Geoinformation for European-wide Integration, Benes (ed.)

Development of an algorithm for the Bayesian fusion of multi-angle, multi-polarisation and multi-frequency remotely sensed data

Claudia Notarnicola & Francesco Posa
Dipartimento Interateneo di Fisica, Università di Bari, INFM, Italy

Keywords: data fusion, inversion, soil moisture

ABSTRACT: This work addresses the possibility of retrieving soil moisture information from remotely sensed data in the microwave domain and develops an algorithm to efficiently merge point measurements. The inversion process is based on the Bayes's theorem and applied to data of a radiometer and scatterometer observing the same area. The flexibility of such algorithm allows incorporating as many as possible sources of information, as multi-angle, multi-polarisation and multi-frequency data. An error analysis indicates that multi-polarisation information provides the best results. Advantages, disadvantages and future improvements of this procedure are also discussed in the analysis.

1 INTRODUCTION

Multi-sensor techniques are fundamental to the development of operationally useful soil-moisture sensing systems in which the soil roughness effects in the microwave system response to soil moisture can be separated by multi-sensor analysis. The effect of soil roughness and/or vegetation can also be corrected by acquiring data at different angles and frequencies. In fact, inversion procedures (Satalino *et al.* 1999) produce best results when multi-frequency, multi-angle and multi-polarisation data are available.

The main objective of this work is to improve the estimation of soil moisture by combining data derived from two types of sensor which satellites frequently have on board: radiometers and scatterometers.

The developed algorithm is based on an experimental/modelling scheme

The synergy of modeled and experimental data is justified by two important observations. An algorithm based only on measurements could be of limited applicability as it represents a specific situation. On the other hand, when adopting simulated data, the inversion procedure might be of general purpose but sometimes not applicable to reality.

This procedure intends to extract soil moisture starting from experimental data of different sensors and from the corresponding simulated data, using a Bayesian approach. In fact, the Bayesian methodology earns much of its power from the ability to incorporate casual models as conditional probabilities. The response to electromagnetic radiation and the spontaneous emission of bare soils have been modelled according to the Integral Equation Model and a semi-empirical expression corrected for roughness effect respectively.

The experimental data set was collected over long periods on agricultural fields and includes radiometric and scatterometric measurements in the angular range from 10° up to 70° as well as ground truth acquisitions. The work is organised in five steps:

1. Simulation of scattering and emission processes using the aforementioned models with soil parameters that meet the experimental environment;
2. Analysis of multiple correlation among simulated scattering, emission and soil moisture with noise added;
3. Application of the Bayesian approach to retrieve soil moisture from scatterometer and radiometer data;
4. Comparison among the results obtained when the inversion procedure is applied to multi-polarisation and multi-frequency data.
5. Application to space-borne and air-borne data.

In all the configurations, the estimated soil moisture values show a reasonable agreement when compared with *in-situ* measurements. Furthermore, the inversion procedure reaches better results when two different polarisations are adopted for backscattering coefficients and emissivity.

2 MICROWAVE SENSOR SENSITIVITY TO SURFACE PARAMETERS

Active and passive sensors reveal same physical processes but produce different responses to surface parameters changes. The backscattering and emission from natural bare soils have been simulated by using theoretical models, to address if the combination of active and passive sensors could be useful in retrieving information about soil properties. In order to obtain the backscattering behavior in the case of active remote sensing, the Integral Equation Model (Fung 1994) has been implemented because works on a wider range of surface parameters.

In the IEM formulation, the like polarised backscattering coefficients for surfaces with small or medium size roughness are given by:

$$\sigma^0_{pp} = \frac{k^2}{2} exp(-2k_z^2 s^2) \sum_{k=1}^{\infty} \left| I^n_{pp} \right| \frac{W^{(n)}(-2k_x,0)}{n!} \quad , \qquad (1)$$

where k is the wave number, θ is the incidence angle, $k_z = kcos\theta$, $k_x = ksen\theta$ and pp refers to the horizontal (HH) or vertical (VV) polarisation state and s is the standard deviation of terrain heights. The term I^n_{pp} depends on k, s and on R_H, R_V, the Fresnel reflection coefficients in horizontal and vertical polarisations. The symbol $W(-2k_x,0)$ is the Fourier transform of the n^{th} power of the surface correlation coefficient. In this context, an exponential correlation function has been adopted that seems to describe better the properties of natural surfaces (Fung 1994).

When the radiometer response is analysed, the simplest soil-emission configuration is represented by a homogeneous isothermal soil medium with a plain air-soil boundary. In this case, the brightness temperature of the soil surface when viewed from air at a nadir angle θ_0 is:

$$T_B(\theta_0, p) = e^{sp}(\theta_0, p) T_s \quad , \qquad (2)$$

where T_s is the soil temperature and $e^{sp}(\theta_0, p)$ is the soil emissivity evaluated at θ_0 with polarization p.

For the evaluation of emissivity, a semi-empirical expression proposed by Wang (1995) including the effect of roughness, has been introduced:

$$e_H = 1 - \left[(1-Q) r_H + Q r_V \right] exp(-4k^2 s^2 cos^2 \theta) \qquad (3)$$

where r_H and r_V are the smooth surface reflectivities for the horizontal and vertical polarisation. Q is a mixing polarization parameter depending on the operating frequency and s.

For the IEM, the input parameters are the real part of the dielectric constant ε, the rms of height, s, and the correlation length, l, and for the emissivity, ε, s.

The backscattering coefficients and the emissivity have been simulated for the following ranges:

1. The standard deviation of height s from 0.5 cm up to 1.5 cm;
2. The correlation length l from 2 cm up to 5 cm;
3. The dielectric constant ε from 4 up to 20 corresponding to volumetric soil moisture values from 6% to 40% for a silty-loam soil.

The dielectric constant is obtained from the knowledge of volumetric soil moisture, soil texture and frequency according to empirical formulae (Hallikainen *et al.* 1985). The range of simulated values corresponds to measured value ranges.

The backscattering coefficients have been simulated for a frequency of 4.6 GHz, with both polarisations HH and VV, and the emissivity for 3.1 GHz and 4.6 GHz with linear polarisation H and V.

In the case of backscattering coefficients, the rms of heights, s, has a heavier impact than the correlation length, l, on backscattering coefficients for both polarisations, with a saturation effect at higher values of s. The range of σ^0 for l varying from 2 cm up to 5 cm is less that 1 dB, and it increases for higher values of the incidence angles, e.g. for 60° it is about 2.5 dB.

The effect of roughness is to increase the emissivity, but to diminish the dependence of emissivity on the dielectric constant (Ulaby *et al.* 1994). These considerations apply for both polarisations.

For 3.1 GHz, the emissivity behavior is quite similar. These few considerations and a more complete analysis indicate that, theoretically, a net dependence of backscattering coefficients and emissivity on soil moisture and roughness exists (Du *et al.* 2000, Fung 1994).

In the case of real data, this dependence is not always evident due to many sources of errors. This reflects in low correlation factors between measured radar data and surface parameters. Three correlation factors have been considered: the first one indicating the correlation between the dielectric constant and the backscattering coefficient, the second one indicating the correlation between the dielectric constant and the emissivity and the third one is a correlation factor of a multiple regression among backscattering coefficients, emissivity and the dielectric constant. Taking into account different soil parameters configurations, random noise has been added in order to produce lower single correlation factors and investigate what happens to the multiple regressions when the dielectric constant is considered as a function of backscattering coefficients and emissivity. Even when the single factors steep down, the multiple correlation factors do not drop. The lower limit is generally 60%, indicating that a combination of both sensors could provide better performance in extracting surface moisture even when single sensor data reveal a poor correlation (Saatchi *et al.* 1994).

3 THE EXPERIMENTAL DATA SET

The experimental data set was acquired by the University of Berne's RASAM, a truck-mounted radiometer-scatterometer operating between 2.5 GHz and 11.0 GHz in the angular range from 10° to 70° (Wegmueller *et al.* 1994). This data set includes backscattering coefficient measurements at HH, VV, HV, VH polarisations and emissivity at H, V polarisations for a great variety of agricultural fields.

Only bare soils are selected in this analysis, which, according to measurements, are within the limits imposed by the IEM model. The experimental accuracy, as indicated in the data set, is around 1 dB for backscattering coefficients and 1-2 K for brightness temperatures.

In the first approach as illustrated in section 4, the backscattering coefficients and the emissivity have been considered at the same frequency of 4.6 GHz and for horizontal polarisation. In this case, the wavelength is 6.52 cm with a penetration depth of less than 2 cm (Ulaby at al. 1994), so the microwave sensor is sensible only to near surface properties. Consequently, no volumetric effects should be taken into account.

4 INVERSION PROCEDURE

Some remote sensing analysis fall within the category of inverse problem where from a vector of measured values, **m**, one wishes to infer the set of ground parameters, **x**, that gave rise to them.

The inverse problem is a typical ill-posed problem. It presents many difficulties due to the non-linearity between remote sensing measurements and ground parameters and generally because more than one value of **x** could produce the same measured **m** (Satalino at al. 1999).

In the second section, two models that associate an approximate value of the backscattering coefficient, σ^0, and emissivity, e, to values of the dielectric constant ε and roughness parameters, s and l, have been introduced and now one would like to make an estimate of the surface parameters that gave rise to the observed values of σ^0 and e. In this approach, the backscattering coefficient and emissivity for horizontal polarisation are considered. The attention is focused on the estimation of the dielectric constant, because even though the standard deviation of height, s, and the correlation length, l, play a key role in electromagnetic scattering, they are very hard to quantify experimentally, showing a great variability (Mattia *et al.* 1994). Regarding the parameter s, the integration will be performed over a range that covers most of measurements. The correlation length will be considered as a parameter to be varied in the model.

Instead of deterministically inverting the theoretical formulae (1, 2), the inversion procedure is based on a Bayesian methodology (Haddad *et al.* 1994, Davis *et al.* 1995). Starting from a data set consisting of soil parameter measurements and the corresponding remote sensing data σ^0_{HH} and e_H, it aims at quantifying the spread of measurements about the theoretical formulae, then incorporate this information into the inversion algorithm. With this strategy, the spread of actual data about the approximate model is built, then this information is utilised to extract the model accuracy. The approach has been used to combine data from two different sensors but can be extended to include as many as available data simultaneously.

The problem can be detailed in the following way: starting from two measured values of σ^0_{HH} and e_H for 4.6 GHz on the same area, one would like to make an estimate of the dielectric constant that has produced the observed couple (σ^0_{HH}, e_H).

As the equality between theoretical and experimental values is never verified due to many factors that include measurements errors, the non-uniformity of the background power distribution, the inhomogeneity of the surface within resolution cells, one needs to make an effort to statistically account for this discrepancy.

Two random variables, R_1 and R_2, representing noisy elements in the theoretical formulae, are introduced. They do not depend on ε, s and l:

$$e_{Hm} = R_1 e_{Hth}\ ,\ \sigma^0{}_{HHm} = R_2 \sigma_{HHth} \quad . \tag{4}$$

To compute the conditional density function, $P\ (\varepsilon,\ s|\ e_H, \sigma^0_{HH})$ to obtain ε and s given the measured values of e_H, σ^0_{HH}, the joint behavior of R_1 and R_2 has to be identified. In fact, applying the Bayes's theorem, this conditional density function will be as follows:

$$P(\varepsilon,s\,|\,e_H,\sigma^0{}_{HH}) = \frac{P_{prior}(\varepsilon,s)P_{post}(e_H,\sigma^0{}_{HH}\,|\,\varepsilon,s)}{P(e_H,\sigma^0{}_{HH})} \quad ,(5)$$

where $P_{prior}\ (\varepsilon,\ s)$ is the prior joint density function for the dielectric constant and the s parameter, in which one includes all the prior information about these parameters, such as estimates based on other instruments. In case one does not know anything "a priori" about them, except their physical range of values, a uniform density function is considered divided by the length of the corresponding interval. The term $P(e_H,\ \sigma^0_{HH})$ is a normalisation factor. The posterior density function $P_{post}(e_H,\ \sigma^0_{HH}|\ \varepsilon,\ s)$ is to be computed based on measured values.

This function $P_{post}\ (e_H,\ \sigma^0_{HH}|\ \varepsilon,\ s)$ can be expressed in terms of the probability density $P\ (R_1,\ R_2)$ (Stuart *et al.* 1996):

$$P(\varepsilon,s \mid e_H,\sigma^0{}_{HH}) = \frac{1}{e_H \cdot \sigma^0{}_{HH}} P(R_1,R_2) \; . \qquad (6)$$

To determine the joint density function, $P\ (R_1, R_2)$, the ratios $R_1 = e_{Hm} / e_{Hth}$ and $R_2 = \sigma^0{}_{HHm} / \sigma^0{}_{HHth}$ are computed using the RASAM data set and the corresponding simulated values.

Their frequency distributions illustrate that an asymmetric distribution function should be needed to represent the data. It is well known that the family of gamma density functions is a suitable solution for the representation of statistical properties of a natural scene. However, a Gaussian probability density function has been preferred, being also commonly used to describe natural scenes and more convenient as mathematical approach (Nezry *et al.* 1998).

In this case, the joint distribution function can be written as:

$$P(R_1,R_2) = \frac{e^{-(R_1-\mu_1)^2/2\sigma_1^2}}{\sqrt{2\pi}\sigma_1} \frac{e^{-(R_2-\mu_2)^2/2\sigma_2^2}}{\sqrt{2\pi}\sigma_2} \quad . \qquad (7)$$

The hypothesis underlying the use of this expression is that R_1 and R_2 are independent gaussian-distributed random variables. In fact, R_1 and R_2 represent the noise element in measurements obtained from different sensors, sensible to different soil processes. Now this procedure is applied to the case where the models are those analysed in the section 2 and the data sets are those acquired by the RASAM scatterometer and radiometer at 4.6 GHz for emissivity and backscattering coefficients with the angular range from 0° up to 60°.

R_1 and R_2 are both gaussian-distributed random variables, where the means μ_1, μ_2, and the standard deviations σ_1, σ_2 can be determined from the joint knowledge of R_1 and R_2. The principle of the Maximum Likelihood (MAP) is applied, so that the parameters μ_1, μ_2, σ_1, σ_2 are those that maximize the joint distribution function. The values, at which the maximum is achieved, are the following: μ_1=0.96, μ_2=1.14, σ_1=0.04, σ_2=0.25. Subsequently, the joint density function can be tested for goodness-of-fit, by integrating equation (7) directly. The obtained χ^2 value is well within the acceptable region and it is reasonable to assume that the expression (7) is indeed the joint density function for R_1 and R_2 in the case of our data.

Once determined the joint density function, given specific values for e_H, $\sigma^0{}_{HH}$, the optimal estimator $\bar{\varepsilon}$ for ε, that has minimum variance (e.g. that minimises the r.m.s error), is the conditional mean:

$$\bar{\varepsilon} = \frac{\iint \varepsilon P(\varepsilon,s \mid e_{Hth},\sigma^0_{HHth})d\varepsilon\ ds}{P(e_h,\sigma^o)} \quad . \qquad (8)$$

The corresponding variance is given by:

$$\sigma^2(\bar{\varepsilon}) = \frac{\iint (\varepsilon-\bar{\varepsilon})^2 P(\varepsilon,s \mid e_{Hth},\sigma^0_{HHth})d\varepsilon\ ds}{P(e_h,\sigma^o)} \; . \qquad (9)$$

The r.m.s error is derived as the square root of the variance. The prior density function $P_{prior}(\varepsilon, s)$ will be assumed uniform over the range $4 < \varepsilon < 20$ and $0.5\text{cm} < s < 1.2\text{cm}$. The integrals are computed numerically using the Matlab environment (v.5.3).

This inversion procedure is now applied to separate data to verify its reliability. The estimates on ε have been obtained for incidence angle of 20° and 30° (table 1). The choice of these incidence angles is due to two main reasons: they are the typical angles employed by space-borne sensors as ERS-1 and 2 and ENVISAT. Furthermore, it should be noted that as the incidence angle increases, the effect of roughness becomes stronger. (Ulaby *et al.* 1994).

For both incidence angles, the values of the dielectric constant predicted by the algorithm fall within the 20% of the measured values. The average error is 3.52 for values at 20° and 3.54 for those at 30°, with a percentage error of 30%. Thus, even if the wet-dry trend is respected, the error bars are still large and this prevents from a finer distinction among different soil moisture conditions.

In order to reduce the variance on estimates, it is possible to make iterative estimates thus reducing the integration window for ε.

Table 1. Comparison between measured and predicted values of the dielectric constant

Place	ε meas.	ε estim. 20°	ε estim. 30°
Marfeld.1	8.78	8.92	11.19
Marfeld.2	14.83	16.09	15.27
Niedir.1	13.51	14.05	16.36
Niedir.2	10.46	9.94	11.67
Suberg1	6.71	8.75	7.46
Suberg2	11.32	12.93	14.36
Suberg3	11.32	9.81	10.59
Suberg4	10.04	8.61	7.87
Suberg5	18.99	15.33	15.35
Suberg6	10.46	15.01	12.94
Beulach1	7.12	11.67	12.60
Beulach2	8.77	10.10	11.79
Suberg7	15.30	17.31	16.20
Suberg8	15.75	17.43	16.24

The new integration window will be centred on the previous estimated value with a width equal to the error (Haddad *et al.* 1994). This method is equivalent to update the prior density function and to apply the algorithm repeatedly. The procedure is reiterated until the error on estimates scales down to less than 10%. The results after the fourth run are reported in table 2. After the fourth run, all estimated values have a percentage error lower than 10%. The error for the experimental measurements is around 10%. As one can deduce from tables 1 and 2, the estimated values obtained after four runs are worse than those obtained after the first. However, after the first run, the error on estimates was so high that the estimates cannot be considered reliable.

Till now, the inversion algorithm has been applied to extract soil moisture information starting from radar measurements of backscattering coefficients, σ^0_{HH}, and emissivity, e_H (indicated as 1f). Theoretically, it can be applied to a wider variety of situations, providing:

1. The knowledge of theoretical models able to describe the interactions between the electromagnetic radiation and natural surfaces;
2. A reliable and complete data set of radar and ground truth measurements;
3. Some prior information would be particular useful in order to reduce the uncertainty on estimates.
4. As the process is divided in a training and test phase, the availability of an exhaustive experimental data set is necessary in order to cover many situations and make the inversion process more robust.

As a further application of the algorithm, the procedure has been extended to the case where multi-frequency and multi-polarisation data are available.

Table 2. Comparison between measured and predicted values of the dielectric constant after the 4th run

Place	ε meas.	ε estim. 4th run	error 4th run
Marfeld.1	8.78	7.90	0.68
Marfeld.2	14.83	16.72	1.66
Niedir.1	13.51	14.10	0.91
Niedir.2	10.46	9.72	0.68
Suberg1	6.71	7.56	0.68
Suberg2	11.32	12.69	0.75
Suberg3	11.32	9.81	1.14
Suberg4	10.04	7.76	0.66
Suberg5	18.99	16.19	1.14
Suberg6	10.46	13.77	1.41
Beulach1	7.12	9.73	0.72
Beulach2	8.77	9.50	1.06
Suberg7	15.30	17.73	1.42
Suberg8	15.75	17.10	1.01

Of course, the crucial point is the determination of the posterior density function and consequently of the joint density function. The following formulation can be considered a generalisation of equation (7):

$$P(R_1, R_2, ..., R_n) = \prod_{i=0}^{n} P_i(R_i) \quad , \qquad (10)$$

where $P_i(R_i)$ is the probability density function of a single source and the expression (10) is valid as long as all the sources are reasonably independent. The algorithm is now applied to the following cases:

1. Backscattering coefficients for HH polarisation at 4.6 GHz, emissivity for H polarisation at 3.1 GHz and 4.6 GHz (indicated as 2f);
2. Backscattering coefficients for HH and VV polarisations at 4.6 GHz, emissivity for H and V polarizations at 4.6 GHz (indicated as HV).

The estimation of the gaussian parameters leads to: μ= 0.97 and σ= 0.05 for e_H at 3.1 GHz, μ= 0.99 and σ= 0.03 for e_V at 4.6 GHz and μ = 1.02 and σ= 0.15 for σ^0_{VV} at 4.6 GHz.

The data in the training and test phase are the same considered in the previous attempt, adding data for 3.1 Ghz and for VV polarisation.

In tables 3, the estimates in these configurations after a single run are listed. Table 4 reports the inversion error in each case. The configuration, where the two polarisations are employed, provides, already after the first run, an error lower than the other configurations.

It should be noted that using also the 3.1 GHz data, no improvements are obtained. This is due to the fact that between 4.6 GHz and 3.1 Ghz there is not a great difference in terrain response. In this case, the L-band, 1.4 Ghz is indicated as the best suited for its radiometric sensitivity (Du *et al.* 2000).

Table 3. Comparison between measured and predicted values of the dielectric constant for different sensor configurations

Place	ε meas.	ε estim. 2 f	ε estim. HV
Marfeld.1	8.78	8.57	6.63
Marfeld.2	14.83	15.93	18.28
Niedir.1	13.51	15.0	17.39
Niedir.2	10.46	10.55	10.20
Suberg1	6.71	8.50	6.53
Suberg2	11.32	12.54	11.30
Suberg3	11.32	9.56	8.34
Suberg4	10.04	8.45	7.59
Suberg5	18.99	17.56	18.95
Suberg6	10.46	14.47	15.44
Beulach1	7.12	11.47	7.74
Beulach2	8.77	9.96	6.91
Suberg7	15.30	17.33	18.74
Suberg8	15.75	18.44	19.02

Table 4. Comparison among inversion errors on the estimated values of the dielectric constant for the different sensor configurations.

Place	error estim. 1f	error estim. 2 f	error estim. HV
Marfeld.1	3.86	3.76	2.21
Marfeld.2	3.05	3.03	1.52
Niedir.1	3.26	2.91	1.81
Niedir.2	3.5	3.19	1.77
Suberg1	3.81	3.75	2.2
Suberg2	4.03	4.07	3.48
Suberg3	4.12	4.12	3.39
Suberg4	3.78	3.77	2.96
Suberg5	3.62	2.07	0.98
Suberg6	3.47	3.67	2.67
Beulach1	4.17	4.24	3.07
Beulach2	4.15	4.16	2.08
Suberg7	2.27	2.21	1.1
Suberg8	2.2	1.43	1.3

The problem of applying this algorithm to space-borne and air-borne data lies in the difficulty of having contemporary acquisitions on the same area.

The results of our preliminary attempt are listed in table 5. The first three lines refer to data of an air-borne radiometer (IROE) operating at 6.8 GHz and of RADARSAT working in the C-band (5.3 GHz), both in horizontal polarisation, at 20°, while the last three ones to the same radiometer in combination with ERS-2 radar acquisitions (VV polarisation, at 23°). The second and third column report results after the first and third processing run respectively. The main drawback of these data is that sensor acquisitions and ground truth measurements have been carried out within a period of 10 days.

5 ERROR ANALYSIS

The analysis developed in this work indicates that the combination of active and passive microwave sensors could be suitable for soil moisture extraction, helping to resolve radar measurements ambiguity due to roughness effect, provided that error sources in processed data are understood and quantified. Figure 1 reports in a contour plot the variation of measured dielectric constant in correspondence of emissivity and backscattering coefficient values.

There is not a net dependence of dielectric constant on backscattering coefficients and emissivity, and different values of backscattering coefficients and emissivity correspond to the same value of dielectric constant. Particularly, there are two contours for $\varepsilon = 8$ and $\varepsilon = 10$, that probably create ambiguity in the inversion procedure. This may be due to measurements errors, both in the radar response and the estimation of surface parameters, and to the influence of roughness.

Table 5. Comparison between measured and predicted values of the dielectric constant using airborne and space-borne data

Field	ε meas.	ε estim. 1st run	ε estim. 3rd run
304 (14/5)	6.76	10.13	7.38
501	5.86	5.75	5.42
121 (14/5)	9.91	10.43	8.89
304 (8/5)	9.16	10.10	7.98
121 (8/5)	5.85	9.07	6.42
102	3.92	10.23	7.26

The contour plot of the estimated dielectric constant (fig.2) does not exactly reproduce that of the measured ones and above all the higher value of dielectric constant are not present.

Admittedly, the algorithm is able to make a rough distinction between wet and dry conditions, but in the first run its estimates have a high variance. The iterative process is necessary to lower the variance, with a little worsening on the dielectric constant estimates (fig.3).

The advantage of introducing other information as other polarisations is immediately evident. If the measured values of dielectric constant are plotted against emissivity and backscattering coefficients in the vertical polarisation, the graph shows a trend that helps the inversion process and produces low errors on estimates (fig. 4). In fact, the average error is already 2.10 at the first run (table 4).

Furthermore, in this case the higher values of dielectric constant are also satisfactorily estimated (fig. 5).

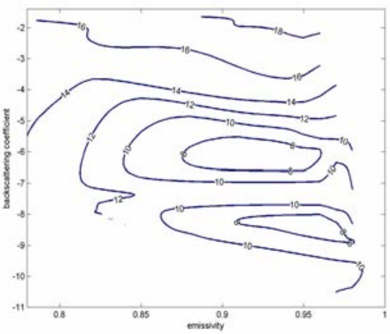

Figure 1. Contour plot mapping the values of the dielectric constant against those of emissivity and backscattering coefficients

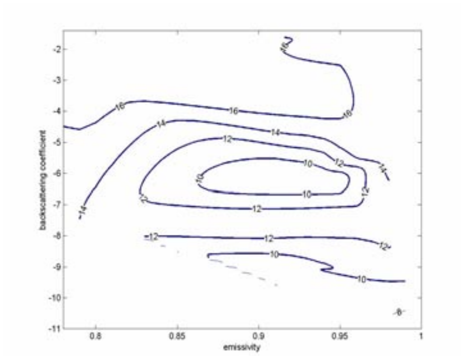

Figure 2. Contour plot mapping the estimated values of the dielectric constant for 20° after the first run.

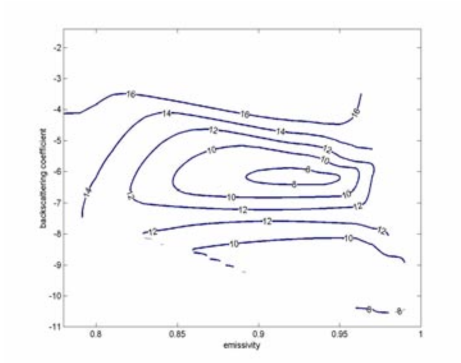

Figure 3. Contour plot mapping the estimated values of the dielectric constant for 20° after the fourth run.

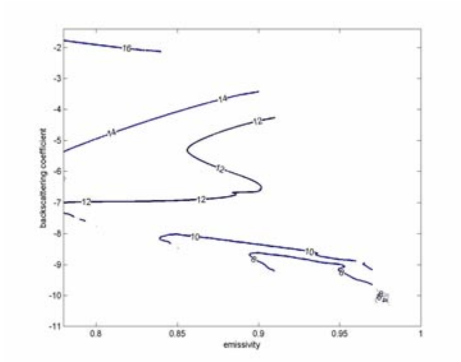

Figure 4. Contour plot mapping the measured values of the dielectric constant in the case of the vertical polarization.

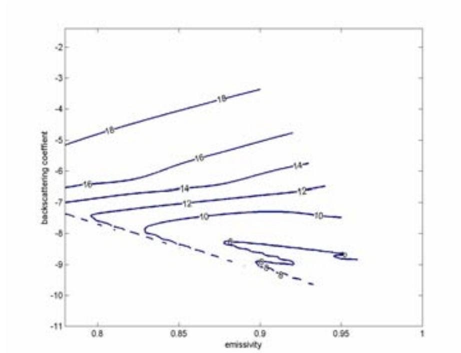

Figure 5. Contour plot mapping the estimated values for 20° using data vertical polarization.

6 CONCLUSIONS AND FURTHER DEVELOPMENTS

This work has analysed and developed an inversion algorithm aiming at estimating soil moisture from remotely sensed data. The procedure is based on a Bayesian approach, including noisy elements in the posterior probability density function.

It could be further improved eliminating its built-in limitation:

- The correlation length is not taken into account;
- It has been applied to data of ground-based instruments.

For the first item, the posterior density function can be written with dependence on all surface parameters as ε, *s* and *l* (Tanner 1996):

$$P(\varepsilon,s,l \mid D_1,D_2,...,D_n) = \frac{P_{prior}(\varepsilon)P_{prior}(s,l)P_{post}(D_1,D_2,...,D_n \mid \varepsilon,s,l)}{P(D_1,D_2,...,D_n)}, \quad (11)$$

where $D_1, D_2,..., D_n$ are the data deriving from different sensors and/or different sensor configurations, and in the prior density function the dependence on soil moisture and roughness parameters has been split. A posterior distribution for only ε can be obtained as follows:

$$P(\varepsilon \mid D_1,D_2,...,D_n) = \frac{\iint_{s,l} P_{prior}(\varepsilon)P_{prior}(s,l)P_{post}(D_1,D_2,...,D_n \mid \varepsilon,s)dsdl}{P(D_1,D_2,...,D_n)} \quad (12)$$

This integral can be computed if prior information on *s* and *l*, are available (Davidson *et al.* 2001}. To have reliable estimates of $P_{prior}(s, l)$, large data sets of profile roughness measurements are needed.

The training and test phases of the algorithm have been performed on data derived from ground-based instruments. These data offer the major advantage that a great variety of radar and ground truth measurements are available. Moreover, the flexibility of an instrument, like the scatterometer, allows designing and carrying out experiments that fit special requirements. However, the testing of the algorithm to a variety of data from airborne and space-borne systems is an envisaged application.

ACKNOWLEDGEMENTS

The Italian Space Agency under contract ASI-ARS I/R/167/00 supports the work.

We thank Dr. Simonetta Paloscia who has kindly provided us with the airborne and space-borne data.

REFERENCES

Davidson, M.W.J., T. Le Toan, F. Mattia, G.Satalino, N.E.C. Verhoest, M. Borgeaud, Improving soil moisture retrieval by incorporating a priori information on roughness parameters, *Proceedings of Igarss 2001*, Vol.3, 1421-1423, Sidney (AU), 9-13 July 2001.

Davis, D.T., Z. Chen, J. Hwang, L. Tsang, E. Njoku, Solving inverse problem by bayesian iterative inversion of a forward model with application to parameters mapping using SMMR remote sensing data , *IEEE Transaction on Geoscience and Remote Sensing,* Vol.33, No. 5, 1182-1192, July 1995.

Du, Y., F.T. Ulaby, M.C. Dobson, Sensitivity to soil moisture by active and passive microwave sensors, *IEEE Transaction on Geoscience and Remote Sensing,* Vol.38, No. 1, 105-113, January 2000.

Fung, A.K., *Microwave scattering and emission model and their application,* Artec House, Norwood, MA, 1994.

Haddad, Z.S., P.C. Dubois, Bayesian estimation of soil parameters from remote sensing data, *Proceedings of Igarss '94,* Vol.3, 1421-1423, Pasadena (CA), 8-12 August 1994.

Hallikainen, M.T., F.T. Ulaby, M.C.Dobson, M.A.El-Rayes, L.Wu, Microwave dielectric behaviour of wet soil - Part I: empirical models and experimental observations, *IEEE Transaction on Geoscience and Remote Sensing*, Vol.G.E.-23, No. 1, 25-34, January 1985.

Mattia, F., T.Le Toan, J.C.Souyris, G.De Carolis, N. Floury, F. Posa, G. Pasquariello, The effect of surface roughness on multifrequency polarimetric SAR data, *IEEE Transaction on Geoscience and Remote Sensing*, Vol.35, No. 4, 954-965, July 1997.

Nezry, E. , F. Yakam-Simen, I. Supit, F. Zagolsky, Retrieval of environmental and geophysical parameters through bayesian fusion of ERS and RADARSAT data, *Proceedings of 3rd ERS Symposium (ESA)*, 18-21 March 1997, Florence (Italy).

Saatchi, S.S., E.G.Njoku, U.Wegmueller, Synergism of active and passive microwave data for estimating bare soil surface mositure, *ESA/NASA International Workshop*, B.J Choudhury, Y.H.Kerr, E.N.Njoku and P.Pampaloni}, 205-224, 1994.

Satalino, G., G.Pasquariello, F.Mattia, T.Le Toan, M. Davidson, M. Borgeaud, The potential of multi-angle C-band SAR data for soil moisture retrieval, *Proceedings of the International Geoscience and Remote Sensing Symposium, IGARSS 1999*, Vol.G.E-18, 288-295,1980.

Stuart, A. , J.K. Ord, *Advanced theory of statistics*, Charles Griffin - Company Limited, London, 5th ed., Vol.1, 1996.

Tanner, M.*, Tools for statistical inference: methods for the exploration of posterior distribution and likelihood functions*, New York, Springer Verlag, 3rd ed., 1996.

Ulaby F.T., Moore R. K., Fung A. K., *Microwave Remote Sensing: Active and Passive*, Vol. I, Artech House, Norwood, MA, 1986.

Wegmueller, U., C.Maeztler, R.Hueppi, E.Schanda, Active and passive microwave signature catalog on bare soil (2-12 GHz), *IEEE Transaction on Geoscience and Remote Sensing,* Vol.32, No. 3 , 698-702, May 1994.

Wang, J.R., B.J. Choudhury, Passive microwave radiation from soil: examples of emission model and observations, *Passive Microwave Remote Sensing of Land-Atmosphere Interactions*, VSP Publishing, 1995.