# ESTIMATION OF PHYSICAL PARAMETERS OF A MULTILAYERED MULTI-SCALE VEGETATED SURFACE

I. Hosni [a,*], L. Bennaceur Farah [a], M. S. Naceur [a], I.R. Farah [b]

[a] LTSIRS, ENIT, Université El Manar, Tunis, Tunisia – hosni_ibtissem@yahoo.fr; lilia.bennaceur@ipeit.rnu.tn; naceurs@yahoo.fr
[b] RIADI, ENSI, Université de la Manouba, Tunis, Tunisia – riadh.farah@ensi.rnu.tn

**Commission VI, WG VI/4**

**KEY WORDS:** moisture, estimating, synergistic methodology, WCM, backscattering, vegetation.

**ABSTRACT:**

Soil moisture is important to enable the growth of vegetation in the way that it also conditions the development of plant population. Additionally, its assessment is important in hydrology and agronomy, and is a warning parameter for desertification.
Furthermore, the soil moisture content affects exchanges with the atmosphere via the energy balance at the soil surface; it is significant due to its impact on soil evaporation and transpiration. Therefore, it conditions the energy transfer between Earth and atmosphere.
Many remote sensing methods were tested. For the soil moisture; the first methods relied on the optical domain (short wavelengths). Obviously, due to atmospheric effects and the presence of clouds and vegetation cover, this approach is doomed to fail in most cases. Therefore, the presence of vegetation canopy complicates the retrieval of soil moisture because the canopy contains moisture of its own.
This paper presents a synergistic methodology of SAR and optical remote sensing data, and it’s for simulation of statistical parameters of soil from C-band radar measurements. Vegetation coverage, which can be easily estimated from optical data, was combined in the backscattering model. The total backscattering was divided into the amount attributed to areas covered with vegetation and that attributed to areas of bare soil.
Backscattering coefficients were simulated using the established backscattering model.
A two-dimensional multiscale SPM model has been employed to investigate the problem of electromagnetic scattering from an underlying soil. The water cloud model (WCM) is used to account for the effect of vegetation water content on radar backscatter data, whereof to eliminate the impact of vegetation layer and isolate the contributions of vegetation scattering and absorption from the total backscattering coefficient.

## 1 INTRODUCTION

Monitoring spatial patterns of properties of the soil in general, and the estimate of the true moisture soil in particular, is a crucial task of the Environmental Remote Sensing [Schmugge et al., 2002]. The spatio-temporal dynamics of soil moisture is especially needed to monitor semi-arid regions where drought stress can determine the productivity of woody and herbaceous vegetation [Kumar et al., 2002; Tansey & Millington, 2001].
The variation in the soil dielectric constant, as a result of the variation of the moisture content, has a greater influence than other characteristics [Svoray et al,. 2004]. Therefore, remote sensing radar is sensitive to soil moisture because the dielectric constant is one of the most important factors in radar backscatter intensity [Wang et al,. 2004].

The characterization of soil surface roughness is also a key requirement for the correct analysis of radar backscattering behavior. Several experimental and theoretical studies have been published dealing with the potential of radar backscattering to aid mapping of the distribution and morphology of shallow sub-surface features within a large spatial variability of classical roughness parameters ([Chen et al., 1988][Davidson et al,. 20000][Fung, 1994][Oh et al., 1992]). They used the classical statistical description of natural surfaces and characterized roughness by statistical parameters namely correlation length and standard deviation.
Nevertheless, the unreliability of the classical description of natural surfaces and their large spatial variability that affects the correlation function may render the classical roughness parameters highly variable and unstable.
Many previous works have been devoted to the analysis of the backscattering characteristics of bare soils and have considered that natural surfaces are better described as self-affine random processes (1/f processes) than as stationary processes ([Farah L et al., 2006] [Birshak et al., 1974] [Song et al., 2009]).
Furthermore, an important number of models simulating SAR backscattering have been developed for bare soils. Nevertheless, these models cannot be applied directly in vegetated areas due to the scattering of vegetation layer above the soil surface, it absorbs and scatters part of the incident microwave signal on it as well as the reflected microwave energy from underneath the soil surface. The amount that the vegetation absorbs is mainly a result of its water content while the scattering is influenced by its geometry. The effect of vegetation on backscattering decreases with increasing wavelength [Ulaby et al., 1981].
Therefore the backscattering on vegetated areas consists of the study of backscattering from the vegetation and the volume scattering from the underlying layers of the soils.
Since natural surface parameters (soil moisture and surface roughness) cannot be controlled, many studies have focused on how best to configure the radar sensor parameters for optimum analysis of vegetation impact on backscattering [Svoray et al., 2002] [Svoray et al., 2001].

Many backscattering models [Bindlish et al., 2001][Prakash et al., 2012] have been developed over the past 30 years to help determine the relationship between the radar signal and certain biophysical parameters, where numerous studies have been carried out to further the understanding of the effect of surface parameters and vegetation [Gutman et al., 1998][Zribi et al., 2003] in radar backscattering systems.

The standard theoretical backscattering model witch is best suited for very smooth surfaces is the small perturbation model (SPM) [Chen et al., 1988].

The SPM was originally developed for scattering from a bare soil surface, and therefore the vegetation scattering effects are not explicitly incorporated in the model.

On the other hand, the semi-empirical water cloud model, has been shown in various studies [Ulaby et al., 1979][Tansey et Millington, 2001] to ensure an adequate representation of vegetation canopy backscattering, as well as the soil beneath over the phenological cycle of crops.

In this study, we tried to develop a microwave/optical synergistic method by coupling the water cloud model and a two dimensional SPM model with considering the multi scale description of soil surfaces, for the purpose of unraveling the scattering problem of electromagnetic waves from randomly rough vegetated surfaces.

Moreover, we aim to develop and test an inversion algorithm in order to retrieve the soil moisture and multi-scale roughness parameters using as input the radar backscattering coefficients simulated by the proposed synergistic methodology and using a multilayer neural network (NN) architecture trained by a back propagation learning rule.

For this purpose, we proceed as follows:

The first section outlines a comparison between the Active and the Passive Microwave Remote Sensing. Section 2 described a two dimensional multi-scale description of natural surfaces simulated as a three-layered structure.

Then, a backscattering model for investigating the effect of bare soil and vegetation parameters on backscattered energy of radar signal has been carried out in Section 3.

The next section showed a sensitivity analysis of the impact of multi-scale parameters (roughness and moisture) on the amount of radar backscattering coefficient.

In the next section a neural network based inversion procedure, the results and their accuracy were applied to estimate soil roughness and moisture.

Finally, we present our conclusions in the last section.

## 2 THEORY BEHIND REMOTE SENSING OF SOIL PARAMETERS

By gathering rainwater, soil likewise gives a place to be stored for rain, and thus helps to prevent flooding.

Water is not the only substance that the soil stores; it also consists of air, which represents a significant percentage of its volume. Thus, oxygen is needed for plant roots and vast masses of people living organisms in the sub-soils.

Besides, plants and variations of the surface roughness can reduce the sensitivity of the microwave observations of changes in soil moisture. These effects increase as the frequency increases.

The low frequencies can help in providing a sensitivity analysis to changes in soil moisture through a wide range of conditions of vegetation. They are better suited to monitoring the soil moisture, as they can easily penetrate plant cover for detecting moisture.

However, with higher frequencies, adjustments are required to reduce atmospheric effects that severely limit the capabilities of microwave instruments.

Moreover, soils and their properties are seen as functions of soil-forming factors. Creatures that live in the ground die there too, generating organic matter disintegrated with a range of dead organisms on the surface: trees and other plants and the decomposed corpses of animals and humans that will ultimately become as well a part of the sub-soils.

Both active and passive microwave remote sensing techniques utilize the large contrast between the dielectric constant of dry soil and water [Zhen et al., 2002] and can be used in all weathers for land-surface monitoring.

Many factors may affect the microwave signature such as description of soil and the vegetation characteristics.

Surface roughness in radar remote sensing has generally been described as a stationary single scale process characterized by the root mean square height (s) and the autocorrelation function.

Investigating the impact of vegetation on backscattering radar signals is a recurring theme in research in remote sensing. The techniques for monitoring and estimating crop yields, estimating biomass and leaf area index and the vegetation classes in cartography are not rich in literature.

These techniques were developed largely for analysis of medium resolution sensor products, suitable for characterizing relatively large areas. However, the advent of commercial high-resolution imaging satellites presents new opportunities for characterizing vegetation in greater detail than previously was practical.

The ability to discriminate crop type and phenology stage with radar may be attributed to changes in both canopy geometry and plant biophysical parameters. The radar frequency and incidence angle will influence the relationship.

The effects of plant parameters including biomass, plant water content, plant height and leaf area index (LAI) on radar backscatter are well documented for a variety of different crops [Brakke et al., 1981]. LAI is defined as the one-sided green leaf area per unit ground [Rozenthal et al., 1985].

### 2.1 The Water Cloud Model for Vegetation

A classical simplified model used for exploring the basic microwave response of vegetation canopies is the water cloud model (WCM) whereby the canopy is modelled as a cloud of identical, randomly oriented scatterers.

The WCM was developed by Attema & Ulaby in 1978 and modified or extended subsequently by various authors [Hoekman et al., 1982] [Ulaby et al., 1984] [Paris, J., 1986]. In these models, the power backscattered by the whole canopy is represented as an incoherent sum of the contributions of vegetation and soil. These models are simple and use few parameters and variables. The canopy is represented by “bulk” variables such as Leaf Area Index (LAI) or total water content.

In the WCM, the vegetation layer is modelled by assuming that its dielectric constant, or permittivity is a random process, the moments of which (i.e. mean and correlation functions) are known. The microwave dielectric constant of dry vegetative matter is much smaller than the dielectric constant of water. Because of the “green” water-rich portion of the canopy (the leaves) constitutes one per cent or less of the overall volume. [Attema & Ulaby 1978] proposed that the canopy can be modeled as a water cloud whose droplets are held in place by structurally dry matter.

In the water cloud model, the power backscattered by the whole canopy ($\sigma^0$) is represented as the incoherent sum of the contribution of the vegetation ($\sigma^0_{veg}$), the contribution of the underlying soil ($\sigma^0_{soil}$), which is attenuated by the vegetation layer and the interaction between the vegetation layer and the soil accounts for multiple scattering effects ($\sigma^0_{veg+soil}$). Thus, the backscattering coefficient can be represented in the following equation:

$$\sigma^0 = \sigma^0_{veg}(\theta) + \gamma^2(\theta)\sigma^0_{soil}(\theta) + \sigma^0_{veg+soil} \quad (1)$$

$\gamma^2$ is the two-way attenuation through the canopy. In co-polarized power scattered, the internal soil-vegetation interactions is not a dominating factor and thus can be neglected [Dobson et al., 1986] [Prevot et al., 1993a]. Many modifications to the model have been reported [Ulaby et al., 1982] [Bindlish et al., 2001]. Hence the equation is modified to:

$$\sigma^0 = \sigma^0_{veg}(\theta) + \gamma^2(\theta)\sigma^0_{soil}(\theta) \quad (2)$$

$$\sigma^0_{veg}(\theta) = A\, V_1 \cos(\theta)[1 - \gamma^2(\theta)] \quad (3)$$
$$\gamma^2(\theta) = exp[-2\, B\, V_2 / \cos(\theta)] \quad (4)$$

$$\sigma^0_{soil}(\theta) = C + DM_v \quad (5)$$

A and B are the vegetation parameters, they are empirical coefficients. A is the growth condition and B is the radar frequency. These two parameters depend on the vegetation type. C and D are bare soil parameters.
$V_1$ is a description of the canopy, and $V_2$ is a second description of the canopy. These two parameters describe the effect of canopy geometry and water content on the backscatter coefficient, and because an important part of the scattering and attenuation is controlled by the leaves, many studies [Lievens et al., 2011] [Moran et al., 1998] [Prevot et al., 1993a] propose using the LAI (kg m−2) as the canopy descriptor.

## 3 A MULTILAYER DESCRIPTION OF NATURAL SOILS

### 3.1 Description of soil moisture

The proposed 2D description of the studied soil is showed below in figure 1. Medium 0 and 3 are half-spaces. $\boldsymbol{d_1}$ and $\boldsymbol{d_2}$ are respectively the thicknesses of medium 1 and medium 2, $\boldsymbol{D}$ is the radar penetration depth. $\boldsymbol{E_i}$ and $\boldsymbol{E_r}$ are the incidence and reflected radar signal between mediums [Song et al., 2009].
This approach is conceptual as there is no physical layer, but rather a continuous variability. $\boldsymbol{\varepsilon_{app}}$ is the effective permittivity of the soil [Zribi et al., 2008].
The interface sandwiched between regions 0 and 1 is a 2D infinite rough interface represented by a continuum of plane waves and considered as a band limited fractal random process corresponding to a superposition of a finite number of one dimensional Gaussian processes [Farah, L et al., 2006].
The calculation of the dielectric constant is based on the consideration of a soil including the two fractions, a fraction of the soil and an air fraction.

$$\varepsilon_{app} = [v_{sol} * \varepsilon^{\alpha}_{sol} + (1 - v_{sol}) * \varepsilon^{\alpha}_{air}]^{\frac{1}{\alpha}} \quad (6)$$

$\nu_{soil}$ is the fraction of the soil, $\varepsilon_{soil}$ is the dielectric constant of soil, $\varepsilon_{air}$ is the dielectric constant of the air, the exponent $\alpha = 0.5$ which represents best the mixing model.

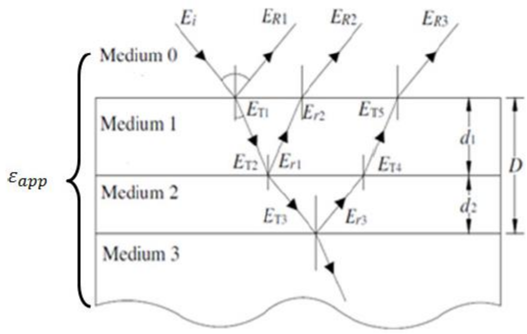


Figure 1: Studied surface geometry

### 3.2 Roughness multi-scale 2D description

Natural roughness is described as a multi-scale process having a $\boldsymbol{1/f}$ spectrum with a finite range of spatial scales going from a few millimeters b ($\boldsymbol{b \leq \lambda/10}$) to several meters ($\boldsymbol{b}$ ≤resolution cell) [Davidson et al., 2000] [Mattia et al., 1999]. We have considered the surface as a superposition of a finite number of one-dimensional Gaussian processes each one having a spatial scale [Song et al., 2009] characterized by:

$$\boldsymbol{Z_p(x) = \sum_{m=-P_1}^{P_2} \sum_{n=-\infty}^{+\infty} Z^m_n \Psi^m_n(\frac{x}{L})} \quad (7)$$

Where $Z^m_n$ is a collection of Gaussian random independent variables with variance $\gamma^2_0 2^{-m}$, x is a normalized distance with respect to an arbitrary length $L = 2^b\, b$ and $\Psi^m_n$ is a collection of orthonormal wavelet (4th Daubechies). The roughness multiscale parameter $\nu$ is related to the fractal dimension ($\nu = 5 - 2D$ for mono-dimensional Euclidean surfaces and $\nu = 7 - 2D$ for bi-dimensional surfaces [Mattia et al., 1999]) and γ is related to the standard deviation and the number of spatial scales is equal to $P$.
In a previous work [Farah, L et al., 2006] [Farah, L et al., 2010], to describe more adequately natural surfaced, we have used the separable dyadic multi-resolution analysis introduced by Mallat [Mallat et al., 1989] to extend the wavelet theory from one-dimensional to two-dimensional case.

Using the bi-dimensional wavelet transform, we have obtained respectively the vertical wavelet component (9), the horizontal wavelet component (8) and the diagonal wavelet component (10) of the height $Z^i_p$, (where *i*=Vertical, Horizontal or Diagonal).

$$z^H_P(x,y) = \sum_{m_x=0}^{P} \sum_{m_y=0}^{P} \sum_{n_x=-\infty}^{+\infty} \sum_{n_y=-\infty}^{+\infty} z^{m_x}_{n_x} z^{m_y}_{n_y} \psi(\frac{2^{m_x}}{B}x - n_x)\phi(\frac{2^{m_y}}{B}y - n_y) \quad (8)$$

$$z^V_P(x,y) = \sum_{m_x=0}^{P} \sum_{m_y=0}^{P} \sum_{n_x=-\infty}^{+\infty} \sum_{n_y=-\infty}^{+\infty} z^{m_x}_{n_x} z^{m_y}_{n_y} \phi(\frac{2^{m_x}}{B}x - n_x)\psi(\frac{2^{m_y}}{B}y - n_y) \quad (9)$$

$$z^D_P(x,y) = \sum_{m_x=0}^{P} \sum_{m_y=0}^{P} \sum_{n_x=-\infty}^{+\infty} \sum_{n_y=-\infty}^{+\infty} z^{m_x}_{n_x} z^{m_y}_{n_y} \psi(\frac{2^{m_x}}{B}x - n_x)\psi(\frac{2^{m_y}}{B}y - n_y) \quad (10)$$

And the standard deviation can be written as:

$$s^2 = r^H_c(0,0) = r^D_c(0,0) = r^V_c(0,0) \quad (11)$$

We have simulated the 3D representation of the MLS surfaces for two different spatial scales, with P=5 in figure 2 and P=10 in figures 2 and 3.

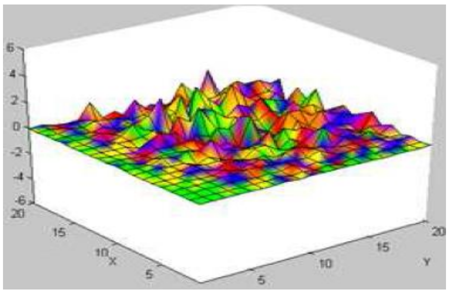

Figure 2: 3D representation of a multi-scale surface using Daubechies wavelet with multi-scale parameters (**$\nu_1$**=1.3; **$\nu_2$**=1.3; **$\gamma$**= 0.2 cm), P=5

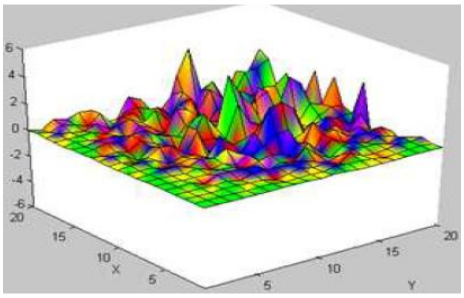

Figure 3: 3D representation of a multi-scale surface using Daubechies wavelet with multi-scale parameters ($\nu_1$=1.3; $\nu_2$=1.3; $\gamma$= 0.2 cm), P=10

## 4 MULTISCALE SURFACE MODEL FOR BACKSCATTERING COEFFICIENT CALCULATING

As humidity increases, the dielectric constant of the soil-water mixture increases and this change is detected by microwave sensors. In general, an increase in humidity of the soil leads to an increased backscattering coefficient. Despite the high sensitivity to soil moisture, the link between SAR signal and soil moisture is attenuated by variations in the geometrical structure of the soil surface (topography, roughness) and the density of the vegetation.

In this study, a MLS SPM 2D was adopted for characterizing the backscattering from a three layered structure.

The backscattering coefficient is calculated by a three-layered multi-scale SPM 2D, and is given by:

$$\sigma_{vv} = 8k^4\sigma_1^2\left|R_{\parallel}cos^2\theta + \frac{sin^2\theta(1+R_{\parallel})^2}{2}\left(1-\frac{1}{\varepsilon_{app}}\right)\right|^2 W(2ksin\theta,0) \quad (12)$$

$$\sigma_{hh} = 8k^4\sigma_1^2|R_{\perp}cos^2\theta|^2 W(2ksin\theta,0) \quad (13)$$

$$I_{qp} = (2kcos(\theta)\sigma)f_{qp}e^{-k^2cos^2(\theta)\sigma^2} + \frac{(kcos(\theta)\sigma)}{2}\left[F_{qp}(-k\,sin(\theta)) + F_{qp}(k\,sin(\theta))\right] \quad (14)$$

$$W^n(-2k_x,0) = \frac{2}{\pi}\int_0^{\infty}\int_0^{\infty}\left(\frac{r_c^i(\xi,\eta)}{r_c^i(0,0)}\right)^n \cos(2k_x\xi)d\xi d\eta \quad (15)$$

$I_{qp}$ is a function of $\theta$, the sub-scripts p and q indicate polarization state. $F_{qp}$ denotes the complementary field coefficient. $W^n$ is the Fourier transform of the n-th power of the surface correlation function. $\theta$ is the incident angle.

## 5 BACKSCATTERING COEFFICIENT DEPENDENCE ON MULTI-SCALE SOIL PARAMETERS

The model is based assumes that the the scattered field by a rough surface can be represented by an overlapping of plane waves propagating to the receiver. The amplitudes are determined using boundary conditions and divergence relationships.

The model of small perturbations is best suited to surfaces of low roughness or smooth surfaces.

The range of validity is limited to ks < 0,3 and m < 0,3 (k is the wave number, s is the standard deviation of heights and m is the standard deviation of slopes).

### 5.1 Impact of Multi-Scale Roughness parameters

To calculate direct backscattering and bi-static microwave scattering from the multi-layer medium has been studied based on three-layered multi-scale SPM 2D.

We study the effect of surface environments such as soil moisture and roughness on changes in SAR backscattering; therefore we have simulated the angular trends of the three layers multiscale backscattering coefficient from 20 to 70 degrees for different roughness parameters.

In order to analyze the scattering dependence on fractal parameter ν, plots of backscattering coefficients are reported in both Figure 4 and figure 5. Thus, we fixed the parameter related to the Root Mean Square at 0.0031cm in VV and HH polarizations for five spatial scales.

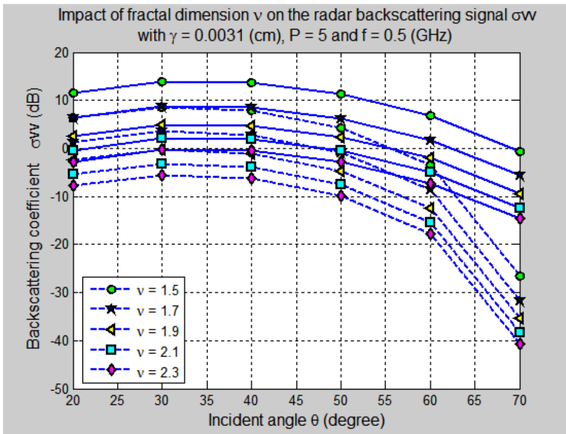


Figure 4: Backscattering coefficient dependence on fractal parameter ν at VV polarization for bare soil (dashed line) and for vegetated soil (full line)

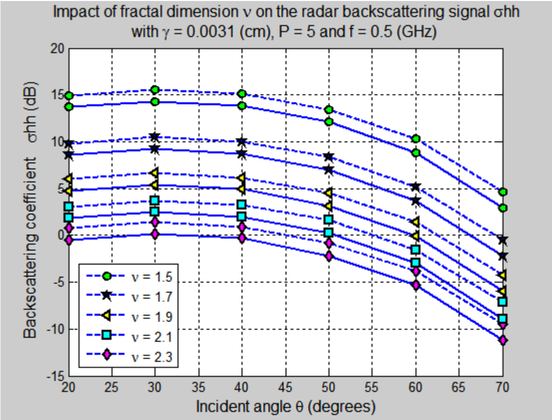


Figure 5: Backscattering coefficient dependence on fractal parameter ν at HH polarization for bare soil (dashed line) and for vegetated soil (full line)

It is noted that at small incidence angles, the backscattering coefficient increases as the fractal dimension *ν* increases, whereas at large incidence angles the dependence is just the opposite.

By setting, as a second step, the ν parameter at 1.3 in VV and HH polarizations for five spatial scales, we get in the Figure 6 and figure 7 the variation of the backscattering coefficient depending on the Root Mean Square γ at both polarizations VV and HH.

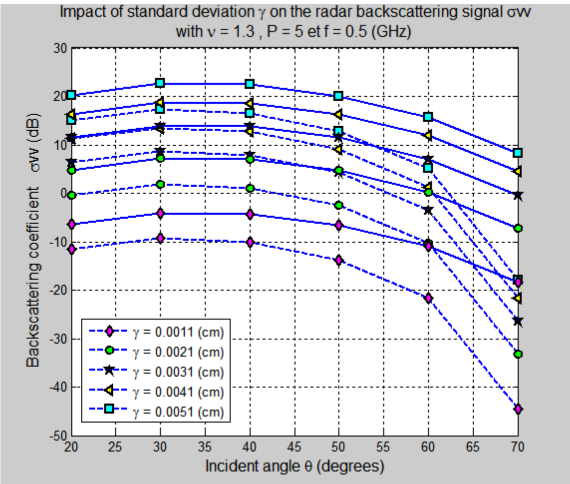


Figure 6: Backscattering coefficient dependence on **γ**, parameter related to the Root Mean Square at VV polarization for bare soil (dashed line) and for vegetated soil (full line)

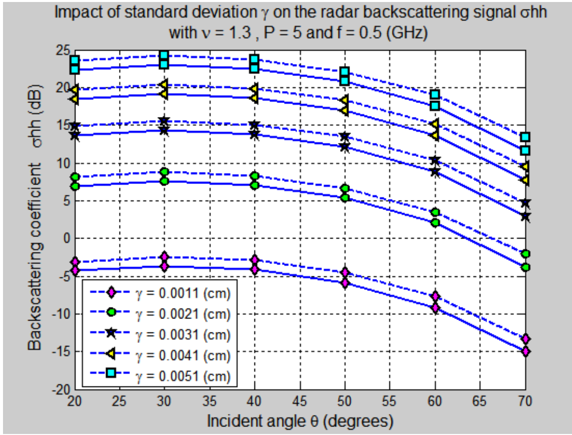


Figure 7: Backscattering coefficient dependence on **γ**, parameter related to the Root Mean Square at HH polarization for bare soil (dashed line) and for vegetated soil (full line)

It can be noted that the backscattering coefficient increases as γ, the parameter related to the standard deviation, increases.
For all the simulations, the backscattering coefficient decreases with the incidence angle. This signal attenuation can be explained by the fact that the vegetation canopy can mitigate the density of soil backscatter through the layer of leaves.

### 5.2 The Impact of soil moisture parameters

The soil moisture is related to the complex dielectric constant ε. In Figure 8, figure 9, figure 10 and figure 11, we have represented radar backscattering as angular trends for different values of the complex permittivity of the second effective layer in the two polarizations VV and HH.

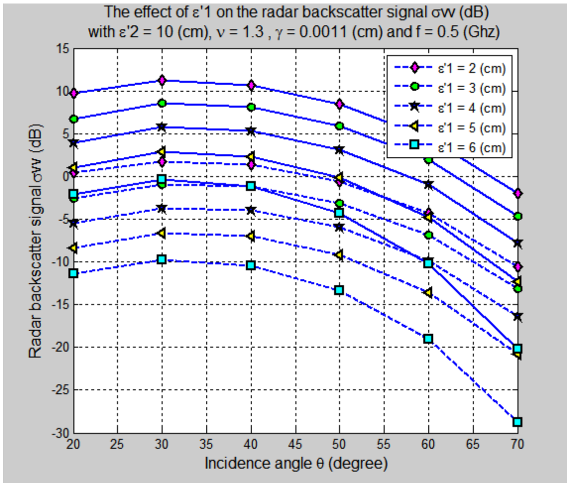


Figure 8: Backscattering coefficient dependence on $\boldsymbol{\varepsilon}_1'$ at VV polarization for bare soil (dashed line) and for vegetated soil (full line)

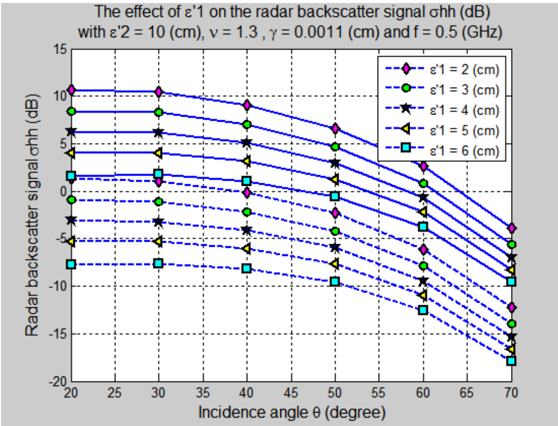


Figure 9: Backscattering coefficient dependence on $\boldsymbol{\varepsilon}_1'$ at HH polarization for bare soil (dashed line) and for vegetated soil (full line)

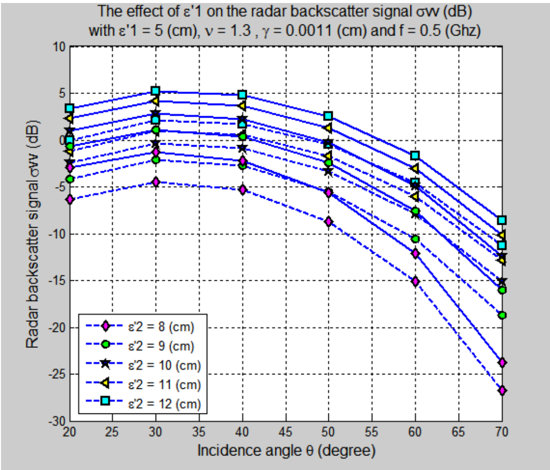


Figure 10: Backscattering coefficient dependence on $\varepsilon_2'$ at VV polarization for bare soil (dashed line) and for vegetated soil (full line)

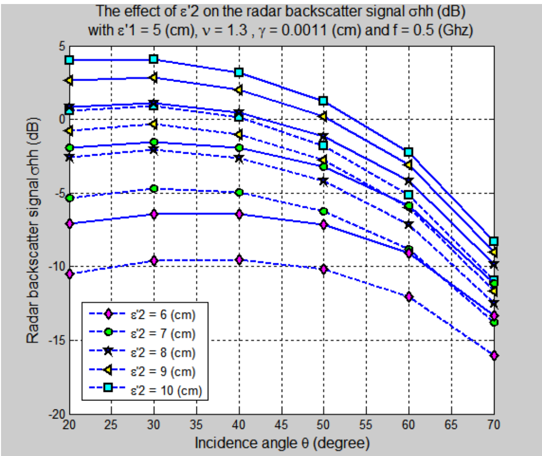


Figure 11: Backscattering coefficient dependence on $\varepsilon_2'$ at HH polarization for bare soil (dashed line) and for vegetated soil (full line)

It can be noted that at small incidence angles the backscattering coefficient decreases as soil moisture related to the dielectric constant, increases.

This can be explained that according to the abundance of vegetation, its dielectric properties, height and geometry (size, shape and orientation of its component parts) the sensitivity of microwave backscatter to volumetric soil moisture may be significantly reduced.

## 6 INVERSION STRATEGY

The input parameters correspond to the multi-angle scattering data. We introduced 12 backscattering coefficients for incident angles varying from 20 to 70 degrees at the both polarizations HH and VV.
We have opted the gradient backpropagation algorithm as learning algorithm that turns out the most appropriate to our inversion problem (Satalino et al., 2002).
We have used an input layer, two hidden layers and an output layer.

### 6.1 Inversion results

We have tested the network on known data to retrieve the sought parameters of moisture and multi-scale roughness. The following tables present respectively original and Retrieval Values.

| | S1 | S2 | S3 | S4 | S5 | S6 | S7 | S8 | S9 | S10 | S11 | S12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $\nu_1$ | 5,00 | 5,00 | 5,00 | 12,00 | 10,00 | 8,00 | 5,00 | 5,00 | 7,00 | 8,00 | 10,00 | 5,00 |
| $\nu_2$ | 10,00 | 10,00 | 10,00 | 14,00 | 14,00 | 12,00 | 12,00 | 10,00 | 15,00 | 12,00 | 15,00 | 10,00 |
| $\gamma_1$ | 1,30 | 1,50 | 1,70 | 1,50 | 1,90 | 1,30 | 1,50 | 1,70 | 1,50 | 1,90 | 1,30 | 2,10 |
| $\gamma_2$ | 1,30 | 1,50 | 1,70 | 1,50 | 1,90 | 1,30 | 1,50 | 1,70 | 1,50 | 1,90 | 1,30 | 2,10 |
| $\varepsilon_1$ | 0,21 | 0,21 | 0,31 | 0,41 | 0,51 | 0,61 | 0,31 | 0,31 | 0,51 | 0,41 | 0,21 | 0,51 |
| $\varepsilon_2$ | 0,21 | 0,21 | 0,31 | 0,41 | 0,51 | 0,61 | 0,31 | 0,31 | 0,51 | 0,41 | 0,21 | 0,51 |

TABLE I. ORIGINAL VALUES

| | S1 | S2 | S3 | S4 | S5 | S6 | S7 | S8 | S9 | S10 | S11 | S12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $\nu_1$ | 5.1032 | 4.9735 | 4.8851 | 11.8575 | 10.2328 | 7.9005 | 4.8195 | 4.8851 | 6.9636 | 7.6306 | 9.6049 | 4.7367 |
| $\nu_2$ | 10.2696 | 10.0558 | 10.1573 | 13.9151 | 14.6175 | 12.1100 | 12.1609 | 10.1573 | 14.9076 | 11.8672 | 14.4559 | 10.0338 |
| $\gamma_1$ | 1.3254 | 1.4962 | 1.7240 | 1.5130 | 1.8648 | 1.2972 | 1.5168 | 1.7240 | 1.5148 | 1.8888 | 1.2363 | 2.0791 |
| $\gamma_2$ | 1.3222 | 1.4954 | 1.7192 | 1.5109 | 1.8613 | 1.2972 | 1.5179 | 1.7192 | 1.5168 | 1.8917 | 1.2391 | 2.0805 |
| $\varepsilon_1$ | 0.2252 | 0.2132 | 0.3040 | 0.4124 | 0.4724 | 0.6076 | 0.3129 | 0.3040 | 0.5203 | 0.4216 | 0.2051 | 0.5100 |
| $\varepsilon_2$ | 0.2158 | 0.2129 | 0.3119 | 0.4151 | 0.4783 | 0.6099 | 0.3230 | 0.3119 | 0.5218 | 0.4157 | 0.1997 | 0.5117 |

TABLE II. Retrieval Values (without impact of vegetation)

| | S1 | S2 | S3 | S4 | S5 | S6 | S7 | S8 | S9 | S10 | S11 | S12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $\nu_1$ | 5.3019 | 5.0163 | 5.0230 | 11.9970 | 10.2260 | 8.0692 | 4.9748 | 4.9778 | 7.0378 | 7.6511 | 10.1575 | 5.6017 |
| $\nu_2$ | 9.9572 | 10.0934 | 9.8727 | 14.0296 | 14.2879 | 12.0246 | 11.9927 | 10.0873 | 14.8063 | 12.5175 | 14.3617 | 10.0220 |
| $\gamma_1$ | 1.3266 | 1.5153 | 1.7143 | 1.5220 | 1.9093 | 1.3049 | 1.5140 | 1.7416 | 1.5065 | 1.8625 | 1.3126 | 2.0858 |
| $\gamma_2$ | 1.3257 | 1.5095 | 1.7220 | 1.5193 | 1.9055 | 1.3011 | 1.5139 | 1.7406 | 1.5047 | 1.8347 | 1.3228 | 2.0980 |
| $\varepsilon_1$ | 0.2275 | 0.2298 | 0.2965 | 0.4169 | 0.5137 | 0.6120 | 0.3153 | 0.3134 | 0.5104 | 0.3822 | 0.2296 | 0.5163 |
| $\varepsilon_2$ | 0.2183 | 0.2227 | 0.3084 | 0.4197 | 0.5141 | 0.6117 | 0.3163 | 0.3247 | 0.5129 | 0.3881 | 0.2215 | 0.5117 |

TABLE III. Retrieval Values (with impact of vegetation)

| | S1 | S2 | S3 | S4 | S5 | S6 | S7 | S8 | S9 | S10 | S11 | S12 | Moy (%) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $v_1$ | 3,1568 | 0,5802 | 2,7056 | 0,6559 | 2,4275 | 1,4328 | 1,6214 | 3,0602 | 1,9098 | 4,5203 | 2,8318 | 4,4127 | 2,4429 |
| $v_2$ | 0,9847 | 0,6191 | 1,1035 | 0,5695 | 0,5765 | 0,1731 | 1,4194 | 0,7585 | 1,7602 | 3,2211 | 2,9684 | 3,7906 | 1,4954 |
| $\gamma_1$ | 1,0475 | 0,7431 | 3,8551 | 0,1863 | 3,1625 | 0,6404 | 0,3442 | 0,5494 | 1,0166 | 1,6278 | 1,1627 | 0,1255 | 1,2051 |
| $\gamma_2$ | 0,8788 | 0,9942 | 4,0231 | 0,1891 | 3,0925 | 0,4883 | 0,2544 | 0,6144 | 0,9049 | 1,5811 | 1,2165 | 0,0359 | 1,1894 |
| $\varepsilon_1$ | 3,0468 | 12,2269 | 11,4732 | 0,0644 | 6,2665 | 0,0242 | 0,0012 | 0,9170 | 1,2799 | 2,9203 | 2,9621 | 0,2807 | 3,4553 |
| $\varepsilon_2$ | 0,0687 | 6,0335 | 10,1777 | 1,0203 | 5,4625 | 0,4556 | 0,4932 | 0,9805 | 1,6833 | 3,4380 | 1,6811 | 0,2500 | 2,6454 |
| | | | | | | | | | | | | average error % | 2,0722 |

TABLE IV. AVERAGE ERROR RATE FOR EACH RETRIEVED PARAMETER (WITHOUT IMPACT OF VEGETATION)

Due to the presence of vegetated layer, radar energy suffers a loss. This loss is known as the vegetation attenuation, whose quantity increases significantly depending on the density of the vegetation area.

## 7 CONCLUSION

The backscattering radar signal inversion in order to recover the physical parameters of large-scale natural surfaces is a major challenge for several applications in hydrology, geophysics and geology for predicting risks, monitoring the erosion and gully erosion. Data supplied by inversion process provide a comprehensive large-scale monitoring of natural surfaces over time and enabling firstly a major time savings compared to conventional data collection and secondly a broader vision.

## 8 REFERENCES

### 8.1 References from Journals*:*

Attema, E.P.W. and Ulaby, F.T. *1978. Vegetation modeled as a water cloud*. Radio Science Journal, 13: 357–364.

Chauhan, N. S. 1997. *Soil moisture estimation under a vegetation cover: combined active passive microwave remote sensing approach*. International Journal of Remote Sensing 18 (5): 1079 - 1097.

Gutman, G.; Ignatov, *A. The derivation of the green vegetation fraction from NOAA/AVHRR data for use in numerical weather prediction models*. *Int. J. Remote Sens.* **1998**, *19*, 1533–1543.

Mattia, F. and Le Toan, T. *Backscattering properties of multiscale rough surfaces*, Journal of Electromagnetic Waves and Applications, Papers 13(4), 493-528 (1999).

Tansey, K. J., and A.C. Millington. 2001. *Investigating the potential for soil moisture and surface roughness monitoring in drylands using ERS SAR data*. Int. J. Remote Sens. 22:2129-2149.

Song. K, X. Zhou and Fan,Y. *Multilayer soil model for improvement of soil moisture estimation using the small perturbation method*, Papers, Journal of Applied Remote Sensing, 3, 033567 (2009).

Svoray, T.; Shoshany, M.; Curran, P.; Foody, G.M.; Perevolotsky, *A. Relationship between green leaf biomass volumetric density and ERS-2 SAR backscatter of four vegetation formations in the semi-arid zone of Israel*. *Int. J. Remote Sens.* **2001**, *22*, 1601–1607.

Svoray, T.; Shoshany, *M. SAR-based estimation of areal aboveground biomass (AAB) of herbaceous vegetation in the semi-arid zone: A modification of the water-cloud model*. *Int. J. Remote Sens.* **2002**, *23*, 4089–4100.

Svoray, T.; Shoshany, M. *Multi-scale analysis of intrinsic soil factors from SAR-based mapping of drying rates*. *Remote Sens. Environ.* **2004**, *92*, 233–246.

Wang, C.; Qi, J.; Moran, S.; *Marsett, R. Soil moisture estimation in a semiarid rangeland using ERS-2 and TM imagery*. *Remote Sens. Environ.* **2004**, *90*, 178–189.

### 8.2 References from Books

Ulaby, F. T., et al. (1982), *Microwave Remote Sensing: Active and Passive*, vol. 2, Radar Remote Sensing and Surface Scattering and Emission Theory, 609 pp., Addison-Wesley, Reading, Mass.

Ulaby, F. T., Moore, R. K., and Fung, A. K. (1986), *Microwave Remote Sensing, Active and Passive, vol.III: From Theory to Applications*, Artech House, Massachusettes.

### 8.3 References from Other Literature:

Brakke T.W., E.T. Kanemasu, J.L. Steiner, F.T. Ulaby and E. Wilson. 1981. *Microwave response to canopy moisture, leaf area index and dry weight of wheat, corn and sorghum*. Remote Sensing of Environment 11:207-220.

Bindlish, R., Kustas, W. P., French, A. N., Diak, G. R., & Mecikalski, J. R. (2001). *Influence of near-surface soil moisture on regional scale heat fluxes: Model results using microwave remote sensing data from SGP97*. IEEE Transactions on Geoscience and Remote Sensing, 39(8), 1719–1728.

Birchak J.C., Gardner J., Hipp and Victor J., *High dielectric constant microwave probes for sensing soil moisture*. *Proc. IEEE*, 62, 93–98. 1974.

Bolten, J., W. Crow, X. Zhan, T. Jackson, C. Reynolds, and B. Doom. 2006. *The Application of AMSR-E Soil Moisture for Improved Global Agricultural Assessment and Forecasting*. In IEEE International Conference on Geoscience and Remote Sensing Symposium, 2006 (IGARSS 2006).

Bouman, B. (1991). *Crop parameter estimation from ground based X-band (3 cm wave) radar backscattering data*. Remote Sensing of Environment, 37, 193-205.

Chen, M.F. and Fung, A.K. *A numerical study of the regions of validity of the Kirchhoff and Small Perturbations rough scattering models*, Papers, IEEE Transaction On Geosciences And Remote Sensing 23(2), 136-170 (1988).

Davidson M.W.J., T. Le Toan, F. Mattia, G. Stalino, T. Manninen, M. Borgeaud. 2000. *On the characterization of agricultural soil roughness for radar remote sensing studies*. IEEE Transactions Geoscience and Remote Sensing 38:630-640.

Dobson M.C., and F.T. Ulaby. 1986. *Active microwave soil moisture research*. IEEE Transactions Geoscience and Remote Sensing 24:23-35.

Dubois, P. C., J. V. Zyl, and E. T. *Engman, Measuring soil moisture with imaging radar*s, IEEE Transactions on Geoscience and Remote Sensing, 33 (1995) 915-926.

Farah, L. B, Farah, I. R., Bennaceur, R., Belhadj, Z. and Boussema, M. R. *Soil multiscale roughness parameters and soil moisture retrieval from radar backscattering using a neural network technique*, Proc. PIERS, Progress In Electromagnetic Research Symposium, Tokyo, (2006).

Farah, L. B, Farah, I. R., Bennaceur, R, Hosni, I. and Boussema, M. R. *A Two Layers Multiscale Bi-dimensional SPM Model for the Study of Radar Backscatter Behavior on Semi-arid Soil Subsurfaces*, Papers, PIERS ONLINE, Progress In Electromagnetic Research, 6 (2010).

Fung, A.K. *Microwave scattering and emission models and their applications* Artech House, (1994).

Hoekman, D., Krul, L., & Attema, E. (1982). *A multi-layer model for radar backscattering by vegetation canopies.* IEEE, IGARSS '82, 2.

Kumar,A.,M.Markandaya and S.C.Girimaji, 2002 Primarymicro-cephaly: *microcephalin and ASPM determine the size of the Tajima*, F., 1989 Statistical method for testing the neutral mutation human brain. J. Biosci. **27:** 629–632.

Lievens, H.; Verhoest, N.E.C. *On the retrieval of soil moisture in wheat fields from L-band SAR based on Water Cloud modeling, the IEM, and effective roughness parameters*. IEEE Geosci.Remote Sens. Lett. 2011, 8, 740–744.

Mallat, S.G. *Theory of multi-resolution signal decomposition: The Wavelet representation*. Papers, IEEE Transactions on Pattern analysis and machine intelligence, 11(7), 674-693 (1989).

Moran, M.S.; Vidal, A.; Troufleau, D.; Inoue, Y.; Mitchell, T.A. *Ku-and C-band SAR for discriminating agricultural crop and soil conditions.* IEEE Trans. Geosci. Remote Sens. 1998, 36, 265–272.

Oh, Y., Sarabandi, K. and Ulaby, T. "An empirical model and an inversion technique for radar scattering from bare soil surfaces", Papers, IEEE Transactions on Geosciences and Remote Sensing, 30, 370-381 (1992).

Paris, J. (1986). *The effect of leaf size on the microwave backscattering by corn.* Remote Sensing of Environment, 19, 81-95.

Prakash, R.; Singh, D.; Pathak, N.P. *A fusion approach to retrieve soil moisture with SAR and optical data*. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2012**, *5*, 196–206.

Prevot, L., I. Champion, and G. Guyot, *Estimating surface soil moisture and leaf area index of a wheat canopy using a dual-frequency (C and X bands) scatterometer.* Remote Sens. Environ. 46, 331-339, 1993a.

Rozenthal W.D., B.J. Blanchard and A.J. Blanchard. 1985. *Visible/infrared/microwave agriculture classification, biomass and plant height algorithms.* IEEE Transactions on Geoscience and Remote Sensing 23:84-90.

Satalino, G., Mattia, F., Davidson, M., Le Toan, T., Pasquariello, G., and Borgeaud, M. *On current limits of soil moisture retrieval from ERS-SAR data*, IEEE T. Geosci. Remote Se., 40 ,2438–2447, 2002.

Schmugge T. Mo, and T. J. Jackson, *Calculations of radar backscattering coefficient of vegetation covered soils*, Remote Sensing of Environment, 15 (1984) 119-133.

Ulaby, F. T., Allen, C. T., Eger, G., & Kanemasu, E. (1984). *Relating microwave backscattering coefficient to leaf area index.* Remote Sensing of Environment, 14, 113-133.

Zhen, L., S. Jiancheng, and G. Huadong. 2002. *Measuring soil moisture change with vegetation cover using passive and active microwave data*. IEEE International Geoscience and Remote Sensing Symposium, 2002 (IGARSS '02).

Zribi, M.; Dechambre, M. *A new empirical model to retrieve soil moisture and roughness from C-band radar data*. *Remote Sens. Environ.* **2003**, *84*, 42–52.

Zribi, M.; Baghdadi, N.; Holah, N.; Fafin, O. *New methodology for soil surface moisture estimation and its application to ENVISAT-ASAR multi-incidence data inversion*. *Remote Sens. Environ.* **2005**, *96*, 485–496.

Zribi, M., Le Morvan, A. and Baghdadi, N. *Dielectric Constant Modelling with Soil–Air Composition and Its Effect on SAR Radar Signal Backscattered over Soil Surface*, Papers, Sensors, 8, 6810-6824 (2008).