ON THE CAPABILITIES OF USING AIRSAR DATA IN SURFACE ENERGY/WATER BALANCE STUDIES

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1. INTRODUCTION

The capabilities of using remote sensing data, and in particular multifrequency/multipolarization SAR data, like AIRSAR, for the retrieval of surface parameters, depend considerably cm the specificity of each application. The potentials, and limitations, of SAR data in ecological investigations arc well known. Because the chemistry is a major component in such studies and because of the almost lacking chemical information at the wavelengths of SAR data, the capabilities of using SAR-derived information in such studies are considerably limited, However, in the case of surface energy/watcx balance studies, the determination of the amount of water content, both in the soil and in tbc plants, is a major component in all modeling approaches. As the information about water content is present in the SAR signal, then the role of SAR data in studies where water content is to be determined becomes clearly predominant.

Another situation where the role of SAR data becomes dominant over other remote sensing systems, is the case of dense canopies. Because of tbc penetration capabilities of microwave data, which is especially superior as compared to optical data, information about the canopy as a whole and even the underlying soil is contained in the SAR data, while only the top-canopy provides the information content in the case of optical data. in the case of relatively dense canopies, as has been demonstrated in this study, such different penetration capabilities provide very different results in terms of the derived total canopy water content, for instance.

However, although ail such capabilities are well known, unfortunately there arc also well known limitations. Apart from calibration-relatcci aspects (that wc will not consider in this study), anti spar-[from other intrinsic problems (like image noise, topographic corrections, etc.) which also significantly affect tbc derived results, we will concentrate on the problem of extracting information from the data. Even at this level, methods arc still not folly well established, especially over vegetation-covered areas.

In this paper, an algorithm is described which allows derivation of three fundamental parameters from SAR data: soil moisture, soil roughness and canopy water content, accounting for the effects of vegetation cover by using optical (Landsat) data as auxiliary. Capabilities and limitations of the data and algorithms arc discussed, as well as possibilities to use these data in erlergy/water balance modeling studies.

All the data used in this study were acquired as part of the Intensive Observation Period in June-July 1991 (European Multisensor Aircraft Campaign-91), as part of the European Field Experiment in a Desertification-threatened Area (EFEDA), a European contribution to the gioba-change. research sponsored by the IGBP program (Bolle et al., 1993).

2. PARAMETERS WHICH ARE REQUIRED IN SURFACE ENERGY/WATER BALANCE STUDIES

Although the actual parameters which are required in surface energy/wziter balance studies depend very much on the kind of modeling approach adopted in each case, it is a general agreement that accounting, for the amount of water available, and changes in water content, both in the soil and in the plants, is always a major component, no[oniy for water balance but also for the partitioning of available energy into latent and sensible heat flux components. However, the way in which each parameter enters into the model anti the assumptions made by each model are always conditioning the so called 'sensitivity' to such model parameters. For this reason, accuracy requirements on the retrievals of each parameter can not be easily stated.

The model used in previous studies (Moreno et al., 1994), which was actually a derivation from the Biosphere-Atmosphere Transfer Scheme ([it\'i'S/ (Dickinson et al., 1993) with significant modifications anti additions, used a total of about 70 parameters (many of them fixed to default values), from which about 15 are potentially derivable from remote sensing data, anti about half of them directly from SAR data or by combination of SAR data with optical data. Such parameters are: (top-)soil moisture, soii roughness, canopy watt'r content, Leaf Area Index, vegetation height (displacement height), Stem Area Index-Canopy 'roughness' (or canopy geometry parameters), soil albedo as a function of soil moisture (see Fig. 4), as well as other parameters indirectly derived from image-classification results. Other parameters (like surface temperature, cloudiness, etc.), are also used, but will not be discussed here.

Because of the complexity of intervening effects, no definite limits can be put *a priori* for the. accuracy requirements over each parameter, and then no fixed limits are put over the capability to provide soil moisture or other parameters from remote sensing data, partly because the use of this kind of data (spatial data) would also require re-parameterization in the models (tile problem of handling spatially distributed data is another reason for the difficulties in deriving clear conclusions from 1D-model sensitivity studies). As the final desired goals (errors of about 10 Wm^{-2} for the derived fluxes) arc still far from the actual capabilities (including gl'ounci-based meteorological networks), all wc can do is to try to achieve tile maximum accuracy possible. Also, the present situation is that the models (including 3D models) use very poor surface parameterization because of the lack of any additional data, so that any information which crrn be provided from remote sensing systems (with ail the involved limitations) would still be in any case very welcome.

3. CAPABILITIES OF SAR DATA TO PROVIDE THE REQUIRED PARAMETERS

The capabilities of SAR data to provide at least some of the parameters required by surface energy/water balance models, especially those related to water content, are well known, and actual use of these data has hccn made in previous field experiments (FIFE, EFEDA, HAPEX). The way in which this has been done is mainly through model-inversion techniques. However, the kind of model used (anti wc actually do not have an appropriate model for the behaviour of natural surfaces at the frequencies at which SAR data arc acquire(i), and the kind of inversion technique used, become critical when retrieved numerical values arc to be compared to ground measurements. As the SAR signal sensitivity to water content in the canopy, anti also in the soil, has been in any case demonstrated (Engman, 199 i), it is expected that this information will come out in the retrievals derived from SAR data, at least in terms of relative values.

The use of full-polarimetry information for tile retrieval of soil/vegetation parameters has been demonstrated to be an essential aspect as compared to the capabilities of single ci]aJ]ncl/single polarization systems (like ERS-1/2). Because of the ability of polarimetric information to separate different contributions, roughness/geometry effects anti water content information can be decoupled, and then [he corresponding values retrieved from the measured data.

Apart from the classical parameters derived from polarimetric information, information about canopy roughness (mainly related to canopy height) can be also derived from interferometric information. However, because the physical meaning of canopy roughness (which is aiso a recurrent function of wind speed) cannot be easily related to such interferometric information, work in this field is still in its beginning. Phase information in standard polarimetric data can also be related to canopy geometry, but the link between such estimates and the required parameters (canopy height and displacement height, canopy 'roughness') is still at tbc level of empirical relationships. The penetration capabilities of SAR data become here a difficulty, because it is the canopy height which is expected to be given as input to the models. However, the actual canopy roughness is not simply related to vegetation height, anti most probably the roughness information derived from the scatter-ing[mechanism in SAR data is more relevant for modeling purposes than the use of a fraction of the total canopy height as a roughness estimator, as is currently being done in the models.

It is true that AIRSAR data alone still have limitations in this type of study because of the ambiguity in scattering mechanisms in (dry) bare soil surfaces and in surfaces with small vegetation amount. The combination of information derived from optical data (where the separability between soil anti vegetation behaviour is more strict, see Fig. 3), with AIRSAR data, significantly improves the capabilities ol'the. retrievals of the required information.

Two main aspects are in any case to be taken carefully into account: data preprocessing aspects (becoming critical for any posterior analysis of the data), and the kind of information-extraction technique used [o derive the required parameters from the data. Both will he discussed in the following sections.

4. DATA PRE-PROCESSING

In any study in which theoretical physically-based scattering models are to bc inverted against measured data, the calibration of such measured data br.collies critical. The reason is that the models are based on physical coefficients which are supposed to be of universal applicability. The way in which such parameters come into the model (usually through highly non-linear relationship) makes impossible the introduction of some kind of (linear) compensation for calibration deviations, so that irremediably any calibration error (including deviations in antenna gain pattern correction for varying altitude/topography and any other related radiometric correction) produces absolute errors in the retrievals by using the theoretical model. For the data used in this study, calibration was done according to standard techniques at JPL. A total of four corner reflectors were deployed in the study area during the AIRSAR overflight, and their response was used to check calibration in the data and to perform the proper tori-cctions when needed.

The synthesized images were geometrically rectified to ground-range projection by using available ephemeris data for the DC-8 aircraft navigation, while at the same time a~inlutb/range pixel sizes were compensated for to make square the resulting pixels through cubic convolution. Finally, the images were resampled by using about 50 ground control points in the common 10 m UTM grid, covering the 10×10 km^2 area, to which all remote sensing datawe.rcco-registered into the image database to make possible the use of multisensor/multitemporal studies. As in the resulting geometrically corrected image, pixel numbering loses the information of the incidence angle, a new image with the corresponding incidence angle for each new UTM pixel was also produced to facilitate. additional processing. Although accurate Digital Elevation Models are available for the area, specially developed as part of the EFEDA experiment, because the study area considered here is completely flat (maximum height differences of less than 20 m and almost constant slope over the full area), no topographic corrections have been applied,

5. MODEL INVERSION TECHNIQUES APPLIED TO MULTI-PARAMETER RETRIEVAL FROM SAR DATA

The first approach that wc consider-cd in the derivation of surface parameters from SAR data was mere ly empirical, based on correlation approaches between some "indices" (hand and/or polarization combinations) and measured surface parameters (LAI, biomass, canopy water content, etc). Different band ratios (mainly L/C and P/L) and polarization ratios (HH/VV, HH/HV, VV/HV) have been considered. Although not intended to be used for tbc actual retrieval of surface parameters from the data, the establishment of empirical relationships allows a preliminary estimation of the capabilities of the data to account for the observed variability (and (he determination of **error** bounds which can bc expected anti used in the fitting of the 'merit function' in the numerical inversion procedure) as well as the derivation of simple relationships to be used in the initialization of the model parameters in the iterative inversion procedure used later for parameters' retrieval. Although the advantages of empirical relationships are well known in terms of speed in calculations anti avoidance of convergence and other numerical problems, the use of empirical relationships is absolutely limited by how well one can extrapolate from the results and the generality of the algorithms. g'hen, even if the usc of empirical relationships could provide an optimum fit in our case where wc have ground measurements of all sLrr face parameters, the use of such empirical methods has been avoided and they have been restricted to be auxiliary elements in the numerical model-inversion procedure.

'l'he central par-t of this study is the development of a model-inversion technique to extract the required information from SAR data. The details of the method arc given else.wi~cre (Saatchi et al., 1993; Moreno et al., 1 994; Moreno, 1 995; Moreno and Saatchi, 1 996), anti oniy the main aspects will be described here.

For the contribution of bare soil, several models have been considered in this study. A model developed by Dubois et al. (1994) was initially used (Saatchi et al., 1993). Another semi-empirical model developed by Oh et ai. (1 992) has hccn aiso used, The present implementation is an updated version of the Oh et al. algorithm after more recent improvements introduced by the same authors. The results obtained for' bare soil moisture are indeed in agreement with the results obtained by other authors (Oevelen et al., 1995) by using the Integral Equation Model over the same dataset. As a major effort is put on the derivation of canopy parameters, because the model is intended to be used over agricultural areas with significant Vegetation Cove.r for some fields, the parameterization of the soil has 10 be kept to a minimum in order to make the model actually invertible.

For the derivation of canopy parameters, tile model has been implemented with a layer of randomly distributed scattering elements over the underlying bare soil. Such a layer represents the vegetation contribution. Three types of scatter ing mechanism arc then considered: volume scattering, surface-volume scattering anti soii surface scattering, The direct scattering from the soil is also attenuated (twice) because of the presence of the canopy, and such attenuation must be also included in the model. '['he surface-voiunJc scattering terms musr be introduced because of the type of vegetation to he considered in this case, giving significant contributions only for the co-polarized terms. The backscattering coefficients for the canopy are obtained by using the distorted Born approximation (Lang and Sidhu, 1983). Finally, the model needs to account for the amount of effects which arc duc to the soil and those which are due to vegetation in the case where no dense vegetation is considered hut sparse vegetation is {anti is still assumed randomly distributed at the scale of a pixel in order to avoid problems in the modeling of very clumpy structures).

An important aspect to be pointed out is the necessity of working with the original channels separately in order to minimize the problems originated by the presence of noise and in order to take full information from the data, without reductions in the dimensions of the original information. Mos[of the empirical approaches work with channel ratios. These channel ratios are supposed to somehow compensate for (deviations in calibration] and secondary effects in the signs], but this is not absolutely true, and also these channel ratios actually enhance the noise as compared to the noise present in each channel separately. The potential advantages of using channel ratios do not compensate for the problems that the use of channel ratios introduces in the inversion procedure.

The method used for numerical inversion of the scattering model is the downhill simplex method, with two limiting conditions: maximum error and maximum number of iterations allowed Although less robust (and especially more time consuming) than other techniques, this method has proven to be more resistant to noises and inadequacies in the model to fit the data, providing always a set of solution parameters for each pixel after avoidance of divergences.

6. RESULTS

Although the data used in this study correspond to only one specific situation (which prevents us from deriving general conclusions), and also the data is old as compared to the new capabilities added to the AIRSAR system in the last few years (especially in terms of data calibration), the conclusions derived from (his study are similar to those previously derived in other field experiments: techniques are promising but still not fully ready for'operational application, at least for the purpose of energy/water balance monitoring.

In the case of soil moisture, because of the very high sensitivity of encr8y/water balance models to the initialization of the soil moisture profile prior to temporal evolution calculations, the values retrieved from SAR data are not very useful for this purpose. However, those values arc in good agreement with ground observations. This is especially significant over the study area used in this case, because it is a very dry area (especially in summer, when the experiment was carried out) and it still seems that the SAR signal is sensitive enough to the top-soil moisture content, provided that the effects of surface roughness variations are properly accounted for.

In the retrieval methods based on single channel-multiple polarization techniques wc have observed that in many cases tile retrieved values of soii moisture at C band are considerably higher that those at L band, anti this is independent of the kind of model inversion used. Because this is in contradiction with the expected behaviour (taking also into account the measured profiles given in Table 1), we have developed a double-channel multiple-polarization inversion technique (which is also actually necessary in order to account for vegetation effects in tile retrievals). In the multiple-channel approach, the results are more consistent Also, the resulting surface roughness terms arc more consistent when duai channel methods arc applied, especially for the correlation length. However, the use of dual-channel approaches requires that the model be applicable to both frequencies, anti this is not true for some roughness conditions. In any case, the uncertainty in the retrievals of soil moisture (at least over oLrr study area) is about 20-50% for the top-soil moisture content.

As part of the data collection for the field experiment, the soil group generated a detailed soii map of each pilot area, including soil type, soil texture, soil depth and other information. Soil density anti hydrological properties were measured both in the field and in laboratory conditions, and special experiments were carried out to test the importance of spatial variability in such soii properties, even at different spatial scales, from the field level Lrp to a network of 10×10 km^2 (Bolle et al., 1993; Droogers et al., 1993; Ogink-Hendriks et al., 1995). However, if all this information is used to calculate the dielectric constant of the soil for comparison with the retrievals derived by model inversion from SAR data, we arc facing the problem of empirical relationships between soil moisture anti dielectric constant (Hallikainen et al., 1985). Because of the large uncertainty in such relationships over varying natural conditions in the field (also coupled to high variability in surface roughness as modeled by statistical estimators based on rms heights and correlation lengths), absolute values of soil moisture must be regarded with some high probability of 'systematic' errors. However, relative values arc in any case comparable, out for that purpose an independent account for variability in intrinsic soii porperties (texture, density, etc.) is needed, and this is something which is rarely available. Even when such information is available for pilot areas (as in the case of the EFEDA experiment), the way in which such information can be used in conjunction with SAR data remains unclear because of the problems of spatial scaling and scale compatibility.

In the case of canopy water content (see Fig. 2), the results arc very sensitive to the geometric characterization of the canopy and [he soil, The retrieved values (see for instance Fig. 2) are quite reasonable, especially taking into account that no ground data arc used for training the model but only theoretical scattering considerations. However, the model was developed for the case of corn canopies irr particular, anti, in the present version of the. algorithms, extrapolation to a full image requires some pre-classification o{ the scene in order to account for scattering mechanisms in a different way over different vegetation types. Work in progress is trying to eliminate this dependence by introducing additional parameters accounting for canopy geometry effects, but it seems that such geometrical effects can only be accounted for by means of multiple data taken with different incidence angles. Otherwise, separation of geometric effects from actual canopy water content will never be possible for absolute-value retrievals.

The modeling of soil roughness underlying the canopy has been demonstrated in this study to have also a major importance. An underestimation of soil roughness results in an overestimation of canopy water content.

The first trials to get information from SAR data alone resulted in difficulties in the interpretation of the retrieved values in the case of partially covered pixels. Because the soil/vegetation algorithms used in combination worked only over bare soil areas or over dense (homogeneous) vegetated areas, the cases where separation between both extreme cases was not quite obvious give wrong contributions for soil moisture and/or canopy water content. The introduction of Landsat TM data (see Fig. 1) as auxiliary information, and the use of just the fractional vegetation cover from optical data (instead of other parameters which could be also derived from Landsat data) give as a result a significant increase in the capabilities of the application of the algorithm (in terms of reduction of the number of iterations needed and avoidance of cases with no convergence as always forcing a linear solution). However, because of the difficulties in modelling partially vegetation-covered soils, the results are still questionable in such cases.

7. CONCLUSIONS

A key point in the results is the necessity of some spatial homogenization of the original data prior to any information-extraction technique being applied, especially in the cases where niocici-inversion techniques are used. Multilooking techniques (spatial average) have been demonstrated to be not enough for the purpose of deriving consistent moisture fields from the data. It is necessary to reduce the spatial resolution to about 100 m to get consistent fields over homogeneous areas, but, as the spatial resolution decreases, more difficulties are added in the inversion technique to get convergence over heterogeneous areas. Actually, as spatial resolution is decreased, the noise level is reduced, but some information is lost. However, tile main impact of reducing spatial resolution is increasing the within-pixel heterogeneity and decreasing between-pixel variance. The result is that over heterogeneous pixels the model cannot be inverted because no convergence is possible or because the retrieved values are out of range for many of the resulting heterogeneous mixtures (lack of physical meaning for the model).

In order to get reliable results it is necessary to work with the highest possible spatial resolution but allow a two-way accounting for inter-pixel variability which is just due to noise: spatial filtering anti multiresolution inversion techniques. The combination of both techniques is the only realistic way to handle the problem of spatial variability, especially when one of the objectives is just to analyze the problem of spatial variability in the derived surface values.

The capabilities to derive soil moisture values which can be realistically used in surface energy/water- balance studies seem tobe very limited, especially over dry areas, where no sensitivity to deep moisture content is present in the SAR signal but where vegetation can take water from very deep levels and still produce a considerable, contribution of latent heat flux in surface energy partitioning. According to our results (see Tables 2 and 3), an uncertainty in soil moisture values between 20-50% is all we can get in the case of relatively dry areas. Note however that *in situ* measurements in controlled conditions also give uncertainties between 16% and 40% (Table 1), in the same range as the variability in the different values derived from SAR data. Even when top-soil moisture can be detected by SAR data, the use of these data in energy/water balance monitoring is still very limited in vegetated areas, because of the predominant role of root-zone moisture, as well as in the case of bare soil, where other mechanisms are determining more strongly the dynamics of water in the soil. Whatever these limitations, the SAR-derived top-soil moisture field can still be very useful to properly account for the variability of soil albedo as a function of soil moisture. In the case of soils with low albedo, variations in soil albedo due to changes in soil moisture can be up to 50% (Fig. 4). As the soil albedo has a major effect on energy balance (actually controlling the amount of energy which is available at the surface), any improvement in surface albedo retrievals (including temporal variability clue to soil moisture changes) would have a dramatic impact in energy balance monitoring through modeling techniques, provided that an observation system, stable enough, could provide routine updates of systematic top-soil moisture changes.

Concerning canopy water-content, the results obtained from AIRSAR data seem to overestimate the measured values of the ground according to tile model used in this case. Although there are several uncertainties in the model that could explain such differences (especially those related to canopy geometry factors), it seems that the critical aspect in the model is the way in which soil scattering is treated. The overestimation in canopy water content is then mainly due. to an underestimation of the roughness of underlying soil. It is interesting, on the other hand, to compare the results obtained from AIRSAR data to those obtained from optical data (Landsat TM) (see Fig. 2). In the case of Landsat TM, a full model inversion technique is also used. The model takes the reflectance values measured in the six (thermal channel 6 is excluded) Landsat channels (after radiometric calibration and atmospheric correction of the data). Then, an inversion technique is applied to fit the 6 measurements to give 6 surface parameters. One of the surface parameters used, and then retrieved by the algorithm, is the canopy water content. The values of canopy water content retrieved from Landsat data represent a strong underestimation of the values measured on the ground.

The reason for that is the sensitivity of optical data only to the top of the canopy (top leaves), so that a high underestimation is always expected from such optical data, However, fractional vegetation cover values derived from optical data are essential to guarantee proper interpretat ion of SAR data over partially covered areas or where confusion between soil and vegetated areas can be present in SAR data, as has been demonstrated in this study. '1'hen, optical-microwave synergy seems to be the only way to overcome the limitations of both optical and microwave data in energy/water balance studies.

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Table 1. Measurements of soil moisture over a reference bare soil field used for multisensor calibrations/intercomparisons (located just at the center in Fig. 1 c), during the two AIRSAR overflights over [he study area Numbers correspond, respectively, to the mean (of the N values available), standard deviation and relative error (%). The N measurements correspond to a spatial grid over the field,

Date	Soil moisture				Soil roughness	
		TDR (N= 29)		*Volumetric:*	σ (cm)	λ (cm)
19 June 91 (a)			crust :	*2,9 ±1.2 (40%)*		
"	5 cm :	3.5 ± 0.8 (2.4%)	o-5 cm :	*4.92. 0.9* (19%)	*1.41*	4.00
"	10 cm :	7.2 ±1.2 (17%)	5-1o cm	10.9 ± 1,8(16%)		
"	30 cm :	16.0 ± 3.5 (22%)				
		Gravimetric: (N= 24)				
14 July 91 (b)	*O-5* cm :	4.0 ± 0.7 (17%)				

(a) Droogers et al., 1993; (b) Saatchi et al., 1993

'Table 2. Derived soil moisture values and roughness parameters from AIRSAR data for the same reference bare soil where simultaneous ground measurements are shown in 'Table 1.

Date	Soil moisture	Soil roughness	
	L band	σ (cm)	λ (cm)
19 June 91	3.9	0.19	3.6
14 July 91	7.1	0.?.7	3.1

Table 3. Comparisons of retrieval of soil moisture by using the same AIRSAR data but applying three different models for the same reference bare soil area where simultaneous ground measurements are shown in 'Table 1. Data shown correspond to model inversion for L band (HH-VV and HH-VV-HV, depending on the model used in each case).

Date	Soil moisture		
	Oh **et** *al.*, 1992	*Fung et al., 1992*	*Duboisetal.*, 1994
19 June 91	11.2	5.6	6.8

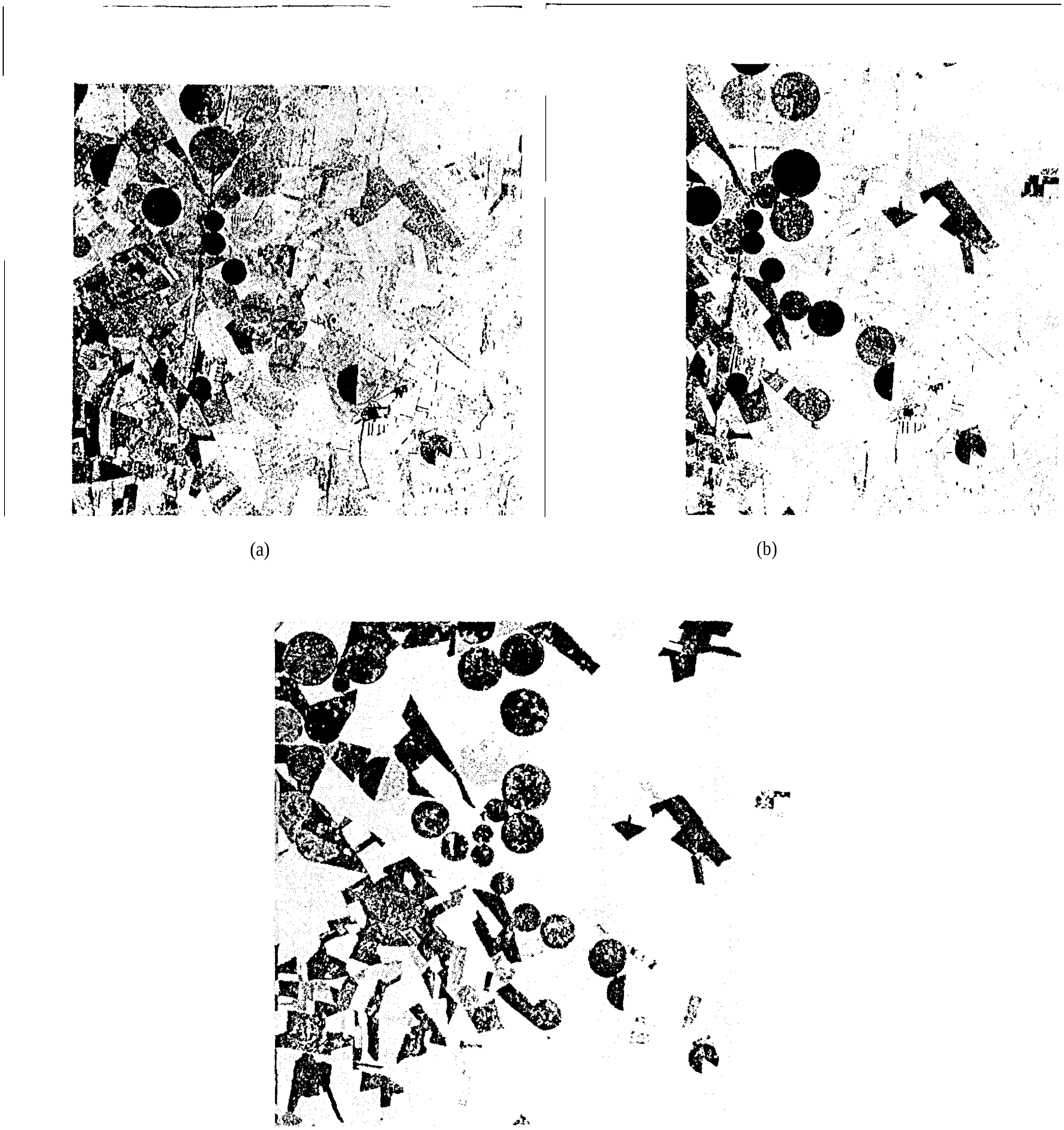

Fig. 1 Multitemporal AIRSAR data: (a) 19 June 1991 (L-HH), (b) 14 July 1991 (L-HH), and (c) Landsat TM data (derived vegetation fractional cover) for 14 July 1991, after geometric registration of the full dataset. The area corresponds to the Barrax test site, one of the pilot areas of the EFEDA experiment in Spain.

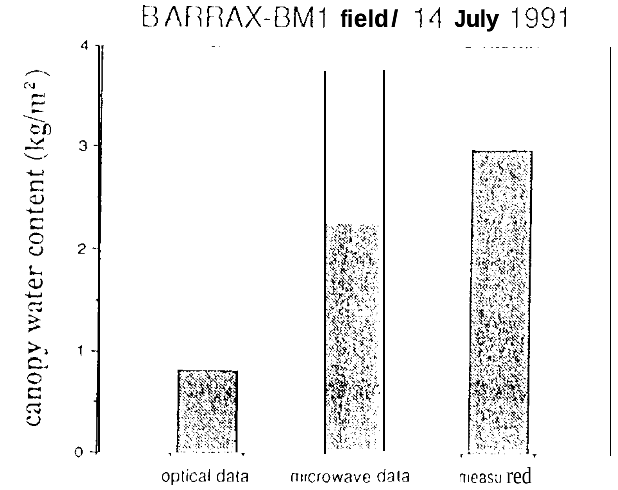

Fig. 2 Comparison of the retrievals of canopy water content from almost simultaneous microwave (AIRSAR) and optical (Landsat "TM) data. SAR data slightly overestimate the total canopy water content in this case, but Landsat data give a very low value as compared to ground measurements.

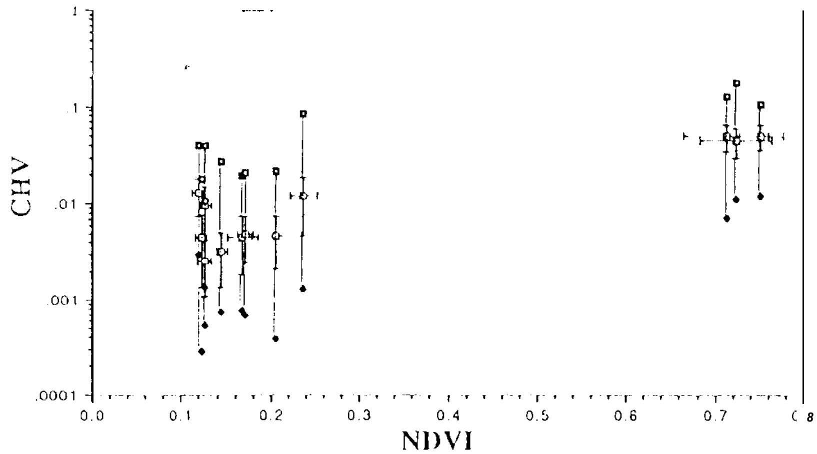

Fig. 3 Backscattering coefficients (C-HV) as measured by AIRSAR plotted against NDVI values derived from simultaneous Landsat TM data, for all the pilot fields used in the EFEDA'9 1 experiment (MAC-Europe campaign). Optical data allows a better separation of bare soil arrd vegetated surfaces for interpretation of SAR data.

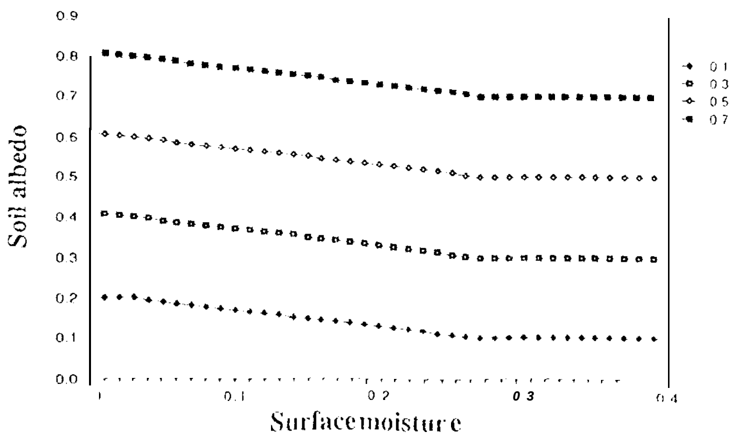

Fig. 4 Bare soil albedo (spectral and angular integration) as a function of top-soil moisture, according to the parameterization used in the Biosphere-Atmosphere Transfer Scheme (BATS) surface energy/water balance model (numbers on labels indicate (he soil albedo corresponding to saturated conditions for each curve).