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Multifrequency SAR data for estimating hydrological parameters(*)

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Summary. — The sensitivity of backscattering coefficients to some geophysical parameters which play a significant role in hydrological processes (vegetation biomass, soil moisture and surface roughness) is discussed. Experimental results show that P-band makes it possible the monitoring of forest biomass, L-band appears to be good for wide-leaf crops, and C- and X-bands for small-leaf crops. Moreover, L-band backscattering makes the highest contribution in estimating soil moisture and surface roughness. The sensitivity to spatial distribution of soil moisture and surface roughness is rather low, since both quantities affect the radar signal. However, observing data collected at different dates and averaged over several fields, the correlation to soil moisture is significant, since the effects of spatial roughness variations are smoothed. The retrieval of both soil moisture and surface roughness has been performed by means of a semiempirical model.

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1. – Introduction

The use of radar in detecting land features has appeared to be very promising since 1976, immediately after the first Synthetic Aperture Radar (SAR) was launched in space onboard the Seasat satellite. Since then, after the first experiments carried out with the NASA/JPL Shuttle Imaging Radar (SIR A) [1], other multi-frequency systems, such as the airborne NASA/JPL AIRSAR [2] and EMISAR [3] (developed and operated by the Technical University of Denmark), and the shuttle borne SIRB and SIR C [4], have been used in experimental missions. Many data have thus been collected worldwide over different sites. In the same time, many research efforts have been and continue to

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be aimed at interpreting radar data and at modelling the mechanisms that control the interaction of microwaves with the most recurrent types of land surfaces (*e.g.*, [5-7]). At present, a few satellites (ERS-1/2, JERS-1, RADARSAT) also have SAR onboard.

In general, remote-sensing techniques can provide frequent updating of the spatial and temporal distribution of land surface features. In particular microwave sensors, thanks their sensitivity to water content and to surface roughness of observed bodies, can make a significant contribution in retrieving the main key parameters of the hydrological cycle. Indeed, the water stored in soil and vegetation is an important fraction of the total amount of water involved in the hydrological cycle and represents a conspicuous quantity subtracted from the rapid loss due to runoff. In addition, besides representing a water resource for plants, the Soil Moisture Content (*SMC*) affects the separation of infiltration from runoff, and is therefore an important parameter for assessing erosion hazards and estimating evapotranspiration.

In this paper the results obtained in recent years using SAR data from both aircraft and satellite and collected in agricultural and forest areas, will be summarized. A major problem in retrieving the hydrological parameters using microwave remote sensors is that each parameter affects the signal in a different way, and separating the effects requires the use of appropriate multi-frequency, multi-polarisation algorithms.

2. – The experiments

Several surveys with airborne and satellite-borne SAR were carried out in the Montespertoli area, which was one of the super-sites chosen for the SIR-C hydrological experiment. This area is representative of the landscape and climate of central Italy. The typical field dimensions are about 4 to 5 ha. The test-site was imaged three times at incidence angles (Θ) between 23° and 55° by the fully polarimetric airborne NASA/JPL AIRSAR at *C*-, *L*- and *P*-band during the MAC-Europe campaign in June and July 1991. Later on, other SAR measurements were made by the fully polarimetric *L*- and *C*-band SIR-C and the VV-polarised *X*-band X-SAR [4] during the two Shuttle missions, in April and October, 1994. Between 1991 and 1994 the same area was also imaged by the SAR satellite: ERS-1 (*C*-Band, VV polarisation and $\Theta = 23°$) and JERS-1 (*L*-band, HH polarization and $\Theta = 35°$).

The results, achieved on the Italian test site by using AIRSAR, SIR-C, ERS-1 and JERS-1 data, are compared with those obtained at the same frequencies with a similar sensor (EMISAR data at *C*- and *L*-bands in HH, VV and HV polarisations) in the Sweden area, in the framework of the ESA European Multisensor Airborne Campaign (EMAC-94/95) [8].

The collected data used in this paper are summarised in table I.

3. – Data analysis and retrieval of geophysical parameters

An example of SAR data is represented in fig. 1, which shows the composite (*P*-, *L*- and *C*-bands) image in HV polarisation of the agricultural area of Montespertoli. We can see that the orography and the hydrographic network is well pointed out together with the various land surface categories. As an example:

- agricultural fields appear in different colours and intensity according to the crop present in the field;

TABLE I. – *Summary of SAR data.*

	Frequency band	Polarisation	Observation angle	Ground resolution (m)	Dates
AIRSAR	P, L, C	Quad	20° 35°–50°	12.2×6.6	22-29/6/1991 14/7/1991
SIR-C/ X-SAR	L, C, X	Quad VV	23°–55°	25×25	12-17/4/1994 3-14/10/1994
EMISAR	L, C	HH, VV, HV	45°–50°	5×5	23/6/1994 5-6/7/1995
ERS-1	C	VV	23°	12.5×12.5	29/5/92 07/8/92 24/4/94
JERS-1	L	HH	35°	18.3×24.6	24/6/92 14/4/94

– several water bodies, characterised by the lowest backscattering values at all frequencies appear dark;

– the small rivers Pesa and Virginio, which cross the scene are easily identified for the high backscattering due to deep vegetation present on the river banks;

– the village of Cerbaia, on the upper part of the image, and the forest, spread over

Fig. 1. – SAR image of the agricultural area of Montespertoli, represented as a composition of P-, L-, and C-bands in HV polarization.

the site are identified as bright areas (strong backscattering).

A more in-depth analysis based on quantitative data made it possible to better characterise the scattering properties of the surfaces observed. In general, backscattering from a vegetated terrain is affected by the soil characteristics as well as by the geometry and dimensions of plant constituents (leaves, stems, branches, trunks). The basic scattering mechanisms involved are surface scattering from soil, volume scattering from leaves and branches and double scattering soil/trunks and soil/stalks [9,10]. These mechanisms can be identified by means of multi-frequency polarimetric measurements and can provide the essential guidelines for developing a classification scheme [11]. As an example, a "supervised box classifier", which uses fully polarimetric data at P-, L-, and C-bands was developed using data collected at Montespertoli. This approach requires that the number of classes be specified in advance, and that the extreme values of the backscattering coefficient of each class be known. The algorithm was tuned by using the AIRSAR data averaged over homogeneous zones of nine types of surfaces (urban areas, water bodies, forest, vineyards, olive-groves, bare soils, wide-leaf crops, colza, mixed small-leaf vegetation) which are characterised by different scattering properties, and tested on a pixel-by-pixel basis [12].

The results are generally good for all classes, with the lowest percentage of correct classification being that of mixed vegetation and olive groves (60% and 76%, respectively) and the highest that of forest (92%) and bare soils (96%).

3·1. *Sensitivity to forest and crop biomass.* – In order to investigate the correlation between multi-frequency polarimetric σ^0 and vegetation biomass, the crop biomass was described by the Plant Water Content (PWC, *i.e.* the difference between fresh and dry biomass, in kg/m^2). For forests the total biomass was expressed by the woody volume (WV, in m^3/ha) by

$$WV = BA \times h,$$

where BA is the basal area (*i.e.* the soil surface occupied by the trunk area, in m^2/ha), h (m) is the average tree height. On the basis of the previous considerations, the vegetation types present in Montespertoli area were subdivided in three classes, according to the dimensions of their stems/trunks and their plant density (δ) [12]:

1) Forests, characterised by large cylinders (with a diameter of several cm) and low plant density ($\delta < 1$ plant/m^2).

2) Wide-leaf crops, such as corn and sunflower, characterised by wide leaves, intermediate cylinder dimensions (diameter in the order of 2–3 cm) and intermediate plant density ($1 < \delta < 50$).

3) Small-leaf crops (alfalfa, wheat) characterised by narrow leaves, very thin cylinders (diameter < 1 cm) and very high plant density ($\delta > 50$).

Experimental data of σ^0_{HV} at P-, L- and C-bands, have been correlated to woody volume (WV) of forests and olive-groves through the following regression equations:

$$P\text{-band} \rightarrow \sigma^0_{\mathrm{HV}} = 10\log(3 \times 10^{-5} WV + 0.009), \qquad R^2 = 0.96, \tag{1}$$

$$L\text{-band} \rightarrow \sigma^0_{\mathrm{HV}} = 10\log(2 \times 10^{-5} WV + 0.02), \qquad R^2 = 0.6, \tag{2}$$

$$C\text{-band} \rightarrow \sigma^0_{\mathrm{HV}} = 10\log(2 \times 10^{-5} WV + 0.03), \qquad R^2 = 0.63. \tag{3}$$

Fig. 2. – Backscattering coefficient measured with JERS-1 L- SAR (L-band, HH polarization, $\Theta = 35°$) (a), and with ERS-1 C-SAR (C-band, VV polarization, $\Theta = 23°$). Continuous lines represent the regression equations.

It should be noted that the good correlations obtained are partially due to the peculiarity of the Montespertoli site, where only species with very low biomass (olive groves) or species with very high biomass (dense forests) are present [12]. Moreover, the saturation occurs at about 1500 m^3/ha, whereas, for data collected on EMAC area, which includes forests less dense than those of Montespertoli, the saturation occurs at much lower biomass values, as already observed in other experiments [13-15].

Although the best performances for estimating biomass have been noted at P-band cross polarisation (HV), it is interesting to investigate the potential of the instruments onboard satellites. Figure 2 shows the backscattering coefficient at the L-band (HH pol., $\Theta = 35°$) from JERS-1 (a) and at the C-band (VV pol, $\Theta = 23°$) from ERS (b), compared with the woody volume of several small forests [16]. We see that, once clear cut areas have been identified and left out from the regression, the C-band signal of ERS-1 SAR becomes very sensitive and correlated to WV. In this case the regression equations and the regression coefficients R^2 are:

$$L\text{-band} \rightarrow \sigma^0_{\mathrm{HH}}(\mathrm{dB}) = 10\log(6\times10^{-5}WV + 0.08), \qquad R^2 = 0.5, \tag{4}$$

$$C\text{-band} \rightarrow \sigma^0_{\mathrm{VV}}(\mathrm{dB}) = 3.7\times10^{-3}WV - 12, \qquad R^2 = 0.65. \tag{5}$$

The sensitivity of the SAR signal to plant water content (PWC, kg/m^2) of herbaceous crops is shown in fig. 3, where σ^0_{HV} at P- (a), L- (b) and C- (c) bands collected with AIRSAR & SIR-C at Montespertoli is combined with EMISAR data collected at the same frequencies and polarisations in the NOPEX area.

Although experimental data at L- and C-bands are rather spread, we see that two groups of crops, characterised by different behaviours of σ^0, can be separated: the "broad leaf" crops (sunflowers, sorghum and corn) for which the σ^0 increase with PWC, and the

Fig. 3. – σ^0_{HV} (dB) at P (a), L (b), and C (c) bands at $\Theta = 35°$ as a function of plant water content (PWC, in kg/m^2) of agricultural crops: corn, sunflower sorghum (▲), wheat, alfalfa and bare soils (◇). (d) ERS-1 data (C-band, VV polarization, $\Theta = 23°$). Continuous lines represent the regression equations.

group of plants characterised by smaller constituents, "small-leaf crops", such as wheat and grass, for which the σ^0 is almost constant or slightly decreasing with PWC. At P-band, herbaceous crops are rather transparent, and the difference between the two groups of crops disappears. In this case, the sensitivity and the correlation to plant biomass is rather poor ($R^2 = 0.5$). For corn, sunflower and sorghum, the best indicator of vegetation biomass is the L-band cross polar backscattering σ^0_{HV}, which is very low for bare soils (-25 dB) and gradually increases up to -14 dB as PWC attains 4 kg/m^2. In this case the correlation coefficient is fairly high ($R^2 = 0.7$). A similar sensitivity, although to a lesser extent ($R^2 = 0.6$), has also been observed in HH polarisation with JERS-1 data [16]. At C-band, $\Theta = 35°$, the early saturation effect is very evident and the correlation coefficient is lower ($R^2 = 0.42$). For wheat and alfalfa, no correlation is shown at L-band, whereas at C-band a decreasing trend with biomass is rather marked ($R^2 = 0.42$). The latter trend was already observed at X-band [17], and can be explained by a major role played by canopy absorption. At the observation parameters of ERS-SAR (C-band , $\Theta = 23°$) (fig. 3d), the backscattering from broad leaf crops increases with biomass and rapidly saturates as soon as PWC attains 2 kg/m^2. On the contrary, for small-leaf crops, σ^0_{VV} decreases as biomass increases. The regression equations and the R^2 are the following [16]:

$$\text{(6)} \quad \textit{Broad-leaf crops} \rightarrow \sigma^0_{\mathrm{VV}}(\mathrm{dB}) = 10\log(0.075\,PWC + 0.18), \qquad R^2 = 0.48,$$

$$\text{(7)} \quad \textit{Small-leaf crops} \rightarrow \sigma^0_{\mathrm{VV}}(\mathrm{dB}) = -2.82\,PWC - 5.74, \qquad R^2 = 0.45.$$

3˙2. *An empirical model for estimating vegetation biomass.* – An empirical approach for retrieving the leaf area index from SAR data has been tailored using the results obtained from multi-frequency/ multi-polarisation SAR data analysis, which indicated a clear correlation between L-band data at HV polarisation and the leaf area index of certain crop types [12,18]. Since other bands, such as C- and P-bands, have also been found sensitive to vegetation biomass, although to a lesser extent, a multi-frequency approach has been attempted in order to extend this relation to other crops. Since dimensions of vegetation constituents can been expressed in terms of the electromagnetic wavelength, a parameter useful for investigating variations in the backscattering coefficient with the increasing dimensions of leaves and stems is the Normalised Volumetric Leaf Area Index ($NVLAI$), obtained by multiplying the Leaf Area Index (LAI in m^2/m^2) by the leaf thickness (m) and by the wave number ($2\pi/\lambda$, in m^{-1}). The use of this normalisation enables the combination of multi-frequency data in the same diagram. A comparison of the backscattering coefficient at P-, L- and C-bands, measured at HV polarisation and at $\Theta = 35°$, is shown in fig. 4, which also includes the regression line, whose equation is [18]

$$\sigma^0_{\mathrm{HV}} = 10\log(0.7514 \times NVLAI + 0.0047), \qquad R^2 = 0.76. \tag{8}$$

Equation (8) can be used to retrieve the LAI from multi-frequency SAR data. The result is shown in fig. 5, where the LAI retrieved from SAR data at P-, L- and C-bands and the measured LAI have been compared. It can be observed that, in spite of some overestimation, the model confirms the possibility of estimating the leaf area index of some types of crops by using multifrequency SAR data.

3˙3. *Sensitivity to soil moisture.* – A moderate sensitivity of radar returns to soil moisture (*SMC*) was noted during several experiments performed in the past years, although the overall backscatter was found to be considerably affected by both vegetation cover and surface roughness (*e.g.*, [19-22]). In this study the L-band radar response to moisture of agricultural fields, σ^0_{HH} measured over the Pesa valley flat land was correlated to the gravimetric *SMC* in the first 0–5 cm soil layer.

Fig. 4. – σ^0_{HV} at P-, L- and C-bands ($\Theta = 35°$) as a function of the Normalized Volumetric Leaf Area Index ($NVLAI$). Labels represent experimental data at different frequencies: $\diamond$ = C-band, $\square$ = L-band, $\times$ = P-band. The regression line is also represented in the diagram.

Fig. 5. – LAI (derived from $NVLAI$ computed from eq. (8) using multifrequency SAR data) *versus* measured LAI.

Fig. 6. – L-band σ^0_{HH} *vs.* 0–5 cm layer $SMCg$ % for fields with $LAI < 1$ and $PWC < 0.5$ kg/m^2. The line represents the best fit of experimental data.

Fig. 7. – Area averaged L-band σ^0_{HH} at $\Theta = 25°$ (♦) and $\Theta = 35°$ (■) *vs.* area averaged $SMCg$%.

In order to reduce the effects of vegetation, we considered the data taken at $\Theta \simeq 25°$ over a sub-set of the bare or scarcely vegetated fields, the borders of which could still be clearly identified in the reduced-resolution images. Figure 6 shows that the correlation is pretty good ($R^2 = 0.62$).

Since at L-band and relatively low incidence angles thin vegetation is expected to be rather transparent, the spread of data in fig. 6 should be attributed to the varying surface roughness of the individual fields. Indeed, when data taken on fields with high surface roughness (Height Standard Deviation, $s > 2$ cm) are removed, the correlation coefficient further increases to $R^2 = 0.71$. The correlation to SMC is again improved if we consider the evolution in time of the backscattering from the same area. In this case the correlation becomes surprisingly high both at 25° and 35° incidence angle with $R^2 = 0.96$ (fig. 7) [23] .

Fig. 8. – Temporal averages σ^0_{HH} at L-band *vs.* surface height standard deviation s of bare or lightly vegetated ($LAI < 1$, $PWC < 0.5$ kg/m^2) fields.

Fig. 9. – *SMC* of bare or lightly vegetated ($LAI < 1$, $PWC < 0.5$ kg/m^2) fields, retrieved by successive use of Oh *et al.* and Dobson *et al.* models from L-band data, *vs.* *SMC* measured at ground.

3·4. *Sensitivity to soil roughness.* – The measurements indicated that the effect of surface roughness on σ^0 appears appreciable at all frequencies and polarisations considered. We have seen that that C- and X-band σ^0_{VV} does not change appreciably with the surface height standard deviation s, whereas L-band appears to be sensitive to surface roughness, irrespective of the vegetation cover. However, the scatter of data is considerable, presumably due to the different values of soil moisture. This latter changes with time. Hence, the effects of the variations of *SMC* of each field, as well as of its vegetation cover, are expected to be smoothed out by a temporal averaging . This is indeed the case, as shown in fig. 8 [23], which reports the time-averaged L-band σ^0_{VV} as a function of s of bare and lightly vegetated fields. The correlation between σ° and s is appreciable ($r^2 > 0.69$).

3·5. *Retrieval of soil moisture and surface roughness.* – Several empirical or semi-empirical models are available for predicting scattering from rough soil. Some of these can potentially estimate the soil parameters by inverting the backscattering measurements [22, 24-26]. A statistical inversion approach which can make use of rigorous scattering models such as the IEM [27] has also been proposed and tested for retrieving soil moisture and roughness [28].

We considered the semi-empirical model suggested by Oh *et al.* [25] for estimating *SMC* and s of bare or lightly vegetated areas. This model relates the two backscattering parameters $p = \sigma^0_{\mathrm{HH}}/\sigma^0_{\mathrm{VV}}$ and $q = \sigma^0_{\mathrm{HH}}/\sigma^0_{\mathrm{VV}}$ (L-band) to surface roughness, described by ks (k is the electromagnetic wave number $= 2\pi/\lambda$), and to soil reflectivity Γ_0. This model was then used to estimate ks and SMC. The latter was obtained from Γ_0 by using a soil permittivity model [29]. The retrieved values of *SMC* are compared with ground truth in fig. 9 [23]. The result obtained appears rather good ($R^2 = 0.55$), in spite of some dispersion, probably due mainly to parameter p, whose small values tend to amplify the fluctuations of Γ_0.

4. – Conclusions

The potential of SAR data for providing parameters of interest in hydrology has been assessed by using multi-frequency and multi-temporal polarimetric measurements, carried out on agricultural areas by the shuttle borne SIR-C/X-SAR, the airborne AIRSAR and EMISAR systems together with the SAR aboard of ERS-1 and JERS-1 satellites.

Results indicate that an SAR operating at P- and L-bands is able to separate agricultural fields from other targets, while a system operating at L- and C-bands can discriminate among agricultural areas. An algorithm trained on the average polarimetric features of vegetation types cultivated in the area has been implemented and successfully tested to separate at a pixel scale nine classes of land cover. The estimation of vegetation biomass is more effectively performed at HV polarisation and at L- and C-bands for herbaceous crops and at P- (or L-) band for forests; in particular, L-band seems to be sensitive to vegetation biomass of wide-leaf crops, whereas its sensitivity to biomass of narrow-leaf crop is negligible. C-band shows two separate trends for wide-leaf and narrow-leaf crops (especially in VV polarisation and $\Theta = 23°$). The information obtained at L-band, HH polarisation and $\Theta = 35°$ (the observation parameters of JERS-1) is still useful for estimating vegetation biomass of herbaceous crops and, to a lesser extent, also of forests. The contribution of ERS-1 data can be important for estimating biomass of both agricultural crops and forests, provided clear cut areas have been identified.

The measurement of soil moisture and surface roughness of rough fields is better accomplished at L-band and at incidence angles between 25° and 35°, but, in general, it is rather low. However, when data averaged in space over several fields are considered, the average radar return becomes significantly correlated to the average soil moisture, due to the smoothing of the effects of the spatial variations in roughness. Analogously, the sensitivity to surface roughness becomes appreciable if multi-temporal data are averaged in time, thus reducing the effects of temporal moisture variations.

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