.7	Minimum DN
59.3	70.4	Maximum DN
40.7	44.4	Third Moment about the Mean
25.9	33.3	Skewness
48.1	55.6	Fourth Moment about the Mean
14.8	22.2	Kurtosis
29.6	29.6	Coefficient of Variation
51.9	48.1	DN Range

Table 4. Comparison of the classification accuracies derived from the unfiltered data and from the median filtered data.

The highest accuracy obtained from this sector with the unfiltered data was 70.4% whereas it was 59.3% for the filtered data. Whist these results are far from conclusive, low pass spatial filtering may not provide any significant increase in accuracy, and was not used further in this study.

A spatial variation in accuracy is evident in Figure 5. This is also shown in Table 5 which gives the chi-squared statistic, transformed from the Wilk's lambda, and its significance (Refs 24, 25) for each variable and each sector treated independently as well as for the entire image pooled. Wilk's lambda is a measure of the within-group variation as a proportion of the total (Ref 24). The smaller it is the more successful is the discrimination between the groups. Since the aim of the classifier is to minimise Wilk's lambda the data in Table 5 illustrate two features. Firstly, different variables classify the data with different accuracies for any sector. Secondly, for any one variable the accuracy with which it can be used to classify land cover varies from sector to sector and so is spatially variable.

Classifications using more than one variable are likely to be superior to those using just one. It may be considered that the more variables and so information used the higher the accuracy will be (Ref 26). However, this is not always the case (Ref 27). Indeed the use of all 10 variables (ie Direct - assuming each variable is tolerant (Ref 25)) gave an accuracy close to that obtained when using just the mean DN, for the sectored data. Whilst the difference was much larger for the pooled data the inclusion of further variables may later lead to the same effect. It is apparent, therefore, that the variables to be used need to be carefully chosen. For instance a stepwise selection of variables to be used in the classification could be made. With this technique the variables enter the classification in an order determined by their discriminating power, given the variables already selected (Refs 24, 25). Usually not all of the variables are entered. Such a classification can only be considered optimal rather than maximal and requires the calculation of all the variables even though not all will be used. Short of trying all the possible combinations of variables the mean and standard deviation could be used. These were chosen because of the relatively low Wilk's lambda for each of them and because they were usually amongst the first variables chosen during the stepwise classifications. This combination gave an accuracy of 61.5% (51-70%) when sectored, the highest accuracy that was obtained.

The choice of which textural variable to use is, however, more complicated than it may seem. Different variables can discriminate the different cover types with varying efficiency. This discriminating power is, however, spatially variable, resulting in the spatial variability of accuracy noted above. This can be illustrated by considering that with the pooled data set 50% of grass fields could be correctly classified in the far range, but none in the near range for a classification using just the standard deviation of DN. Conversely with the third noment about the mean, 60% of grass fields were identified in the near range and none in the far range. The differences are less for the sectored data set. In both cases 25% of grass fields were correctly classified in the far range and 40% in the near range. There therefore appears to be not only a spatial dependency of accuracy but also a spatial variation in how well each cover type is classified, although the two are not independent and are also related to the proportions of each cover type in each sector. However, vegetation appears to be more separable after sectoring than do the urban and water classes. though the differences for the latter classes are small (Table 6). Sectoring SAR data therefore seems a suitable method to use for vegetation mapping.



Figure 5. Comparison of the classification results for the pooled and sectored data from the per field sample, using each variable and the combination of variables shown in Table 3.
	All va Direct	ariable	õ	All v Stepw	/ariabl /ise	0 8	Mean Stand Devia	and lard ltion		Mean	DN		Stand evia	arđ tion		Minim DN	um	
	k's		nif- nce	k's		nif- nce	('s		nif- nce	('s		nif_ ce	t's		nif- nce	's		if- ce
SECTOR	Wilk A	Χ-	Sign ican	Wilk A	χ²	Sign ican	Wilk A	χ²	Sign Ìcan	Wilk A	χ²	Sign icanc	Wilk A	χ²	Sign ican	Wilk A	χ²	Sign ican
1	.000	58.0	.000	.005	49.2	.000	.216	16.8	.009	.693	4.21	.239	.289	14.2	.002	.799	2.57	.461
2	006 1	74.3	.000	.007	174.6	.000	.078	97.7	.000	.148	74.5	.000	.257	52.9	.000	.323	44.0	.000
ω	.033	57.5	.012	.007	52.9	.000	.096	47.9	.000	.519	13.7	.008	.137	41.6	.000	.674	8.28	.081
4	.091	50.2	.057	. 255	33.4	.000	.355	25.3	.001	.586	13.3	600	.529	15.8	.003	.603	12.63	.013
Pooled	.232 1	51.7	.000	.236	150.6	.000	.390	56.6	.000	.857	16.5	.002	.623	51.0	.000	.895	11.95	.017

Table 5.	Results from discriminant analysis for each sector individually and for all four pooled. The smaller Wilk's Λ becomes the higher is the discrim- ination between the land cover types.
	The chi-squared statistic (χ^2) and its significance for each Wilk's Λ are also given.

Pooled	4	ω	N	1	SECTOR	
•		•		•	Wilk's	
748	555	322	182	568	Λ	Maxin
31.3	14.7	23.7	66.4	6.49	X ²	זעח DN
.000	.005	.000	.000	.089	Significance	
.776	.471	.392	.751	.979	Wilk's A	Third about
27.3	18.8	19.7	11.1	.239	x ²	the m
.000	.000	.000	.025	.971	Significance	ean t
.863	.669	.673	.635	.886	Wilk's A	Skewi
15.9	10.0	8.29	17.7	1.37	x ²	less s
.003	.039	.081	.001	.710	Significance	
.736	.494	.395	.544	.282	Wilk's A	Fourt about
33.1	17.6	19.5	23.7	14.5	x ²	h mome the m
.000	.001	.000	.000	.002	Significance	nt ean
.894	.762	.786	.730	.609	Wilk's A	Kurto
12.06	6.77	5.03	12.2	5.68	χ ²	s Ľs s
.016	.148	.284	.015	.127	Significance	
.954	.570	.677	.534	.985	Wilk's A	Coeff of Va
4.97	14.0	8.16	24.4	.172	x ²	icient riatior
.289	.007	.085	.000	.981	Significance	
.691	.569	.197	. 392	.419	Wilk's	DN F
39.8	14.1	34.1	36.5	9.97	x ²	lange
.000	.007	.000	.000	0.18	Significance	

		All Variables Direct	All Variables Stepwise	Mean and Standard Deviation	Mean DN	Standard Deviation	Minimum DN	Maximum DN	Third Moment about the Mean	Skewness	Fourth Moment about the Mean	Kurtosis	Coefficient of Variation	DN Range
GRASS	Pooled	29	21	18	4	36	14	7	21	3	25	18	0	21
	Sectored	32	39	43	36	18	39	39	32	25	32	11	39	25
ARABLE	Pooled	62	58	33	6	27	13	13	6	23	21	12	2	23
	Sectored	67	63	69	52	54	46	60	36	42	46	27	17	36
FOREST	Pooled	56	56	6	0	6	6	0	19	38	19	94	63	19
	Sectored	38	38	56	56	19	44	31	31	25	13	38	31	19
URBAN	Pooled	48	48	56	68	52	60	64	32	12	20	16	16	52
	Sectored	72	72	60	60	44	56	52	28	8	48	36	20	48
WATER	Pooled	78	67	100	100	89	67	89	33	33	100	11	67	100
	Sectored	33	56	89	89	78	67	78	33	33	78	22	22	78

Table 6. Comparison of the accuracy with which individual cover types are classified when using pooled and sectored data (%).

7. SUMMARY AND CONCLUSIONS

Sampling on a per pixel basis is unsatisfactory for land cover mapping with SAR. An improvement can be made by allowing for the spatial dependency of DN by sectoring the data. A more suitable method involves sampling on a per field basis, including textural information and sectoring.

Whilst the highest classification accuracy obtained, 61.5% (51-70%), may not be as high as that obtainable from data collected by other sensors it must be noted that only X band HH data have been used. Multi-feature radar data will probably yield higher accuracies. The use of more and therefore narrower sectors would also be preferable. With both more data and narrower sectors the classification of less generalised vegetation classes may be attempted.

The six main conclusions of this study are:-

- (i) As a result of the changing viewing geometry the typical DN of a cover type is spatially variable.
- (ii) Since the spectral response of a cover type is a function of the viewing geometry for any given cover type it will vary across the swath. As different cover types exhibit different spectral responses the separability of the cover types will vary across the swath.
- (iii) The location of training sites is therefore important, and will control not only the overall land cover map accuracy but also

the spatial distribution of this accuracy.

- (iv) Even if the image is sectored, land cover map accuracy will vary across the swath, because of (ii) above. Land cover map accuracy is spatially variable.
- Different variables have different efficiencies in discriminating between the cover types at different spatial positions.
- (vi) As a result of the above factors, it may not be valid to give a single accuracy figure for a classification of the entire image. Whilst such a procedure may be justifiable in making general comparisons between different classification method sor study areas it could be misleading. Accuracy may be better expressed per sector and per cover type, or at least some measure such as the maximum and minimum accuracies obtained. Thus a more precise accuracy assessment for the classification of the sectored data using the mean and standard deviation would be to state a minimum accuracy of 34.5% (18-54%) and a maximum of 75.5% (61-86%).

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A REVIEW OF RADAR ANALYSES OF WOODLAND

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ABSTRACT

With the launch of a number of satellite borne SAR's in the next decade, the need to research the potential of imaging radar to made land use determinations becomes apparent. This paper reviews the woodland aspect of land use. In so doing two major themes are studied. The first major theme is to assess and review the ability of imaging radar to make woodland determinations and to summarize the optimum radar parameters required. The second major theme is to review the imagery and methods used in the analysis of imaging radar data of woodland. In conclusion this paper states that imaging radar has demonstrated great potential in making woodland determinations, but as yet insufficient data exists to ascertain its full potential and to fully define optimum system parameters for the analysis of woodland. Further, it is noted that more work needs to be undertaken on the elimination of speckle and the incorporation of some texture or pattern measures in machine classification.

Keywords: Synthetic Aperture Radar, Woodland, Forest Interpretation.

INTRODUCTION

Imaging radar, and particularly Synthetic Aperture Radar (SAR), has been used on a worldwide basis for the study of land use. To date the majority of the studies have been undertaken in areas predominantly covered with cloud; specifically tropical West Africa, Central and Southern America and Indonesia. However, with the launch of a number of satellite borne SAR's in the next decade (ERS-1, Radarsat, J-ERS), the ability, and the need, to expand this capability to other areas of the world , and the need to assess the full potential of SAR in land use analysis becomes apparent..

Predominent in the study of land use is the ability of SAR to make woodland determinations. It is apparent from the review of studies to date that although woodland has been extensively imaged, the interaction of microwaves with woodland canopies is not fully understood. Fundament research utilizing volume scatter models and scatterometers has not been undertaken to the same extent as for cropland. Despite this, results from studies undertaken in West Africa, Central and Southern America, Indonesia and more particularly in the Canadian and European SAR 580 aircraft campaigns and the space-borne Seasat and SIR-A studies have indicated that SAR can be applied to woodland analysis. In reviewing the conclusions of these studies this paper has examined two main themes.

The first major theme of this paper is to assess and review the ability of SAR to make woodland determinations and to summarize the optimum radar parameters for so doing. It is apparent from studies to date that it is generally possible to delineate woodland from non-woodland, and that it is possible to make broad, and sometimes specific species and age determinations. Further, it has been found possible, using airborne SAR, to delineate forest boundaries and in some cases, with the aid of ground data, areas of disease and windblow. However, many factors remain unclear, for example: the degree to which radar waves penetrate the canopy; the effects of weather (solar radiation, wind, rain) on backscatter; and the effects of diurnal change on backscatter (moisture on the leaf, leaf turgidity, leaf angle).

The second major theme is a review of the imagery and methods used in the analysis of SAR data of woodland. This aspect is partially controlled and complicated by the application to be undertaken. Indeed the applications to date have ranged from the general delineation of woodland from other land uses to the calculation of stand density.

The overall conclusion of this paper is that SAR has potential in woodland analysis. In order for the full potential of SAR to be realised for the forthcoming satellite programmes limitations in terms of the amount of existing data need to be rectified. Specifically there is a requirement for a multi-temporal, multi-location, multi-frequency, multi-polarization, multi look-angle data base, backed by research utilizing volume scatter models and scatterometer data.

WOODLAND APPLICATIONS OF IMAGING RADAR

Forestry and woodland has not been extensively studied by investigators using active microwave remote sensing. Survey using airborne imaging radar has been undertaken over large areas of forest land, particularly in Central and Southern America

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and West Africa. Little work has been undertaken however to ascertain the form of the interaction of microwaves with woodland or to analyse the ability of imaging radar to undertake more detailed species, age, yield and crop state determinations. In this study, trees as a form of land cover have been grouped as follows:-

Single trees - hedgerow, parkland or urban trees Tree groups - small clumps and rows of trees Woodland - tree cover of 0.25 ha minimum size, 20m mimimum width and 20% minimum crown closure

Early Development

Imaging radar has been used extensively, and successfully, throughout the world on a commercial basis. Since the limited declassification of radar in the 1950's radar has been used to survey vast tracts of previously unmapped land, much of it covered by woodland. Although the prime motive for many of the overflights was not, however, vegetation mapping, but geological survey, it became apparent from an early stage that radar did permit the classification of vegetation classes, albeit on a generally broad scale. Table 1 lists the major commercial surveys to date.

Project/Country	Date	Area Surveyed (Km ²)	Imaging System
United States	1965/66	500,000	Westinghouse
Project Ramp (E.Panama and N.W. Columbia)	1967 and 1969	40,000	Westinghouse
Project Radam/ Radam Brazil (Brazil)	1970/76	8,500,000	Aero Services/ Goodyear
Nicaragua	1971	80,000	Westinghouse
Peru	1974/75	600,000	Aero Services/ Motorola
Nigeria	1976/77	950,000	Motorola
Venezuala	1975/76	900,000	Aero Services
ProRadam (Columbia)	Mid 1970's	320,000	Aero Services

Table 1. Major Commercial Airborne Radar Surveys

In addition overflights have been undertaken of Indonesia, New Guinea, the Philippines, the Solomon Islands, Western Australia, Togo, Guatemala, Ecuador, the United States, Canada, Scotland and South East England.

Some of the surveys were prompted by a real need to map vegetation. Nigeria provides a particularly good example of this where a complete county-wide land use/vegetation map was provided by imaging radar (<u>Hunting Technical Services 1978</u>, <u>Parry and</u> <u>Trevett</u> <u>1979</u>). Other surveys with a geological mapping requirement have also permitted the analysis of vegetation. It was noted for example in one of the earliest of these, Project Ramp, that six types of woodland could be delineated <u>(Viksne,</u> 1970):

- (a) Evergreen rain forest
- (b) Mixed semi-deciduous and evergreen forest (jungle)
- (c) Sub-montane forest
- (d) Palm forest, wetlands
- (e) Swamp with low trees
- (f) Fresh water and brackish swamp with tall trees

This has been corroberated by other studies, particularly Nicaragua where eleven classes of woodland could be delineated (<u>Hunting Geology & Geophysics</u> <u>1972</u>, <u>Martin-Kaye</u> <u>1972</u>):

- (i) Hardwood forest
- (ii) Hardwood mountain and hill forest
- (iii) Hardwood forest on severely dissected low hill land
- (iv) Riverain hardwood forest
- (v) Riverain hardwood forest with cultivation
- (vi) Hardwood forest with cultivation and grazing
- (vii) Hardwood mountain and hill forest with cultivation and grazing
- (viii) Hardwood forest remnants in savannah
- (ix) Swamp forest
- (x) Swamp savannah with scattered woodland
- (xi) Low swamp forest with palms

The Ability of Imaging Radar to Make Woodland Determinations

More recently the results of the Canadian and the European SAR 580 Campaigns, in conjunction with the results of other investigations in the United States, Canada and Europe has permitted more in-depth studies of particular aspects of the ability of imaging radar and SAR in particular, to make woodland determinations.

The Delineation of Woodland From Non Woodland. Fundamental questions such as the ability of radar to delineate woodland from non-woodland are not yet completedly clear from the literature. Generally woodland has been found to be clearly discerned from non-woodland on radar imagery. <u>Daus and Lauer (1971)</u>, for example, stated that by using K-band radar in the Sierra Nevada mountains, California, they were able to delineate timber from all other vegetation types.

The ability to delineate woodland from non-woodland was later confirmed by Parry (1974) using X-band radar and Le Toan (1980) using L-band radar of the Foret Landaise in France. In the European SAR 580 Campaign, with optically processed data Lband was found to provide the most obvious tonal separation of general woodland from other land cover classes (Horne and Rothnie 1984). However, experimenters also reported success with both X and C-bands. Further, analysis of satellite Seasat imagery demonstrated that woodland over 5ha could be readily discerned (Hunting Geology & Geophysics 1981).

Problems have, however, been encountered. <u>Ulaby (1980)</u> found that he was unable to successfully delineate woodland from corn using L-band radar over Huntingdon County, Indianna, and <u>Beaubien (1980)</u> in the Canadian SAR 580 Campaign found that he was unable to discern between woodland and non-woodland in Canada using X and L-band.

More particularly classification problems were noted in the European SAR 580 Campaign in the confusion between felled or recently planted woodland cover and other non-woodland cover types (Horne and Hildebrandt 1984). Both Le Toan (1980) and Knowlton et al (1981) have also noted the inability of radar imagery to delineate between older clearcuts and emergent crops.

Forest Boundary Delineation. Identification of woodland types requires similar responses from similar crop types in different parts of the image. Where crop type boundaries are to be recognised, tone and texture differences need only be noted for adjacent stands. In comparing boundary identification to forest stock maps in the European SAR 580 Campaign <u>Horne</u> and <u>Rothnie</u> (1984) found that 85 per cent of boundaries were visible on X-band, dropping to 66 per cent with the less detailed C-band. HH polarisation was best suited to the linearity of crop and road boundaries. These results compared to 90 per cent success rates with black and white photography and 94 per cent with colour. Most main mapped boundaries were identified, omissions being slight crop age differences, small intimately mixed stands and differences between pure and mixed crops of similar species. Some minor roads at right angles to line of flight were also missed.

<u>Species Classification.</u> Within forest and woodland areas the ability of imaging radar to delineate broad species categories has been apparent from an early stage. <u>Morain (1967)</u> using the Westinghouse real aperture system found he could delineate pine forest, juniper woodland, grassland and sagebush on Horsefly Mountain, USA. <u>Peterson et al</u> (1969) confirmed Morain's conclusions. In a later study of K-band radar imagery <u>Peterson (1969)</u> was able to delineate ponderossa pine, juniper woodland, white fir forest, hardwood forest, sagebush areas, shrub areas, grassland and recent burns.

The ability of imaging radar to image large areas of previously unmapped territory, and produce maps incorporating broad woodland categories was further proven in the late 1960's and the early and mid 1970's in Central and Southern America and West Africa, as has been stated previously.

The delineation of species within woodland remains however, a largely unresearched area. From an early stage it was established that image tone and texture was vital to vegetation delineation and that the vegetation tended to govern the texture of the image, whilst topography governed the tone (Daus and Lauer 1971). Bertholome (1983) placed this in the context of woodland when he stated that the texture of the image was specifically related to tree species.

However, the degree to which tree species can be delineated on SAR imagery is not yet fully determined, and only a few investigators have attended the problem. The results of these investigations tend to be mixed, and are isolated to a few Test Areas. <u>Churchill et al (1983 and 1984)</u>, for example, found that by using X-band SAR 580 imagery they were able to discriminate clearly by texture between coniferous woodland and older stands of mixed and deciduous woodland in Thetford Forest, England. Conversely, <u>Kessler et al (1983)</u> were not able to delineate 22 year old stands of Douglas Fir from 25 year old stands of oak by texture on X-HH imagery. Indeed it was only the darker tone of the coniferous woodland that permitted a successful classification. Age Classification. Several investigators to date have noted that broad age groups may be delineated within woodland, particularly coniferous forest. <u>Goodenough (1980)</u> and <u>Lee (1980)</u> both noted during the Canadian SAR 580 campaign that shorter, less mature trees exhibited a smoother texture than the more mature woodland. This feature is confirmed for satellite borne SAR sensors; young growth was found to be distinguished from mature stands on Seasat imagery (Hunting Geology & Geophysics, 1981).

Le Toan et al (1980) were more specific. They noted that for Maritine Pime (Pinus Pinaster) in the Foret Landaise in France three age classes could be denoted using L-band and HH and HV imaging radar:

(i) 0 - 4 years
(ii) 4 - 10 years
(iii) >> 10 years

Indeed, a quasi-linear correlation was noted between radar response and tree age from 9-3 years.

<u>Churchill et al (1984)</u> were similarly able to make broad age group determinations within Scots Pine (Pinus Sylvestris) and Corsican Pine (Pinus Nigra) in Thetford Forest, England, using X and C HH and HV polarized SAR 580 imagery. They reported a lightening of tone and a roughening of texture with increasing age. This was thought to be associated with thinning practice resulting in decreased stand densities with a resultant roughening of the canopy.

<u>Crop State and Yield Determinations</u>. Very little work has been undertaken in attempting to assess crop state and yield potential in woodland. <u>Daus</u> and <u>Lauer (1971)</u> firmly stated that it was not possible to assess timber quality and stand volume using real aperture SLAR imagery. However, using SAR certain relationships have been noted between backscatter characteristics and crop state and yield potential. <u>Bertholome (1983)</u>, for example, noted that texture in deciduous woodland corresponded to the size and density variation of the stand. In addition <u>Le Toan et al (1980)</u> were able to distinguish two stand density classes using L-band imagery of Maritine Pine (Pinus Pinaster). They were:

(i) < 1,000/ha (ii) > 1,000/ha

In the European SAR 580 Campaign, Anthony (1984) used stereograms of X and C-band imagery for the counting of single tree crowns in woodland conditions. Stands had to be middle aged to mature to give sufficient crown separation. It proved to be necessary to calculate correction factors to allow for lack of illumination of the lower storey trees in the overall canopy.

In non-woodland situations, a crown width of at least 10 metres was needed for successful identification (Horne and Rothnie, 1984). Large trees and tree clumps showed most clearly in L-band although the detail and radar shadow of X-band also aided identification. Location was an important factor, urban trees and small trees in hedgerows being impossible to count.

Despite these indications, as $\frac{\text{Hoekman}}{(1984)}$ states, there is a need for a thorough knowledge

of the interaction of microwaves with forest and free structures before conclusions on the feasibility of forest inventory can be utilized.

Similarly, little work has been undertaken in assessing disease and crop dramage in woodland using radar imagery, and that which has been undertaken has produced mixed results. <u>Goodenough (1980)</u> found during the Canadian SAR 580 experiment that he was unable to delineate trees damaged by pine beetle.<u>Churchill et al (1983)</u> found that by using X-band SAR imagery clearings and disturbance could be delineated with the aid of ground truth, and could, in turn, be related to the effects of fomes annossus or windblow.

<u>Crop Geometry Effects.</u> Crop geometry has been seen by many researchers to be of importance to radar backscatter. It has been proved possible to differentiate between high and low vegetation.. Sicco-Smit for example in his study in the Mahogany forest of the State of Goi'as in Brazil found he was able to successfully delineate swamps, savannas and shifting cultivation from the surrounding high forest. This he was able to do with the aid of radar shadow and differences in tone and texture (Sicc-Smith 1974).

Hardy was able to make a similar distinction in the Yellowstone National Park in 1971. He found that of the seven conifer species in the park, each of them unique in form when observed from the ground, only Douglas Fir was distinguishable to the radar. The primary reason he found for this was that this particular species of fir grows in relatively pure, somewhat open stands, and is the tallest growing conifer in the park.

Hardy pursues this point when he states that features such as tree heigh and general shape may affect the image appearance, particularly if the stands are pure but of different species. He found such macro-characteristics to have a major influence on the image textural characteristics of each plant community. He further states that micro-characteristics such as leaf shape, length and orientation might create a species image signature (Hardy et al 1971).

Canopy Penetration. The degree of penetration of radar waves into the canopy is unclear from the literature. The EASAMS report in 1973 (Vol. CR-138) states that if the forest is viewed at a low incident angle the tree trunks will scatter the incident radar waves to such an extent as to hide the ground beneath. The report further states that if woodland is viewed vertically it may be penetrated by radar waves, especially in winter when there are no leaves.

Davis (1973) in his study of the Saginaw Forest confirms that the tree canopy may be penetrated by radar waves. He further states that in his study X-band penetrated the canopy to a far greater extent that L-band. However, this overflight took place in the spring before the deciduous trees were in leaf, and this factor may have had a considerable bearing on the results.

In contrast <u>Shuchman and Lowry (1977)</u> found that longer wavelengths will penetrate the vegetation to a far greater extent. <u>Macdonald and Waite (1978)</u> partially confirmed the ability of long wavelengths to penetrade woodland vegetation. They noted that the backscatter from forest land using L-band were essentially the same for full and partial foliage development. They therefore assumed that the backscatter was caused by a combination of branches, trunks and even the ground below. From this Macdonald and Waite also concluded that at low incident angles L-band was of no use for delineating seasonal changes in vegetation types.

Further evidence has been provided by <u>Macdonald et</u> <u>al (1980)</u> who detected variation in the Seasat image for supposedly homongenous tree canopies. It was established that the variation occurred where standing water was located on the ground.

To test radar penetration of the forest canopy in the European SAR 580 Campaign <u>Churchill et al (1983)</u> erected corner reflectors at various levels in a continuous pine canopy. No reflectors were visible on X or C-bands, indicating a penetration/reflection of less than 6 metres. This limited penetration seems confirmed by the lack of lower canopy illumination in crown enumeration studies <u>Anthony</u> et al (1984) and by radar shadowing behind linear tree features <u>Curtis (1984)</u>. Work by <u>Sieber (1984)</u> indicates that X-band reflects from tree leaves while L-band has more penetration, reflecting from tree branches.

<u>Topographical Effects.</u> It is apparent from the literature that topography is regarded as being of prime importance in governing the strength of radar return. <u>Parry (1977)</u>, for example, states that it is apparent that the prominent patterns on radar imagery are the product of surface morphology. <u>Daus and Lauer (1971)</u> note that topographical variations affect the image of identical stands, whilst <u>Beaubien (1980)</u> states that he was unable to delineate coniferous woodland from deciduous because of the effect of slope. This has been further corroberated by <u>Viksne (1971)</u> and <u>Hardy (1971)</u>.

Other Variables. Other variables that might effect the backscatter response from woodland have not yet been studied in any significant manner. Variables such as diurnal effects, weather and management practice have as yet received very little attention from investigators.

Optimum System Parameters for the Analysis of Woodland. It is noted in attempting to define the optimum system parameters for the analysis of woodland by radar that the results from which these conclusions are drawn are defined by the following variables:

- (i) The Test Site over which the sensor was flown (in terms of management practice, species and age)
- (ii) The time of year at which the sensor was flown
- (iii) The weather at the time of flight
- (iv) The time of day at which the sensor was flown
- (v) The sensor (in terms of bands and polarization availability) that undertook the flight

(vi) The application requirement (broad land use classification to compartment ride delination).

There is no data set that will permit a range of frequencies and polarizations to be compared over a time series.. Further, with particular regard to the European SAR 580 Campaign, conclusions with regard to wavelength are defined by the poor quality of the C-band data.

<u>Wavelength.</u> The optimum wavelength for the analysis of forestry is not clear from the literature and seems to some extent to be defined by the desired application. In regeneration and cutover areas <u>Pala (1980)</u> found that, during the Canadian SAR 580 campaign , by using X-band data little detail could be discerned, although feature boundaries could be clearly defined. Conversely L-band imagery was found to provide much greater detail and, with density slicing, the delineation of regeneration and failure areas was permitted. Indeed it was found to be possible to delineate three levels of regeneration:

(i) Good
(ii) Medium
(iii) Poor

Pala concludes by suggesting that coarse resolution L-band may serve surveillance needs.

For mapping clearcut areas Lee (1980) found that recently cleared areas could be delineated on both X and L-bands; this was confirmed by <u>Goodenough</u> (1980). Goodenough further states that the X-HH channel is best for visual analysis overall.

<u>Macdonald et al concur</u> with this conclusion. They found during experiments with SAR over Arkansas using Ka, X and L-band that the L-band provided substantially reduced dynamic range in comparison to the other frequencies, thus inhibiting delineation. This they found to be not surprising due to the larger wavelength of the L-band and its increased ability to penetrate the canopy. The general requirement for a shorter wavelength for forestry analysis is further supported by <u>Rubec</u> (<u>1980</u>), <u>Kessler</u> (<u>1983</u>), <u>Bertholme</u> (<u>1983</u>) and <u>Horne et al</u> (<u>1984</u>).

Due to the varying requirements for woodland and forestry analysis, and the varying responses for each waveband, the need for a dual or multi-channel approach has been noted by many investigators. This approach has been particularly noted by investigators in both the Canadian and European SAR 580 Campaigns.

<u>Polarization.</u> The majority of investigators to date have suggested that for forestry analysis the optimum polarization is like polarized. <u>Knowlton</u> et al (1981), for example, states that an X-band radar with HH polarization is best for deciduous/ coniferous delineation. This is confirmed by <u>Goodenough (1980). Wu (1983)</u> simialrly suggests a like polarized radar (VV) for forest classification.

Peterson (1969), however, states that the forest/ non forest boundaries were more perceptible on cross polarized radar. A similar distinction was found for burned areas. <u>Resolution.</u> <u>Moore (1979)</u> found that for resolutions less than 10m interpretation accuracy was less than 37 percent for woodland species. Moore also established that there was a negative exponential reduction in interpretation with resolution.

In comparison <u>Inkster (1980)</u> found that interpretation accuracy was a weak function of resolution upto a threshold beyond which it decreased rapidly. Inkster concurred with Moore in respect of the minimum resolution of 10m; he stated that at resolutions coarser than 10m interpretation ability decreases rapidly. He further states that to be able to delineate between clear cut areas covered with stands of various species becomes difficult at resolution coarser than 6m.

Incident Angle and Look Direction. In respect of the optimum incident angle for forest land evaluation, too little work has been completed to make any firm conclusions. Hardy et al (1971) has stated that for accurate interpretation a given ground element should be imaged in the near, mid and far ranges. This is also suggested by Lewis (1971).

<u>Rubec</u> (1980) suggests that shallow incident angles are best for land classification, whilst <u>Wu</u> (1983) states that no change in the image is apparent between 40° and 58° for X-band.

The results from investigators also suggest that flight lines and the number of flights are important in obtaining optimum data. Hardy et al (1971) found that flight lines perpendicular to the major topographic features gave the best data for vegetation analysis. <u>Macdonald and Waite (1971)</u> have indicated that for unknown topographic configurations four orthogonal looks are desirable when the orientation of the geologic structures is known.

<u>Multi-temporal Imagery.</u> The need for a multitemporal approach to woodland analysis has been suggested by several investigators, however very little has beenundertaken in that field, due partly to a lack of multi-temporal imagery. <u>Hoekman (1984)</u> for example, suggests that for the analysis of woodland at least one overflight in summer and one in winter ought to be undertaken. The need for a multi-temporal approach is exemplified by <u>Davis</u> (1973) who was able to delineate four forest types using X-band like polarized multi-temporal data. They were deciduous trees, deciduous bush, long leaf pines and short leaf pines.

<u>Bush et al (1976)</u> have also attempted a multitemporal approach. Using ground based scatterometer measurements they attempted to define differences between autumn and spring stands of deciduous woodland. They established that the radar scattering coefficient σ° as measured in the spring can be substantially larger, by as much as 10 dB., than the σ° measured in the autumn. They also found that this effect was most apparent between incident angles of 30° - 50°.

Table 2 presents a summary of these results:

Description	Band	Optimm Ra Polariz- ation	dar Parame Grazing Angle ^O	ters Resolution	Sensor
Woodland from non- woodland	х	HH	-	2m	SAR
Deciduous from coniferous	Х	HH	-	-	SAR
Species	X & C	HH	60 ⁰	-	SAR
Age	X & C	ΗH	-	10m or less	SAR
Regenera- tion	L	!	!	Coarse	SAR

Table 2. Optimum Radar Parameters for Woodland

IMAGERY AND METHODS USED

To date the majority of interpretors and investigators have utilized optically processed imagery. This is particularly true of the commercial surveys of the 1960's and 1970's, and also true for many of the investigators in the Canadian and European SAR 580 campaigns. In general, the optically processed imagery took the form of hard copy that could be manually interpreted using traditional estimators such as tone, texture, contexture and interpreter experience.

Certain investigators have attempted to pursue the analysis of optically processed data further, particularly in the Canadian and European SAR 580 Campaigns. Kessler et al (1983) applied densitometer analysis to back up their visual interpretation results. Further, other investigators have used optically processed data on colour additive viewers to advantage (Churchill et al 1983). Indeed, the application of colour was found to greatly enhance the ability to manually interpret radar imagery of woodland.

The analysis of digitally processed imagery has been undertaken by far fewer investigators, due generally to the fact that there is far less available digital iamgery of woodland.

As with the optically processed data, colour composites were found to greatly enhance manual interpretation. It was noted, however, in the European SAR 580 Campaign that there was a need to radiometrically balance the imagery for variations in scene brightness to permit the most accurate analysis of imagery (Wooding, 1983). Colour composites of radiometrically balanced data with X-HV in red, X-HH in green and C-HH in blue gave the best image for delineation of woodland from non-woodland and for forest type separation while use of two C-band channels assisted the tonal separation of pine species (<u>Churchill et al 1984</u>). <u>Kessler (1984</u>) got best results from a composite of C-HH (low pass 7 x 7 filter) on red, X-HH (low pass 5 x 5) on green and a ratio of X-HH (5 x 5)/CHH (7 x 7) on blue. Both experimenters found visual analysis of enhanced digital data gave best results.

Despite the success of colour composites for manual interpretation, considerable problems have been encountered when applying traditional pixel by pixel classification algorithms. Two reasons have been stated for this; firstly the presence of speckle that is inherently incorporated in SAR images, and secondly the fact that pixel by pixel classifications do not incorporate estimators such as texture which have been found to be of considerable importance in making optical forest type determinations.

Some initial work has been undertaken utilizing a median and a Marconi Research Centre designed PRSMT speckle removing filter over imagery of woodland (Hunting Technical Services and Marconi Research Centre, 1984b). Recent work on texture measures of woodland areas, particularly the Spatial Grey Level Dependancy Mabix, has demonstrated that certain very rough textures can be delineated from other textures by machine (Churchill and Wright, 1984, Hunting Technical Services and Marconic Research Centre, 1984a).

It is worth noting that in the addition to the analysis of imaging radar data, there has been very little work utilizing scatterometer data and scatter models, in contrast to the work on cropland. As such much of the fundamental work on the understanding of the interactions of microwaves with woodland has yet to be undertaken.

CONCLUSIONS

From work to date it is apparent that the following general conclusions can be drawn:

- Imaging radar shows potential for forestry applications, particularly when radar's all weather capability is taken into account.
- (ii) Insufficient data exists to define fully optimum radar parameters, for woodland analysis but L-band was found to provide the best woodland/non-woodland separation X-band is most suited to detailed studies.
- (iii) Visual interpretation of enhanced imagery has proved more successful than automated digital analysis to date
- (iv) Multi-channel SAR is most suited to forest studies but new algorithms need to be developed to utilize textural and pattern aspects if automated classification is to be improved
- (v) Data quality needs to be improved to correct system, naviation and processing errors
- (vi) More imaging radar data is required if the potential of multi-look, multi-angle, multidirectional, multi-channel, and diurnal and seasonal variations is to be fully tested.
- (vii) Fundamental research using scatterometers and scatter models needs to be undertaken in order to understand the interaction of microwaves with woodland
- (viii) Some of the applications discussed are resolution dependant and could not be achieved with current space borne SAR systems. There is a case for continued use of airborne SAR in addition to satellite systems.

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SESSION B



MULTIPLE-INPUT SEGMENTATION ALGORITHM FOR SLAR-IMAGERY

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ABSTRACT

One of the research goals of the Dutch ROVE team is the development of methods for the automated quantitative analysis of SLAR images for crop identification and classification purposes. A major step in this analysis is the automated segmentation of the image into the agricultural fields. The segmentation procedure discussed here is based on a sequential split-and-merge approach. The procedure allows for the simultaneous segmentation of multitemporal or multi-angular views of the same scene yielding one segmentation plan. The criteria for merging, splitting or grouping the tentative regions are based on the random scatterer model for natural backgrounds like vegetation.

Keywords: digital image processing, image analysis, segmentation, split-and-merge algorithms.

1. INTRODUCTION

In the Netherlands, the multidisciplinary working group ROVE (Radar Observation of Vegetation) investigates the properties and possibilities of radar in the context of remote sensing as a tool in agriculture and forestry for vegetation mapping, crop classification, etc. In ROVE the following institutions participate: the Centre for Agrobiological Research CABO, the Physics and Electronics Laboratory TNO, the National Aerospace Laboratory NLR, and various laboratories of both the Agricultural University Wageningen and Delft University of Technology. An expose of the ROVE program has been published recently (Ref. 1).

In the ROVE project, a specially developed SLAR system is used with digital data recording and accurate absolute signal handling. The recorded data are subject of intensive preprocessing, including geometric and radiometric corrections. As these tasks are performed at NLR and TNO, they will not be discussed here. The digital images emerging from the preprocessing stages contain square pixels. Each pixel corresponds with a ground area of 15 m by 15 m, and its value is obtained by averaging over approximately 30 uncorrelated radar observations.

One of the research goals of ROVE is the development and implementation of methods and algorithms for the automated quantitative analysis and, eventually, for the automated interpretation of the digital SLAR images. A major step in the analysis is the automated segmentation of the image plane into regions, which correspond to the agricultural fields. The segmentation algorithm discussed here is based on a sequential split-and-merge approach. The method allows for the simultaneous segmentation of multi-temporal or multi-angular views of the same scene, yielding a single-segmentation plan. The criteria for merging or splitting tentative regions are derived from the random scatterer model for natural backgrounds like vegetation.

2. THE IMAGE MODEL

In this section we define an image model which forms the basis for the segmentation procedure. The image model is based on a random scatterer model for the radar observations. Natural backgrounds like vegetation behave like distributed targets. If the illuminated area is large enough to contain a sufficient number of uncorrelated scatterers, the probability density function of the amplitude of the envelope of the received signal is a Raleigh distribution. From this distribution it can be derived that the probability function of a single observation of the reflection coefficient $\boldsymbol{\gamma}$ shows a standard deviation of 5.6 dB. In relation to a dynamic range of some 20 dB for crops and vegetation, this value of the deviation is unacceptably large. The value of a pixel in our digital image, however, is obtained by averaging over approximately 30 uncorrelated observations, yielding a standard deviation of 1.0 dB. In this model, the deviation is independent of crop type, etc. This leads to the following image model. The agricultural fields are represented by regions in the image which differ in mean value (depending on crop type, crop coverage, moisture, etc.) and the withinregion variance is the same for all regions. This variance will in the sequel be denoted as σ^2 . Furthermore, the pixel values are assumed to be Gaussian, as they are obtained as the average value of a reasonably large number of uncorrelated observations.

This image model is illustrated in Fig. 1.

The variability in the pixel values is still too large to allow for direct classification of pixels into crop types. This implies that the traditional approach is to be chosen in which the image is first segmented into regions. The reflection coefficient may then be averaged over the pixels belon-

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ging to one region to obtain a more accurate estimate of γ , thus facilitating the classification of regions. The segmentation problem is the main issue in this paper.

The difference between the mean reflection coefficients of adjacent agricultural fields, as observed in our images, may be in the same order as the standard deviation of the noise. This prohibits the use of simple segmentation procedures like multi-thresholding or straight-forward edge detection. Obviously, one has to use locally averaged estimates of image properties.

The image model described above suggests the following approach. Let us observe a small portion of the image by looking at the pixels within an observation window. If all pixels in the window lie in the same agricultural field, as illustrated by window W in Fig. 1, the pixel values are all samples from the same Gaussian distribution with mean value μ_1 and variance σ^2 . If, however, the pixels originate from more than one agricultural field, as indicated by window W' in Fig. 1, the pixel values are samples from a mixture of Gaussian distributions with different mean values but identical variances. The variance of the mixed population is larger than σ^2 , as we will show for the case of two classes. If we have a fraction p_1



Figure 1. Image model with Gaussian distributions for the regions. W and W' are observation windows.

of pixels from a Gaussian distribution with mean value μ_1 and a fraction p_2 of pixels from a distribution with mean μ_2 , the mixed variance is

$$\sigma_{\rm rr}^2 = \sigma^2 + p_1 p_2 (\mu_1 - \mu_2)^2$$

which is larger than σ^2 , except when the means are identical or when one of the fractions is zero. This corresponds with the single field situation.

So we can use the sample variance s^2 of the pixel values in the window to test the following hypo-

theses:

H₀:
$$\sigma_{w}^{2} = \sigma^{2}$$

H₁: $\sigma_{w}^{2} > \sigma^{2}$

If H_0 is rejected, we conclude that the window contains (parts of) different agricultural fields. We may now divide the window into smaller subwindows and repeat the test for each subwindow. In principle, one could start with a large window containing the entire image. It is computationally more attractive to use a split-and-merge algorithm.

3. SPLIT-AND-MERGE

The split-and-merge approach to image segmentation as developed by Pavlidis and Horowitz (Refs. 2,3) belongs to the family of sequential region growing techniques (Ref. 4). Image processing algorithms are called sequential if the processing in one part of the image may be influenced in any way by the results of processing some other part of the image. Major advantages of sequential methods are easy adaptation to local image properties and natural exploitation of adjacency and connectivity. A major disadvantage, however, is the dependency on starting points and processing order.

The split-and-merge algorithm can be described most easily by introducing the quartic picture tree QPT. If we start with a square image of size $2^{L} \times 2^{L}$, this image can be divided into its four quadrants. Each of these quadrants can be divided into quadrants recursively. This process can be described with a quartic tree. We start at level 0 with one node, which represents the complete image. The node at level 0 has four sons at level 1, which represent the four quadrants, and so on. Nodes which are not developed further are called terminal nodes. The leaves of the tree at level L correspond with the pixels of the image.

3.1. Initialisation

The algorithm starts with a tentative partitioning of the image into squares of size 2^{L-k} , which corresponds with a choice of starting level k in the QPT. Each node at level k is assigned some attributes that are of importance for the segmentation problem, e.g. the mean and variance of the values of the pixels in the corresponding square in the image. At this stage all nodes at level k are terminal nodes.

3.2. Merging

In the merging operations any quadruplet of sons of the same father is tested for a possible merge. The merge decision depends on their attributes. If the four sons can be merged, the attributes of the father are computed and the quadruplet of sons is deleted from the tree. This procedure is repeated for all quadruplets at level k, then for all possibly emerging quadruplets of terminal nodes at level k-1, and so on. If no more merges can be accomplished, we return to the starting level k.

3.3. Splitting

Each remaining node at level k is now tested for a possibly necessary split operation. If splitting is necessary, the four sons are created at level k+1 in the QPT and their attributes are computed. This process is recursively repeated.

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In principle, the merging operations could proceed up to level 0 in the tree if the image consists of one single region. On the other hand, the splitting operations may very well proceed to level L, which corresponds with the pixel level. After completing all possible merges and all necessary splitting operations, the image has been segmented by means of a partioning with squares of various sizes. The smallest squares may be just single pixels. All pixels in a square are assumed to belong to one single region, because evidently no further splitting was necessary.

3.4. Grouping

The next step is called the grouping stage. This process is guided by the region adjacency graph (RAG), where the nodes represent the regions and an edge between two nodes indicates adjacency of the two regions. When the grouping procedure starts, all nodes represent square regions. Select one of the squares with maximum size and test all adjacent squares for a possible merge on the basis of certain grouping criteria. If an adjacent square can be absorbed. the attributes of the resulting region are computed and the RAG is updated. The growth process of the current region stops when the grouping test fails for all current neighbors. The procedure is then repeated starting from a newly selected starting square. As the squares which result from the merge and split stages may be as small as single pixels, the regions which are created by combining squares of various sizes may have any shape.

4. DECISION CRITERIA

In this section we specify the tests for the split, merge and grouping decisions for the segmentation of the SLAR images with a split-and-merge algorithm.

The decision to split a square containing n pixels is based on a statistical test for the hypotheses

H₀:
$$\sigma_w^2 = \sigma^2$$

H₁: $\sigma_w^2 > \sigma^2$

where σ^2_w is the variance of the distribution underlying the window population and σ^2 is the known variance derived from the radar observation model. Usually one would test the sample variance s² of the square in a one-sided test involving the Chisquare distribution, which, however, may be approximated by a Gaussian distribution. In this way we arrive at the following critical region:

$$s^2 \ge \sigma^2 (1 + u_n \sqrt{2} / \sqrt{n-1})$$

with u_a defined by $Pr(\underline{u} \ge u_a | \underline{u} \in N(0,1)) = a$ where $a = Pr(H_0 \text{ rejected} | H_0)$ is the significance level of the test, which is defined as the probability that the hypothesis H_0 is rejected while it actually holds. This corresponds with a decision to split the square in a situation where the square actually contains pixels from one agricultural region only. The value of a should not be chosen too small, because that would lead to unacceptably large values for the probability that H₀ is not rejected when it actually does not hold, i.e. the decision no to split the square although it actually contains pixels from more than one region. An error of this type can never be corrected in later stages of the split-and-merge algorithm. A somewhat larger value of a will obviously lead to some unnecessary splitting actions, but errors of that type may be corrected by the grouping procedure.

The decision to merge a quadruplet of sons of the same parent in the merging stage is based on exactly the same test. The sample variance of the parent square is computed and used in the test. If H₀ is not rejected, the parent square may exist and the four sons are merged.

In the grouping procedure, the decision to merge two adjacent regions is based on the u-test for differences of means with the following hypotheses:

H₀:
$$\mu_1 = \mu_2$$

H₁: $\mu_1 \neq \mu_2$

Н

where μ_1 and μ_2 are the population means of the two regions. We use the absolute value d of the difference between the two measured sample means with the following critical region:

$$d \ge u_1 \sigma \sqrt{1/n_1 + 1/n_2}$$

with $u_{\frac{1}{2}a}$ defined by $Pr(\underline{u} \ge u_{\frac{1}{2}a} | \underline{u} \in N(0,1)) = \frac{1}{2}a$ where a is again the significance level of the test and where n1 and n2 are the number of pixels in the regions.

5. CLEANING

The segmentation map resulting from the described procedure will be somewhat fragmented, in the sense that many small regions remain in existence along the boundaries of the actual fields. Due to the pixel size of 15 m by 15 m, these pixels often contain a mixture of various crops, roads, ditches, etc. One can decide to leave these small regions unclassified or decide to let them be absorbed by an adjacent region with similar greylevel. Usually we eliminate regions with an area less than 20 pixels. This is based on the following heuristics: the accuracy in the reflection coefficient estimated over less than 20 pixels is hardly sufficient for region classification purposes; in our agricultural test region fields are much larger than 20 pixels; elimination of all segmentation fragments below this threshold yields a clean segmentation result.

6. MULTIPLE INPUT IMAGES

The reflection coefficient does not depend on crop type only, but a.o. on growth stage and grazing angle as well. A single SLAR image does not carry sufficient information for relatively simple tasks as single crop detection. For more general classification purposes, the use of multiple SLAR images is therefore unavoidable (Ref. 5). These multiple images can be obtained at various grazing angles (by flying along the same track at various altitudes) or at various stages in the growth process (by flying on various dates) or by a combination of both. For automated processing the multi-angular and/or multi-temporal views of the same scene must be in registration.

In the classification stage of the complete analysis scheme, the objects to be classified are the agricultural fields. The use of multiple images, say q, leads to the use of a q-dimensional feature vector for each field. The feature values can only be evaluated correctly if the detected field boundaries are identical in all images. If the multiple images are segmented independently, this is very unlikely to happen. Common boundaries in the segmentation plans of the multiple images will almost

never have identical positions and specific boundaries that are present in the segmentation plan of one of the images may be missing in another. It is therefore necessary to obtain one single segmentation plan of the underlying scene on the basis of the multiple views of that scene. In principle, one could still segment the multiple images separately, take a logical OR of all binary valued boundary maps to obtain one combined boundary map and recompute the feature values for all emerging regions from the original images. This approach, however, will lead to an extremely fragmented segmentation result, containing numerous small regions which are hard to classify. It is possible to extend the split-and-merge procedure itself in the sense that it will produce one segmentation plan for the underlying scene on the basis of multiple input images, i.e. simultaneous segmentation.

Two adjacent fields in the scene may be quite indistinguishable by viewing from one angle but be quite distinct from another angle. The same holds for multitemporal views: two fields may have rather similar reflection values in May, but quite distinct reflection coefficients in July. We take the position that if there is a significant difference between two parts of the scene at any time or from any angle, these parts should be identified separately. This leads to the following proposal to combine the multiple inputs into one common segmentation plan. The split-and-merge algorithm has multiple input images, but only one grid of squares. The decision to split a square, merge four squares or group regions together is based on statistical tests performed on each of the input images separately. The answers from the multiple tests are combined in the following way.

The decision to merge a quadruplet of squares in the common segmentation plan requires all independent tests to be in favour of such a merge. This can be described as a logical AND on all multiple positive merge decisions. In the splitting phase of the algorithm, a square in the common plan is split as soon as any of the separate tests indicates a split. This corresponds with a logical OR on multiple positive split decisions. Finally, two regions are linked in the grouping phase if and only if again all input images support such a decision.

7. EXAMPLE

We have implemented an experimental split-and-merge segmentation algorithm on a VICOM digital image processor. The program accepts up to four input images of size 256 x 256 pixels. Larger input images must be divided into subimages, which are then processed independently.

Figure 2 gives an example of a SLAR image of one of four test regions (Flevopolder, July 1980, 660 m). From this image two subimages of 256 x 256 pixels were segmented. Figure 3 shows the segmentation result. The gray values in Fig. 3 represent the mean values of the various regions. The region boundaries are displayed in Fig. 4. The most important output of the segmentation package is a file containing for each region its identification code and average reflection for each input. This file can then be used in our software package for statistical pattern recognition to classify the regions.



Figure 2. ROVE SLAR image Flevopolder, July 1980, 660 m.



Figure 3. Segmentation result 512x256 pixels, regions displayed by mean values.



Figure 4. Region boundaries of segmentation result of Fig. 3.

8. CONSISTENCY

In Section 2 we mentioned that, in principle, one could start with one large window covering the entire image. In that case one would apply many splitting operations, followed by the grouping phase. The opposite approach would be to start with a raster of tentative squares at the pixel level, and apply many merging operations and the grouping stage. It is computationally more attractive to start at an intermediate level to minimize the required computation time. The question then arises whether the segmentation result depends on the starting level or not. Theoretically the result is independent from the starting level if and only if the decision criteria in the merging, splitting and grouping constitute a legitimate uniformity predicate. The most important constraint for an uniformity predicate is that if the predicate is true for a region, it should be true for all subsets of the region.

Well-known uniformity criteria are, for example, that all pixels in the region have identical gray value or that the difference between maximum and minimum gray value lies below a certain threshold. Criteria of these types are not applicable to the SLAR-segmentation problem. On the other hand, the tests on region mean values or region variances developed above do not constitute a legitimate uniformity predicate: if the variance of a large region is below a specific threshold, this is not necessarily true for all subsets of the region.

It is quite disappointing to learn that our tests, which are so nicely based on the physics of the imaging process, are not acceptable from a mathematical point of view. We have therefore attempted to quantify the effect of the choice of the starting level on the resulting segmentation, by measuring the similarity between various segmentation results in an experimental study. The details of this study have been reported before (Ref. 6). From this study we concluded that the effect of the choice of the starting level is neglectable.

9. CONCLUDING REMARKS

In general, the segmentation results obtained with the split-and-merge algorithm discussed here are quite acceptable. Interactive tuning of the few parameters which are selectable at runtime requires some experience. The overall processing time is certainly not neglectable: a three-input 512x256 scene requires in the order of 50 minutes, both on a special purpose image processing computer (e.g. VICOM) and on a general purpose minicomputer (e.g. PDP-11/34) supplied with a fast floating point processor. A similar split-and-merge program has now been implemented on the RESEDA facility of the Dutch National Aerospace Laboratory NLR.

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OPTIMIZATION OF AGRICULTURAL CROP IDENTIFICATION IN SLAR IMAGES: HIERARCHIC CLASSIFICATION AND TEXTURE ANALYSIS

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ABSTRACT

In 1980 a large SLAR flight program was carried out over an agricultural area in The Netherlands. A classification study on this multitemporal dataset (Ref. 1) showed that high accuracies are obtained from a simultaneous classification of 3 flights. In this paper the results of a followon study will be discussed. The goal is to obtain the best possible classification result in the earliest possible stage of the growing season. Therefore the SLAR flights from April, May, June and July were analyzed and the hierarchic classifier is introduced. Very satisfying results were obtained from a combination of 3 flights: 1 in May, 2 in July at different incidence angles.

In a next part of this paper, within field texture is investigated as a possible extra feature. Texture measures were determined from the Gray Level Co-Occurence Matrix (Ref. 2), which is known to be rather sensitive for small texture elements, in the order of pixel dimensions. Sofar the within field variations do not seem to contribute substantially to a classification process.

1. INTRODUCTION

In this paper the results will be discussed from a follow-on study on previous classification experiments (Refs. 1, 3). This study forms a part of a broader national remote sensing research program for agriculture and forestry, carried out by the ROVE-team (Radar Observation on VEgetation), a collaboration of several institutes (Ref. 1). This study was carried out in a cooperation between the Information Theory Group of the Delft University of Technology and the Physics and Electronics Laboratory TNO (formerly Physics Laboratory TNO) in The Hague.

The testsite on which the study is performed is situated in the Flevopolder, a reclaimed land area. Figure 1 shows a part of this polder, including the testarea. The latter contains 195 agricultural fields, of which 164 were suitable for this experiment (crop type known, reasonable dimensions). Frequently used crop types in this area are winterwheat, potatoes and sugarbeets (80 % of total area). Onions and peas are also important crop types, but grown on smaller fields and therefore make up only 8.5 % of the area. These 5 most occurring crop types were used in designing the classifier.



Figure 1. Map of the Flevopolder with the testarea indicated (near 'Biddinghuizen'). The map shows an area of 35 x 35 km. The testarea measures 3.7 x 6.2 km.

The area was imaged with an X-band SLAR system, using digital recording, on 5 different dates throughout the growing season. At each flight date recordings were made from 3 different altitudes, resulting in 3 incidence angle ranges, and from 2 opposite sides of the testarea. This flight campaign resulted in a multitemporal and multiangular database of the area. A selection of these flights is shown in fig. 2. The development of the radar backscatter through time can be viewed from this selection. The sampling interval is appr. I month. For July two images are shown: one is flown at 660 m altitude, like the other images shown, which results in a grazing angle range from 7.5° to 16° (right to left in the images). The second July image is flown at 1600 m, resulting in grazing angles between 18° and 35° .

For comparison a croptype map is shown in figure 3. This figure results from the radar images, after

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18/04/80 L



11/07/80 L







10/06/80 L



12/08/80 L



Figure 2. X-band SLAR flights over the testarea on the indicated dates. Dimensions: 3.7 x 6.2 km. L = low altitude, 660 m (16⁰ - 7.5⁰ grazing angle) H = high altitude, 1600 m (35⁰ - 18⁰ grazing angle)

registration and field segmentation. The segmentation is done manual by drawing the field boundaries in the image on an image processing system. Only the 3 main croptypes could be indicated here, because of the limited separability of gray tones in a black and white image after reproduction. However 80 % of the area is covered by these 3 croptypes. The advantage of field segmentation of the radar data is two fold:

- The influence of speckle on the classification result is reduced to practically zero. This also holds for small inhomogeneities within the fields.
- The amount of data is tremendously reduced, since we end up with one value per image for every field, thus 164 values for one image.

For the classification experiment the radar data of the 6 mentioned images were combined with the groundtruth into one datafile. For every field there are 7 features, i.e. the true field label (croptype) and 6 average backscatter coefficients.



Figure 3. Croptype map of the testarea for the 3 main croptypes.

2. CLASSIFICATION EXPERIMENT

The purpose of the experiment was to design a classifier on basis of the radar data of the 5 most important croptypes. The classifier should be able to distinguish between these croptypes as early as possible in the growing season. This is different from the previous experiment (Ref. 1), where we used the flights of June, July and August for classification. For operational applications an early result would be much more useful. Certainly, an improvement over the older experiment should be possible, considering the high contrast in the early season flights (fig. 2, April and May). Figure 4 shows the development of the radar backscatter coefficient throughout the growing season for the 4 most important croptypes. Although the digital



Figure 4. Development of radar backscatter throughout the growing season for some croptypes. X-band SLAR, horizontal polarization, 15° grazing angle.

radar images have known intensity scales, an absolute calibration lacks in these measurements. Therefore the average backscatter coefficient of the sugarbeet fields was determined in the images and compared to calibrated ground based measurements, which were always taken at the same date and in the same area. The resulting correctionfactor was applied to the whole image. The data in figure 4 is for horizontal polarization and 15° grazing angle. The frequency is 9.4 GHz (X-band).

From figure 4 it can be seen that a large contrast exists between winterwheat and the other croptypes in April and May. In June the contrast is very small, while all the crops are in their growing stage. In July a good contrast is present between all the croptypes, whereas in August the development of the backscatter coefficient of potatoes interferes with the one for winterwheat. The large contrast between winterwheat and

the other croptypes in the early growing season only exists at low grazing angles. It can be explained as follows: the wintercrops, like winterwheat, are planted before winter and start growing in this area in April. The other croptypes are planted in April and May an show their biomass not before the end of May. Although the ground coverage by the new plants is small, the backscatter at low grazing angles is increased, because the smooth soil alone gives a very small amount of backscatter at these angles, so the small leafs sticking out of the ground contribute considerably to the total backscatter. At larger grazing angles say around 40°, the backscatter from the fields is much increased and the previously described effect is smaller, resulting in very little to no contrast between these croptypes.

Thus we should be able to distinguish between winter- and summer crops from one flight in April or May, and since our testarea contains mainly one wintercrop, namely winterwheat, we should be able to identify all winterwheat fields. Figure 5 shows the histogram of the field averaged radar backscatter coefficients of the SLAR image from May. From this



Figure 5. Histogram of the May flight: winterwheat (right) is separated from the other croptypes.

figure it is clear that the winterwheat fields can be completely separated from the other fields, simply by applying a threshold level.

Now that the winterwheat is identified, we must try to classify the remaining fields from other flights. This demonstrates the hierarchy in our classifier in contrast with the previous classification experiment (Ref. 1) where the time dependence of the radar backscatter throughout the growing season was used as discriminator.

Sofar the design of the classifier was straight forward and rather simple. However to derive an optimum result more elaborate methods should be used to investigate the data. Our main purpose is to make a selection from the available features per field. Eigenvalue or principal component analysis can be used to reduce the dataset into a set of uncorrelated features. This is done by a dataprojection on two or more Eigen vectors, which are determined from the covariance matrix of the dataset.



Figure 6. Feature space plots of May vs July and the 2 July-features (low and high altitude).

An evaluation of the dataset using this method showed that the first two eigen vectors contained 91 % of the total variance, which means that the other four eigen vectors may be deleted. The first eigen vector is mainly determined from the April and May-features, whereas the second eigen vector is in fact a combination of the two July-features, so the two flights at different altitudes.

Since the datasets from April and May are highly correlated (correlation coefficient 0.91), the dataset of May was chosen as before and furthermore we selected the two July-features. Figure 6 shows feature space plots for May versus July and for the 2 July features. A cross reference of the labels used in this and other figures can be found in Table 1. In both plots clusters of croptypes

croptype	label	label
potatoes	А	1
sugarbeet	В	2
winterwheat	Т	3
peas	E	4
onions	U	5
oats	Н	6
winterbarley	GR	7
beans	BO	8
grass seed	GΖ	9
spinach	SP	10

Table 1: legend to plotlabels

can be distinguished. A projection on one of the axes makes the classes inseparable, except for the wheat in May of course and the sugarbeets in July. The combination of the two July features means that we deal here with angular dependences to obtain discrimination. The short time interval between these two measurements more or less guarantees that the differences are only caused by the change in incidence angle. Therefore the clusters are rather small. Even the winterwheat seems to be separable in this plot, but since this can be done in May, no further attention is paid to it. To reduce the dataset, we now introduce a linear combination determined as the first eigenvector of the two July features, to optimise the separability of the crops.

Figure 7 shows the plot of May versus the combination of the July features. Figure 8 shows a histogram of the July data projected on the new axis. Winterwheat fields are excluded in this histogram. The peaks are from left to right potatoe, peas, onion and sugarbeet. The classes can be separated with the parametric Bayes classifier for normal distributions.

A test of the designed classifier on the same data as used for the design, produced a very high classification result, which is not surprising. However since we have no other data available, it is difficult to test the classification algorithm.



Figure 7. Plot of May versus the projection feature (linear combination of the 2 July features)



Figure 8. Histogram of the projection feature. Peaks are (left to right) potatoe, peas, onion and sugarbeet.

	1	С	LΑ	S S	ΙF	ΙE	R L	A B	ΕL
		1	2	3	4	5	6	7	8
Т	1	33]	1				
R	2		36						
U	3			53					
E	4	1		1	5	-1			
	5	2			1	11			
L	6			3			1		
А	7			3					
В	8	1							4
E	9			3	1	1			
L	10				1				

Table 2. Classification result after automatic field segmentation of the testarea (see table 1 for legend of labels).

To perform some sort of test, the data from fig. 2 was automatically segmented using a split and merge algorithm (Ref. 5) and then classified. This brings a little variation in the data, because the field boundaries now differ from the ones in the manual segmentation. Of course, this is only a small effect, therefore care should be taken in the interpretation of the classifier results. Table 2 shows these results. The first 5 classes were used for optimizing the design of the classifier. Classes 6 - 8 represent a very small amount of data and cannot be considered to be representative. Class 8 (beans) is not planted until July, so in July these fields are still almost bare, and therefore easy to recognize (see fig. 2). Classes 9 and 10 are not considered in the classifier and therefore identified as other croptypes.

3. TEXTURE ANALYSIS

Sofar we have only considered the use of field averaged backscatter coefficients as input to a classification algorithm. The reason is that the within field variations are believed to be caused by speckle, a phenomenon of coherent illumination. This leads to a multiplicative noise in the images, with a standard deviation of 5.6 dB for a 1 look image. The pixels in the SLAR images have 30 independent samples, which reduces the standard deviation to 1 dB and converts the negative exponential distribution of the individual measurements to a nearly normal distribution.

In some cases however, the inhomogeneities in the illuminated area may cause larger standard deviations and even produce textural effects. In such cases texture could be used as a feature for classification (Ref. 6). In theory it is even possible that the speckle statistics are influenced by the microstructure. It is for the optimization of the classifier of interest to know what contribution may be expected from statistical measures to the classification result. Therefore experiments were conducted on the dataset of figure 2 and on a SAR image (SAR 580, d.d. 3/7/81, X-band, HH polarization) of the same area.

First of all the standard deviation per field was calculated for the SLAR images of April and July (low altitude). Figure 9 shows the results. In April there is a difference in standard deviation between the bare fields and the vegetated fields. The standard deviation of the vegetated fields is in the order of 1 dB, which corresponds to our expectation on basis of the speckle. The bare fields however, have larger and more varying standard deviations, which is probably caused by variations in roughness and soil moisture of the top layer. For the vegetated fields the influence of the underlying soil on the backscatter is reduced by the attenuating effect of the vegetation. However, the difference in average backscatter between bare and vegetated fields is much larger than the difference in standard deviation. Therefore an important contribution to the classification is not expected from this feature in April.

In July, when all the fields, except beans, are fully covered, the standard deviation is always around 1dB, the expected value from the speckle noise. No contribution to the classification result can be expected in this case.

The principal component analysis, discussed earlier, confirmed these findings, when it was extended with the field standard deviations as features.

Although we find little or no contribution from the standard deviation to the classification, this does not necessarily mean that there is no texture. One needs higher order statistics to investigate this. An often used method to measure texture in images is based on the Gray Level Co-Occurence Matrix (GLCO or GLCM, Ref. 2), which provides a sensitive means of measuring small scale textures in images.

The GLCO is a matrix of relative frequencies P. with which 2 neighboring resolution cells separated¹ by a distance d occur on the image, one with gray level i, the other with gray level j. Such a matrix can be produced by counting all the gray level pairs i,j with the specified distance d between them.

From the GLCO several textural measures can be calculated (Refs. 2, 7). One of them, which is used here, is the correlation measure:

GLCO-CORR
$$\Sigma$$
 Σ $\sum_{i=1}^{M} \sum_{j=1}^{m} \sum_{s}^{m^2}$, with



Figure 9. Within field standard deviation versus field-averaged backscatter coefficient for the SLAR flights of April and July (some labels differ from table 1: GZ→Z, WG→Δ, BO→P, SP→S).



Figure 10. The GLCO-CORR measure plotted for varying horizontal pixel distance for the SLAR flights of May and July (low altitude). Three crop types are used: potatoe (A), winterwheat (T) and sugarbeet (B). They are plotted in separate columns to keep them recognizeable.

m = mean and s = standard deviation of the sums of the rows or columns. A second measure used here is the Gray Level Difference vector (GLD). This is in fact a histogram (relative frequencies) of gray level differences. It can be computed from the GLCOmatrix. The measure that is used here is:

GLD-MEAN:
$$\sum_{i=1}^{M} i \cdot P_i$$

Figure 10 shows the computation of GLCO-CORR for the SLAR flights in May and July. In May the wheat fields are distinguishable, with a few exceptions whereas potatoe and sugarbeet are mixed. In July all the croptypes are mixed. This result is similar to

i.

the croptypes ar





the result from the standard deviation. There is not much dependence on the distance between the pixels as it is varied from 2 to 10 pixels.

Figure 11 shows the GLD-MEAN for the SLAR flight of May and calculated for the same horizontal distances as before. The total range of the measure now increases with the pixel distance. The separability seems to be a little better than for GLCO-CORR, but once again hardly any extra information is added, if compared with the field averaged backscatter data.

Other textural measures based on the GLCO and the GLD were tested as well, but no significant extra information could be derived, also not if these measures were plotted in feature space plots. The conclusion based on this information must be, that for agricultural fields texture does not play an important role in these X-band SLAR images.



After having completed the first plot, the idea arose that field A4 (potatoe) perhaps had a different row direction, compared to the other potatoe fields. However, since the vertical and horizontal steps show the same result, this is not likely. The row direction in these fields is not known to us, but is probably parallel to the horizontal or vertical field boundaries (see fig. 1-3), which corresponds with the horizontal and vertical steps taken for the GLCO.

As before the conclusion seems to be, that the radar images investigated, show no textural variations within the agricultural fields, that can be applied for crop identification.

4. CONCLUSIONS

In this paper a follow-on study into the possibilities of crop identification was presented. The goal was to optimize the classification result from a previous study by adding early season SLAR flights and by investigating the potential of small scale texture in agricultural fields.

A hierarchic classification procedure is proposed. The success of this classifier is based on the separability of winterwheat or rather wintercrops at low grazing angles $(5^{\circ} - 15^{\circ})$ in the early growing season (April, May) and the ability to discriminate other crop types in the mid-season on basis of their angular dependence in the grazing angle range $5^{\circ} - 35^{\circ}$. Field averaged radar backscatter values are used. The test of the classifier was performed on the



Figure 12. Plot of the GLCO-CORR measure for an X-band SAR 580 image at varying pixel distances, horizontal (left) and vertical.

same dataset as was used for the design of the classifier, although for the test the fields were segmented in a different way (automatic instead of manual). Care should be exercised in the interpretation of the test results, since the success percentages may be over estimated in this situation.

Further investigations should incorporate a test in ecologically different area's and area's with different and more varied crop distributions. Also the use of angular dependence should be further investigated. In The Netherlands a research project is running to cover these subjects.

The use of features other than the average radar backscatter, i.e. the standard deviation and GLCO textural measures, has sofar not shown to provide a significant contribution in crop classification. Although it is in theory not impossible, that small scale texture (even if it is smaller than the resolution of the radar) in agricultural fields is imaged by the radar, no sign of it was found in SLAR images and a SAR 580 image. If subresolution structures like row direction, plant distance, etc. influence the speckle statistics in an image, then this could perhaps be better judged from the raw SLAR data, where no averaging of single measurements has taken place. This was not investigated sofar.

5. ACKNOWLEDGEMENT

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The classification study was mainly performed at the Information Theory group of the Delft University of Technology by mr. P.J. van Leeuwen, a student of mr. J.J. Gerbrands. The texture analysis was performed at the Physics and Electronics Laboratory TNO. Mr. R. Vlaardingerbroek of this institute is credited for the many calculations and plots he produced on the subject.

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CROP MAPPING WITH X-BAND RADAR

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During the years 1976 through 1981, the Dutch ROVE team (Radar research on vegetation) collected a data bank of X-band scatterometer measurements. In trial fields, a number of crop types were grown and sampled at least once a week for growth analysis. Backscatter measurements for HH, HV and VV polarisation were also made, at grazing angles of 15 to 80 degrees.

In this paper, an analysis of the data is made for the purpose of crop classification, and the results are compared with SLAR flight data.

Most crops show a specific time sequence in radar backscatter. Apart from the influences of the crop calendar, crop morphology and canopy structure seem to be more important factors in explaining backscatter patterns than, say, biomass or soil moisture content. For this reason (sensitive response to crop structure) crop types anf growth stages do show a specific backscatter pattern as a function of the grazing angles used. Consequently, a combination of multitemporal and multiangular observations offers a good chance of identifying crops with X-band SLAR. The number of images needed and the choice of optimum time and angle depend on the agricultural system observed (main crop type, field size) and the required accuracy.

A difficulty inherent in radar backscatter on vegetation is a considerable degree of speckle and variation, caused by interactions between crop type, soil type and weather. Analysis of the ROVE data set shows that the highest information content (ratio of variation between crops to variation within crops) is achieved by measurements made in the period of stable growth (after almost complete soil coverage and before ripening) with grazing angles between 30 and 60 degrees. VV polarisation is preferable to HH polarisation. A second measurement (at different time or angle) increases classification accuracy, but further repetition yields only small increases.

In 1983 and 1984, the Dutch SLAR equipment was used to test the concept in a practical, operational environment. Test areas of 4 x 20 km were flown over three times per growing season. Only grazing angles not exceeding 40 degrees could be used. The Reseda image-processing system was used to bring the images into registration, to apply a median filter and to classify according to crop type with the aid of training samples. The results are in good agreement with expectations based on the ROVE data set.

On average, 80% of fields were classified correctly (potatoes 85%, sugar beet 95%). This would appear to be a satisfactory result for such purposes as a general survey for crop statistics, or as a basis for stratified sampling and

for field checks in mapping activities. (For studies on improving the classification algorithm, see the papers to be presented at the workshop by Messrs. P. Binnenkade, J.J. Gerbrands and P. Hoogeboom.)

SESSION C



MICROWAVE EMISSION FROM VEGETATION: GENERAL ASPECTS AND EXPERIMENTAL RESULTS

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ABSTRACT

The objective of this research was to investigate the relationships between microwave (MW) emission and crop physical parameters.

The knowledge of crop radiometric features is important both to evaluate the influence of vegetation on Soil Moisture Content (SMC) measurement and to assess the possibility of measuring some vegetation parameters which are useful in agriculture management.

Much research has been carried out to estimate the reduction in sensitivity of SMC measurements due to vegetation cover. Several theoretic models, based either on coherent or incoherent theory, have been developed to account for emission due to the vegetation layer. In this paper we show the results of experimental investigations carried out on different crops with two ground based X and Ka band radiometers.

Keywords: Microwave emission, crop MW signatures, vegetation water detection.

1. INTRODUCTION

An efficient use of microwave (MW) sensors in remote sensing requires a deep knowledge of the electro magnetic characteristics of the observed media. To this end theoretical and experimental studies with different approaches are still necessary, although much research has been carried out over the past years.

MW radiometry is a good way to study the dielectric properties of soil and vegetation in their natural environment. Most of these studies have so far been devoted to the relationship between MW emission and Soil Moisture Content (SMC) of bare and vegetated soils (Ref. 1). Since MW emission depends on physical and morphological characteristics of the emit ting medium, soil texture, roughness and tillage have been recognized as factors which affect SMC measurements (Refs. 2, 3, 4); the observation parameters which minimize these spurious factors have been established. For canopy covered soils, vegetation is probably the most important factor to affect the accuracy and the sensitivity of SMC measurements.

1.1 Experiments

Experiments performed under Laboratory conditions and from aircraft (Refs. 1, 5, 6) have shown that the screening effect of vegetation increases as both biomass and observation frequency increase. The sensitivity reduction to SMC measurements, earlier reported by Kirdiashev (Ref. 5) has been confirmed by Wang (Ref. 7), Jackson (Ref. 8).

Shutko (Ref. 6) found that the influence of grain crops, alfa-alfa and grass is high in the centimeter band, while L band emission from such vegetated covers is fairly similar to bare soil emission. On the other hand wide leaf crop emission (e.g. corn or sorghum) can decrease as λ increases. This behaviour can be explained by the increase of wide leaf reflection properties with the decrease in λ .

Results of several investigations, carried out by NASA researchers over many years, have shown that even L band data are affected by the presence of vegetation. Reduction in SMC measurement is rather low under pasture and very high under trees (Ref. 9). The sensitivity reduction factor due to corn has been computed by Ulaby (Ref. 10) at 1.4 and 5 GHz.

Meteorology, Agriculture and Hydrology can largely benefit by a timely knowledge of SMC gained on an appropriate space scale. In agriculture SMC is an important parameter for the estimation of evapotranspiration, the knowledge of which is fundamental for correct irrigation scheduling and yield forecast. When SMC is not easily available or when transpiration mainly depends on meteo parameters, a direct information on plant water conditions is very useful. Moreover the specification of relationships between MW features and vegetation parameters, such as leaf area index (LAI) and biomass, could greatly improve the accuracy of remote sensing systems even in crop monitoring and identification.

An integrated multiband remote sensing system can

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indeed explore several layers of the Soil-Plant-Atmosphere-Continuum; if radiation at frequencies as low as 1 GHz penetrates most herbaceous crops and even soil, at higher frequencies most emission comes from vegetation.

A frequency dependent response to different components of a corn crop was found by O'Neilletal. (Ref. 11); C band emission appears to be affected more by leaves and cobs, while stalks mainly influence L band emission.

The different response of bare soil and vegetation to two linear polarizations of the X band emission enables one to detect the soil covering index. Observations of alfa-alfa growth cycle have shown a correlation between X band polarization index (PI) and LAI (Ref. 12). Ka band PI from a corn crop was found to be dependent on plant water conditions (Ref.13).

1.2 Modelling

Physical properties of canopy covers can be obtained by remote sensing data with the aid of adequate theoretical models which allow one to investigate the interaction mechanisms of electromagnetic energy with soil and vegetation having recourse to fundamental physical laws.

Radiation from natural media, which vary in a random pattern in space and time, can be described by means of the transport equation (Ref. 14). This theory is not as mathematically rigorous as the analytical one in that it was developed on the basis of addition of powers rather than of fields, nevertheless its usefulness in solving many physical problems has been largely proved. Moreover Ishi maru (Ref.15,16) demonstrated that the brightness used in the transport theory and the mutual coherence function used in the analytical theory are related through a Fourier transform.

In a plane parallel stratified medium with randomly distributed scatterers embedded in a low loss dielectric, the radiative transfer equation can be written as follows:

$$\label{eq:2.1} \begin{array}{ll} \mu \; \frac{dB(\; \tau \;,\; \mu)}{d\tau} \; = \; -B(\; \tau \;,\; \mu) \; + \; \frac{W}{2} \int_{1}^{1} P\;'\; (\; \mu \;, \mu \;') \; B(\tau \;,\; \mu \;') \; d\mu \;\! + \; J \; (\; 2 \;) \\ \text{where:} \end{array}$$

 \boldsymbol{z} is the normal to plane of stratification

 $B(\tau,\mu)$ is the brightness: average power flux density within an unit frequency band per unit solid angle (w m^{-2} Hz⁻¹sterad¹)

(1)

- ∫_{Z₀}[►] kdz is the optical depth(dimensionless) т = μ = $\cos \theta$ cosinus of the polar angle
- $k_{a} + k_{s}$ volume extinction coeff. (m⁻¹)
- k_e = volume absorption coefficient
- k_a = volume scattering coefficient
- $k_s =$ W =
- k_{s}/k_{e} albedo per single scattering $P'(\mu,\mu')$ is the normalized phase function applicable, where there is azimuthal simmetry $\frac{1}{2} \int P'(\mu, \mu') = 1$ J(z) is the source function

For a layered medium in local thermodinamic equilibrium at temperature T, the radiant energy in the MW region is given by the Rayleigh Jean's equation. Since the emission coefficient is given in terms of absorption coefficient by Kirchoff's law, it is:

$$J(z) = \frac{k_{a}}{k_{e}} \frac{2kT}{\lambda^{2}} = (1-W)\frac{2kT}{\lambda^{2}}$$

where k is the Boltzmann constant.

The absorption coefficient can be related to the complex dielectric constant of the medium ($\epsilon = \epsilon \; ' + j \epsilon \; '')$ by means of the relationship:

ka =
$$(2\pi(\epsilon')^{\frac{1}{2}}/\lambda_0)\epsilon''/\epsilon'$$

The scattering coefficient is given by:

$$ks = N\sigma_s$$

where N and $\sigma^{}_{\rm S}$ are respectively density and cross section of the scatterers.

By using the linear relationship between the bright ness and the brightness temperature(Tb)established by the Rayleigh Jean's law, Eq.(1) can be written as follows:

$$\mu \frac{\text{Tb} (\mu, \mu')}{d\tau} = -\text{Tb}(\tau, \mu) + \frac{W}{2} \int_{-1}^{1} P'(\mu, \mu') \text{Tb}(\tau, \mu') + (1-W) T \quad (2)$$

In a simple model developed by Basharinov and Shutko (Ref. 17) vegetation is treated as an absorbing non scattering (W=O) medium having both constant temperature and absorption factor bounded by soil surface. The brightness temperature Tb above the canopy, obtained by solving the radiative tranfer equation for this two-layer model, is given by:

$$Tb = (1-Rs)Ts exp(-\tau/\mu)+Tv(1-exp(-\tau/\mu))+RsTv exp(-\tau/\mu)$$
(1-exp(-\tau/\mu)) (3)

where τ = kalis the vegetation optical depth, l is the thickness of the vegetation layer " Ts and Tv are the soil and vegetation temperature and Rs is the soil reflectivity. The soil contribution as well as the direct and reflected (by the soil) vegetation emission are clearly distinguishable in this equation.

The optical depth of vegetation was linearly correlated to plant water content per unit area (mv) by Kirdiashev et al. (Ref.5) in the following equation:

$$\tau = \frac{g \sec \theta}{3\lambda} \ 10^{-5} \ \text{mv}\,\text{c}^{"}$$

This relationship however contains a plant shape parameter g, the knowledge of which requires a lot of measurements.

A more sofisticated model, studied by Mo et al. (Ref.18) assumes that vegetation is an uniform layer of absorbing and scattering material bounded by the soil surface and by air. The model is based on the radiative transfer equation written as in Eq.1, which is invariable in form under the following transformations:

$$P(\mu,\mu') = 2\alpha\delta(\mu,\mu') + (1-\alpha)P^*(\mu,\mu')$$

$$\tau^* = (1 - \alpha W)$$
(4)
$$W^* = \frac{(1 - \alpha)W}{1 - \alpha W}$$

where 2α is the fraction of radiation scattered in the forward direction, $\delta(\mu,\mu')$ is the delta function and $P^*(\mu,\mu')$ a phase function which is not strongly

peaked in the forward direction (Ref. 19).

Solving Eq.1 under the transformations of Eq.4 and including scattering only in the forward direction $(P^*(\mu,\mu^+)=0)$ the observed brightness temperature Tb is:

$$Tb_{p} = (1 - R_{Sp}^{\Gamma}(\mu)Ts)exp(-\tau^{*}/\mu) + (1 - W^{*})Tv(1 - exp(-\tau^{*}/\mu)) + R_{Sp}^{\Gamma}(1 - W^{*})Tv(1 - exp(-\tau^{*}/\mu))exp(-\tau^{*}/\mu)$$
(5)

where: p is for H or V polarization and R^r is the reflectivity of soil which may be rough.

Eccept for the factor $(1-W^*)$ this equation is formally identical to Eq.3. The two equations coincide when the scattering is negligible.

If the optical depth is very large, we have:

 $Tb_{D} \simeq (1 - W^*)Tv$

This model then suggested that for high absorbing media the brightness temperature is indipendent from the angle of observation.

Authors found that their model is in good agreement with experimental data from L and C bands over corn, soybean and wheat. The linear relationship between optical thickness and plant water content per unit area was confirmed, moreover the effective canopy single scattering albedo W* was found to be dependent on vegetation type.

The wide theoretical treatment of radiative properties of layered media, carried out by Ulaby et al.(Ref. 20) leads to similar conclusions of Eq.5.

An important aspect in development and pratical use of radiative transfer models is connected to the knowledge of the dielectric properties of the natural media and to the relationships between their dielectric constants and those of their constituents.

Plant materials are heterogeneous systems which contain free and bounded water; in the MW region free water is much more important than the bounded one, because the latter has dielectric properties similar to those of dry materials. Dielectric characteristics of vegetation have been investigated mainly by De Loor, Carlson and Ulaby and Jadlike (Ref. 21 - 24). Relationship between the dielectric constant of a heterogeneous mixture and that of its components have been given by De Loor who trea ted plant material as a mixture with high water content.

Laboratory measurements utilizing waveguide resonator techniques were carried out by Carlson (Ref. 23) at 8.5 GHz and by Tan (Ref.25) at 9.5 GHz.

Dielectric constant measurements of leaf and stalk materials as a function of volumetric water content have been recently carried out by Ulaby and Jadlicke in 1-8.5 GHz band. Experimental results have been compared with several multicomponent models of vegetation constituent parts (bulk vegetation air, bounded and free water). A very good fit to data is obtained when one uses a three-component model in which air and water are considered random needle-like inclusions in bulk vegetation. Ulaby's paper however points out that further work must be carried out to better understand the role of free and bounded water in heterogeneous materials

2. EXPERIMENTAL RESULTS

Vegetation emission measurements were carried out on different test sites through 1980-84 by means of truck mounted MW and infrared (IR) radiometers. The IR sensor was a commercial type operating on the 8-14 $_{\mu}$ m band, with a temperature accuracy of \pm 0.5 K. The X (10 GHz) and Ka (36 GHz) band radiometers, described elsewhere (Ref 26) are Dicke type radiometers with two simultaneous V and H polarization outputs and an internal calibration system which takes into account a variable temperature load and a precision noise source. In addition to these systems, an external blackbody was used to obtain an accuracy of 1 K or better. Relative accuracy between the two polarizations can be more than 0.2 K.

Ground truth data were simultaneously collected and recorded together with MW data (Ref.27). Crops measured were corn, alfa-alfa and wheat.

2.1 Soil and vegetation emission

The basic parameter used to express MW emission was the normalized brightness temperature obtained from the ratio between MW and IR outputs.

Previous research (Ref.10) showed that at frequency higher than C band most emission from canopy cover is due to plants. Nevertheless we measured a contribution from soil under vegetation even from Ka emission.

Measurements, carried out before and after flooding of a corn field, show that emission is

sensitive to SMC and soil temperature. The normalized temperature difference A Tn between wet and dry conditions, as a function of the incidence angle θ , is shown in fig.1 (a) X band and b) Ka band). From these diagrams we can deduce that in this field (plant height = 120 cm, density = ~ 6 $plants/m^2$) the normalized temperature is indipendent of SMC if $\theta \approx 40-50^{\circ}$. This condition can change according to the crop type, plant density and height. Moreover, since vegetation and soil thermometric temperatures often have similar and correlated values, separating the contributions from the two media is rather difficult. The contribution from soil under ripe wheat (90 cm tall, 280 plants/ $/m^2$) was estimated (Ka band, $\theta = 0.40^\circ$) using the radiative transfer equation, for a two layer model, and a multilinear regression analysis carried out between measured values of Tv, Ts and Tn (Ref.27). In this analysis we only used those measurements where Tv and Ts could be considered statistically indipendent; nevertheless it is rather difficult to rigorously verify these conditions in a natural environment.

Our observations and those by other experimenters seem however to confirm that, at frequencies equal or hiher than X band, and with an incidence angle higher than $30-40^{\circ}$, the soil contribution to the observed MW amission of a canopy cover is negligible for most crops.

Emission of several crops measured on different test fields shows that small variations occur be-

tween well developed crops; moreover, the range of normalized temperature (Tn) among different crops may be similar to the range of variations due to differences in plant physical conditions. Nevertheless, high accuracy Tn measurements, from X and Ka bands, show that spectral signatures of some crops can be identified. The bidimensional diagram of fig.2 is a simplified sketch of the average behaviour of corn, wheat, alfa-alfa and bare soil, as resulting from manyyears' observations. This diagram confirms that a broad leaf culture, such as corn, has almost the same emission from X and Ka bands, whereas emission of wheat and alfaalfa increases with frequency; the highest difference between two frequencies was found for bare soil, where roughness height variations were of the order of a few centimetres, while the highest emission at both frequencies was found in wheat crop.

An example of simultaneous observations of corn and alfa-alfa is represented in the same bidimensional diagram of fig.3, where the two clouds of points can be separated.

A shift of experimental points from left to right and from the lower to the upper side was observed during the day, maybe due to a change in the physical conditions of the crop. This daily variation gives a significant contribution to the spread of the measurements ; therefore, observations carried out at the same time of day should however allow one to achieve a clearer identification of the two crops.

The spectral response of bare soil and well developed cultures suggested the advisability of exploring the relationships between MW emission and the crop coverage of soil, or perhaps the canopy leaf area index (LAI), in greater depth. The latter is in effect one of the main important parameters in yield forecast models.

In fig.4 the difference Δ Tb (= Tb_{Ka}- Tb_X) between the Ka and X band brightness temperature of a corn crop, measured at midday, is compared with the LAI as a function of time (days) during the growth cycle. In a first approximation the trend of the two parameters, Δ Tb(t) and LAI(t), versus the time can be represented respectively by a decreasing and an increasing exponential function.

If the results of the measurements are represented in the Δ Tb, LAI plane (fig.5), a linear relationship appears between the two variables; this may mean that Δ Tb decreases in time while the LAI increases with about the same time constant.

Only five LAI measurements are available for this growth cycle, however other points can be added to the diagram of fig.5 (stars) by using Δ Tb measurements and simultaneous values of LAI obtained from fig.4. All these points lie very near to the regression line.

2.2 Crop water conditions

Whereas the difference between Ka and X band emission seems to be an index of the crop coverage of soil, emission from the Ka band has different values in two linear V and H polarizations depending on the percentage of water content in the observed medium. This behaviour has been already pointed out for bare soil at lower frequencies (Ref. 28). Data from Ka band taken during the growth cycle of corn show that the polarization index (PI = (TbV-TbH)/%(TbV+TbH)) measured at an incidence angle $\theta = 50^{\circ}$, has very low values when vegetation is in stress conditions and increases when the plant reassumes water (Ref.13). The diagram of fig.6 shows the temporal behaviour of the two V and H polarization outputs from the Ka band radiometer employed for the observation of corn, with $\theta = 50^{\circ}$. Two different conditions of heavy water stress and good plant health are marked in this diagram; the two polarization outputs are almost equal in the first phase (stress), while they are different to each other when vegetation is well watered.

On the basis of this and other similar observations further research was carried out to investigate the relationship between the PI and plant water content.

A non linear relationship was first recognized between PI and the Crop Water Stress Index, as defined by Idso et al.(Ref. 29). Afterwards, simultaneous measurements of PI and leaf water potential (ψ_{g}) were compared and correlated with the following linear relationship:

$$PI = 14 - 0.46 \psi_0$$
 (6)

As shown in the diagram of fig.7 the sensitivity of PI to $\psi_{\rm g}$ is rather low, nevertheless if we compare the $\psi_{\rm g}$ values computed by means of Eq.6 for a corn crop, with the water available to the plant in the soil, we obtained the diagram in fig.8 which shows a rather good agreement between these two parameters and confirms the capacity of Ka PI in sensing $\psi_{\rm g}$.

3. CONCLUSIONS

Theoretical and experimental research demonstrated the potentiality of MW radiometry in SMC measurement. Vegetation cover however reduces this sensitivity above all at wavelenghts lower than 20 cm. The effect of vegetation can be studied by referring to the radiative transfer theory and considering the canopy cover as uniform absorbent and scat tering medium. At wavelenghts lower than 3 cm most emission comes from the plants and can give information on vegetation type and conditions.

The results of measurements carried out on different test sites have shown that the difference between Ka and X band brightness temperatures depends on the crop leaf area index. Moreover, a sensitivity of the Ka band polarization index to plant water content was determined for corn and a linear relationship between this MW parameter and the leaf water potential was found.

Many questions still remain open such as the relative role of absorption and scattering and the different contributions of stalks, leaves and fruits to the emitted power.
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Fig.1 : The difference Δ Tn between the normalized temperature of a corn crop, measured before and after a soil flooding, as a function of incidence angle (a : X band, b : Ka band). Vegetation water conditions don't change during the two measurements Plant height = 120 cm; density = 6 plants/m².



Fig.2 : Bidimensional diagram of the normalized temperature ranges $({\rm Tn}_{Ka} \mbox{ versus } {\rm Tn}_{\chi})$ of bare soil, corn, wheat and alfa-alfa.



Fig. 3 : Bidimensional diagram of simultaneous observations of corn (•••) and alfaalfa (•••). (••) represent measurements taken during the same day at regular time intervals.

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Fig.4 : Δ Tb = Tb_{Ka} - Tb_X measured at midday (continuos line) and LAI (dashed line) as a function of time. (corn)



Fig.5 : Δ Tb = Tb_{Ka}- Tb_X, as a function of LAI For star points (*****) LAI is deduced from diagram of fig.4.



Fig.6 : Tb(Ka) of a corn crop as a function of time (days). Continuous line = vertical polarization, dashed line = horizontal polarization. The two polarization outputs have the same value during a stress phase, whereas in well watered conditions V polarization is higher.



Fig.7 : The polarization index (PI) from the Ka band as a function of leaf water potential (corn)(ψ_{ρ} .



Fig.8 : The leaf water potential of corn computed from PI(Ka band) (continuous line) and plant available water (dashed line) as a function of time.

MODELLING VEGETATION : EFFECT OF BIOMASS AND STRUCTURE OF A WHEAT CANOPY ON RADAR BACKSCATTER

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Due to the wide variety of parameters involved in the radar backscatter on vegetation canopies, it is necessary to use generalized models to explain the radar backscatter behaviour of a class of vegetation canopies with similar structure.

This paper will discuss some results of modelling applied to a wheat canopy in order to understand the angular behaviour and the value of the radar backscatter coefficient, in relation with the structure and the biomass of the canopy.

Results obtained with experimental data acquired with in_situ scatterometer and examples from airborne images will be presented.

VARIATION OF THE RADAR BACKSCATTER OF VEGETATION THROUGH THE GROWING SEASON

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ABSTRACT

In the period between 1975 and 1981 the ROVE team (Radar Observation of VEgetation) in the Netherlands collected data on the radar backscatter of crops through the growing season. Using these data general trends in the behaviour of the radar backscatter through the growing season (temporal signatures) can be determined for a number of crops. The results are reported. Comparisons are made with data from the literature and with the vegetation model developed by Attema and Ulaby. This last model can be used also to obtain information on the soil under the vegetation.

1. THE TEMPORAL SIGNATURES OF CROPS AT MICROWAVE FREQUENCIES

Figure I gives an example of the seasonal dependence of the radar return for a number of crops as measured by the ROVE team (Ref. 1) in 1980 for 10 GHz and a grazing angle θ of 30°. Up till June 2 the coverage of the soil by vegetation is still small, so the soil plays the most important role in the reflection. After that date differences begin to occur due to the increasing influence of the vegetation. In this figure the peak on May 7 is due to a variation in soil moisture due to 10 mm rainfall shortly before the measurement. Further sudden peaks in the bare soil measurements later in time are indications for such sudden variations in soil moisture. They then also occur in the vegetation measurements but to a lesser extent: the canopy has a damping effect. The slow decrease in the radar return γ of the bare soils through time is caused by the effect that due to rainfall and slaking the roughness of the soil decreases through time. As can be seen the total range in $\boldsymbol{\gamma}$ is small: in the order of a 10 to 15 dB. It is within this range that discrimination between crops, or within crops, must be done.

Having available a number of such data sets as a function of time it becomes possible to show that



Figure 1. The radar return parameter γ as a function of time; ROVE data 1980; 10 GHz, HH polarization; grazing angle θ =30°.

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Figure 2. The temporal signature for peas. ROVE data, 1980; 10 GHz, VV polarization, θ = 20°.



Figure 3. The variation in the temporal signature for peas due to varying meteorological conditions. ROVE data; 10GHz, VV polarization, $\theta = 20^{\circ}$.

the shape of such curves is typical for specific canopies. The measurement procedure used by the ROVE team (measurement of 10 to 15 fields in one day at 2 frequencies and 3 polarization conditions; Ref. 1) is particularly suited to adapt the number of observations per week to the growing stage. Since also measurement series are available for several growing seasons it so becomes possible to determine "temporal signatures" for specific crops. Figure 2 gives an example for peas in 1980. Even small variations, as e.g. the period of flowering, can be indicated because of the high density of the temporal measurements. This general behaviour can vary somewhat from year to year due to variations in the meteorological conditions but the general trend remains the same as figure 3 demonstrates. Similar variations (lengthening, resp. shortening of the growing cycle) occur for the other crops and in the same way in the same year.

This enables us to determine these general trends and figure 4 finally gives them for a number of crops. Figure 5 gives a similar example for data sets taken at Kansas University by Ulaby (Ref. 2). When we compare these last two figures two things can be remarked. Growth and growing stage is dependent on the place on earth and the meteorological conditions. For instance both figures show curves for wheat. They are similar in behaviour and values for γ but in figure 5 growth started earlier and the growing cycle is shorter also. Such variations have to do with latitude (climate) and are - in general - smaller than the variations in time due to local meteorological conditions as mentioned above.

Using the similarity in shape of the temporal pattern of the radar return γ for a specific crop Smit developed a method to use these temporal changes for croptype inventory purposes (Ref. 3). His proposal was later verified by the ROVE team (Ref. 4) with good results. Table 1 gives an example. In this example the data were taken at X-band and HH polarization and grazing angles under 20°. Correct classification increased from 35% for one look to 88% for three looks in time. As we see in table 1 very good classification results are obtained for sugarbeets and potatoes after two flights already. At this moment it is investigated if this property can be used for the control on



Figure 4. Average shape of the temporal signature of four crops. ROVE data. S: sugarbeets; P: potatoes; W: wheat; O: oats; a: flowering; b: panicles come; c: leaves begin to die; d: lodging begins; 10 GHz; $\theta = 50^{\circ}$; VV polarization.





			11/7		1	0/6 +	11/7	1	1/7 +	12/8		10/	6 + 11	/7 + 12	/8	
croptype	number of fields	сс	nc	ic	cc	nc	ic	cc	пс	íc	cc	nc	ic	% of cc	area nc	ic
sugarbeets	40	40	0	0	40	0	0	40	0	0	40	0	0	100	0	0
potatoes	40	12	28	0	39	1	0	32	7	1	39	0	1	97.1	0	2.9
wheat	58	0	54	4	3	49	6	39	14	5	42	1.2	4	76.2	18.9	4.9
onions	22	5	17	0	7	15	0	18	4	0	19	3	0	88.5	11.5	0
oats	5	0	5	0	2	3	0	1	4	0	4	1	0	87.3	12.7	0
peas	12	3	9	0	6	6	0	S	7	0	5	7	0	45.1	54.9	0
beans	5	3	2	0	5	0	0	4	1	0	5	0	0	100	0	0
	182	63	115	4	102	74	6	139	37	6	154	23	5	88.0	9.6	2.4

Table 1. Classification results (X-band; HH polarization) for 1, 2, and 3 flights, after Hoogeboom (Ref. 4); cc is correctly classified; nc is not classified; ic is incorrectly classified.

crop rotation for potatoes.

The procedure for such crop type inventories will differ per area in the world due to differences in growing speed at different latitudes as we have seen (fig. 4 and 5). Ulaby et al. (Ref. 2) so developed a completely different procedure for Kansas (USA). They used two time segments per season which they covered each with 4 looks taken 3 to 9 days apart. These time segments were determined by the presence of specific crops in each segment. The first was determined by the occurence of winter wheat (fig. 5) which was harvested in late June or early July and the second by the milo and soybeans. We also give their results as an example in table 2 (Ref. 5). They are for data taken between 1974 and 1976. We give results only for one frequency (14.2 GHz) and polarization (VV) to make comparison possible with the results reported above in table 1.

	after look									
segment	1	A	1	2	3	4				
1974 1975 1976		7.1 2.8 8.7	53.0 68.7 49.7	75.0 96.7 83.5	93.0 99.0 85.3	95.5 99.8 88.2				
segment	2									
1974 1975 1976		7.1 2.8 8.7	45.5 54.7 82.4	70.0 67.2 85.1	80.5 75.8 85.5	88.0 80.3 88.1				

A: average time between looks (days)

Table 2. Percent correct crop classification at 14.4 GHz; after Ulaby (Ref. 5).

The results reported by Hoogeboom and Ulaby are comparable. Seen the fact that these good results were obtained for different procedures, at very different places in the world and different incidence angle ranges justify the hope that radar can be used for vegetation inventories using the temporal variation in the radar return. The final procedures used, however, may depend on the place on earth.

2. PROPERTIES OF THE SOIL UNDER A CANOPY; OTHER PROPERTIES OF THE CANOPY

The measurement series of the radar backscatter versus time also gave an impetus to the modelling of the radar return. Such models are very useful, among others, to investigate the problem of measuring the properties of soils through a vegetation canopy. For this purpose we used the model developed by Attema and Ulaby (Ref. 6) and later extended by Hoekman et al. (Ref. 7).

Since the dielectric permittivity of the dry matter of plant material is at least an order of magnitude smaller than that of water, where this plant material is only in the order of a few percent of the total volume of the canopy and since the volume scattering is the predominant mechanisme for the radar backscatter of vegetation, Attema and Ulaby (Ref. 6) proposed to model a vegetation layer as a cloud of water droplets. For details of this model and its derivation the reader is referred to the references mentioned. The following formula for the radar return is then obtained:

$$\gamma = C[1-\exp(-DWh/\sin\theta)] + G(\theta) \cdot \exp(K \cdot m_s - DWh/\sin\theta)$$

or with $\tau = \exp(-DWh/\sin\theta)$ and $M(\theta) = G(\theta) \cdot \exp(K \cdot m_s)$

$$\gamma = C (1-\tau) + M(\theta) \cdot \tau$$

with $M(\theta)$ the return of the soil under the vegetation, approximated by $G(\theta)$, the properties of the dry soil, and a loss term due to the water content m of the soil. W is the watercontent of the vegetation in kg/m³ and h (in m) the measured height. C is a constant representing the backscatter of the vegetation canopy as such and D is the two-way attenuation in m³/kg/m of the vegetation layer. To express D in dB we must multiply it by 4.343.

D in dB we must multiply it by 4.343. Knowing W, h and m from observations in situ it is, in principle, possible to determine $G(\theta)$, τ , and the model parameters C and D from measurements



Figure 6. Measured data (crosses) compared with the model of Attema and Ulaby (Ref. 6), after Hoekman (Ref. 8); ROVE data of 1979, Xband, VV polarization.

of γ . Attema undertook such an effort on the data collected by Ulaby's group at Kansas University and Hoekman undertook a similar exercise for the ROVE data of 1979 (temporal data). They both did a regression analysis to the groundtruth supported data mentioned. For details of these analyses the reader is referred to their work (Refs. 6, 7).

In figure 6 we give an example of the results obtained by Hoekman (Ref. 8) on the ROVE data for 1979. It gives the contributions of the soil and the vegetation layer separately, together with the surface data for soil moisture and Wh. $G(\theta)$, the radar return of the dry soil under the vegetation, can also be determined and compared with measurements of the same soil, corrected for soil moisture. An example of such a comparison is given in figure 7 (ROVE data of 1980).



Figure 7. Comparison of the radar return γ of the (dry) soil under a vegetation layer as obtained from direct measurements and through the model.

Knowing D the attenuation [exp(WhD)] of the microwave radiation by a crop can be determined. Table 3 gives an example. It shows that accuracy of the determination of the backscatter properties of the underlying soil will diminish when going to

Attenuation at	θ:	15 ⁰	20 ⁰	45°	80 0
Cuc ark + -		()	10		16
Sugarbeets	ι:	01	40	22	10
Potatoes		28	21	10	7
Peas		21	16	8	6
Winter wheat		47	36	17	12
Summer wheat		55	42	20	14
Oats		32	24	12	8
Barley		55	42	20	15

Table 3. Average attenuations in dB for fully grown crops (ROVE data) as a function of grazing angle; 10 GHz, VV polarization.

lower grazing angles, due to the larger attenuations of the canopies involved. It also means that the backscatter itself is then primarily (and sometimes wholly) determined by the canopy only at these lower grazing angles.

3. CONCLUSIONS

The radar backscatter of crops shows typical temporal patterns depending on species. The place and length in time of this temporal signature can vary with latitude (climate). This means that optimum classification procedures for crops vary depending on the place on earth.

The vegetation model developed by Attema and Ulaby (vegetation modelled as a water cloud) proves to be a useful tool to obtain information about the vegetation canopy and the underlying soil.

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ANALYSIS OF DIGITAL RADAR DATA FROM SAR-580 IN RELATION TO SOIL/VEGETATION MOISTURE AND ROUGHNESS

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ABSTRACT

A comprehensive survey of soil and vegetation characteristics was undertaken in two test areas in southern England to evaluate the capabilities of digitally processed X and L band synthetic aperture radar, collected during the European SAR-580 Experiment, to detect spatial and temporal variations in soil and vegetation moisture. One test area lay on homogeneous clay soils where local variations in soil moisture would be minimised to simplify the study of vegetation effects. The other area was of mixed soils and varying subsurface permeability where local variations in soil moisture would be maximised. Here, flat, bare-earth sites were preferred to simplify the study of soil moisture effects. This paper describes field sampling methodology, digital data extraction techniques, radiometric balancing of digital data and the effects of soil and vegetation moisture and roughness on radar relative backscatter.

Keywords: Soil Moisture, Vegetation moisture, SAR-580, Digital Processing, Microwave, Backscatter, Surface Roughness

1. INTRODUCTION

Our prime interest in the European SAR-580 Experiment was to determine whether variations in soil moisture of both vegetated and unvegetated fields could firstly be identified and secondly be quantified using the available synthetic aperture radar configurations.

The theoretical basis explaining the possible relationship between radar backscattering coefficient σ^0 and soil moisture is well documented (eg.Ref.1) and several excellent field scatterometer programmes have been undertaken both in USA (eg.Ref.2) and Europe (eg.Ref.3) to identify the optimum radar configurations for soil moisture monitoring. It is not possible to give a detailed description of the results of these experiments, but a reasonable consensus of opinion exists on the most useful starting point for radar studies of soil moisture in terms of radar frequency, polarisation and angle of incidence.

Figures 1 and 2 show that an increase in moisture content of either soil or vegetation causes an increase in the electrical conduction properties of the medium (permittivity) which in turn influences the degree of internal backscattering of microwave radiation. Unfortunately these effects are





generally secondary to the influence of local roughness and surface slope which must be considered in relation to the angle of incidence of the radar beam to the ground surface. However, results from work in Oklahoma (Ref.6) based on extensive ground data sets relating to aircraftacquired radar have confirmed the earlier findings of ground-based scatterometer experiments which show that the effects of surface roughness can be greatly reduced by careful selection of the radar parameters. Maximum correlations of σ^0 with soil moisture were obtained at C-band frequencies provided that the cross-over region between diffuse and specular reflection was used and which occurs at incidence angles around 7-15 $^{\circ}$ where the influence of surface roughness is minimised as shown in Figure 3. At angles approaching nadir, 'smooth' soils induce specular reflection of the radar resulting in a high return signal whilst at grazing angles most of the power is reflected away from source. In contrast, for 'rough' surfaces, diffuse reflection occurs at angles approaching nadir resulting in a relatively weak return signal, but

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at grazing angles diffuse reflection is still occurring; the rougher the surface, the higher the return.



Figure 3. Angular response of scattering coefficient in relation to surface roughness at 4.25 GHz (from Ref.7)

2. TEST SITES AND THEIR INSTRUMENTATION

The SAR-580 Experiment provided the first opportunity to compare radar data with measured ground conditions within our two test areas which were selected primarily to study the relationship of soil moisture with radar backscatter. GB8 (approx. 50 km^2) is an area in Buckinghamshire of homogeneous clay soils where local variations in soil moisture would be minimised. Seven test sites were chosen here to sample a variety of vegetation densities on various slopes and aspects relative to the look direction of the radar. GB12 (approx. 75 km²) is an area in the Thames Valley in Oxfordshire of mixed soils with underlying geology of varying permeability where local variations in soil moisture would be maximised. Where possible the 10 test sites were located on flat, bare-earth to reduce the factors affecting radar backscatter. However, as a delay of 4 weeks was encountered on the first aircraft pass, many of the sites had some vegetation cover. For both GB8 and GB12, test sites were located within the planned radar swaths to sample the full range of available incidence angles (θ) with a concentration on the $\theta = 5^{\circ} - 20^{\circ}$ region. Unfortunately drift in the aircraft inertial navigation system caused it to fly a path which was consistently too far away from the test areas with the result that for all 5 passes, no near nadir data was acquired, the steepest angle being 25°. Table 1 summarises the ground conditions at each site which in most cases comprised a single field unit.

2.1 Corner Reflectors

To successfully relate σ^0 to soil and vegetation conditions, both within a single scene but especially between different scenes, accurately calibrated data is required. To aid this calibration, two pairs of calibrated corner reflectors were installed by the Royal Aircraft Establishment in both test areas (Figure 4.) Sites were chosen near to Ordnance Survey triangulation points which were used to accurately locate the height and position of the reflectors and azimuth and inclination angles were carefully set in relation to the planned aircraft flightpath and altitude. In addition, 6 non-calibrated reflectors were installed in GB8 and 5 in GB12 to aid geometric rectification of the radar data.



Figure 4. RAE calibrated corner reflector showing elevation adjustment and absorbant padding to reduce spurious ground reflections.

2.2 Automatic Instrumentation

Didcot Automatic Weather Stations located within both of the test areas recorded at 5 minute intervals the following meteorological data:- wind speed and direction, solar radiation, net radiation, air temperature and humidity, rainfall. Whilst all of these data may not be essential for this type of study, they provide a useful record of conditions at the time of radar operation which will be of value in time-separated studies. Windspeed can affect the perceived shape of tall crops and the

· · · · · · · · · · · · · · · · · · ·	1						
Field no	Soil Type	Land	Use	Actu	al	L I °	Soil Moisture
		29.6.81	13.7.81	X&L	Х	Х	
(a) GB12				094	170	171	
A	Sandy alluvium	Early potatoes	Early potatoes	60	55	35	Spray irrigation
В		Late potatoes	Late potatoes	55	50	35	
с	Gault clay	Long hay	Mown hay	35	25	50	Wet
D	27 11	Bare earth-smooth	Bare earth-smooth	35	25	55	Dry
E	Alluvium	Bare earth-mixed	Bare with rough	50	45	55	Medium
		N	grass	6	4.0		Dec
r	gravel	Young maize	Young maize	50	45	*	Dry
G	17 II	V. voung maize/	Young maize/	*	60	*	Drv
		cabbage	cabbage				
н	River gravel	Bare earth-smooth	Bare/young veg.	*	*	40	Spray irrigation
J		Bare earth-smooth	Bare/young veg.	*	*	40	Spray irrigation
М	Gault clay	Bare - v. rough	Bare - rough	40	30	45	Dry surface
(b) GB8				093	172		
N	Outend Clev	Chase preture store			*		Maddium
0	Oxforu Clay	Dry how stubble	Sheep pasture	5.5			Davi
0	11 11	bry hay stubble	acubore + regrowth	50	55		Dry
R	11 11	Cattle pasture	Cattle pasture	50	55		Dry
S		Long hav	Shoop grazed hav	25	25		Modium
т	11 11	Barley	Barley	25	45		Modium
1	11 11	Cattleinacture	Long hav	40	50		Dry
		Cattle pasture	LOUE Hay	-*0	50		DIY
L	1						

Тa	ıb	1	е	1
			-	

* Test sites not recorded by radar

presence of surface water after rainfall or heavy dew may also affect radar returns.

3. DATA COLLECTION ON EACH OVERFLIGHT DAY

In each of the 17 fields, at least 20 volumetric soil samples were taken of the top 50 mm of soil and where possible 150 mm cores were extracted, some of which were sliced into 20 mm sections. When vegetation was present in significant amounts, 5 bulk samples were taken per field over either 0.25 m^2 or 1 m^2 for the estimation of vegetation biomass and moisture content. Some manual air and soil temperature measurements were made and cloud and atmospheric conditions were recorded.

3.1 Soil and Vegetation Roughness

Within a maximum period of 3 days, measurements of surface roughness were made at all sites. Alloy plates of dimension 1000 mm x 300 mm bearing a 20 mm grid pattern were used to make a photographic record of both soil and vegetation roughness, generally at the four corners and centre position of the soil moisture sampling network. To record soil roughness, the plate had first to be hammered into the soil. Initially this process was found to be very difficult in all but the lightest of soils. The process was made easier by welding spikes to the bottom rear edge of the plate to provide some initial support in the soil and then by attaching a cutting edge of hardened steel along the bottom edge of the plate. Finally a grooved striking block was positioned over the top edge of the plate to prevent damage during hammering (Figures 5 and 6). This plate was also used to record details of crops up to 300 mm high, but for taller crops a plate of similar dimensions and markings was held above ground level on two vertical tubes hammered into the ground. The plate was adjustable for height and levelness via thumbscrews locating the plate to the vertical tubes and before making a photographic



Figure 5. Soil roughness reference plate seen from rear

record of the vegetation canopy, the distance from the top of the plate to local ground level was measured to enable mean crop height to be determined (Figure 7). At each sample point, the plates were aligned by prismatic compass to lie both parallel and at 90° to the aircraft flightline.

At the same 5 sites per field as the above measurements, vertical photographs were taken from a height of 3 metres to provide a record of leaf area. However, this value differs considerably from the leaf area seen by the radar. To record this, oblique photographs were taken from the same look direction (using prismatic compass) and incidence angle (using clinometer) as the radar. Figures 8 and 9 illustrate the difference in geometry of the crop seen from vertical and oblique viewpoints and the importance of including reference scales within such photographs to enable reasonable estimates



Figure 6. Rough soil surface in relation to 20 mm grid marked on 1000 mm long plate



Figure 7. Tall barley seen against 20 mm reference grid

of leaf area to be made at a later date. Wide angle, oblique photographs of each field were taken from a height of 4 m. This extensive photographic record was invaluable for determining surface changes which had occurred during the 2 weeks separating the radar overpasses. Due to the large number of similar photographs acquired, the



Figure 8. Vertical photograph of maize to determine crop cover



Figure 9. Oblique photograph taken from expected look direction and angle of radar

use of a data back on the camera was found to be an essential aid as it provided a unique reference number on each image.

3.2 Landuse Survey

Limited manpower precluded a detailed land use survey, but major categories and growth stages were noted within the visibility of metalled roads. On 8 July, midway between the two radar passes, vertical 35 mm colour and panchromatic aerial photography was taken of both test sites using a light aircraft. The data was subsequently found to be of great value for extending the limited land use survey and for providing in-field information on crop cover and other anomalies which were depicted on the radar data. Variations in density of new crops such as maize were readily apparent from the air but went undetected from ground observation alone.

4. DATA PROCESSING

4.1 Soil Samples

Around 600 soil samples were oven dried to determine their free water content. The majority of these were volumetric samples taken from the top 50 mm of soil and where possible at least one 150 mm deep sample per field, the core of which was sliced to provide information on the nearsurface soil moisture profile between 0-20 mm, 20-40 mm, 40-60 mm and 60-150 mm. In some fields of very rough bare earth, the surface soil was unconsolidated which prevented accurate volumetric samples from being obtained. In these situations, samples of both the hard, dry surface soils and the moister sub-surface layers were taken for subsequent gravimetric analysis. Mean soil and vegetation moisture values are summarised in Table 2. Single bulk samples of around 5000 grams weight were taken for each of the GB12 test sites to determine soil texture in terms of the fractions by weight of sand (2.0 to 0.05 mm), silt (0.05 to 0.002 mm) and clay (<0.002 mm).

		Mean Soi		Mean Vegetatio	on Moisture	
Site No	% by weight	standard deviation	% by volume	% field capacity	% by weight	• g/m²
29 June 1981						
C912						
A	10	1.8	12	80	?	5500
в	8	2.0	9	58	96.9	3544
с	89	1.0	51	415	41.4	999
D	14	5.5	11	47	-	-
E	41	8.7	31	194	51.1	85
F	11	2.3	14	76	95.4	20
M surface	5	0.7	6	19	-	-
sub-surface	15	5,9	13	55	-	-
GB8						
0	39	6.8	34	109	67.2	333
0	63	14.6	60	175	?	minimal
R	38	3.8	42	105	2	minimal
S	53	6.5	31	147	80.0	1837
S'	50	1.6	33	139	76.7	374
Т	22	3.3	22	60	69.7	1669
U	71	8.8	50	196	75.0	261
13 July 1981						
CB12						
B	10	2.1	13	75	90.2	5120
B'	11	2.4	14	83	-	
с	85	20.9	51	397	67.2	5707
D	12	3.6	10	40	-	-
E	34	6.0	36	159	76.6	343
F	9	2.9	14	59	94.2	250
G	7	1.4	8	49	?	?
н	9	-3.2	12	64	-	minimal
J	8	4.3	10	54	-	minimal
M surface	5	1.1	7	20	-	-
sub-surface	19	6.8	20	71	-	-
GB8						
0	30	3.0	25	82	64.5	588
Q	44	8.7	44	122	50.1	520
R	32	3.8	38	90	80.3	223
S	38	14.4	43	105	72.2	1567
S'	35	14.7	23	97		
Т	20	2.7	24	55	41.1	1127

Table 2

It is necessary to take account of the texture of soils as well as their moisture content as both affect the dielectric properties and hence the volume backscattering properties of both bare earth and vegetated fields. The most commonly used method of comparing soils of different texture is to relate to their 'field capacity' or 'wilting point'; terms which describe the free water holding properties of the soil. Both of these conditions are time-consuming to determine by experiment, so indirect methods based on the texture of the soil have been developed. Schmugge et al (Ref.8) performed a multiple regression analysis on 100 different soils for which the texture and moisture characteristics were known. The results of these regressions enable reasonable estimates of the field capacity of any soil to be determined in terms of its proportions of sand, silt and clay using the following relationship:-

FC = 25.1 - 0.21 sand + 0.22 clay

where FC = field capacity (% by weight) and the proportions of sand and clay are also expressed in terms of % by weight.

Field capacities of all soil types used in the experiment were calculated using the above expression to enable all soil moisture values to be normalised to percentage of field capacity.

4.2 Vegetation Samples

Depending on the density of vegetation at each site, bulk samples, carefully cropped to ground level, were collected within quadrats of either 0.25 m^2 or 1 m^2 to obtain samples of a manageable size. These were weighed wet and after oven drying to determine water content per square metre of vegetation and also vegetation dry biomass per square metre (Table 2). The former is of major importance in determining the effect of vegetation on radar back-scattering.

Over recent years several models have been developed to try and quantify the effects of vegetation on radar backscatter. For example, Tsang et al (Ref.9) suggest that the backscattering coefficient σ^0 of vegetation-covered soils viewed from an incidence angle of θ can be expressed as:

$$\sigma^{0}(\theta) = \sigma_{v}^{0}(\theta) + \sigma_{z}^{0}(\theta)e^{-2\tau/\cos \theta}$$

where $\sigma_{\psi}^{0}(\theta)$ is the vegetation backscattering coefficient, $\sigma_{\delta}^{0}(\theta)$ is the soil backscattering coefficient and τ is the radar path length through the vegetation which varies with incidence angle.

The vegetation scattering component $\sigma_{\mathbf{V}}^{0}(\theta)$ can be approximated by

$$\sigma_{v}^{0}(\theta) = \frac{\eta \cos \theta}{2\tau} (1 - e^{-2\tau/\cos \theta})$$

where $\boldsymbol{\eta}\,,$ which depends on the canopy water content per unit area (Ref.10) is a vegetation volume scattering factor. Mo et al (Ref.6) have recently tested a two part model based on the above relationships describing the combined radar scattering from a vegetation covered soil and have found it to perform well against observed values of σ^0 . They confirmed that coherent scattering from the soil surface is most important at angles approaching nadir (where vegetation effects are reduced) while vegetation volume scattering is dominant at larger incident angles (>30 $^{\circ}$). It was hoped that simple models like the above could be tested on SAR-580 digital data, but the absence of suitable radar calibration unfortunately introduced an unacceptable number of unknowns into the values of relative backscatter. Under these circumstances, only broad, general conclusions could be safely drawn.

4.3 Surface Roughness Measurements

When recording soil and vegetation roughness against the calibrated alloy plates, the scale and angle of photographs varied from image to image. To compile a comparable record of surface data from which statistically acceptable estimates of surface roughness could be made, it was necessary to firstly rectify the images. This was achieved with the aid of a Zeiss Sketchmaster; a desktop instrument which, by means of a split-image viewfinder, enables the operator to superimpose a hard copy photographic image held in the vertical plane, with a sheet of graph paper held in the horizontal plane. Scale differences and image distortions were removed by instrument adjustment until the calibration lines seen on the alloy plates were in agreement with those on the graph paper. The outlines of both soil surfaces and vegetation were then traced onto the graph paper to provide a permanent and directly comparable record of surface roughness at each site. Figure 10 is a scaled record of a typical maize crop where both soil and



Figure 10. Rectified record of soil partially covered by vegetation

vegetation details are recorded, whilst Figure 11 shows the profile of a tall barley crop with mean height about 1 metre above ground level. The difficulty in defining such a crop 'surface' is evident and will vary both as a result of operator interpretation and of the wavelength of radar in use.

The surface roughness data were now in a form suitable for digitizing at 2 mm increments on a coordinate digitizer, this representing an increment





in the field of 10 mm. Values of r.m.s. height (d) and correlation length (ℓ) could then be readily extracted. However, the surface roughness as perceived by the radar is dependent on both the wavelength of the radar and on the angle of incidence of the radar beam relative to the soil surface. Mean surface slopes were therefore determined for each field relative to the direction of the radar in order to calculate the effective angle of incidence at each site. Rayleigh's criteria were used to determine whether surfaces were rough or smooth at both X and L band under the prevailing conditions of each radar pass, viz:

a smooth surface has a r.m.s. height of

$$< \frac{\lambda}{8 \cos \theta}$$

a rough surface has a r.m.s. height of

> $\frac{\lambda}{4 \cos \theta}$

where λ = SAR wavelength and θ = effective angle of incidence of radar.

Tables 3a and 3b show the results for each test site based on soil surface roughness only as at this stage no suitable model could be found to describe the surface roughness of vegetation.

5. DATA ANALYSIS

Our interest in this particular experiment was restricted to the study of soil moisture effects on radar backscatter, so only digital radar data was used. As previously mentioned the most significant correlation of soil moisture to σ^0 have been obtained at C band at incidence angles of $5^{\circ}-20^{\circ}$. However it appeared at the start of the experiment that there were problems with the calibration of the SAR-580 C-band, so X and L band data were requested in preference. At the outset of our experiment, it was intended that with the aid of the field installed corner reflectors, geometric and radiometric rectification of the digital data would be carried out to a relatively high precision to enable the position of data extracts to be controlled relative to survey measurements taken in the field. Unfortunately the deviation of the final aircraft flightlines from the planned flightlines was so great that in many cases the corner reflectors could not be detected. As there appeared to be no means of calibrating the data over the test areas,

Site	Approx r.m.s. roughness (d) in mm	Pass X band	094 L band	Pass 170 X band	Pass 171 X band
	-				
A	100	+	*	R	R
В	100	*	*	R	R
B ¹	10	*	*	I	R
с	25	R	S	R	*
D	4.5	S	S	I	*
Е	35	R	S	R	R
F	7.5	I	S	I	*
G	10	*	*	I	*
Н	6.5	*	*	*	I
J	10-5.5	*	*	*	I
М	45 then 25	R	I	R	*

Table	3a
-------	----

Roughness Estimates for GB12, Thames Valley

Based on Rayleigh's criteria:- S = smooth, I - intermediate,

R	= rough						c	_	,	λ
*	denotes	site	not	imaged	hv	radar	5			8 cos θ
	denotes	5110	not	ImaBea	53	rauar.	R	н	>	$\frac{\lambda}{4\cos\theta}$

Table 3b

Site	Approx r.m.s.	Pass	Pass 172	
	roughness (d) in mm	X band	L band	X band
0	10	R	S	R
Q	17.5	R	S	R
R	15	R	S	R
S	18	R	S	R
Т	10	R	S	R
U	20	R	S	R

Soil Roughness Estimates for GB8, Grendon Underwood

a less rigorous approach was chosen in the extraction of digital values.

5.1 Extraction of Pixel Values

Extraction of digital values from the CCT's was carried out interactively using both the NERC I^2S System 101 and the NRSC GEMS image processing facilities. Polygons were defined in relation to the position of soil and vegetation samples within each field site and care was taken to position the polygons well within the field boundaries to avoid edge effects. In general, 4 or 5 polygons per site were selected with the aim of detecting any major in-field variations. Each polygon normally comprised several thousand pixels with the smallest plots comprising about 500 pixels. A balance had to be accepted between over generalisation of surface variation through the selection of large plots and running the risk of introducing errors through the local effect of random coherent speckle on very small plots.

5.2. Radiometric Rectification of Digital Data

The method of normalising the antenna variations followed the procedure suggested by Sieber (Ref.11). Adequate land-use information was not available to enable the procedure based on a single crop type to be used, although this would have undoubtedly produced a more accurate correction. The method adopted was to calculate the root mean square (r.m.s.) pixel value of each line of a whole image as supplied on CCT. The assumption is made that

each line passes over an area of 'average' or 'typical' land use and that no large areas producing unusually high or low pixel values are present in the image such as large urban areas, factories etc. or large water bodies. On the assumption that there is no major change in land-use across the radar swath, the line by line r.m.s. values should replicate the gain pattern of the antenna. An example showing the results of this procedure for the Thames Valley test area is given in Figure 12 and it can be seen that the main lobe and side lobes of the antenna are clearly defined in the X band HH image. In contrast Figure 13 is the result of the same procedure carried out on an L band HH image, also of the Thames Valley area which shows much more variability and skewed antenna pattern.



Figure 12. Radiometric profile of XHH image





Under normal procedure, each line of the original image is divided by the r.m.s. value of its corresponding line after smoothing of the r.m.s. line profile. This has the effect of increasing pixel values lying towards the darker edges of the image, thus effectively normalising the image to a standard level of illumination. Examination of the line by line r.m.s. pixel value graphs for all of the passes obtained over our two test sites showed some marked variations such as poor dynamic range, unusually high signal variation as in the L band image of Figure 13 and other anomalies which are not fully understood. The majority of results given here are from passes which produced 'antenna diagrams' of shape similar to that shown in Figure 12 i.e. exhibiting full use of the available dynamic range and of conventional shape with no marked anomalies.

6. RESULTS

Based on the above criteria, five images were identified as being suitable for comparison in that their 'antenna diagrams' could be overlaid with only very minor adjustment required to obtain superimposition. Over GB8 at Grendon Underwood pass X09301 of 29.6.81 was compared with pass X17202 of 13.7.81. Similarly pass X09401 was obtained over GB12, the Thames Valley site on 29.6.81 and passes X17001 and X17101 were flown over the same area on 13.7.81 along flightlines lying 90° to one another.

6.1 GB12 Thames Valley

As a result of poor reproduction of flightline position, only one test site appears in all three images - Site E. On examination of the field data it was found that neither the soil moisture, surface roughness nor sparse vegetation had varied appreciably over the two week period between flights. It was therefore decided to use this site as a reference between the three passes rather than relate conventionally to maximum power within each band. Site E therefore appears as OdB in Figures 14 and 15. Figure 14 shows backscatter in dB's relative to Site E, against soil moisture values expressed as a percentage of field capacity for each area of interest within the 9 test sites and Figure 15 deals similarly with vegetation moisture. In addition to the three corresponding X band passes, pass L09401 has been included for comparison even though its 'antenna diagram' is markedly different to the others. Again site E appears as OdB after normalisation.

The two immediately apparent features of Figure 14 are the bunching of data which retain individual test site identity, and the absence of any general relationship between relative backscatter and soil moisture. If the shapes of the bunches are considered, there appears to be a predominance of major axes running horizontally rather than vertically, suggesting a marked lack of sensitivity to soil moisture. The only suggestions of an increase of relative backscatter with increasing soil moisture are to be found at sites G and H at X band and site B at L band. Site G is problematic as it lay at the far edge of the radar swath at a shallow incidence angle where the detection of soil moisture effects would be unexpected. If a relationship were to be expected, it would be at site H, a flat floodplain of homogeneous alluvial soils which was subjected to spray irrigation resulting in what was expected to be an ideal control site. As previously mentioned, the only drawback lay in the relatively narrow widths of differently cultivated and irrigated strips. It was felt at the time of data extraction that difficulty in accurately identifying the areas of interest for polygon delineation may have led to cross-contamination of digital extracts relative to the wet and dry areas on the ground. Even so, the resulting difference of only 1dB relative to a 40%



Figure 14. Effects of soil moisture on relative backscatter for Thames Valley sites.

FC increase in soil moisture can only be described as poor. Site B was a potato field which again had been subjected to local spray irrigation but which had an almost complete canopy of dense vegetation. On examination of both the L band and X band data, no obvious difference could be detected between the sprayed and unsprayed areas even after smoothing and contrast stretching of the digital data, unlike site H where variations over this essentially bare earth site could be seen. This suggests that the vegetation canopy was obscuring variations in underlying soil moisture.

Site B was also the only field other than the OdB reference site E to be imaged by both X band passes on 13th July. The fact that its relative backscatter is the same for both passes (Figure 15) suggests that the radiometric correction of the two passes has been reasonably successful and that neither the furrow direction or soil variabilities below the vegetation canopy are affecting the X band return signal.

Site F provides the opportunity to look at the effect of change over the two week period between flights. During this period soil moisture levels fell from about 75% FC to about 60% FC, but an increase in relative backscatter was experienced. This could have been due to the fact that the young maize crop on this site increased its mean moisture content during this period from 19.5 g/m² to 208 g/m² (Figure 15); more than a 10 fold increase. Again, however, this only corresponds to an increase in relative backscatter of 1dB.

The only other point of significance in Figure 15 is site C, a rough wetland site with soil moisture values off scale on Figure 14. The higher return signal in L band relative to X band on 29th June could conceivably be due to the effect of underlying saturated soil, but more detailed measurements would be required to prove this. The large difference in return signals for the two X band passes is consistent with the increase in vegetation moisture over the 2 week period, but may also have been enhanced by uncorrected antenna effects.





Site M experiences a remarkable increase in relative backscatter over the two week period of about + 6dB even though no change in soil moisture occurred. Although the field is classified as rough by Rayleigh criteria on both occasions, the change is undoubtedly associated with its change in surface roughness. For pass 094X site M had a r.m.s. roughness factor (d) of 45 mm as a result of subsoiling which threw up large clods of earth in a random fashion over the surface. By the time of pass 170X the field had been disced to break up the clods resulting in a r.m.s. roughness of around 25 mm. Thus although the absolute roughness of the field had been reduced, its backscattering efficiency at the X band wavelength of 32 mm had increased; a factor which could not have been readily predicted. L band data was only available for the first series of flights because of a failure in the system shortly before the second flight. Although the Lband data is limited, the results do appear to be somewhat more predictable than X band in that a smooth surface with a relatively high soil moisture such as site F produces a brighter backscatter than site D which is also smooth but at a lower moisture level. Site M, although of similar soil moisture to site D, appears brighter, presumably as a result of its rougher classification, whilst site B, the potato field, again of similar moisture level, is 3 and 4dB brighter than site M and D respectively, thus carrying on the progression from smooth, to intermediate, to rough.

It is unlikely that any more than general observations such as the above can be made from Figures 14 and 15 primarily as a result of the small number of comparable data points. Although 3 radar passes were obtained over this test site, only a small proportion of data collected in the field could be put to use. If all 10 test sites had been imaged on 3 occasions, the data set would probably have been large enough to draw more concrete conclusions. Nevertheless, the results from GB12 highlighted the problems associated with soil moisture sampling of bare earth fields.

Bell et al (Ref.12) laid down recommendations for sampling soil moisture over large fields and it is generally accepted that at least 20 samples are required per field to define within-field variabilities. Volumetric soil sampling is time consuming both in the field and in the analysis of soil samples. It is therefore not practicable to sample a large number of fields at such an intensive level. In the case of SAR.580 the local surface soil moisture variation appears to be greater than the variation recorded in the digital data after speckle reduction. There would therefore appear to be little point in describing the soil moisture variability through intensive sampling if the radar is not capable of resolving this variability. Jackson (Ref.13) has suggested that the problem of surface soil moisture variability can be partially overcome by sampling in the 0-150 mm depth range rather than the 0-50 mm range, beyond which radar wavelengths will not penetrate. His assumption is that there will be some correlation between surface and sub-surface soil moisture. Certainly for SAR.580, a more meaningful data set may have been produced by taking two or three 150 mm core samples over 40 or 50 fields rather than 20-25 samples in 10 fields. This procedure would be recommended for future radar studies provided that the whole soil surface profile was relatively damp. Problems are still likely to arise when a dry surface crust forms over damp

subsoil.

Prior to this experiment it was thought that a bare soil surface would be simpler to deal with than one covered with vegetation as the number of parameters to be modelled would be fewer. This may not necessarily be the case as a vegetation cover such as short grass will not greatly influence surface roughness as perceived by the radar, but it will prevent drying of the surface soil so as to retain a good correlation between surface and sub-surface soil moisture levels.

It was hoped to test the above procedures in relation to the SIR-B L band experiment in October 1984. Flat, permanent short grassland sites were identified within U.K. to sample a range of soils and soil moisture regimes which were determined through permanent neutron access tube measurements and by core sampling to 150 mm depths. Unfortunately, at the time of writing it appears that no radar data will become available for these sites.

6.2 GB8 Grendon Underwood

Figures 16 and 17 show the results of two X band passes over the Grendon Underwood test area where soils were of an homogenous clay and various types of vegetation were present in all cases. The indications are once again that X band at relatively shallow incidence angles is poorly correlated with soil or vegetation moisture. During the 14 days between passes, drying of the test area occurred and this is reflected in the general reduction of soil moisture values over this period.

Sites O and Q were both mown hay where interference from the vegetation would be minimal, as indicated by its low moisture content (Figure 17). A wide spread of surface soil moisture is evident within these fields, ranging from about 65% to 230% field capacity but this is recorded within a range of only 1.5dB on the radar digital data. A reduction in soil moisture is evident in both fields over the 2 week period. Sites R and U are of grazed pasture where the vegetation ranged from shortly cropped grass to short grass plus fine grass seed heads. For pass X17202 on 13 July, a considerable soil moisture variation existed between these fields, (Figure 16), low vegetation moisture levels were evident (Figure 17) but no significant difference in relative backscatter was observed. Conversely, taking site R alone, although both vegetation and soil moisture levels are almost identical for both passes, the backscatter (relative to Q max) for site R on 13 July is 2.5dB higher than for 29 June. The reason for this is unclear. Only 2 factors are known to have changed:- 1) the mixed pasture, being subjected to cattle grazing was slightly shorter for the second pass and the number of tall seed heads had been reduced, 2) the angle of incidence of the radar had changed from 50° to 55° . Neither of these changes would normally be associated with an increase in radar backscatter and it can be seen that most of the other sites exhibited a reduction in relative backscatter from 29 June to 13 July. It must be assumed therefore that the above two changes have combined to produce an increase in perceived surface roughness resulting in increased relative backscatter.

Site S was a field of hay, one half having been established for several years, comprised a wide mixture of grasses, nettles and other weeds. The other half (S') had been freshly seeded and was



Figure 17. Effects of vegetation moisture on relative backscatter for Grendon Underwood sites

therefore of a single uniform fine grass species. Figure 16 indicates that little difference exists between the two halves in terms of soil moisture, but the fine hay produces a 3-4dB brighter signal than the coarse hay, even though the former has a much lower vegetation moisture content as shown in Figure 17. Again this suggests that the perceived surface roughness at X band is probably of greater influence to radar backscatter than either soil or vegetation moisture. The fine hay was cut and left to dry some days prior to the second overflight and a reduction of relative backscatter of about 6dB was the result, demonstrating that in this case, the X band response was greater from the vegetation itself than from the underlying soil. Site T was a field of tall barley which progressively ripened during the 14 days between passes. This is illustrated in Figure 17 by a fall in vegetation moisture of around 30%, whilst during the same period, no appreciable change in soil moisture was recorded. A 4dB reduction in relative backscatter occurred during this period, thus supporting the findings at site S that the structure and moisture content of tall vegetation has significant influence on X band values of relative backscatter.

It must be appreciated in interpreting the information in Figures 16 and 17 that large system variations may be present between the two passes which could make some of the observations invalid. Because of these possible unaccountable errors, coupled with the marked lack of sensitivity to variations in soil/vegetation moisture, there was no suggestion that proceeding with more complex soil/vegetation models such as outlined by Mo (Ref.6) would have yielded more meaningful results.

7. CONCLUSIONS AND RECOMMENDATIONS

It was known prior to the planning of this experiment that any possible effects of soil or vegetation moisture on the relative backscatter of airborne radar data would be small in relation to the effects of surface roughness and angle of incidence, and that in order to detect such variations a well calibrated radar system would be required. On paper, SAR.580 could not provide the ideal instrument set up for such a purpose. Nevertheless it provided us with the first opportunity to work with radar over our own test areas, so efforts were made to make as much use as possible of the data through indirect calibration via a network of ground based corner reflectors. It was unfortunate that these corner reflectors could not have been used to obtain a reasonable intercalibration of the various passes, as from a soil moisture point of view, the lack of calibration was disastrous. Although attempts at radiometric balancing were made via image line smoothing in the azimuth direction to try and reproduce an antenna diagram, these were inadequate for our purposes and evidence of major errors exists.

No evidence of a consistent relationship between either surface soil moisture or vegetation moisture against radar backscatter could be seen in the data which was reduced in volume by the non-imaging of a number of test sites. The lack of such evidence is not unexpected as no data was available at incidence angles of $5-15^\circ$ where the effects of surface roughness would have been minimised.

Whilst the result of our experiment was inconclusive for this particular radar configuration, the experience gained during the course of the experiment in the use of radar for hydrological purposes has been great especially in ground data collection, radar calibration and digital data handling. The experiment has greatly increased our knowledge of methods of field survey and ground control in relation to radar remote sensing programmes and has indicated that a) soil and vegetation sampling over many fields at less frequent spatial intervals may be more fruitful than intensive ground sampling within a few fields, b) bare earth sites may not be the best places to build up our understanding of soil moisture/radar interaction; short grassland sites could be simpler to model. Further work is required in the modelling of surface roughness of tall vegetation as perceived by radar of different

frequencies as this is very difficult to quantify at present. Efforts should be made to define standard measurement procedures for the quantification of vegetation shape and roughness for different radar frequencies to allow intercomparison between data sets. Future work in soil/vegetation moisture estimation should centre on C-band SAR within the $5-20^{\circ}$ range of incidence angles, with a future eye on multifrequency systems which may provide the opportunity of directly estimating surface roughness.

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SESSION D



SOME PRELIMINARY RESULTS ON LAND USE EVALUATIONS BY TEXTURE ANALYSIS OF SAR-580 DATA OVER THE TEST SITE FREIBURG

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ABSTRACT

The study presents first results on texture investigations of digital SAR-580 data in X-HH of testsite Freiburg, performed at the Department of Photogrammetry and Remote Sensing of the University of Freiburg, West Germany. Different training sites of forest and agricultural classes have been tested with an texture analysis programme, which informs about the statistical distribution of radar reflection intensities. The results show textural properties of the here tested sites by demonstrating the statistical variations of backscatter intensity graphs along an adjustable boundary, which is located parallel to the mean intensity value.

Keywords: SAR-580, digital evaluation, texture, forestry, agriculture

1. INTRODUCTION

The present study is extract and preliminary result of texture analyses by the Department of Photogrammetry and Remote Sensing of the University of Freiburg, West Germany. The results so far were obtained with image data of the European SAR-580 campaign. The image data the test-site Freiburg were previously of analysed by the Department by means of traditional optical and digital evaluation methods (5). These analyses have shown among that a Standard Maximum other things, Likelihood Classification, commonly used within the LANDSAT image data evaluation, makes little sense within the SAR-580 image data evaluation and that other evaluation methods are required. Other analytical procedures, described and successfully tested by various authors, result from the analysis of visible structures and textures of image surface targets (cf.2,3,4). This paper contains some calculation examples on texture, investigating texture as a regular tonal variation within a certain image section (1). It is meant to be a concise extract of current investigation results which are as yet not statistically secure and may not be regarded as a basis for scientific proof.

2. SAR DATA DESCRIPTION

For the purpose of the present investigation, digitally processed SAR-580 data in X-HH have been used. The data are from the European SAR-580 campaign and have been been taken on July 7th, 1981, registered as Pass 14508 of the Test Site D 6 Freiburg. The data recording was acquired in steep angle and at a flight altitude of 20.000 ft. Supporting data from underflights and ground truth experiments are available.

3. GROUND TARGETS

The investigated test site Mundenhof/Mooswald is a flat agricultural and wooded area in the Rhine Valley to the West of Freiburg. The area has previously been described (5,6). For the purpose of demonstrating the analysis, 8 training sites, representing 3 forest crops, 4 agricultural crops and 1 example of a water surface, have been selected (Table 1). The 4 agricultural classes are located in the Mundenhof Farm, the 3 forestry classes are situated in the Mooswald forested area around the Mundenhof Farm. Figure 1 shows an optically processed SAR-580 enlargement of the area including information about the location of the training sites.

4. EVALUATION METHODS

The investigations were conducted with the Module TEXAS (Texture Analysis by means of Boundary Values) of the programme system FIPS (Freiburg Image Processing System). For image management, the data bank system PODIUM (Polygon-Orientated Digital Image Utilization Management System) is used. The software runs on the UNIVAC 1100/82 of the Freiburg University Computer Centre. For the purposes of the present investigation, SAR-580 radar data with a 16 bit resolution of the reflection intensity were used. The geometrical size of one pixel corresponds to approximately 3 x 3 meters.

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Figure 1: SAR - 580 optically processed enlargement in X-HH showing the test site Mooswald/Mundenhof and the numbered training sites 1 - 8 as described in Table 1.

The software module Texas processes rectangular image sections line by line, of optional size. Each image line is read and, if necessary, filtered in order to subsequently determine the texture parameters. The results of all individual lines of the image sections are added up or the mean value is ascertained. There is a choice of two different types of filters:

- 1. <u>Blockfilter</u>: n pixels each are grouped together and simultaneously replaced by the mean group value.
- Smoothing filter: the filtered value of each pixel is calculated separately from the mean value of the original pixel and of the (n-1)/2 pixels to the left and right. Therefore, only odd values of n can be used.

The image line is processed as follows (cf. Figure 2): After filtering, mean value and standard deviation of the reflection intensity along the line are determined. The mean value is represented in Fig. 2. Equidistant above and below the mean, an upper and a lower boundary are fixed, whose distance from the mean value (boundary distance) is either measured in units of the standard deviation or absolute. The continuous parts of the image line, whose reflection values are greater than the upper boundary, are called bright spots. Dark spots, on the other hand, remain below the boundary.



Figure 2. Process Schedule of the TEXAS module.

The following parameters are quantitatively acquired for bright and dark respectively (cf. 1):

- 1. Number of spots
- 2. Average length of spots
- 3. Relative portion of the complete image section

Further parameters, worthy of investigation, are:

- The mean local frequency (number of intersections between mean value line and intensity curve)
 The roughness of a line (the mean
- difference of intensity between two neighbouring pixels)
- 3. The auto-correlation function (the

probability, with which the value of a neighbouring pixel can be deduced from the value of a given pixel)

Table 1.

site no.	type
1	Young Douglas Fir, Age 22 Years
2	Oak, Age 25 Years
3	Mixed decidious Forest With Pre- dominantely Robinia, ∅ Age 100 Years
4	Water Surface
5	Corn Field, Not Fully Grown, Short Time Before Flowering
6	Meadow, Fully Grown
7	Winterwheat Field, Ripe
8	Summerwheat Field, Fully Grown, But Not Yet Ripe

5. DISCUSSION

5.1 Evaluation of unfiltered images

For the purpose of clarifying the numerical results, the outcome of the digital image evaluations is transferred into graphical representations and discussed. The texture parameters under discussion here are designated as follows:

- Bright Spot Number = bsn
- Dark Spot Number = dsn
- Bright Spot Average Length = bsal
- Dark Spot Average Length = dsal
- Bright Spot Relative Portion = bsrp
- Dark Spot Relative Portion = dsrp

For the purpose of this investigation, sections of equal size, containing 16 lines and 49 columns, were chosen for all training areas. When using unfiltered image sections, this amounts to 784 pixels per training area. Mean value and standard deviation of the unfiltered training areas are shown in Table 2.

Figures 1 and 2 show the number of bright or dark spots of various land use classes for

relative boundaries, which deviate from the curves are falling, as value. The mean expected. On the bright spots, the curves are parabolic, similar to an exponential function, exceeding the 4-fold standard deviation. The numerical curves of the dark spots show a steep drop and terminate approximately at the 2-fold standard deviation. This result was to be expected in the present image statistics with mean values between the grey value steps 4000 and 6000 and standard deviations between 2000 and 3000 grey value steps. Within the range between the mean value and the standard deviation, the number of dark spots is in all cases greater than the number of dark spots is in dark This relation is inverted starting from the boundary value of approx. 1.2-fold standard deviation. All classes of land use showed little variability among each other. Representing land use classes depending upon absolute grey value boundaries (Figs. 5 and 6),





a distinct variability among the classes shown can be discerned, which is due to the influence of the standard deviation, which, in turn, can only be filtered out by using relative boundary values. The theoretical considerations of this paper aim at extracting and recognizing the pure texture features, which are independent from the standard deviation. For this end, the relative boundaries appear to be the more suitable medium.

Τa	bl	е	2	

	SF 5			SF9			BF 5			BF 9			unfiltered		
raining	pixel no.	9	ž	pixel no.	9	ž	pixel no.	3	ž	pixel no.	5	x	pixel no.	5	x
1	720	1937	4993	656	1137	5025	720	1496	5009	720	1094	5009	784	2694	4982
2	720	1708	5989	656	1319	5982	720	1699	5977	720	1308	5977	784	3120	5979
3	720	1977	5665	656	1490	5679	720	1876	5697	720	1514	5697	784	3464	5722
4	720	271	881	656	212	885	720	275	877	720	207	877	784	446	882
5	720	1885	6505	656	1416	6488	720	1976	6420	720	1340	6420	784	3440	6516
6	720	1354	3951	656	977	3941	720	1414	3967	720	943	3968	784	1662	3952
7	720	2006	4789	656	1545	4793	720	1981	4851	720	1782	4851	784	3075	4832
8	720	1364	4263	656	997	4243	720	1444	4268	720	976	4268	784	2312	4300



Figure 6: Number of dark spots depending upon absolute boundaries.



Fig. 10: Relative portion of dark spot pixels depending upon relative boundaries.



Fig. 11: Relative portion of bright spot pixels depending upon absolute boundaries.



Fig. 12: Relative portion of dark spot pixels depending upon absolute boundaries.

The mean course of the curve of the relative portion of bright and dark spots corresponds to that of the exponential function (Figs. 9 and 10). The relative portion of the spots of the examples illustrated lies in its mean value approx. between 40 and 50%, while the portion of dark spots lies in its mean value between 50 and 60% higher correspondingly. The curves of the dark and the bright spots intersect roughly at 1.2-fold standard deviation. The curves of the relative boundary values vary only slightly in comparison to each other. However, upon using absolute boundaries, a pronounced variability due to the influence of the standard deviation can be seen (Figs. 11 and 12). This corresponds to the result in 5.1

4.2 Evaluation of filtered images

Filtering is one possibility to eliminate image noise. In the course of visual radar image analyses it was demonstrated that ground structures and textures can be made visible by means of filtering techniques (1).

Table 2 shows the statistical values for the unfiltered original sections , as well as for the filters used in this case. For statistical evaluation of the filtered sections only that part of an image line is used which is fully covered by the filter. This is the reason why, due to the type of filter used, some marginal pixels are not analysed and why smaller pixel numbers are listed in the table for the filtered image sections. After filtering, the intensity mean value is essentially maintained. Smaller deviations result by disregarding the unfiltered marginal areas. The standard deviation is greatly reduced by filtering. This is to be expected since individual "highlights" above or below strongly influence the standard deviation. These extreme pixels are suppressed by the filter to a larger or smaller degree, depending on the choice of filter length used.

Figures 13 to 16 show the graphic results of parameter analyses of the mean length of the bright spots in 5 training areas each. It can be seen that the variability among the classes is higher in filter factor 9 than in filter factor 5 and that it is greater in the block filter than in the smoothing filter. Figure 17 shows an example of the parameter number of bright spots for filter SF 9. Figure 18 shows the course of the parameter relative portion of bright spots for filter BF 5 and figure 19 shows the parameter mean length of dark spots for filter SF 9. Parameter analyses which aim at finding a connection between parameter values and object characteristics are a necessary further step in the investigations.



Fig. 13: BF 9



Fig. 14: GF 9



Fig. 15: BF 5



Fig. 16: GF 5





Fig. 17: Number of dark spots depending upon relative boundaries for filter SF 9.





Fig. 19: Mean length of dark spots (numbered in pixels) depending upon relative boundaries for filter SF 9.

6. CONCLUSION

The investigations have shown that radar images have texture characteristics which can be described by means of dark and bright spots and which can be calculated digitally. These dark and bright spots occur more frequently in number and in relative portion in the vicinity of the reflection intensity mean value of an image object. The parameter "mean length of bright spots", however, appears evenly distributed with its parameter values around the mean within the intensity spectrum. The texture parameters introduced in this paper were tested on examples of varying land use classes without submitting a statistical proof. Investigations are not concluded yet but a tendency can already be recognized, indicating low separability for unfiltered radar images using the evaluation methods herein described. It was also shown that a separability exists nonetheless due to the standard deviation. Filtering methods were examined which were supposed to eliminate the texture-overlaying image noise. The comparison of the resulting curves of various land use classes lead to a pronouncedly higher variability of the texture parameter values in the case of filtered image examples. Since only few examples have been tested, no firm opinion can be expressed with

regard to the texture characteristics of individual land use classes. This experiment is continued at the Department of Photogrammetry and Remote Sensing, University of Freiburg, with the aid of new SAR-580 and SIR-B image data with the aim of describing possible texture parameters and filter techniques for the purpose of land use classifications.

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SAR IMAGE SEGMENTATION USING DIGITISED FIELD BOUNDARIES FOR CROP MAPPING AND MONITORING APPLICATIONS

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ABSTRACT

Conventional image classification techniques as used for the analysis of optical remote sensing data operate on a pixel by pixel basis and are therefore unsuited to the classification of speckled SAR images. As one development of special significance to agricultural applications, this paper is concerned with the use of digitised field boundary data to carry out segmentation of images into fields which are then treated as separate units for backscatter measurement and image classification.

This technique is demonstrated with reference to the analysis of SAR 580 data for the GB6 test site in E. Anglia. Digitised field boundaries are overlain on SAR 580 images geometrically corrected to fit the UK National Grid. Image analysis includes the preparation of images showing mean backscatter values for individual fields, the measurement of backscatter for different crop types and the analysis of changes in backscatter on different imaging dates. Relationships between backscatter and ground data are examined in the context of both crop mapping and monitoring crop growth.

1. INTRODUCTION

Synthetic aperture radar images are characterised by speckle, or noise, which is an inherent product of the radar imaging process. Variation in SAR image pixel values of as much as 5 or 6 dBs are common for uniform areas of ground and extensive averaging is required to obtain a reliable value for the detected backscatter (Smit, 1978). In order to develop fully the application of SAR data it is important, therefore, that specialised image analysis techniques are used. Conventional techniques such as those used widely for the classification of optical remote sensing images cannot be used satisfactorily for the analysis of speckled SAR images because they operate on a pixel by pixel basis. Image segmentation techniques which are used to subdivide images into areas which can then be analysed as separate units are of special interest in this context.

One approach to SAR image segmentation which is currently receiving attention involves the use of automated image smoothing, pixel bonding and edge detection techniques to identify field and woodland boundaries and obtain averaged backscatter values (Quegan and Wright, 1984). The development of an automated technique of this type is clearly necessary if large area crop classification of spaceborne SAR images is to be developed, however, the techniques are complex and high levels of accuracy have still to be demonstrated.

An alternative approach whereby SAR image segmentation is achieved by using digitised field boundary data is the subject of this paper. This approach is based on the digitising of field boundaries from large scale maps and the geometric transformation of SAR images. Following the registration of maps and images, techniques are used for automated backscatter measurement and the generation of segmented images.

Airborne SAR 580 images for the GB6 test site in E. Anglia are used to demonstrate these techniques and their relevance to crop mapping and crop monitoring applications. Attention is focussed on small images of a test area measuring 2.5 x 1.5 km which has a range of crops, including winter and spring cereals, sugar beet and potatoes which are the most important crops grown in the region. Problems caused by the lack of SAR 580 data calibration and details of the method of radiometric balancing used to compensate for systematic variations in scene brightness have been described as part of a previous paper (Wooding, 1983). SAR 580 images used here are radiometrically balanced XHH digitally processed images for two dates in June 1981. The basic processing which has been carried out has involved 3 x 3 smoothing to obtain amplitude images with 9 m pixels.

2. IMAGE TRANSFORMATION AND MAP DIGITISATION

In order that a SAR image and a digital map of field boundaries can be registered, the image is geometrically transformed to the same projection as the map. Standard programmes developed for the transformation of optical satellite data were used for the geometric transformation of the SAR 580 images. Unsystematic image distortion due to aircraft movement means that the use of these techniques is liable to more inaccuracies than occur when working with satellite images. Nevertheless, acceptable results of to within 2 pixel

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Figure 1. XHH image taken on 30 June



Figure 2. Field boundary map superimposed on the XHH image taken on 30 June

accuracy have been achieved using approximately 20 UK National Grid control points for SAR 580 images covering 10 km x 7 km. Resampling associated with the geometric correction involved linear interpolation and the generation of 10 m pixels. Fig 1 is an extract for the test area taken from the geometrically corrected XHH image dated 30 June 1981.

Field boundaries are shown on UK Ordnance Survey maps at scales larger than 1:25,000. Adjustments to these boundaries need to be made to take account of changes since the maps were produced and any within-field cropping differences. When working with relatively high resolution airborne SAR images, these images themselves may be used for this purpose. Aerial photography or high resolution optical satellite data obtained in the same growing season as the radar image would seem to be important as additional sources of information when low resolution spaceborne SAR images are being studied.

Standard manual map digitising equipment and associated software were used to produce a digital map of field boundaries for the test area using a 1:10,000 scale Ordnance Survey map. This digital map was initially in vector format, but then a vector to raster conversion was carried out to produce a map with 10 m pixels suitable for registering with the raster image data. In producing this raster map, a field boundary width of 5 pixels was chosen. This was useful both for covering up small inaccuracies in the geometric registration of the image with the map, and for removing the headlands; the edges of fields which often have more variable crop growth. Fig 2 shows the field boundary map superimposed on the SAR image.

3. AUTOMATED FIELD BACKSCATTER MEASUREMENTS AND GENERATION OF SEGMENTED IMAGES

Image analysis software at the UK National Remote Sensing Centre has been developed to enable mean and standard deviation digital values to be calcaulted for individual fields. Fields are given digital values on the field boundary map which is then used as a mask overlying the SAR image to calculate the number of pixels and the mean and standard deviation of pixel values, or amplitude values, falling within the area of each field.

Mean and standard deviation amplitude values were used to calculate a measure of power (I) for each field in the test area, as below:

$$I = (mean)^2 + (std)^2$$
 (1)

This was followed by the calculation of backscatter values for each field in the form of the Backscatter coefficient (σ°) relative to the field with the maximum power (I_o), using the formula,

$$\sigma^{\circ} (dB) = 10 \log_{10} \left(\frac{I}{I}\right)$$
(2)

The field with the highest backscatter, therefore, has a backscatter of 0 dBs. Other fields have negative values in dBs relative to this maximum. Segmented images are generated by feeding field backscatter values into the image to replace the speckle by a uniform density value. This is illustrated for the test area in Fig 3, where 25 density levels for each dB have been used to accommodate the range of 0 to -8.5 dB within a total of 256 levels.

4. CROP MAPPING AND CROP MONITORING

Automated backscatter measurement for individual fields and the preparation of segmented images have been demonstrated based on the use of digital maps of field boundaries. The use of digital maps of sample areas, such as areas used for ground data collection, is another alternative which would provide a similar basis for backscatter measurement. In considering the application and value of these techniques for crop studies it is important to distinguish between crop mapping and crop monitoring applications. While it may be impractical to consider the use of digitised field boundaries for operational large area crop mapping, the use of these techniques for crop mapping of sample areas, or for monitoring crop growth in sample fields distributed over a large area, can both be contemplated. Moreover, these techniques would seem to be particularly appropriate for experimental studies to investigate relationships between radar backscatter and ground conditions.

The potential of radar for crop mapping has been demonstrated by work carried out in The Netherlands, where a crop classification accuracy of 90% was achieved using airborne SLAR images taken on three dates in 1980; 10 June, 11 July and 12 August (Hoogeboom, 1982). The selection of optimum flying times has been found to be important and this was based on the analysis of temporal curves for the backscatter of different crop types obtained from ground based scatterometer work.

The two flying dates on which SAR 580 data were collected for the GB6 test site were only two weeks apart, on 16 June and 30 June, and so based on the Dutch experience, the images are far from being optimally timed for crop mapping purposes. Examination of the segmented image for 30 June (Fig 3) in conjunction with a crop map (Fig 4) reveals a tendency for sugar beet and potato crops to have higher backscatter than the cereal crops and grass, and carrots to have the lowest backscatter values of around -8 dBs. A plot of these backscatter values for 30 June against those measured from the XHH image for 16 June is presented in Fig 5. This indicates that the majority of crops fall within a much narrower range of dBs on the first date, approximately 3 dBs as against 6 dBs on the 30 June. It further illustrates the relatively large variability in backscatter of different crops, although values for both dates can be seen to follow a similar overall pattern.

This variability in backscatter is caused by a particularly large range in growth stage for most of the crops during this period of the growing season. For example, sugar beet crop cover varied between approximately 10% and 65% within the test area on 16 June and between 20%



Figure 3. Segmented image for 30 June



Figure 4. Crop map

and 85% on 30 June. Crops such as carrots and field beans were only just emerging at this time and in most cases the backscatter is essentially that of bare soil. Cereal crops had more uniformity in terms of growth stage at this time and this is reflected in more consistency, within 2 dBs on both dates, in the backscatter of winter wheat, spring wheat and spring barley. That winter barley crops have a large range of values is explained by the susceptibility of this crop to wind damage and the fact that crop roughness was dramatically increased in some fields.

Although field backscatter measurements and segmented images have been usefully employed in this analysis, the results do indicate the limited value of images taken at this time for crop mapping purposes.

The potential for radar crop monitoring is dependent upon the existence of relationships between crop growth parameters and radar backscatter. Results obtained from the analysis of backscatter measurements made for 1 hectare sample areas of crop which had been field sampled indicate that such relationships, at least to a limited extent, do exist for sugar beet and potato crops (Wooding, 1983). For example, a correlation with crop cover and associated crop growth parameters was found for sugar beet crops within the 5% to 65% cover crop range. However, considerably more work is required in this area fully to evaluate different wavebands and polarisations, temporal factors and a wide range of crops in order to establish what the potential really is.

Change detection is a relatively simple operation using segmented radar images. This is illustrated by Fig 6 which has been obtained by subtracting the XHH segmented image for 16 June from that taken on 30 June. With the crop type annotation it can be seen clearly that the largest differences in backscatter, shown by the lightest tones, are associated mainly with the sugar beet and potato crops. It was these crops which were growing most strongly during this two-week period. Most of the cereal crops have dark tones indicative of little change. The use of such change detection techniques undoubtedly has an important role to play both, in developing our understanding of relationships between crop growth parameters and radar backscatter, and in developing methods of crop monitoring.

5. CONCLUSIONS

The integration of digital map data with image data is of widespread importance for the development of applications of remote sensing. In this paper the usefulness of digital maps of field boundaries to provide a basis for the segmentation of SAR images has been demonstrated. Image segmentation is an essential first step for the analysis of speckled SAR images for crop mapping and crop monitoring purposes.

This approach to image segmentation may be compared with the alternative approach involving image smoothing and edge enhancement. Advantages are the relative simplicity of the techniques which are used, the high levels of accuracy which can be achieved regardless largely of image quality, and the flexibility which is available to subdivide an image into units which do not possess definite boundaries. These may be within-field sample areas, fields which are poorly depicted on spaceborne images, or any other meaningful ground units. The main disadvantages are the necessity for images to be geometrically corrected, and the time involved in preparing the field boundary maps. The approach which has been demonstrated is seen, therefore, as being particularly valuable for experimental work, in general, and for future operational crop monitoring. The Ordnance Survey have long term plans to digitise fully the preparation of its maps and this could eventually be an important source of field boundary maps for large area crop mapping.

Future developments of the techniques which are planned include a facility to edit field boundaries on a display of the field boundary map superimposed on the image, and the development of a segmented image database system fully to exploit and extend the analysis possibilities that exist after image segmentation.

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Figure 5. Backscatter values for 30 June plotted against backscatter values for 16 June



Figure 6. Image prepared by subtracting the segmented image for 16 June from that for 30 June. Annotated crop types

TEXTURE ANALYSIS OF SLAR IMAGES AS AN AID IN AUTOMIZED CLASSIFICATION OF FORESTED AREAS

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ABSTRACT

Texture is considered to be an important discriminating tool in forest type classification. This is emphasized by the fact that differences and temporal dynamics in radar backscatter level in most forests are relatively small. Experiments were performed in order to elucidate the usefulness and behaviour of statistical texture measures derived from gray level co-occurence and gray level difference counts. As a test case a fine resolution SLAR image was choosen of the Speulder forest at the Veluwe. It features stands of tree species in the pole phase together with mature beech forests occuring in various spatial structures related to canopy roughness. The proposed measures reveal the potential to discriminate these forest structures well. An integral classification approach for forests is suggested by the results of this analysis.

Keywords: active microwave remote sensing, forest texture analysis, forest classification.

1. INTRODUCTION

Classification results of Dutch forests using Xband SLAR imagery, obtained during the 1982/1983 measurement campaign, have been reported before (ref. 1).

It was shown that a multitemporal and monospectral (X-band) approach, e.g. one image taken in winter and one in summer, is likely to yield good results of main species classification. Simulated twodimensional classifications yielded overall error fractions ranging from 10 - 16% in the Roggebotzand test area and 14 - 28% at the Veluwe test area. However these results are only indicative. They are valid under the assumption of a priori knowledge of boundaries, the exclusion of small stands, stands with strip cutting and stands with a mixed species composition and the absence of transition zones. In the case of the Roggebotzand test area, which is a young forest in the pole phase, with relatively large and homogeneous stands, automatic segmentation procedures can be applied. A few tests with multi-dimensional Split & Merge (ref. 2) were successful. At the Veluwe test area this technique would largely fail because of the abundance of small parcels, parcels with strip cutting and the presence of mature beech

forests with coarse textures. Since presence of different texture classes and transition zones is characteristic for most natural forests more advanced techniques for the automatization of classification are desirable. It will be shown that use of image texture has great potentials.

Based on the gained experiences of the last campaign a new series of experiments were executed during the summer of 1984 for the nurpose of further (physical) modelling of radar backscatter of forests. (a) A flying scatterometer system was employed yielding accurate C-band data, both VV-and HH-polarized, of forest parcels at 15, 30, 45, 60 and 75 degrees incidence angle. (b) The Dutch X-band SLAR was employed with an increased range resolution (7.5 m instead of 15 m) yielding imagery with fine resolution, very useful for texture analysis of forests. (c) And with the SLAR an external calibration experiment using corner reflectors was performed in order to determine absolute radar backscatter levels of forest stands. Some huge corner reflectors were placed under the forest canopy yielding data on the attenuation of X-band microwaves in the canopy. Lower bounds for one-way attenuation factors of poplar and oak canopies could be determined.

The measurement results have not all been analysed yet. In this paper only the first results of the texture analysis shall be presented.

Texture may be viewed as a global pattern arising from a deterministic or random repetition of local subpatterns or primitives with or without a preferred direction. It is one of the characteristics useful in discriminating objects or regions of interest in an image. On the other hand textural phenomena are useful in the characterization and identification of physical objects like forests (refs. 3,4). Therefore, in remote sensing, it is of interest to extract from remotely sensed data information on the physical texture. Which can be done in the case of SLR-imagery by (automized) interpretation of image tone, image texture and radar speckle.

In this paper only the relation image texture - physical texture is dealt with. It applies to

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Fig. ••• Panchromatic aerial photograph of the 'Drieersingels' in in fig. 13. are indicated. The corresponding SLAR image can be found is ~1600 x 1250 meters. Some of the major surface types scale 1:12.300, stereo pair. The size of the area shown the Speulder forest, recorded at June 20th 1983, original





physical subpatterns with spatial dimensions greater then or equal to the spatial resolution of the imaging system. Whereas image tone and radar speckle implicitly can give information about smaller physical subpatterns.

The method discussed here only deals with the empirical relation between image texture and physical texture for this case. In order to arrive at general applicable (physical) models for the relation image texture - physical texture the effect of the choice of sensor parameters, the imaging geometry and radar backscatter models should be included. This is beyond the scope of this paper. A pragmatic procedure is proposed to get insight into the feasability of texture transformations as an aid in automized classification of forests.

Many approaches and models to derive textural phenomena out of digitized images have been used e.g. Fast Fourier Transforms (FFT), gray level run lengths, split spectrum processing, variance filters, gray level co-occurence (GLCO) matrices, gray level difference (GLD) vectors etc. (refs. 5-9). In this study analysis has only been done with GLCO and GLD, since these approaches have been found among the most useful for analysing the content of a whole variety of remotely sensed imagery (refs. 10-12). However there is no reason to suggest that the other approaches might not have given useful results for this case.

2. THE 'DRIEERSINGELS' BEECH FOREST TEST AREA

A part of the Speulder forest; the 'Drieersingels' beech forest complex and its surroundings, is selected as a test area for texture analysis. It features several large stands of old beech forest with distinct structures of tree crown canopy and one large stand of oak forest. Further it comprises small stands of Douglas fir, Scots pine, yound beech, larch, agricultural sites and stands with strip cutting and clear cut areas. The mature beech forests can be differentiated, for the purpose of this analysis, in three major classes according to the tree crown canopy structure of its eco-units.

In the mature beech forests structure differences emanate mainly from forest management. The first structure (henceforth referred to as type 1) is characterized by a smooth physical texture of the canopy as can be perceived in the aerial photograph (fig. 1). The second structure (type 2) is characterized by a rough texture of the canopy. The crown coverage is in the order of 60 - 70% whereas type I has a crown coverage of almost 100%. The third structure (type 3) has a smooth texture like type I, has a crown coverage of 60 - 70% like type 2, but has large (30 x 30 meter) gaps in the canopy which are small clear cut areas created for forest regeneration experiments.

A more detailed division incorporating crown diameters, mixing percentages with other tree species like birch and oak, undulations of the canopy, emerging trees, crown shapes etc. can easily be made by use of stereoscopic pairs of aerial photographs with a large scale. But this refinement will not be used in the initial approach as described here.

3. DEFINITION OF TEXTURAL FEATURES

In this study textural phenomena are described with statistical measures derived from the elements of the GLCO-matrix and GLD-vector. The elements of the gray level co-occurrence matrix (GLCO-matrix) contain the relative frequencies of pixel pairs, in the picture segment of interest, characterized by their mutual distance and gray level values. The i,j-th entry in the GLCO-matrix p(i,j) is defined as the relative frequency of pixel pairs, for each possible pixel pair realization in the picture segment, for which the source pixel with gray level i is at position (x, y) and the target pixel with gray level j is at position (x, y)+d (with d the so-called displacement vector).

The elements of the gray level difference vector (GLD-vector) contain the relative frequencies of pixel pairs characterized by their mutual distance and absolute gray level difference. The i-th entry in the vector v(i) is defined as the relative frequency of pixel pairs, for each possible pixel pair realization in the victure segment, for which the source pixel with gray level k is at position (x,y) and the target pixel with gray level k+(i-1) or k-(i-1) is at position (x,y)+d.

Thus for the GLCO appraoch as well as for the GLD approach the results are dependant on \overline{d} i.e. displacement length $|\overline{d}|$ and displacement direction ϕ .

If N_g is the number of gray levels in the digitized image then some of the most commonly used textural features extracted from the GLCO-matrix, also being the ones used in this analysis, are defined as:

- 1) Angular Second Moment (GLCO-ASM): $N_{g} N_{g} 2$ $\Sigma \Sigma p(i,j)$ i=1 j=1
- 2) Contrast (GLCO-CONT): Ng Ng 2 Σ Σ p(i,j) ★ (i-j) i=l j=l
- 3) Correlation (GLCO-COR): $N_{g} \sum_{\Sigma}^{N_{g}} p(i,j) \star \frac{(i-m_{\chi})(j-m_{y})}{s_{\chi}}$

 m_X , m_y , s_X and s_y stand for the mean values and standard deviations of the row and column positions of the counts in the matrix.

- i=1 j=1
 5) Inverse Difference Moment (GLCO-IDM):
 - $\sum_{\substack{\substack{\Sigma \\ i=1 \\ i\neq j}}}^{N_g} \sum_{\substack{p(i,j) \\ i=1 \\ i\neq j}}^{p(i,j)} \star \overline{1 + (i-j)(i-j)}$
- 6) Maximum Probability (GLCO-MAX PROB): max p(i,j) i,j

Some of the commonly used textural features extracted from the GLD-vector, also being the ones used in this analysis, are

```
7) Angular Second Moment (GLD-ASM):
    Ng 2
    Σ v(i)
    i=1
8) Entropy (GLD-ENT):
    N<sub>φ</sub>
```

```
Ng
-Σ<sup>v</sup> v(i) x log(v(i))
i=1
```

```
9) Mean (GLD-MEAN):

Ng

Σ (i-1) ★ v(i)

i=1
```

In order to add to statistical reliability the gamma values in the (logarithmically scaled) SLAR image were rescaled from the original 0.2 dB per gray level to 0.4 dB per gray level.

Since some values of the implemented textural features depend on the number of gray levels taken into account and in order to get easy manageable figures some normalizations were made so that new values for each feature range from 0 to 100 except for GLCO-COR which ranges from -100 to 100. It should be noted that these ranges are based on extreme conditions of the distributions of the probabilities in the GLCO-matrix and GLD-vector. It can be proved however that for some of the distributions no corresponding subimage can be constructed. So in fact the range is smaller for some of the features.

The GLCO-matrix and the GLD-vector and consequently values of textural features depend on the displacement vector, i.e. displacement length and displacement direction. Dependency on displacement direction however is not related to texture. Instead of choosing another direction the image could as well be rotated; the texture remains the same, the values of textural features don't. To avoid this problem directional averaging of values of textural features in all directions is needed. It follows from the mathematical description of the 9 features given here that a displacement d yields the same result as a displacement - \overline{d} therefore it suffices to average over values of textural features corresponding to displacement directions ranging from 0 - 180 degrees. To preserve the relation with physical distances as close as possible the displacement vectors corresponding with the 4 displacement lengths implemented were choosen as illustrated in the figure below.



Fig. 2. Discrete Euclidian distance or displacement length from source pixel (x) to target pixel. Only the displacement vectors used for this analysis are shown.

Since the 9 features described here have been calculated for 4 displacement lengths we eventually arrive at 36 textural features, which all describe the textural phenomena in an indicated region or subimage in a somewhat different way. The measures in general showed to be strongly correlated. Upon inspecting the various measure definitions this is quite obvious. This phenomenum is elaborated by the theory of generalized texture measures (ref. 13). As a result a combination of 1, 2 or 3 of these features will do in practice as well as all 36 jointly to describe the textural content of a particular scene, as will be shown later on.

4. DEFINITION OF ANALYSIS PROCEDURES

It is well-known that two general ways exist to extract textural information of a given scene in a quantitative way. The first makes use of a priori knowledge of the boundaries of objects, the second doesn't. In the first approach pre-defined regions (corresponding with picture segments) will be classified based on textural and spectral features of that region. This approach has proved to be successful for landuse classification on Landsat-MSS images (ref. 14).

In the second approach regions are not (yet) defined. Classification and/or segmentation will then be based on the spectral and local textural characteristics assigned to individual pixels. A texture characteristic of a pixel is defined as the value of a textural feature calculated in a small rectangular area of which this pixel is the centre pixel. By scanning a small rectangular window (e.g. 11 x 11 pixels) across the image, textural characteristics can be assigned to each pixel in the scene, except for small strips along the border of the image. The resulting image is then called texture transformed.

Use of texture transforms allready has been proven useful in panchromatic aerial photography (ref. 15) and Landsat-MSS (refs. 16,13).

To account for both concepts two analysis procedures: the Gross Texture Analysis (or GTA) and the Moving Window Analysis (or MWA) will be defined here. Both procedures make use of large polygonally shaped regions, consisting of only one physical texture class, indicated in the image by a human observer (but this can also be done automized e.g. by using an expert system containing maps of the region of interest). The assumption of homogeneity of physical texture in these 'training areas' is based on ground truth information. The regions should be made as large as necessary to ensure the statistical reliability of the distribution of the probabilities in GLCO-matrix and GLD-vector. The first procedure, named GTA or Gross Texture Analysis, calculates values of textural features in this large region. Since the number of possible nixel mairs is substantial and the distribution is characteristic for the texture class under research, the results are accurate. The second procedure, named 'MA or Moving Vindow Analysis, calculates textural values in a small rectangular area (or spatial window) inside the indicated (large) region. Since the number of nossible pixel pairs is small the results can be non-accurate. This calculation is repeated however for all possible spatial window positions in the region yielding, for a given window size, the mean feature values and the standard deviations of the feature values. The number of spatial window realizations should be taken large to ensure re-



Fig. 3 (left column at the top): Results of GTA for 6 large areas representing the 6 major texture classes in a two-dimensional textural feature space.

Fig. 4 (right column at the top): Results of MWA for 6 large areas representing the 6 major texture classes in a two-dimensional textural feature space. The bars indicate the +/- one standard deviation interval of the textural values for each class. The window size is 15 x 15 pixels.

Fig. 5 (right column in the middle): Results of MWA for window size 11.

Fig. 6 (right column at the foot): Results of MWA for window size 7.

liable results. The results of this procedure are very helpful in analysing the usefulness of texture transforms.

5. DEFINITION OF PHYSICAL TEXTURE CLASSES

Based on ground truth information 14 relatively large regions with homogeneous physical texture properties were indicated. After an initial GTA performed on these regions 6 major texture classes could be identified in the image.

These major texture classes in the image represent the following physical textures:

- Type 1 beech forest (for descriptions of type 1, 2 and 3 beech forest see chapter 3.2).
- 2) Type 2 beech forest.
- 3) Type 3 beech forest.
- P) Young forest in the so-called pole phase, but also mature beech forest with a very smooth physical texture.
- M) Mixed areas e.g. beech forest with small stands of pine or Douglas fir. Mixtures of very small stand in the pole phase (with different radar backscatter properties).
- E) (Edges) Strips of increased radar backscatter



0 ∟ -10

0 10 20 30 40

50 60 70 GLCO-COR[1]

Fig. 7 (right column at the top): The mean values of GLCO-CONT(3) for the 6 texture classes as a function of window size. The results of the GTA (value for whole region) are indicated with crosses.

Fig. 8 (right column in the middle): The mean values of GLCO-COR(1) for the 6 texture classes as a function of window size. The results of the GTA (value for whole region) are indicated with crosses.

Fig. 9 (right column at the foot): The mean values of GLD-ENT(4) for the 6 texture classes as a function of window size. The results of the GTA (value for whole region) are indicated with crosses.

(due to layover) and strip of radar shadow resulting from boundaries between parcels with relevant height differences. Formally speaking this is not a real texture since there is no repetition of subpatterns. Strip cutting is sometimes falling into this class and sometimes in class 'M' depending on the geometry of the strips and the geometry of radar imaging.

These classes were found to be characteristic for the test area. Of course also other texture classes are present in the image but they appear less frequent or correspond with transition zones between e.g. type 1 and type 2 beech forest.

6. THE OPTIMIZATION OF FEATURE CHOICE AND WINDOW SIZE

The analysis was continued with 6 large training samples of physical textures, each representing one of the major texture classes found in the image. Therefore results should be interpreted with care since they are only related to these 6 samples. For these areas a MWA with sizes 5, 7, 9, 11, 13 and 15 and a GTA were performed. With the aid of a search program the features with the best discriminating power (for these 6 classes and window size 9, 11 and 13) were found to be GLCO-Correlation at displacement length 1 (GLCO-COR(1)) and GLD-Entropy at displacement length 4 (GLD-ENT(4)).

The search was continued in order to find a second best feature in combination with the first one. It yielded four combinations, namely:

CO-COR(1)	with	GLCO-CONT(3),
CO-COR(1)	with	GLCO-COR(4),
D-ENT(4)	with	GLCO-COR(1),
D-ENT(4)	with	GLCO-COR(4).
	.CO-COR(1) .CO-COR(1) .D-ENT(4) .D-ENT(4)	CO-COR(1) with CO-COR(1) with D-ENT(4) with D-ENT(4) with

Further combinations with third best features didn't improve the discriminating power mentionable.

A lot of experience was gained in the sometimes capricious behaviour of these measures. Some of the most relevant results are summarized in the next figures. Figure 3 shows the texture values obtained with GTA for the 6 classes under research in a two-dimensional textural feature space. Figures 4-6 show the texture values obtained with MWA for different window sizes in the same two-dimensional feature space. The bars indicate the +/- I stan-



Fig. 10 (right column at the top): Mean standard deviation of the 6 texture classes under research as a function of window size for the measure GLCO-COR(1).

Fig. 11 (right column in the middle): Mean standard deviation of the 6 texture classes under research as a function of window size for the measure GLD-ENT(4).

Fig. 12 (right column at the foot): Results of MWA for window size II in a two-dimensional feature space. This combination of features differs from the one in fig. 5.

dard deviation interval. Figures 7-9 show the mean values for a specific feature for the 6 classes as a function of region size i.e. for the whole region (GTA) and for several window sizes. Figures 10-11 show the mean standard deviation of the 6 classes for a specific textural feature as a function of window size. Figure 12 is the same as figure 5 but for another combination of best features. Upon considering the outcome of the search for best features and their mathematical expressions, a few facts become apparant with respect to textural phenomena observable in the different major texture classes. GLCO-COR(1) is related to coarseness. It is sensitive to the size of clusters of more or less the same gray level and the contrast between these clusters. An image cluster size corresponds with sizes of shapes found in the physical forest canopy. GLCO-COR(4) acts as the inverse of GLCO-COR(1). This can be explained by the ratio of spatial dimensions of these clusters and the pixel size. However when the coarseness is very high e.g. at edges COR(4) acts like COR(1) and as a result the combination of COR(1) and COR(4) is useful in discriminating the edges (see figure 12).

GLD-ENT(4) was found superior to GLCO-ENT(4). This is explained by the lower statistical reliability of GLCO-ENT. GLD-ENT(4) is related to the variance of the gray level distribution. The same is true for GLCO-CONT(3) as can be seen in table 1 and the figures.

TABLE 1. Statistics of gray level distributions of the 6 selected areas.

class	mean gamma (dB rel)	s.d. of gamma (dB)
(P) (1) (2) (M) (3)	0.00 -0.66 -0.18 -0.88 -1.04	1.00 1.04 1.42 1.62 1.96
(E)	-0.90	1.66

These data indicate that other approaches e.g. a combination of an edge detector, a variance filter and GLCO-COR might be a good alternative. It was found, for this case, that GLCO-COR combined with a variance filter has a slightly better performance with respect to classification accuracy then GLCO-COR combined with GLCO-CONT(3) or GLD-ENT(4).

It can be noticed from the figures 7-9 that the mean values of the features are dependent on











Fig. 13 (right column at the top): X-band SLARimage of the test area, recorded at August 14th 1984, with pixel size 7.5 x 7.5 m, ground range resolution 9 m, azimuthal resolution 10 m and an angular range of 22 (right) to 32 (left) degrees grazing angle. In each pixel an averaging is performed over 15 independent samples. The size of the area shown is 1600 x 1250 meters.

Figs. 14-16 (left column): Texture transforms of the SLAR image in fig. 13 made with GLCO-COR(1), GLCO-COR(4) and GLD-ENT(4) and window size 11.

window size but not for all features in the same way. GLCO-CONT(3) doesn't show relevant dependancy for these window sizes, GLCO-COR(1) shows a gentle decrease of mean values with decreasing window size, while GLD-ENT(4) shows a significant decrease. For this last feature the difference between the mean values for the 6 classes also decreases dramatically. This can be explained out of the mathematical formulation of this measure and the small number of pixel pairs at small window sizes.

The standard deviations of the features are also dependant on window size. The general trend is an increasing standard deviation with decreasing window size as is shown in figures 10 and 11. If *textural resolution* of a specific texture measure is defined as the mean of standard deviations of the feature values, obtained from MWA, for all textural classes under research. And if the spatial resolution in the texture performed image is defined as being equal to the window size, then geometric resolution in the texture transformed image is not exchangeable for textural resolution since the product window size * mean standard deviation is not a constant but increases significantly with decreasing window size. It is therefore advantageous to start from window sizes as large as acceptable instead of starting from small window sizes (for better spatial resolution) and performing a spatial averaging in the texture transformed image afterwards. There are exceptions. For GLD-ENT(4) the product

mentioned above decreases again with very small window sizes. However since differences in mean

values almost disappear it is again not advantageous to apply small window sizes.

7. RESULTS OF CLASSIFICATION BY TEXTURE

The results are promising. As can be seen e.g. in the figures 5 and 12, combinations of 2 out of the initial set of 36 features and a window size of 11 show the potential to resolve textural classes in the SLAR-image. A few texture transformed images and texture based classifications were made with a window size of 11. This choice has been a pragmatic one. Since textural resolution and spatial resolution in a texture transformed image were shown not to be exchangeable it is not advantageous to choose a small window size. However since most stand sizes or areas of beech eco-units in this forest are not large, window sizes cannot be choosen larger than about 11 x 11 in order to avoid too many spatial window realizations containing physical borders.

Texture transforms of the SLAR image (fig. 13) are shown in figures 14-16.

Classifications of the scene based on two texture transforms resulted in coloured texture maps (not incorporated in this publication). The results were good, textural classes found by classification rules based on two textural features (e.g. GLCO-COR(1) and GLCO-CONT(3)) agreed well with the ground truth.

Interesting phenomena were observed in the classification results.

(1) An area within an extended oak forest in the pole phase, class 'P', showed up in the classification as class 'M'. This could only be explained after re-examining this oak forest by stereoscopic viewing of low altitude aerial photographs. The part of the area classified as class 'M' appeared to contain clusters of emerging birches!
(2) Sometimes small areas in beech 'type 3' forest showed up as beech 'type 1' forest. This can be explained by the locally absence of the large gaps in the smooth canopy and the spatial dimensions of the window applied.

(3) If a pixel is labeled with the texture characteristic 'pole', one can be highly confident about the fact that the whole local region contained in the corresponding spatial window, of which the characteristic is extracted from, is forest in the pole phase with homogeneous backscattering properties (for this incidence angle and time). Thus it contains a single species with one stand age, unless it is a mixture of different species and/or ages with identical backscatter properties and no stand height differences. The latter facts can be verified of course by inspecting the texture characteristics multitemporal or multiangual. The same properties could be noticed for the pixels labeled with the texture characteristic 'type 1'. It can be explained out of the fact that these texture classes are among the smoothest and mixing with other texture classes always results in 'rougher' characteristics. This is an important property of which can be taken advantage of in classification as will be discussed later on. (4) The texture class 'pole' contains several physical texture classes of forests in the nole phase but also seedlings and saplings and even mature forests with a very smooth canopy. As a consequence of the spatial resolution resolution of the SLAR imaging system (~10 x 10 m) this differentiation could not be made when this kind of texture analysis is applied.

(5) In general the other texture classes: 'type 2', 'type 3', 'mixed' and 'edges' were also classified well. But, as could be expected, in small textural regions and at boundaries of textural regions the results were disturbed. This is a consequence of the low spatial resolution of texture transforms. (6) While interpreting the results of classification by texture using large scale aerial photography as ground truth it is tempting to extrapolate the newly gained insights to other types of forests. This was done with the aid of (stereo) photo interpretation keys of natural forest types (ref. 17) and other ground truth information (ref. 4). From their spatial structures it could readily be concluded that the use of texture transforms as proposed here together with fine resolution SLAR imagery as can be obtained from the Dutch SLAR will result in the potential of discriminating a whole set of forest texture classes. Therefore this technique can be useful in classifying forest types and the diverse stages of growth in eco-unit development.

8. A CLASSIFICATION STRATEGY

It should be noted that though results are quite satisfactory, the procedure can be improved. It was possible to determine optimal spatial window sizes for the texture transforms and to select optimal combinations of textural features. But these were selected from a set of 36 only containing features derived from gray level co-occurrence and gray level difference at displacement lengths not exceeding 4. Other textural features might do better. The behaviour of the measures at boundaries of textural classes has not been taken into account. Also from the sensors point of view some critical notes should be made. Optimal sensor parameter choice and optimal imaging geometry were not known for this case. To solve this problem in a general way there is need for accurate physical models describing the radar backscattering of forests and models that describe the structure and architecture of forest components. That also implies of course that optimal and general applicable texture measures can be derived theoretically from these models.

The obtained new insights in classification indicate that an integral approach is recommendable, combining several image processing techniques and physical models. In the case of the Roggebotzand test area the classification procedure is simple and straightforward. When no a priori knowledge of boundaries is at hand or is inputted by a human observer, automized segmentation procedures like Multitemporal Split & Merge (ref. 2) will do resonably well. Since the whole forest is in the pole phase and stands are homogeneous there is no textural information concerning subpatterns greater then or equal to the pixel size. Therefore this kind of texture analysis will not yield vital information.

In the case of the Veluwe test area the matter is more complicated. The area consists of stands in the nole phase ranging in size from very small to large and it contains areas with mature beech forests. Automized segmentation procedures not incorporating texture will largely fail. In contrast to the Roggebotzand area were classification can be based on models using multitemporal spectral information averaged over picture segments the Veluwe test area can only be classified on a pixel base. However when use is made of suitable texture transforms a more sophisticated approach can be followed. It was found that pixels with the textural characteristics 'pole' or 'type !' are very likely to be located in the centre of a local region of the same species. Then the centre pixel can be classified based on models using spectral and temporal information of a small local region. The speckle problem is greatly avoided through (weighted) averaging over that local region. As a result a part of the scene can be classified quite accurate. The remaining part of the scene consisting of pixels characterized as 'non smooth' can be classified based on models using these characteristics together with local multitemporal spectral information. But since accurate spectral information from a region with rough texture (and speckle) can only be obtained through an adequate averaging over a local region and texture characteristics are always based on a local region it implies that this part of the scene is always, inherently to its nature, classified with low spatial resolution.

Application of edge detectors might locally improve the results somewhat since averaging and extraction of textural features across distinct boundaries can be avoided (e.g. artificial boundaries like stand borders or natural boundaries like rivers). In transition zones, characteristic for most natural forests, automized segmentations (like Split & Merge) cannot be applied in contrast with methods based on local texture characteristics and locally averaged spectral characteristics.

9. CONCLUSIONS

Texture analysis was found to be a promising tool in the classification of forests in SLAR images. Some statistical texture measures based on GLCO and GLD in combination with optimized displacement lengths and window sizes can deliver useful texture transforms. Especially GLCO-Correlation proved to be successful. This could be explained out of the dimensions of physical structures in the canopy, the spatial resolution of the imaging system and the displacement length. Measures like GLCO-Contrast or GLD-Entropy at displacement length 3 or 4 were found useful. For the texture classes under research they were related to the variance of the gray level distribution. This suggests that alternative approaches are feasible. It was found e.g. that the combination of GLCO-COR with variance has good potentials.

Textural resolution was found to be non-exchangeable for spatial resolution in texture transformed images. As a result it is always advantageous to start from large spatial window sizes directly instead of starting from small window sizes (for a better spatial resolution) and performing a spatial averaging in the texture transformed image afterwards.

By means of suitable texture transformed SLAR images the major forest texture classes in the scene, with the exception of small and bounded textural regions, could be classified well. The method is by no means inferior to human visual perception with regard to the quantification of several relevant textural phenomena. This can be explained by the fact that automized procedures can fully and objectively incorporate the dynamic range of radar backscatter levels in the digitized image.

The newest insights clearly suggest that a classification strategy is recommendable in which local textural characteristics and spectral characteristics as well as line detection and segmentation algorithms are the major components. Physical models of radar backscattering and models that describe the physical structure of forest components must be developed further in order to arrive at general applicable (optimized) texture measures and optimized sensor parameter choice and imaging geometry with respect to classification accuracy. In extrapolating the results to natural forests by means of ground truth information it was obvious that the SLAR system used, with fine radiometric and geometric resolution, has great classification potentials and can be useful in monitoring the diverse stages of growth in eco-unit development.

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SESSION E



MICROWAVE REMOTE SENSING OF AGRICULTURAL CROPS IN CANADA

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ABSTRACT

The objective of this paper is to review current knowledge concerning synthetic aperture radar applications to agriculture in Canada. Using results of studies during SURSAT (1978-1980) and RADARSAT (1981 to present) projects, the issues considered include crop classification accuracies achieved with SAR or SAR and VIR data at various sites; important crop and soil parameters affecting SAR images; the procedures for digital SAR image analysis; and the relationship between airborne SAR data future satellite SAR data. lopments in new ground and and Recent developments airborne microwave instrumentation for agricultural studies are presented, and planned research and development activities are outlined.

1. INTRODUCTION

The potential of satellite remote sensing for the monitoring of agricultural crops and for estimating crop production was recognized by Canadian scientists in the early 1970s. Shortly after the launch of LANDSAT 1, several investigations were undertaken to evaluate the feasibility of crop area estimation using satellite data. Of special interest were cereal crops which are a major Canadian commodity on the domestic as well as international markets (Crosson et al., 1974; Mack <u>et al.</u>, 1975). Other studies focussed on crop condition monitoring (Mack <u>et al.</u>, 1977; Schubert and Mack, 1978). In addition to demonstrating the potential of visible and infrared (VIR) data for agriculture, these studies also highlighted the limitations of LANDSAT data caused by the relatively infrequent revisits and frequent clouds. This is particularly relevant in higher middle latitudes where the growing season is short and crop development therefore rapid.

As a partial solution to the cloud cover problem, a thorough evaluation of the information content of the NOAA AVHRR (Advanced Very High Resolution Radiometer) data was undertaken. It was found that the wide scan angle and low resolution of the AVHRR distort the crop information present, and procedures were developed to correct for these effects (Brown <u>et al.</u>, 1982a, 1982b, 1985). Using these procedures, it is possible to generate an AVHRR product showing crop condition in three to five classes. Since AVHRR data are available daily and given the large area shown on a single image, this product can be an effective monitoring tool with respect to general growing conditions; for example, the entire Canadian prairie agricultural area is shown on one image. Nevertheless, AVHRR data also suffer from serious limitations. They can be acquired only when the sky is clear (on roughly 15% of the days during the growing season in the subhumid to semiarid Canadian prairie regions according to the experience from the last four years), and the data are not suitable for crop area estimation or for requiring field-by-field other assessments analysis.

Agricultural applications are not only case where the limitations of the VIR satellite data have been encountered. In Canada, useful VIR data cannot be obtained in the North because of insufficient solar illumination resulting from a low sun angle (including arctic night beyond the Arctic Circle). In addition, important potential applications of satellites such as ship navigation in ice-infested waters require navigation in ice-infested timely and reliable data which cannot be provided by VIR sensors alone. For these reasons, Canada showed an early interest in satellite microwave remote sensing. In 1975, a study was undertaken (Canadian Astronautics Ltd., 1976) to define the potential of a synthetic aperture radar (SAR). In September, 1975, a government task force was appointed to assess the feasibility of using satellite Canadian surveillance technology to meet requirements with emphasis on ice and oceans. The task force recommendations led to the establishment of the Canadian Surveillance Satellite Program (SURSAT) in 1977 which included a participation in the NASA SEASAT program and a complementary research and development program. As part of SURSAT, an X/L SAR was acquired from the Environmental

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Research Institute of Michigan and placed onboard the Canada Centre for Remote Sensing (CCRS) Convair 580. This sensor was used during 1978 and 1979 to acquire SAR data for many Canadian investigators in several disciplines (Intera Environmental Consultants, 1980). SURSAT also led to the development of the first digital SAR processor in 1979 and to the addition of a C-band capability to the X/L SAR in 1980.

Encouraging results of the SURSAT Program formed the basis for a recommendation that the Canadian Government initiate a program which would lead to the launch of a Canadian satellite carrying a SAR. This recommendation was accepted and a new project, RADARSAT, commenced in 1981. The current Phase B of RADARSAT is scheduled to end in March, 1987, with a planned launch in 1990.

In parallel with the growing interest in SAR and environmental surveillance, the possibility of using SAR data for agricultural applications was studied in an experimental program which started during SURSAT and was expanded as part of RADARSAT. The purpose of this paper is to review results of agricultural studies in Canada employing SAR data, to discuss some current issues relevant to satellite SAR data applications in agriculture, and to outline future Canadian activities in this area.

2. REVIEW OF PREVIOUS CANADIAN STUDIES

2.1 SURSAT data

The SURSAT Program provided the first opportunity to acquire coincident (airborne and in some cases satellite) SAR and ground data sets. Several sites have been identified representing both prairie and eastern crop growing systems (Table 1). Airborne SAR data were acquired near the peak of the growing season (Table 1) at six sites: Melfort, Swift Current, Raymond, Guelph, Simcoe, and Grand Falls. Except where stated (Table 2), four channels were optically recorded: XHH, XHV, LHH, LHV.

An initial analysis of the airborne data of the prairie sites was undertaken using film transparencies* or prints from the four channels (Garron and Schubert, 1979) and at Simcoe (Remotec Applications Inc., 1979). Garron and Schubert (1979) developed manual interpretation keys based upon an evaluation of film density ranges for individual land cover types at each site and then applied these keys to determine classification accuracies. Image texture was not used explicitly but may have played a role in the visual assessment. Table 3 shows the correctly identified crop areas for three sites (commission and omission errors were also determined). The accuracies varied among crops and sites. In some cases, individual crops could not be separated and were therefore grouped as grains, broadleaf crops or all crops. Classification accuracies in the combined classes were quite high,

*All images discussed in this paper were positives.

particularly for fallow, pasture and broadleaf crops (Table 3). Accuracies for grains varied substantially.

In the Simcoe study, image tone and texture classes were assigned to each field, separately for each channel (Remotec Applications Inc., 1979). Results of this visual examination showed (Table 4) that most crops occupied the middle range of tones in the X-band and extremes (low or high) in the L-band. In particular, broadleaf crops were readily distinguished on the LHH image. The XHV image exhibited a broader range of tones than XHH, while LHV was similar to LHH. Quantitative classification accuracies were not established in this study.

Data from the Guelph site were analyzed by Briscoe and Protz (1980, 1982). They achieved an overall classification accuracy of 73% for five classes (grain, corn, hay-pasture, woods, roughland) using a manual tone/texture interpretation key. Corn and woods could be readily discriminated because of a high L-band return and different textures on X-band. In particular, corn identification accuracies exceeding 90% could consistently be achieved with X and L images. Hay-pasture and grain fields were most confused (accuracies 40-50%) as a result of similar tone and texture. The authors suggested that data acquisition missions should be scheduled for periods of maximum differences in geometric and dielectric properties of the crop canopies, for example after hay has been cut to minimize the hay-grain confusion.

Goodenough et al. (1980) analyzed a data set representing a 9 km^2 area near Grand Falls which consisted of LANDSAT Multispectral Scanner (MSS) and three channel SAR (XHH, XHV, LHV, Table 2) collected with two azimuth headings. All images were rectified to the UTM projection and resampled to 25 m or 50 m pixel size. A feature selection algorithm identified LHV as the most useful SAR channel followed by XHH and XHV. This suggests that LHH would also have yielded important information had the data been recorded. The average classification accuracy using the best four SAR channels was 67%; when using SAR data from one pass only (50 m pixels), the accuracy was about 53%. The combination of the best LANDSAT MSS (bands 5 and 6) and SAR (LHV, XHH) bands yielded an overall accuracy 05 78%, a substantial improvement over LANDSAT MSS (65%) or SAR alone.

During Phase A of the RADARSAT project, Hirose <u>et al</u>. (1983) assembled a multisensor data set for six sites (Table 2) consisting of XHH and LHH data from the previous studies, SEASAT L-band images and LANDSAT MSS images. All data were produced in digital form, registered to a UTM projection using LANDSAT MSS DICS products (Butlin <u>et al</u>. 1978) as the base, and resampled to a 25 m X 25 m pixelsize. Individual fields for categories with a sufficiently large sample were delineated on a "ground data image" which was also co-registered. Using a feature selection algorithm that iteratively identifies (and then eliminates from the next iteration) the band containing most information, they found that both LANDSAT MSS and SAR data can provide useful input to crop identification (Table 5). The apparent preference for L-band at the Melfort site was probably influenced by the high discrimination of fallow fields and the lower quality of XHH data. Furthermore, for Melfort, Navan and Simcoe, the ranking reflects the improved LHH response to broadleaf (including corn) compared to graminoid plants (such as grains). Hirose <u>et al.</u> (1983) also determined the improvement in classification accuracy using a set of the best four bands (from all available at each site) compared to LANDSAT MSS only. An overall improvement of 4.1% resulted from adding SAR data but variations occurred among crops and sites (Table 6). Grains appeared to be more adversely affected than other crops.

The analysis of the above data set was extended by Cihlar and Hirose (1984) for the prairie sites to include various combinations of SAR and VIR data and to consider per pixel as well as per field classification approaches. The maximum likelihood decision rule was used in both cases and because of the data set size, the same data were employed as training and testing sets. When expressed as the overall average accuracy of correctly identified pixels, the results show that one or more SAR bands can approach the accuracy obtained with LANDSAT HSS (Figure 1). This is the case in Helfort and Swift Current, presumably because the classes differed principally in "effective" roughness (e.g., graminoids vs. broadleaf plants vs. fallow in Helfort). The low SAR accuracies for Kaymond are primarily due to misclassification or winter wheat and pasture; values for spring grains and fallow were above 70%. In Outlook, a contributing factor seemed to be the larger number of classes. Figure lalso indicates that when mean field intensities are classified instead of individual pixel values, the results generally improve. Data sets including LANDSAT HSS classified in this way snowed accuracy increases between 5 and 27%, the average being 12%. SAR data alone snowed a smaller improvement and an actual decrease in two cases; this could be due to the quality of the airborne data (Table 2).

2.2 RADARSAT data

The proposed RADARSAT satellite will carry three sensors; a C-band SAR, a high resolution VIR sensor and a scatterometer. The VIR sensor and the SAR could be used to supply information relevant to agriculture. Since 1983, efforts have been directed towards determining the extent to which C-band SAR and a combination of SAR and VIR data can be used to assess crop 1985 condition and crop type. During the growing season, SAK and VIR data were collected over four test areas in Western Canada (Helfort, Swift Current, Uutlook, Raymond). Ir. Helfort, SAR data were collected five times between mid-June and mid-August and airborne VIR data in the LANDSAT Thematic Mapper (TM) bands were collected on three occasions. In addition to the airborne data, detailed description of the crop and soil conditions was obtained for approximately 225 fields throughout the test area (Table 7). Since CVV has been specified for the RADARSAT SAR the initial analysis focussed on a multitemporal

CVV data set (Brown et al, 1984); Teillet <u>et</u> <u>al</u>., 1984).

As early as June 26, 1983 canola was clearly separable from the grains on the CVV imagery even though the crop was only 8 to 10 cm high and covered less than 40% of the ground. At this point in the phenological development canola and peas were also separable from each other with canola giving a higher backscatter. The classification (for a pixel classifier which accuracy excluded field boundary pixels) was 89% for canola. The early identification of canola is significant because LANDSAT MSS does not separate canola from grains and summerfallow until the canola plant is in bloom (Brown et al., 1980). This occurs in late July, approximately three to four weeks later. In the 1980 study, canola classification accuracy was 63% using LANDSAT MSS data from July 9, 1979 (full bloom for canola was not for about another ten days in 1979). Hence it appears that CVV would be a preferred data source for canola mapping because the information on canola area can be acquired substantially earlier in the growing season. There was, however, substantial confusion between grains and summerfallow on CVV images from late June.

As in the case of VIR data the classification accuracy associated with SAR imagery depends upon the acquisition date. The best overall classification accuracy using CVV data from three dates (June 26, July 31 and August 13) was in July, d7% with a standard error of 7% for 3 classes (canola, grains and failow). This contrasts with other studies (Van Kasteren, 1981) which have indicated that crop type separation is test at maturity, and it illustrates the complex nature of the interaction of microwave energy with vegetation which must be understood before definitive statements can be made on optimum time interval for maximum classification accuracy. This optimum date may be a function of the phenology of crops grown in the area.

3. DISCUSSION

In assessing the expected performance of a satellite SAR for agriculture, the following issues should be considered: the information about crops which is present in the SAR image; ways of extracting this information; and the validity of extrapolating results obtained with present airborne images to future satellite sensors. These items are considered below with reference to results of studies in Canada.

3.1 Importance of crop and soil parameters

An understanding of the causal relationships between crop and soil parameters and image tone is of key importance in assessing the usefulness of a SAR. It can provide the confidence required for extending results from limited test sites to larger geographic regions, and it is necessary for constructing inversion models whereby SAR might be used to a crop monitoring tool. Background work in this area has been conducted with ground scatterometers in the U.S., the Netherlands and France. These studies, typically carried out on controlled plots, have shown that depending on the sensor parameters (frequency, incidence angle, polarization), important variables may include crop type, growth stage, soil moisture, soil roughness, row direction, and others. One of the objectives of the Canadian agricultural projects involving SAR has been the identification of target parameters which strongly influence SAR image tone. Ground observations are normally obtained near the time of SAR data acquisition to assist in this process. The procedure for ground data acquisition employed so far is similar to the LACIE approach (King and Mack, 1980). Since 1983, this procedure has been enhanced by including ground and low altitude photography.

To date, only a limited success has been achieved in this area and the findings of Canadian studies can be summarized as follows.

- (i) Wheat vs. barley discrimination. Cinlar and Hirose (1984) observed no clear distinction between these crops at any site or SAR frequency. Barley fields tended to be lighter at two sites and darker at the remaining two but in each case, there was a large overlap between these crops. This is not too surprising considering that confusion also exists between grains and hay or pasture.
- (ii) Canopy and soil parameters (plant height, plant cover, growth stage, <u>stand quality</u>). In most cases, Cihlar and Hirose (1984) did not find consistent relationships between these parameters and image tone at X or L. There were some exceptions. For example, a statistically significant relationship (0.01 probability level) was found between row spacing (range 18 to 23 cm) and spacing (range 18 to 23 cm) and SEASAT image intensity (r = -0.76for descending pass, -0.65 for ascending pass) for 20 barley fields at Kaymond. A significant relationship (0.05 probability level) was also found between the width of ridges on fallow fields at Raymond (range 20 to 81 cm) and SEASAT image intensity (r = 0.53for descending pass, 0.59 for ascending pass) 16 fields. At the Helfort site, lower L-band return from barley corresponded to a more advanced crop and/or lower stand quality, i.e. less total water in the plant canopy. Higher green biomass (approximated by the LANDSAT MSS 7/5 ratio) was in some cases related to a change in XHH return but not consistently so. Greener spring wheat was darker in some fields at Swift Current although the pixel-to-pixel correlation of XHH data with the MSS 7/5 ratio varied depending upon the fields included. On the other

hand, greener winter wheat at Raymond (in a more advanced growth stage) appeared lighter on the XHH image. On the SEASAT images, the amount of green biomass had no effect on the tone. This was particularly evident in alfalfa fields at Outlook where LANDSAT HISS and SEASAT were available within one day (Table 2) but similar effect was observed in other sites (e.g., lack of contrast between adjacent grain and fallow fields at Raymond or between adjacent grain and rangeland at Swift Current). For C-band, Teillet <u>et al.</u> (1984) found at Helfort that SAR image tone was in many cases insensitive to canopy height variations although several statistically significant relationships were observed (r = 0.54 (CVV, barley, 5% probability level), 0.66 (CdH, canola, 0.5%), and 0.69 (CHH, canola, 0.5%) on 26 June; and r = 0.58 (CVV, wheat, 2%) and -0.55 (CdH, 5%) for wheat on 19 July).

brown et al. (1984) found that the amount of confusion between fallow fields and grains strongly depends upon the condition of the fallow fields on C-band images. The backscatter from fallow fields increases substantially as the roughness as measured by the percentage and size of clods of soil increases. This appeared to be the dominant parameter in determining the magnitude of the backscatter from fallow fields at C-band, more important than row direction. Dry standing stubble on the field appears to have little or no effect upon the magnitude of the backscatter.

The lack of consistent relationships between canopy consistent parameters and radar return could be due to various factors. These include the type of ground parameters measured, the scale parameters measured, the scale (resolution) used to record each parameter, insufficient information on within-field variability which is known to be large in most fields (data were recorded at one site considered representative of the field), narrow range of values for a given parameter such as plant height, and SAR image quality problems, particularly for the airborne data. Experience to date suggests that in some cases, the that in some cases, the relationships may be very difficult to establish. For For example, it is sometimes not possible to identify reasons for backscatter difference on an image taken the previous day while standing at the exact spot in the field where the difference

appeared.

(iii) Row direction. In analyzing XHH and Lill images, Cihlar and Hirose (1984) found that row direction had a strong "bowtie" effect on radar return in some cases. This effect was most prevalent on airborne L-band (Table 2) in grain fields at Swift Current. nowever, the same images from Melfort did not show any bowties, and in Kaymond only one of 11 fields displayed this effect. On the SEASAT images, several fields were very bright (assumed to be due to row direction), including one potato field at Outlook and one fallow, two winter wheat and some barley fields at Raymond. Two cases of "reverse bowtie" (i.e., lower backscatter from rows parallel to the flight direction) were also observed. Une case was some wheat fields on Xilli at Swift Current, and the other was one barley field on SEASAT at Kaymond; in both instances, the reverse effect was fairly weak.

brown et al. (1934) found no row direction effects on CVV mages at the welfort test site at incidence angles ranging from 30° to 50° . Nowever, at the Switt Current test site where the fields tend to be long and narrow, row direction effects were seen in both fallow and grain fields at incidence angles of 35° .

Crop type. Studies to date (Garron (iv) and Schubert, 1579; Kemotec Applications, inc., 1979; Cihlar Applications, inc., 1979; Cihlar and ilirose, 1984; Brown <u>et al.</u>, 1984) established that in general, crop type is the single most important parameter among those recorded in the field. In some situations, crop type results in a unique radar return (Brown <u>et al.</u>, 1984; Cihlar and Hirose, 1964). nowever, it is not clear exactly which target parameter(s) cause this effect and their relative importance. Canopy structure (preferentially vertical for grains vs. lack of preferential orientation for canola) could explain backscatter differences between CHH and CVV images at Nelfort (Teillet et al., 1934). Broadleaf crops generally provide higher return than other field cover types in the frequency range L to X (parallel polarizations) (Remotec Applications. Inc., 1979; Brisco and Protz, 1932; Cihlar and dirose, 1984; Brown <u>et</u> <u>al.</u>, 1984). There also seems to be lack of consistency among sites, both as to the range of tones for each crop and the rank order of crops. This implies a limit to the distance over which signature extensions may

be possible and is thus of key importance from an operational viewpoint.

- Growth stage. Brown et al. (1984) (v)found that crop ripening can in some cases be detected on SAR imagery. Within the Melfort test area there were two types of canola, <u>Brassica</u> napus and <u>B.</u> canpestris. The <u>B.</u> canpestris В. variety ripens approximately ten to fourteen days sooner than \underline{B} . napus. On the August 13, 1983 \overline{CVV} images of fields planted at the same time but different varieties of canola, the early maturing B. campestris had less backscatter and in many instances was indistinguishable from the grains. This suggests that SAR imagery may be used for monitoring the development of some crops but more work is required in this area to better understand the scattering mechanisms. For example, the opposite trend (oackscatter increase with ripening) was observed for grains by Ulaby and bush (1976).
- (vi) Soil moisture. From a qualitative assessment of the SAK data brown <u>et al</u> (1964) observed a correspondence between wet areas containing no vegetation, as identified from aerial photography, and higher C-band radar backscatter at incidence angles 30° to 45°.
- (vii) Within-field variations. Tonal variations within individual fields are frequently observed on SAK images. They can sometimes be readily explained from features observed on photographs, sucn as bowties. However, often they are more obscure and thus require detailed canopy and soil data for specific portions of the fields. Previous procedures relied on data from a "representative" site in the field because the collection of extensive within-field data was impractical, and it still is.

One of the problems in identifying significant crop parameters which affect microwave backscatter is the speckle inherent in SAK images. Hence pixel-to-pixel comparison, as might be done in VIK data analysis, is less appropriate. Ground data acquisition must therefore be geared to larger areas because it is usually necessary to spatially average SAK intensities to reduce the speckle.

To get better ground data and rapid feedback for image interpretation the ground data collection procedures have been modified in 1984. Quick Look SAR imagery is taken back into the field the day following SAR data acquisition to example and document any field anomalies. This way found to be a very useful

procedure. In addition, a light aircraft is used to acquire oblique large scale photos as an aid in describing field variations. There is also a great need to combine airborne SAK acquisition with ground measurements using a microwave scatterometer. This helps to improve the radiometric characterization of the SAR images and to explain reasons for differences in observed radar backscatter.

3.2 Information extraction from digital data

Nost of the studies of digital SAR imagery which have been carried out by Canadian investigators involved performance comparisons of SAR and VIR data. The principal steps in such experiments include radiometric and geometric preprocessing and subsequent classification.

- Radiometric Correction. The principal source of SAR imagery has been the X/L/C SAR system. The (i) data produced by this instrument are uncalibrated and therefore the user must apply corrections for range effects such as antenna power pattern. The antenna power patterns for the X/L/C SAR are not well defined (Corr and Smith, 1982); hence, an empirical technique was developed to remove range-related gain variations (Guindon <u>et al.</u>, 1984). This technique involves acquiring a mean grey level profile for each scene and then using the profile to estimate multiplicative correction factors for each range interval by means of a low order polynomial. When applied, these correction factors will generate a corrected scene with a constant mean brightness at all ranges. Good results have been achieved in cases where the scene content does not change with range. The technique has not been successfully applied to remove azimuth radiometric variations or to correct for the complex nature of the antenna pattern outside of the main lobe (Briscoe and Protz, 1982).
- (ii) <u>Geometric Correction</u>. Accurate geometric registration of scenes is a prerequisite to sensor performance comparisons. A conceptually simple flight modelling technique has been developed to rectify high resolution airborne radar and optical imagery. Briefly, this approach involves the use of map and image coordinates and elevation information for ground control points to derive parameters of the aircraft flight path, namely aircraft heading, altitude and the map coordinates of one ground location over which the aircraft passed. The modelling procedure assumes that the aircraft is flying in a constant heading-constant altitude orientation with zero

roll, pitch and yaw. Over level terrain, registration accuracies of less than 10 meters root mean square (r.m.s.) were achieved (Goodenough et al., 1980). The flight modelling approach also allows for the inclusion of digital terrain models to account for geometric distortions due to relief. In an area with elevation range of 700 meters, registration accuracies of 13 meters r.m.s. were obtained (Guindon <u>et al.</u>, 1982a).

(iii) <u>Classification</u>. Extensive maximum likelihood classification experiments have been performed on both agricultural and forest targets. In general, SAR is outperformed by optical sensors when data are acquired at the same date(s) and multispectral VIR data are used. This result is partly due to the significant overlap of the grey level distribution of important target classes on SAR imagery. Median filtering has been successfully applied to reduce SAR speckle and hence, to improve classification accuracy (Goodenough <u>et al.</u>, 1980; Hirose <u>et al.</u>, 1983; Brown <u>et al.</u>, 1984). Even with filtering, some classes such as grain varieties, remain confused. Efforts have therefore been directed recently toward the development of techniques to extract and classify homogeneous segments on SAR images rather than to classify scenes on pixel-by-pixel basis (Goodenough et al., 1984). Segmentation of SAR imagery is difficult because of speckle but improved results have been achieved through a prior application of an adaptive filter (Frost <u>et al.</u>, 1982).

> Another factor in classification performance which proves important when classes overlap are the accuracies of the parametric class descroptors. A standard practice is to approximate class grey level distributions by gaussian functions. Guindon <u>et al.</u>, (1982b) found that because of the substantial amount of spatial averaging during preprocessing, SAR data distribution is not significantly different from LANDSAT MSS distribution. More recently, Chi-square testing has shown that gaussian description is appropriate for SAR images in which grey level is proportional to the square root of amplitude but not for power, amplitude or log amplitude imagery.

3.3 Satellite image simulation

Compared to the large amount of SAR data that has been obtained by aircraft over

Canadian agricultural areas, relatively little data acquired from space platforms is available. In particular, no X or C-band spaceborne SAR images have been acquired. To fully evaluate the information content of spaceborne SAR imagery two radar image simulation packages are in use at CCRS. One package starts from known relationships between radar backscatter, calculates a reflectivity map, and introduces a specified amount of speckle. This package is an improved version of previously used radar image simulation software (Komp <u>et al.</u>, 1983). Its advantage is the possibility of simulating radar image for any hypothetical sensor, provided the input values are properly defined. The second package starts with an actual speckle-free radar image and likewise introduces a specified acount of speckle. The advantage of starting with an actual SAX image is that the exact relationships between radar backscatter and crop and radar parameters are inherent in the image and no assumptions or extrapolations are necessary. Un the other hand, one is limited by the sensor parameters of the sensor used to acquire the original image.

Since no backscatter measurements are currently available for land targets in Canada, the second approach has primarily been used to date (Gray et al., 19d3a, 1983b). The input aircraft data used in simulating satellite images were collected with the high resolution (\pm 3 metres) $\lambda/C/L$ band SAK of CCKS. To simulate the lower resolution (25 m) spaceborne SAR imagery it is necessary to spatially average the aircraft data and then to introduce additional speckle into the image. These steps result in correct spatial resolution and a correct number of looks in the simulated image. In the simulation package this is achieved by (i) spatially averaging the high spatial resolution aircraft image to produce a radar reflectivity map; (ii) the generating speckle images with user-defined radiometric distribution and number of looks; and (iii) the multiplying the smooth radar reflectivity map by the speckle image.

We have found that a critical parameter in determining the resultant image quality is the amount and type of pixel-to-pixel correlation. With a dayleign speckle distribution and no correlation between pixels the image is considerably more noisy than one in which a correlation coefficient of 0.25 is assumed between neighbouring pixels. In the absence of detailed information on pixel correlations for the KAWARSAT SAK, an autocorrelation function calculated from SEASAT imagery has been used.

4. CURRENT ACTIVITIES AND FUTURE PLANS

Substantial progress has been made in Canada in the development of the technology required for conducting microwave R&D in agriculture. Further experiments are also underway or planned or the future.

4.1 Ground-based scatterometer measurements

Accurate measurements of microwave Dackscatter from well described crop canopies or soil are essential for developing an understanding of factors affecting SAR image brightness. In the case of rapidly growing crops, such measurements are needed frequently. Experience to date indicates that findings from one geographic area are not directly applicable in another, Kansas and Saskatchewan being a case in point (Dobson, 1984). In conducting such studies, it is highly desirable to consider a wide range of radar parameters to ensure that the findings will be of value for the next 10 to 20 years. The above considerations lead to the use of ground-based scatterometry as an effective experimental method.

To further the use of SAR technology in the management of Canada's resources, CCRS is establishing a ground-based micorwave measurements program. An essential component of this program is a multifrequency scatterometer attached to a boom which is in turn mounted on a truck. The system will be capable of a simultaneous acquisition of calibrated backscatter coefficients at three trequencies (1.5, 5.3, 13.4 GHz) and polarizations (like and cross), from and two the neight of about 17 metres, in standing mode or while the vehicle moves. Data will be recorded digitally. The data acquisition procedure will be preprogrammed from the cabin of the truck using operator console built around a microcomputer and two TV monitors. During the first three years, the program will concentrate on the measurement of agricultural targets.

4.2 Digital C-band SAR

A new SAR called INIS (Integrated Radar Imaging System), to be delivered to CCRS in February 1985, will replace the present X/L/C SAK on the Convair 580. This would be an all-digital, microprocessor-controlled, dual-channel, moderate-resolution SAR. The design philosophy of this instrument has been to provide an optimum compromise between swath wiath and resolution, and between system flexibility and operational reliability. The instrument will initially be C-band only but there are plans to add an X-band capability by 1900. Some relevant characteristics are given in Table 8. All of the imagery will be processed digitally, including the real-time output which may be displayed on a CRT or printed on dry silver paper. The radar will also have an internal calibration capability which will permit absolute calibration. The antenna pattern effect will be removed through data preprocessing.

4.3 Experimental studies

Our current studies are directed towards:

(a) The development of an understanding of the interaction between microwave energy and vegetated and fallow fields. A qualitative analysis is being carried out on the X, C and L-band SAR data acquired in 1983 and 1984 over the four prairie test areas. The objective of this study is locate apparent anomalies in the imagery and attempt to identify their causes from an examination of the various sources of ground and airborne VIR data.

- (b) An investigation of the complementary role of SAR and VIR for both crop condition assessment and crop area estimation. In particular, biomass variations as mesaured on the VIR data are being related to variations in radar backscattering coefficients.
- (c) A study of the variation in backscattering coefficients as a function of angle. Since the RADARSAT SAK will be capable of acquiring data at incidence angles ranging from 20° to 45° it is important to know how backscatter will vary over this wide swath. Cand Ku-band airborne scatterometer data were acquired at all prairie test areas in 1984 and are presently being analyzed.
- (d) An evaluation of the importance of field classifiers (as opposed to pixel classifiers) for SAR data.
- (e) An assessment of the relationship between airborne scatterometer backscatter coefficients and soil moisture.
- (f) An evaluation of L-band images obtained from the Shuttle Imaging Kadar (SIR-B) in October, 1984 over Saskatchewan. The effects of vegetation, cultivation practices and soil moisture are of interest, as well as variations due to SAR parameters.

In the long term, the thrust of R&D agricultural SAR investigations at CCRS is determined to a large extent by the expected future satellite data sources. These include ERS-1 in 1988 and RADARSAT in 1990, both C-band systems. An additional consideration is the most effective use of all available satellite data for agricultural applications. One must thus include optical data from MSS, TM, HRV (maute Resolution Visible) or similar sensors. Finally, it is desirable to learn as much as possible about the electromagnetic response of agricultural targets over a wide range of sensor parameters.

Based on the above, agricultural studies in the next few years will continue to focus on the capabilities of a C-band SAR. Crop classification accuracies achievable with satellite data in an operational setting will be a major objective of this work. The variability of agricultural conditions over large areas will be an important consideration. The airborne C-band SAR (IRIS) will be used, in combination with the ground-based scatterometer when required. Airborne X-band SAR data will also be obtained and analyzed when possible. As in the past, VIR data from satellite and airborne sensors will continue to be acquired to develop effective ways of using multisource data sets. The second objective is the determination of the potential of satellite SAR data to monitor crop condition, including growth and potential yield. This will be an important task for the measurement program involving the ground-based scatterometer. It is expected that airborne sensors will be employed only after the initial ground studies are completed.

4.4 Information extraction

The improvement of information extraction from SAR imagery will require the refinement of existing techniques and also the development of new approaches, particularly in the area of image classification. Algorithms are being developed in the following areas at the Canada Centre for Kemote Sensing.

- (a) Improved edge detection in SAR images. The objective is to achieve accurate delineation of agricultural fields and thus to be able to use automated, segment-based classification of SAR data.
- (b) Automated techniques to aid in the registration of radar/optical image pairs. VIR imagery could be used to define field boundaries as well as to improve classification results. Automated methods for the rapid identification of registration control points are being investigated.
- (c) SAR segment classification.
- (d) Non-gaussian maximum likelihood classification. Because of the extensive overlap among crop classes, the precise description of class probability density functions becomes critical. Work is being carried out to identify suitable parametric descriptors for a range of extended target types and to incorporate relevant functional forms within the context of the maximum likelihood decision rule.
- (e) Image texture extraction and use in classification. It is unlikely that agricultural crops will exhibit significant texture at satellite resolutions. However, texture could prove useful in discriminating between agricultural and non-agricultural targets which exhibit a similar mean grey level.

5. SUMMARY

Studies conducted in Canada since 1978 have provided valuable initial insight into the potential usefulness of SAR images for agricultural applications. The findings to date can be summarized in the following broad statements.

 Crop classification. High accuracies can be achieved with SAR (particularly multiband) data under some conditions. Accuracies for "rougher" targets such as broadleaf crops and fallow are

generally superior to those for other crops, particularly at the lower frequencies. Grains are frequently confused with hay fields and less often with rangeland. Classification accuracies often vary among sites and between dates at one site. The extension of test site results to larger areas has not been carried out. SAR data provide information which is different from and complementary to that obtained using VIR data.

- (ii) Canopy and soil parameters. Crop type is the most important field parameter. No definite relationships between SAR intensities and individual canopy parameters have been established to date although some progress has been made. Row direction effects have been observed but their importance varies with site and SAR frequency.
- (iii) SAR frequency. While X-band provides good crop type discrimination, the value of L-band for separating broadleat crops and fallow at some sites should be noted. On the otner hand, L-band is sometimes sensitive to row direction effects while A-band is not. Kesults to date suggest that the crop discrimination potential and the row direction sensitivity of C-band are intermediate between X- and L-bands.
- (iv) Digital classification. Digital filtering prior to classification improves results. Per field classifiers are generally preferable to pixel classifiers. Image texture offers some potential out has not been explored thoroughly. Image segmentation followed by classification appear to offer an effective approach to digital analysis of SAR data.

Huch work remains to be done to determine the practical value of SAK data for crop monitoring. Although C-band will be given most attention in view of the planned satellite programs in the late 1980s and 1990s, other frequencies and complementary VIK data must also be considered. New ground-based and airborne microwave instruments will be available starting in 1985 to allow Canadian scientists to conduct the needed experimental work.

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		July 24	Aug 11	
Moderately Large-Scale Dryland Farming Subhumid Conditions Dark Brown Chernozems	Spring Wheat Barley Canola Fallow	Headed Headed Headed	Ripening Ripening Ripening	9 21 13 9
		July 26	Aug 11	
Large Scale Farming Subarid Conditions Brown Chernozems	Spring Wheat Barley Native Grasses Fallow Hay	Headed Headed Grazed - Harvested	Ripening Ripening Grazed - -	26 4 7 22
		July 28	Aug 15	
Mixed Irrigated and Dryland Farming Subhumid Conditions Dark Brown Chernozems	Spring Wheat Winter Wheat Barley Fallow Sugar Beets Pasture Flax	Headed Ripe Headed Headed Headed	Ripening Harvested Ripening Ripening Ripening	11 15 25 33 2 11 4
		Late July		
Mixed Dairy Farming Humid CondItions Poorly Drained Gleysolic Soils	Corn Pasture-Grasses Mixed Grains Bushland Other	Heading Grazed Ripening -		20 25 8
		August 3		
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		August 24		
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Table 1. Test Sites Description

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2.
Table

SITE	SENSOR(1)	OF 1978	(GMT)	IMAGE QUALITY(2)
44 Lforr	LMSS	10-08		Goud
1.41.016	AX	1-()8	2:10	Fairb
	AL	1-08	2:10	Good
Swift Current	LMSS	3-08		0000
	AX	31-07	22:05	Good
	AL	31-07	22:05	Fairc
	SL (desc.)	12-08	4:04	Good
hit Look	TWSS	11-08		Good
100 M	SL (desc.)	12-08	4:10	Good
promora	SSWI	6-08		Poora
	AX	31-07	21:25	Fairb
	AL	31-07	21:25	Fairc
	SLI (desc.)	3-08	13:36	Good
	SL2 (asc.)	20-08	13:36	Good
	-10 -07 - 1	20-02		Good
Navan	CCMT	10-07		
	SL (desc.)	30-07	0:47	Good
	2.2%	18-08		Good
armente		2-08	20.20	Fairb
	14	2-08	20.20	Good
	SL (asc.)	23-07	10:43	Faird
Guelph	AX.	2-08	N/A	(3)
	AL	28-09		
Grand Falls	LMSS	19-08		0005
	AX AL	1 08	N/A	(4)

LMSS - LANUSAT MSS; AX (AL) = airborne X HH (L HH) SAR with incidence angle approximately 65° (centre swath); SL = SEASAT L Band SAR.

a = cloud cover (hand 7 fair quality); b = banding or streaking; c = blooming; d = low signal to noise. (2)

Images from 2-08: XHH and LHH Good; XHV and LHV Fairb; Images from 28-09: XHU, HHV and LHH Good; LHV Fairb. (3)

(4) XiIII, XIIV, AND LNV recorded; quality Good; incidence angle $47_{\rm O}$

Hirose et al. (1983) analyzed data from the first six sites. (2)

Table 3. SAR Classification Results for Three Western Sites(1)

XHUR XHV LERH All Bands(3) Spring Wheat 59 63 Barlev 80	XHB				
Spring Wheat 59 63 Barlev 80		XHX	All Bands(3)	HX HHX	V All Bands (3)
Barlev 80	100	68	100		
			33		
Grains 75					
Canola and Peas 77 82 81 91					
All Crops				74	83
Pasture/Grasses	93	92	93	63	58
Fallow 100 100	67	72	2.6	77 87	06

Table 4. Tone and Texture Characteristics of Individual Crops: Simcoe Site(1)

	X-i	H		VH-3	н	HH-,	П	VH-
Crop Type	Tone(2)	Texture	Tone	Texture	Tone	Texture	Tone	Texture
Corn	2-3(3)	B-C	2-3	B-C	3-4	B	2	A-B
Barley	2-3	В	2-3	C	1	8	I	A
Hay	2	В	2	8-C	1	A	1	A
Uats	2-3	83		B-C	1	<	1	V
Uais & Barley	2	В	2-3	B-C	1	۷	1	A
Winter Wheat	(H)3(NH)1	IJ	2	U	1	A	1	A
Soybeans	2-3	C	ŕ	В	2	Я	1-2	A
Tobacco	3	Ŕ	2-3	8	3-4	зî	2-3	ß
Potatoes	2-3	â	2	8	ĉ	В	2	A
Rye	2-3	В	1-2	C	1	A	I	A
Bare (Rye)	2	В	l – 2	В	I	A	I	A
Bare (Hay)	2	A	1	9	1	A	1	A
Strawberries	2	A	$1 \rightarrow 2$	A	1 - 2	Ĥ	1	V
Cucumbers	2-3	Я	2-3	B-C	2-3	æ	2	8
Tomatoes	č	В	e	20	3-4	13	2	ß
Cabbage	3	Я	3-4	8	e	8	1 - 2	A
Cauliflower	2	B-C	1 - 2	B-C	2	8	2	з <u>р</u>

(1) From: Remotec Applications Inc. (1979).

 $^{(2)}\mbox{The}$ tone and texture classes are relative, established separately for each band (positive images used).

(3)The tone and texture classes indicated are those to which most fields belonged.

Tonal and Textural Classes: 1-Very Dark; 2-Dark; 3-Bright; 4-Very Bright; A-Smooth; B-Rough; C-Very Smooth; H-Harvested; NH-Not Harvested.

Table 5. Sequential Single Band Feature Selection Results (1)

NIK ORDER OF INGLE BAND	MELFORT	CURRENT	RAYMOND	OUTLOOK	NAVAN	SIMC	OE
lst	MSS 6	A/B X	S SSM	N/A	MSS 5	MSS	
2nd	MSS 7	MSS 7	MSS 7	N/A	MSS 4	MSS	5
3rd	A/B L	MSS 6	7 SSW	N/A	SEASAT	A/B	
4ch	MSS 4	SEASAT	A/B X	N/A	MSS 7	MSS	1

Table 6. Changes in Classification Accuracy Due to SAR Bands(1)

Site	-	Best P	our	Bands(2)	Differences ⁽³⁾ (2)	Å٦	rerage (2
laymond	MSS 5	MSS	7, Xŀ	iH, SEASAT	1.8, 6.5 ⁽⁴⁾ , 2.2 ⁽⁴⁾ , 4.5 ⁽⁴⁾ , 12.2,	5.0, 6.5	5.5
Swift Current	MSS 7	, хнн,	гнн	, SEASAT	3.4, -19.3(4), -8.3(4), 33.3, 14.8		4.8
felfort	MSS 5	MSS	6, XI	нн, снн	0.0, -3.1(4), 6.3(4), 1.9		1.3
lavan	MSS 4	MSS	5, MS	SS 7, SEASAT	1.8, 21.3, 0.6, 11.4		8.8
incoe	MSS 5	MSS	6, MS	SS 7, XHH	-1.8(4), -2.6, 2.4, -7.1, 6.7, 3.8		0.2

(1)Based on data by Hirose et al. (1983).

(2)Best set of four bands available for the site based on a feature selection algorithm.

(3)The numbers indicate the difference between classification accuracy using the best set and accuracy using LANDSAT MSS alone for individual classes, in percent.

(4)Wheat or barley.

Table 7. Ground Data Acquired in 1983 on a Field Basis*

- 1. Crop type, variety and yield.
- 2. Crop height and development stage.
- Anomalies in crop quality and presence of growth detractants.
- Plant row direction, intra-row spacing and inter-row spacing.
- 5. Surface soil moisture and roughness.
- 6. Plant moisture (selected fields).
- 7. Soil moisture (in the top 5 cm of selected fields).
- 8. Precipitation (multiple locations per site).
- 9. Vertical, oblique and close-up ground photos of fields.

*From: Brown et al. (1984).

Table 8. Integrated Radar Imaging System (C-IRIS) Specifications

Frequency:		5.3 GHz
Range Resolution:	High Resolution: Low Resolution:	4.8 metres 18.7 metres
Azimuth Resolution:	High Resolution: Low Resolution:	6.0 metres 10.0 metres
Polarization:	Transmit: Receive:	H or V H and V
Swath Width:		Maximum 18.3 km from incidence angle of 45° and aircraft height of 7 km
Noise Equivalent σ°	for distributed targets:	-40dB

DUTSCAT, A 6- FREQUENCY AIRBORNE SCATTEROMETER.

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ABSTRACT

Groundbased scatterometry has proven to be essential in studying the scattering of microwaves by vegetation. Groundbased measurements not only result in the well known "growing curves" but the results can also be used for the development of suitable models and for the improvement of the classification in images collected by airborne or spaceborne sensors.

There are however some limitations set to the groundbased measurements. In the first place the possible number of test fields is limited, therefore the statistical spread of the radarsignature for different fields with the same crop type (ecological noise) cannot be investigated. Secondly the illuminated area in groundbased measurements is relatively small and in some cases even too small, which sometimes leads to differences in scatter values between groundbased and airborne measurements. In the third place groundbased scatterometers can only use X-band and higher frequencies. There is however also a need for the use of lower frequencies e.g for experiments in relation of soil moisture mapping. The mentioned limitations can be overcome with an airborne instrument. At the same time such an airborne scatterometer can be used for the performance prediction of imaging radars.

1. INSTRUMENT DESCRIPTION

DUTSCAT (Delft University of Technology Scatterometer) is a multiband coherent pulse scatterometer. The system is installed in the Beechcraft Queen Air research aircraft of the National Aerospace Laboratory NLR. The radar system uses a 0.9 meter diameter dual polarized parabolic dish antenna mounted on a support structure and protected by a radome. In the support structure the RF parts of the radar are mounted. This whole system can be tilted between 0° and 80° incidence angle, looking to the left. Power and control signals are fed into the RF module from inside the aircraft cabin by flexible cables, while the IF signals are fed to and from the RF module by coax. The incidence angle and polarization are selected by the operator inside the aircraft.

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Fig.1:Block diagram of Dutscat

The system consists of four basic section RF, IF, data asquisition and power supply (fig. 1.). The RF section, which is mounted behind the antenna uses stable IF and LO sources to generate the signals needed by the transmitters and receivers, thus assuring coherency throughout the sensor. The output of a LO source is amplitude gated with a pulse width of 100 ns. The pulsed LO is then mixed with the output of the IF source to produce the RF signal. The pulsed RF is amplified in the final output stage by a solid state medium power amplifer. The output signal is coupled to the antenna system through a switch and a circulator.



Fig.2:RF subsystem

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A sample of the transmitter signal is coupled to a short-circuited delay line and is used as an internal calibration signal. The received signal is fed to the mixer RF port through the circulator, switch and a low noise amplifier. The output of the receiver mixer is fed into the IF section by a coax cable. In fig. 2 a RF subsystem is shown operating at one frequency. The whole RF section consists of six of these subsystems. The different frequencies are combined by a special microwave multiplexer.

The IF section uses six attenuator-amplifier pairs to bring the received signals in the dynamic range of the coherent detector (I & Q mixer). The attenuators are controlled by the operator using the video output of the amplifiers as a monitor signal. The IF signals are time-multiplexed and fed to a coherent detector. Fig. 3 shows an IF-sub section.



Fig.3:IF section



Fig.4:Dutscat digital processor

The analog I & Q signals are digitized and fed into the processor (fig. 4). The range data of each channel is accumulated coherently to improve the signal to noise ratio. The power of each range sample is calculated and a second adder stage is used to perform speckle reduction. Besides the digital output data of the scatterometer processor, aircraft data, including antenna position, roll angle and altitude are recorded by the digital data recording system.

The processor also contains circuits for generating the modulator pulses and the timing signals. The operator can select one up to six frequencies to operate virtually at the same time.

The specifications of Dutscat are summerized below.

Radar type	:coherent pulse radar
Frequencies	:1.2, 3.2, 5.3, 9.65, 13.7 and
	17.25 GHz
Pulse repetition	
frequency	:78.125 KHz
Pulse width	:100 ns
Peak power	:250 mW
Operating range	:50 - 1920 meters
Antenna	:0.9 meter parabolic dish
Polarization	:VV and HH
Incidence angle	:0 - 80 degrees
Data acquisition	:I & Q 8 bits 20 Msamples/s
Square law de-	
tected output	:A-scan 5 scans/s

The scatterometer subsystem operating at 5.3 GHz (C-band) is available since autumn 1983, recently a second subsystem has been added operating at 1.2 GHz.

2. C-BAND SCATTEROMETER

During november 1983 and february 1984 the Dutscat took, as one of four airborne scatterometers, part in the ESA C-band Scatterometer Campaign. The main objective of that campaign were measurements over sea. All scatterometers where internally calibrated. The Dutscat is equipped with a delay line for internal calibration. The calibration mode is selected by the operator and uses a fixed attenuator setting. During a measurement over sea the calibration signal was recorded at least two times. The maximum variation of the calibration signal was 2.5 dB over a period of one month, 0.9 dB over a period of one day. In most cases the standard deviation for the calibration recordings was less then 0.08 dB.

For intercalibration of the airborne scatterometers the normalized radar cross section of a distributed target (grassland) was measured after each flight mission over the sea. In fig. 5 an example of a grass measurement is given.



Fig.5:Measurement of grassland
The aircraft height was 330 meters, the incidence angle 45° degrees and the polarization VV. The measured avarage NRCS of the grassland is -10.4 dB, which came within 0.5 dB of the measured values by the other scatterometers.

3. ACKNOWLEDGMENT

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HUMAN AND AUTOMATIC INTERPRETATION OF RADAR IMAGES OF LAND COVER

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ABSTRACT

This paper examines and classifies the methods used in the human interpretation of SAR imagery. Of the features so defined tone and texture are the most readily machine implementable. Using SAR580 data in XHH, XHV and CHH bands regions were selected which visually appear to contain different textures and these were examined using the Spatial-Grey-Level-Dependency-Matrix (SGLDM) technique. The theory of the SGLDM's for homogeneous regions with fully developed speckle is derived and used in interpreting the computed results.

Keywords: SAR, Texture, SGLDM, Speckle.

INTRODUCTION

In order to make effective use of the very large volume of data which would be produced by a space-borne synthetic aperture radar (SAR), automatic or semi-automatic techniques for image interpretation need to be developed. This is particularly true if the SAR is to be a routine vegetation monitoring tool, with revisit times measured in days and ground coverage measured in millions of km^2 . At present the feasibility and characteristics of such a sensor are not welldefined, due partly to the lack of empirical data, and partly to the difficulty of producing acceptable and useful models of the microwave backscatter from land targets. Sufficient data exists, however, to allow worthwhile investigation of the means and difficulties of interpreting radar images both manually and by machine.

The interpretation of SAR imagery is a broad subject with techniques that are very much dependent on the type of information it is required to extract from the data: the detection and recognition of ships at sea requires different processing from that useful in the Land classification which is the concern of this paper Land classification can itself be further sub-divided into different areas dependent on the eventual aim and with different processing and data requirements. An agricultural/woodland/ urban classification, which might be of immense value to town planners, will not require the same type or amount of data in terms of the wavebands or the higher resolution which will probably be necessitated by an agricultural crop classification.

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Our main purpose here is to define the methods used in the manual interpretation of SAR imagery and to investigate how these can be implemented on a computer. In Section 2 we describe the data which has been used and in Section 3 we review the manual approach to image interpretation. Section 4 describes the Spatial Grey Level Matrix method for texture measurement and analyses this method for a particular measure (INERTIA) when applied to a speckled region as well as giving results obtained from real imagery.

2. IMAGERY AND TEST AREA DESCRIPTION

2.1 Imagery

The imagery selected for this study was one look amplitude, digitally processed SAR 580 data of Test Area GB6, Thetford Forest, England. This included X and C-Band HH and HV polarised 3 metre spatial resolution imagery obtained on the 16th June, 1981.

2.2 Test Area:

The Test Area selected for this investigation is located to the North West of Brandon in Norfolk and is centred around the village of Weeting (Figure 1). The Test Area is topographically flat, incorporating a gentle southerly slope away from the line of flight to the valley of the River Little Ouse.

Figure 2 shows a photograph of some of the XHH data from the test area which has been sampled (every 3rd pxl) purely in order to enable a larger area to be depicted.

The Test Area is dominated by part of the Forestry Commission managed Thetford Forest, particularly the Feltwell, Mundford and Santon beats. Within the Forestry Commission managed woodland Corsican Pine (Pinus nigra) and Scots Pine (Pinus sylvestris) predominate, with other stands of Oak (Quercus robur) and Beech (Fagus sylvatica). The Forestry Commission woodland is grown in components of, generally, several hectares separated by compartment rides of 10 metres width.

Non-Forestry Commission woodland is also to be found within the Test Area. The species composition is very mixed, incorporating the species stated above and also including Ash (Fraxinus excelsior).

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Further to the woodland arable farming is predominant with potatoes, sugarbeet and ceareals being grown. In addition there are also extensive areas of grassland and heathland, some of the grassland being grazed by pigs.

3. MANUAL INTERPRETATION:

Initially a manual interpretation of the imagery was undertaken in order to assess the estimators that were utilised by the interpreter and also to consider how such estimators could be implemented by machine.

3.1 Definition of Estimators:

In interpreting the image it was apparent that the interpreter uses a combination of the following estimators:

- a) Tone: as defined by the average backscatter over a uniform land use parcel of an image Variation of pixel intensity can exist within any given parcel, but the human eye has a capability to average the result.
- b) Texture: this incorporates information about the spatial distribution of tonal variations within a uniform land use parcel.
- c) Contexture: this estimator places features in the context of others; for example physiographic regions can relate to vegetation communities.
- d) Interpreter Experience: interpreter experience provides the link that relates each of the pre-stated estimators to each other and to ground features in order to permit a successful interpretation. It is particularly significant in relating contextural data to unit classification.

It is noted that none of the above mentioned estimators are exclusive; indeed each can only be fully utilised in relation to the others.

3.2 Image Interpretation:

Tone

Analysis of imagery (Figures 2 & 3) showed that five classes of tone and five classes of texture could be delineated. They were:

Texture

Very light	(a)	Very smooth
Light	(b)	Smooth
Medium tone	(c)	Mid-texture
Dark	(d)	Rough
Very dark	(e)	Very rough
	Very light Light Medium tone Dark Very dark	Very light (a) Light (b) Medium tone (c) Dark (d) Very dark (e)

Figure 3 shows the original XHH data, unsampled, for the area chosen for the computer measured results described in Section 4. The regions selected for measurement are outlined and numbered and their texture classes are included in the heading for the figure.

By applying these tone and texture classes to the image on a multi-channel basis it was established that ten classes of land use could be delineated,

as described in Table 1.

From this it was clear that the X-band images presented the most detailed imagery. Clear delineation, in terms of tone and texture, could be made between stands of woodland and areas of grassland and some arable land on all channels. The grassland and winter cereals presented a very dark and smooth signature, whilst the spring cereals presented a very light and smooth signature. In contrast the woodland presented a rougher textured image. Root crops and felled coniferous woodland, however, presented an image similar to that of young coniferous woodland and could not be successfully delineated on either the X-HV, C-HH or C-HV channels. Conversely, the root crops and felled coniferous woodland presented a signature similar to that of mature Scots and Corsican Pine stands on the X-HH channel. Consequently, by utilising a multi channel analysis successful delineation was allowed.

Further classification of tree species could be made on the X-band imagery. Stands of coniferous woodland could be clearly delineated from stands of deciduous and mixed woodland by texture. Stands ofconiferous woodland presented a 'mid-textured' image, whilst stands of single aged deciduous woodland presented a 'rough' image and stands of mixed woodland presented a 'very rough' image. Further tree species classification proved impossible.

Classification in terms of the age of coniferous woodland could also be undertaken on the X-band images. Scots and Corsican Pine stands planted before 1960, 1960-1974 and after 1974 could be separately classified.

Stands planted after 1974 presented a very dark toned smooth signature with fine, light parallel linears crossing the compartments. From the analysis of ground data it was established that the linears were caused by the bunds of trash formed during the pre-planting process. The very dark and smooth signature of the image was due to the lack of canopy cover and the resultant predominance of ground reflection.

Stands planted between 1960 and 1974 could be delineated from those planted before 1960 by a generally darker tone and smoother texture. This was thought to be due to the more even and dense canopy presented by the younger trees resulting in a smoother recipient reflecting surface.

In addition shadowing and highlighting caused by the changes in the heights of trees aided the age classification in that height differences could be directly related to tree age. This was found to be particularly the case on the X-HH image. This introduces contexture as an estimator for image interpretation.

It is also worth noting that the age groups denoted within the coniferous woodland are to an extent defined by the data available. A complete set of data for all ages of Scots and Corsican Pine woodland is not available, but the results do indicate that broad age classification is possible.

The C-band imagery, in comparison, provided a less texturally detailed image. Stands of decidious and mixed woodland could not be so clearly differentiated from stands of coniferous woodland. In addition, rivers, hedgerows and clearings could not be so clearly defined. It is not clear whether this is due to the longer wavelength of the C-band in comparison to the X-band or whether it is due to the poor quality of the C-band data generally.

The loss of textural detail, however, enhanced the capability to delineate tonal variations within the image. Boundaries between coniferous age groups became much more clearly defined.

A further classification of coniferous tree species was found to be possible on the C-band imagery. The delineation of Scots Pine planted before 1960 from Corsican Pine planted before 1960 and Corsican Pine planted between 1960 and 1974 was made possible by the lighter tone of the Scots Pine. This tonal difference was not apparent on the X-band imagery.

Variations in the image due to polarisation differences were also noted. It was established that only upon the HH polarised channels could urban areas be separately classified from mixed woodland. On the HH imagery urban areas were characterised by the numerous fine light linears parallel to the line of flight caused by the reflection of radar waves on the side of buildings.

Diseased and windblown coniferous stands could not be directly delineated from the imagery as the image presented was similar to that of mixed woodland.

Overall, by utilising a multichannel analysis of the imagery a ten class classification could be undertaken (Table 1).

From the results the following conclusions can be drawn:

- (a) It is apparent that within grassland/arable land the prime estimator for making land use determinations is tone
- (b) For delineating woodland from non-woodland the major estimator is texture
- (c) For delineating different classes within woodland, the major estimator is texture
- (d) For delineating urban areas and coniferous woodland planted after 1974 the prime estimators are contexture and texture
- (e) It is also apparent that each of the four estimators; tone, texture, contexture and experience, are not used in isolation, but indeed are inextricably linked.

4. MACHINE INTERPRETATION

4.1 General

This Section describes some of the machine (computed) measures that have been used in an attempt to achieve the same classification as that defined in the visual interpretation described in Section 3. Of the attributes used in human image interpretation the first, tone, is readily implemented on a computer. Tone is a first order statistic that for a speckled region is most easily represented by the mean intensity. Other statistics such as standard deviation, skewness and kurtosis are also readily calculable and their use in estimating the homogenity of a region will be commented on later.

The second of the human classification features mentioned in Section 3, texture, is considerably harder to measure satisfactorily by computer. In fact even to define texture causes problems which are probably still not fully resolved. Various authors have attempted this definition and some typical examples are given here:

Hawkins (Ref. 1)

'Texture has 3 ingredients.

- Some local order is repeated over a region large in comparison to the order.
- The order consists of the non-random arrangements of elementary parts.
- (iii) The parts are rough entities having approximately the same dimensions everywhere.
- Blom and Daily (Ref.2)

'Texture is the spatial variation of image tone'.

Haralick (Ref.3)

'...textural features contain information about the spatial distribution of tonal variations'.

- also, 'Texture and tone are inextricably linked'.
- and, most revealing:

'Texture has been extremely refractory to precise definition and to analysis by computer'.

The texture present in a non-noisy optical image is perhaps most easily understood initially; a uniform scene of the same tone (colour) all over would be said to have no texture whereas two sets of parallel lines crossing at right angles presents a very rigid 'grid'texture.

Less rigid textures exist in pictures of leaves on a tree or the grain in a piece of wood. The common factor of all scenes with texture is the existence of a variation in tone which consists of the distribution of similar elements over a background.

The elements do not have to be all exactly the same either in tone or size or shape (also more than on e element type can be present) and their distribution can range from a precise well-defined structure (e.g. the grid) to others where the elements are randomly distributed and only the mean and variation of their density is known. It follows that texture is not predictable simply from a knowledge of the tonal values present in an image but their geometrical relationships must also be known.

SAR images present a more complicated problem because of the speckle which is invariably present. Speckle arises from the coherent nature of the radiation and consists of the variation of pixel tones which occurs even in images of homogeneous areas (i.e.regions where the ground backscatter characteristics do not change significantly). The probability distribution of the pixel tones in a homogeneous area can be predicted theoretically for a given SAR type (e.g. a Rayleigh distribution for 1-look amplitude) and has often been experimentally verified. An important characteristic of pure speckle is its multiplicative nature which results in the ratio of standard deviation to mean intensity being constant.

It follows that texture measures for SAR must distinguish between pure multiplicative speckle and tonal variations due to a genuine change in the backscatter coefficient.

4.2 <u>Spatial Grey Level Dependency Matrix</u> (SGLDM) Methods

Various algorithms have been suggested for the computation of texture in digital imagery but the one which has proved most popular and that which is used here is based on the Spatial Grey Level Dependency Matrix (SGLDM) (Refs. 3-6).

The SGLDM, sometimes called the grey level co-occurrence matrix (GLCM), is a square matrix of order ,Ng, the number of grey levels used in its calculations which is usually rather less than that present in the original image. Element S (i,j) of the SGLDM is the frequency of occurrence of pairs of pixels, the first having grey level i and the second j. The second pixel is geometrically related to the first by a vector d which is kept constant in the calculation of a matrix. Because many different d are possible so many different SGLDM's can be calculated for the same image. A SGLDM contains information on the tonal variation over a particular direction and distance from which various more compact texture measures can be obtained. It is usual to normalise the SGLDM elements by dividing by the total number of pixel pairs used so obtaining a matrix of probabilities of occurrence.

Examples of texture measures which can be obtained in this way are;

$$INERTIA = \sum_{i,j} (i-j)^2 P_{ij}$$
(1)

ABSOLUTE DIFFERENCE = $\sum_{i,j} i - j P_{ij}$ (2)

$$CORRELATION = \sum_{i,j} (i-i^{-})(j-\overline{j}) P_{ij} / (\sigma_{i} \sigma_{j})$$
(3)

INVERSE DIFFERENCE =
$$\sum_{i,j} P_{ij} / (1 + (i-j)^2) (4)$$

where i,j are the grey levels, \overline{i} , \overline{j} are mean levels, P_{ij} are the SGLDM probabilities and the

Many other expressions are obviously possible and Haralick (Ref.3) lists 14 useful measures. The advantage of the above 4 is that, being linear in the P_{ij} , they do not necessitate calculation of the SGLDM explicitly as they can be expressed as the average of functions;

INERTIA = average of
$$(i-j)^2$$

Even for a noiseless image the physical meaning of the measures defined in Eqs. 1-4 is not as apparent as one would like but nonetheless their function can be discerned by examination; the INERTIA and ABSOLUTE DIFFERENCE values increase as the SGLDM off-diagonal frequencies rise and hence can be taken as a measure of the degree of non-uniformity in the direction of the pixel pair separation vector. Conversely the INVERSE DIFFERENCE measure is at a maximum when all the off-diagonal components are zero and hence increases as the degree of linear uniformity in the direction of the separation vector increases. The CORRELATION measure is the standard statistical coefficient used to gauge the degree of correspondence between the first and second pixels in the pairs used.

As already mentioned a variation in pixel tones, commonly called speckle, is always associated with SAR images even where the object region has a constant radar backscatter. Therefore it is important to understand the effects of pure speckle on any texture measures that are used.

4.3 SGLDM methods and Speckled regions

For SAR systems the probability distribution of pixel grey levels in a homogenous region is known and is a function dependent only on the mean grey level, the number of looks of the system and whether it is an amplitude or power measurement.

Let the probability density distribution function be P(x); P(x) dx = the probability of any pixel having a grey level in the range x to x +dx. Now the SGLDM uses joint probabilities based on a finite number of grey levels and in order to calculate these from a knowledge of the continuous probability density function we first need to discretise it.

If the spacing of the grey levels is Δ then the probability of a pixel having grey level i (that is of being within the limits i to i + Δ) is given by,

$$P_{i} = P(x=i)\Delta$$
 (5)

The verbal definition of a homogeneous region or a region of pure speckle and no texture can now be expressed mathematically in terms of the joint probabilities by;

$$P_{ij} = P_i \times P_i$$
(6)

This simple equation utilises the fact that for such a region the grey levels of the pixels in each pair are unrelated and hence the probability of a particular pair of grey levels occurring is simply equal to the product of their separate probabilities.

Using Eqs. 5 and 6 we have

$$P_{ij} = P(i). P(j).\Delta^2$$
(7)

)

which enable the calculation of the SGLDM elements in terms of the speckle probability density function.

The imagery used in part of this study is SAR 580 data which is a 1-look amplitude system for which the pixel intensities are known to follow a Rayleigh probability distribution very well.

$$P(x) = \frac{\pi}{2\mu} x \exp \left[\frac{-\pi}{4} x' / \mu\right]$$
(8)

.

where x = pixel intensity

From Eqs. 7 and 8 we can calculate the joint probabilities in a homogeneous region;

$$P_{ij} = \left(\frac{\pi}{2}\right)^{2} \quad ij \exp \left[-\pi \left(i^{2} + j^{2}\right)/4\mu^{2}\right] \Delta \quad (9)$$

and using this expression formulae for the texture measures can be found. In particular the INERTIA measure becomes:

INERTIA =
$$\sum_{\substack{i,j \\ 2u}} (\pi_{i})^{2} ij exp[-\pi(i^{2}+j^{2})/4\mu]^{2}(i-j)^{2}\Delta^{2}(10)$$

In practice the computation of the inertia measure can be easily accomplished without necessitating calculation of the SGLDM by simply finding the average of the expression $(i-j)^2$. This is equivalent to using the largest possible SGLDM with $\Delta = 1$. The result of this can be theoretically estimated from Eq. 10 by approximation to a integral expression.

INERTIA =
$$\int dx \int dy \left(\frac{\pi}{2\mu}\right)^2 xy \exp\left[-\pi \left(x^2 + y^2\right)/4\mu^2\right]$$

(x-y)² (11)

which can be calculated using standard integrals resulting in

INERTIA =
$$\frac{4}{\pi}$$
 $(2 - \pi)_{\mu}$
= 0.5464 μ^{2}

It follows that,

$$\sqrt{\text{INERTIA}} = 0.739\mu, \qquad (12)$$

For a homogeneous region for a 1-look amplitude SAR image.

A better known result for a SAR image is that the ratio of the standard deviation, σ , to the mean, μ , is a constant. Using the Rayleigh distribution (Eq. 8) it is easy to calculate the expected value of this ratio using the definition of the standard deviation,

$$\sigma^{2} = \int P(x) (x-\mu)^{2} dx,$$
 (13)

from which it follows that

$$\sigma^{2} = \mu^{2} \left(\frac{4}{\pi} - 1\right)$$

$$\sigma/\mu = \sqrt{\left(\frac{4}{\pi} - 1\right)} = 0.523 \qquad (14)$$

The expected value of the skewness and kurtosis of the same distribution can be derived similarly:

2

Skewness =
$$\int P(x) (x-\mu)^{2} / \sigma^{2} dx$$

= $(2 - 6/\pi) (\mu / \sigma)^{3}$
= 0.631 (15)
Kurtosis = $\int P(x) (x-\mu)^{4} / \sigma^{4} - 3$
= $(32/\pi^{2} - 3) (\mu / \sigma)^{4} - 3$ (16)
= 0.246

4.4 SAR580 Results

As described in Section 2 regions with visually different tone and texture were selected from a SAR580 image. The boundary codes of these regions were stored in a data base specifically developed for work in image segmentation and classification (ref 7) and this enabled the calculation of attributes using the intensities of pixels situated in these regions only. Tables 2, 3 and 4 list some typical results which were obtained from the X-band, HH polarisation data. As can be seen the skewness and kurtosis results for the 'rough' regions deviate significantly from the predicted values for a homogeneous area, Eqs. 15 and 16. The plot of the standard deviation versus mean in figure 4 indicates a similar result in which all but the 'rough' regions lie close to a line following Eq. 14. The indication then of these first order statistics is that the pixel intensities in the regions classified XSMOOTH, VSMOOTH, SMOOTH and M1D are distributed according to the Rayleigh distribution. This impression is strengthened when the second order measures using the SGLDM technique are examined (tables 4 and 5).

Table 4 which lists the results for nearest neighbour pair of pixels (separation vector d =(0,1)) shows a marked and consistent correlation of about 0.33 for the XSMOOTH to MID classes inclusive increasing to about 0.55 for the ROUGH regions. Thus correlation is to be expected and is a property of the system point spread function which is purely a function of the SAR data processing and not of the ground characteristics. A comparison with table 5 where the pixel pair separation vector has been increased in magnitude (d now = (0,8)) shows insignificant correlation figures for all but the ROUGH regions.

Figure 5 shows a plot of $\sqrt{INERTIA}$ (calculated with d = (0,8)) versus the mean intensity on which the predicted slope Eq. 12, has been marked. Again only the ROUGH regions deviate appreciably from the expected result for homogeneous regions.

The ABSOLUTE DIFFERENCE results closely parallel those for the INERTIA measure which in view of their similar definitions is not surprising. The INVERSE DIFFERENCE results are very low and show a tendency to reduce further as the mean intensity (and hence speckle variation) rises. It seems likely that the form of this measure is such that it is too easily swamped by speckle to enable any real texture to be measured. The above results were largely reiterated for all 3 data types which were available (XHH, XHV and CHH) and for all values of the pixel pair separation vector which were tried ((0,1), (0,4), (0,8), (1,0), (4,0), (8,0)). In fact the texture measures did not vary significantly with either the direction or magnitude of the separation vector once its magnitude exceeded nearest neighbour separation.

4.5 Summary

In conclusion the computed results indicate that for all but the ROUGH regions, the intensity variation can be related to the speckle statistics to be expected for a homogeneous region and that no significant texture is present in these areas. However it is important to realise that the same classification as that defined manually can still be achieved by computer as examination of Figures 4 and 5 indicates. By choosing appropriate thresholds in mean intensity and a measure of σ/μ or $\sqrt{INERTIA/\mu}$ it is evident that the different classes can be separated.

5. SUMMARY

We have presented a review of the methods used in the manual interpretation of SAR imagery of agricultural and woodland areas. In so doing a 10 class categorisation has been produced which is based on visual tone and texture as seen in XHV, XHH, CHV and CHH imagery. A representative selection of these different classes was analysed using both simple statistics and the SGLDM method for measuring texture. These computed results indicate that for all classes apart from 'ROUGH' the regions have a pixel intensity variation compatible with the speckle to be expected in a homogeneous area. It is believed (by one of the authors, AW.,) that the different visual textures seen in the selected regions is the effect of the increased pixel variation (speckle) with mean intensity. However the most important result of this study is that the same classification can be achieved using computed measures as is defined manually.

6. ACKNOWLEDGEMENTS

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FIGURE 1. TEST AREA USED IN NORFOLK, ENGLAND.

Class	X-HH Channel	X-HV Channel	C-HH Channel	C-HV Channel	Class
No.	Description	Description	Description	Description	Description
1	Rough texture,	Rough texture,	Rough texture,	Rough texture,	Single age
	mixed tone	mixed tone	mixed tone	mixed tone	broadleaves
2	Very rough texture Very mixed tone	Very rough texture Very mixed tone	Very rough texture Very mixed tone	Very rough texture Very mixed tone	Mixed woodland; Windblown and diseased conifer
3	Medium texture,	Medium texture,	Medium texture,	Medium texture,	Scots Pine planted
	Light tone	Light tone	Light tone	Light tone	before 1960
4	Medium texture,	Medium texture,	Medium texture,	Medium texture,	Corsican Pine planted
	Light tone	light tone	medium tone	medium tone	before 1960
5	Medium-smooth	Medium-smooth	Medium∹smooth	Medium-smooth	Scots and Corsican
	texture, medium	texture, medium	texture, medium	texture, medium	pine planted between
	tone	tone	tone	tone	1960 and 1974
6	Very dark tone,	Very dark tone,	Very dark tone,	Very dark tone,	Scots and Corsican
	light fine	light fine	light fine	light fine	Pine planted after
	parallel linears	parallel linears	parallel linears	parallel linears	1974
7	Smooth-very smooth texture. Dark- very dark tone	Smooth-very smooth texture. Dark - very dark tone	Smooth-very smooth texture. Dark - very dark tone	Smooth-very smooth texture. Dark - very dark tone	Grassland and Winter Cereals
8	Smooth-very smooth texture. light- very light tone	Smooth-very smooth texture. light- very light tone	Smooth - very smooth texture. light- very light tone	Smooth-very smooth texture. light- very light tone	Spring Cereals
9	Medium-smooth texture. Light tone	Medium-smooth texture. Medium tone	Medium~smooth texture. Medium tone	Medium-smootb texture. Medium tone	Root Crops
10	Very mixed tone,	Very rough texture	Very mixed tone, short	Very rough texture	Urban
	short light linears parallel to line of flight	very mixed tone	light linears, parallel to line of flight	very mixed tone	

TABLE 1. TEN CLASSES OF LAND USE





FIGURE 2: XHV data of test site sampled at every 3rd pixel.

FIGURE 3:	XHV data show	ing regions	selected
	for analysis;	XSMOOTH 11	, VSMOOTH
	2,3,4, SMOOTH	8,9,10, MII	5,6,7,
	ROUGH 12, 13,	14.	

Region Class/Number	Mean	Std. Deviation	Skewness	Kurtosis
XSMOOTH 11	693	347	0.655	0.409
VSMOOTH				
2	1062	549	0.550	-0.040
3	964	513	0.690	0.236
4	1023	538	0.655	0.191
SMOOTH				
8	1331	689	0.612	0.246
9	1276	641	0.687	0.621
10	1457	775	0.750	0.876
MID				
5	1719	902	0.637	0.229
6	2017	1080	0.612	0.076
7	1815	1000	0.755	0.525
ROUGH				
12	1682	1283	1.818	5.278
13	1520	1011	1.317	2.172
14	1563	1245	1.987	5.787

Table 2 Statistics obtained from selected regions of a SAR580 image

Region Class/Number	Correlation	√Inertia	Abs. Value	Inv. Difference	4 ≥(*10)
XSMOOTH 11	0.319	405	326	23.7	
VSMOOTH 2 3 4	0.334 0.325 0.323	634 595 623	50 467 485	30.4 18.2 23.5	
SMOOTH 8 9 10	0.351 0.328 0.330	785 745 897	624 591 715	22.5 19.6 14.3	
MID 5 6 7	0.332 0.320 0.321	1039 1265 1163	824 997 914	13.9 8.5 8.1	
ROUGH 12 13 14	0.590 0.507 0.589	1167 1002 1132	840 752 792	13.0 18.6 12.2	

Table 3

Texture Measures obtained from selected regions of a SAR580 image using the SGLDM technique with a pixel pair separation vector = (0,1).

Region Class/Number	Correlation	√Inertia	Abs. Value	In V. Difference (*10 4)
XSMOOTH				
11	0.005	503	398	16.0
VSMOOTH				
2	-0.065	819	659	19.7
3	-0.028	736	582	13.3
4	0.037	744	585	8.9
SMOOTH				
8	-0.020	987	782	14.4
9	-0.068	917	722	4 4
10	0.017	1078	844	9.7
MID				
5	0.018	1259	992	14.8
6	0.030	1512	1197	10.4
7	0.032	1392	1116	1.7
ROUGH				
12	0.166	1698	1199	9.7
13	0.032	1417	1050	10.9
14	0.208	1590	1104	13.8

Table 4 Texture Measures obtained from selected regions of a SAR580 image using the SGLDM technique with a pixel pair separation vector = (0,8).



KEY: XSMOOTH O, VSMOOTH X, SMOOTH +, MID \diamond , ROUGH \square Figure 4, Standard Deviation versus Mean Intensity for the test regions



KEY: XSMOOTH O, VSMOOTH X, SMOOTH +, MID \diamond , ROUGH Figure 5, \checkmark Inertia versus Mean Intensity for the test regions

POSTSCRIPT



REMARKS ON THE SYSTEMATICS OF APPLICATION

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Attention is asked for a more fundamental study of the systematics of applications. Suggestions are given to start. The relative importance of microwaves is indicated.

The rapid development of existing and new measuring techniques has increased the interest in what is often called interpretation. It seems therefore useful to reflect on what might be meant by this concept.

The original meaning of the word is 'translation'. A relation between types of information seems indicated and one might ask for the difference or relationship between the two languages. Even the question arises whether this translation may take immediately place in a single way or whether the fundamental aspects must be studied first. From the fact that the application in RS is mostly related to field conditions and so to disciplines that consider in more detail field or natural behaviour, once can conclude, that at least for a large part visual criteria must be taken into account too. These criteria will be defined in practice as phenomena, derived and determined in a visual control system incorporating the use of uncorrected images. It may be stressed, that large series of natural processes are governed by the spectral bands, where the human eye is sensitive as well.

All this leads to a preliminary classification of the parameters to express a factual base for interpretation. One can divide the parameters into three groups. They differ in reference level and in the manner in which calibration is or must be described.

First there is the pure physical content of the signal. The numerical value and the possession of a measure originates from the existence of far more absolute descriptions of the reference. The classical way in which time and place is accepted predominates in this series of parameters. Essentially the basic parameters can be found in the ISO-normalised criteria. Secondly we have a series or set of image related parameters. Their reference level is found in the psycho physics of the human eye, or in cases indirect by the specifications of the automatised systems of image treatments, based upon the same set of criteria.

Subdivisions can be made, starting from the memorising and associative relationships, that are formalised in the perception studies of image handling.

The third group of parameters deals with the values connected to an operational use of the data collected. Here the reference level can only be found as a result of a series of comparisons.

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Their need and existence follows from the complexity of the interrelated natural and evaluating processes. The parameters passess analogous properties and are per definition not absolute. They may and will vary with the actual importance given to them.

It goes without saying, that an adequate description of the result obtained in a research program requires the incorporation of the values and arguments of each of the three groups mentioned. In effect this consideration presents part of a type of system analysis directed towards guiding further research efforts.

From the foregoing text one may conclude that the use of microwaves has a very special significance. As a consequence of the absoluteness of the signal in an active radar system and the neglible atmosferic interference one may accept the reflected or scattered signal as a reference base itself, even for the reflectivities and emissivities at shorter wavelengths. This is even more true for application of radar data concerning vegetation. This is due to the nonequilibrium status of the covered soil surface and the many interactions and growth development stages. In effect a resolution element represents the time - place projection of a large numer of processes, some being at equilibrium. The increased sensivity of radar technique to detect and follow natural behaviour may even guide further research in the use and effectiveness of the parameters, of the sustaining field disciplines.