

RETRIEVAL BARE-SOIL MOISTURE USING L-BAND SAR

Jiancheng Shi

Center for Remote Sensing and Environmental Optics
University of California, Santa Barbara, CA 93106

Jakob J. van Zyl

Jet Propulsion Laboratory
California Institute of Technology

Joao Vianei Soares

Instituto de Pesquisas Espaciais
Av dos Astronautas, Brazil

Edwin T. Engman

NASA/GSFC
Hydrological Sciences Branch

ABSTRACT

This paper reports a study of algorithm development and testing for soil moisture retrieval for bare fields using L-band SAR imagery. First-order surface scattering models predict that the co-polarization ratio is sensitive to soil moisture but not to surface roughness. Our previous study indicated that the measurement of σ^{vv}/σ^{hh} at L-band is proportional to soil moisture. In this study, the effect of volume scattering of soil on estimating soil moisture is evaluated. To minimize the effect of the volume scattering, an algorithm which includes both the surface and volume scattering has been developed and tested using JPL AIRSAR data. The results show that the estimation of soil moisture can be improved after removing the system noise and including the volume scattering effect at large incidence angles.

I. INTRODUCTION

The purpose of this study is to develop an algorithm for soil moisture retrieval from L-band SAR imagery. Estimates of soil moisture are of great importance in numerous environmental studies, including hydrology, meteorology, and agriculture. In spite of its importance, soil moisture data is not generally used in resource monitoring or prediction because they are difficult and costly to measure on a routine basis over large areas [1]. Experiments of radar backscatter from agricultural fields have been conducted quite extensively at ground level [2][3] and at satellite altitude [1][4]. Those studies indicated that the backscattering coefficient is sensitive to soil moisture up to 5 or 10 cm below the surface, and that the optimal radar parameters to estimate soil moisture are C-band HH polarization with incidence angle between 5° to 20°. At small incidence angle, surface roughness effect on the received radar signature is minimized when comparing with other incidence angles. However, the great range of the suggested optimal incidence angle and the sensitivity of the backscattering coefficient to soil moisture from different investigators indicate the local dependence of the algorithms. Furthermore, the small incidence angle requirement limits the spatial application, especially for airborne radar system. While it may be possible to operate at these angles for spaceborne radar systems, many other effects, such as layover etc., make it difficult to analyze spaceborne radar images acquired at such steep incidence angles. The algorithm should be applicable over as much of the swath as possible.

The imaging radar polarimeter permits measurement of the full polarization signature of every resolution element in an image. The radar polarization signature of an object permits a more accurate description of the object of interest than single-polarization measurements [5]. Thus, the solution for geometric shape and dielectric constant of an object is less ambiguous, making the development of a quantitative algorithm for soil moisture retrieval from Synthetic Aperture Radar (SAR) data possible. Our previous work [6] indicated that the ratio of the co-polarization signals could be used for soil moisture retrieval at longer wavelengths (L-band) and at larger incidence angles (> 40°). The

algorithm to infer soil moisture from imaging radar data was based on a first-order surface scattering model. This model predicts that the co-polarization ratio is sensitive to soil moisture at large incidence angles but not to surface roughness. However, the polarization signal ratio measurements are sensitive to the radar system noise and the other scattering contributions such as the multi-surface and volume scattering even if these effects only contribute a small portion of the total signal in the measurements. These factors result in an underestimation of soil moisture when the first-order surface scattering algorithm was applied to imaging radar data. Therefore, it is necessary to evaluate the effects of these factors on the polarization ratio measurements to develop a quantitative algorithm for inferring soil moisture.

In this study, the problem of volume scattering on estimating soil moisture is addressed. Based on a first-order backscattering model which considers both the surface and volume scattering, the physically based algorithm for retrieval of soil moisture has been developed and tested using NASA/JPL aircraft SAR data in May 1988 and September 1989 over an agricultural area, near Fresno, California.

II. EFFECT OF VOLUME SCATTERING OF SOIL

To evaluate the applicability of the first-order surface scattering model for soil moisture retrieval, we show the sampled measurements of σ^{vv}/σ^{hh} in 1989 data from dry bare fields in Figure 1. These measurements present samples from 10 x 10 pixel boxes. The backscattering coefficients for VV and HH polarizations were determined from an averaged Stokes matrix. The solid line in Figure 1 is the predictions by the first-order small perturbation model for soil moisture at 3 percent by volume, while the dashed line is the prediction for 9 volume. The soil moisture measured during the over flights ranged from 3 to 9 percent for dry bare fields. Figure 1. indicates that a direct application of the first-order surface scattering inversion algorithm will result in an underestimation of soil moisture.

The surface scattering models assume that the scattering medium is a homogeneous dielectric half-space. In practice, natural soil

is not a perfectly homogeneous dielectric medium. Instead, it is a mixture of soil particles, air pockets, and liquid water. This results in dielectric discontinuities inside the soil. Therefore, natural soil should be described as an inhomogeneous dielectric medium. Because soil is a densely packed medium, the effects of these discontinuities will be reduced for longer wavelengths, especially when the distance between scatterers is much smaller than the wavelength. The result is that the volume scattering of soil contributes only a small portion of the observed signals at longer wavelength and that the dominant scattering source is the surface backscattering at the air-soil interface. In evaluating the magnitude of each co-polarization signal, the surface scattering can be used to explain the general relations between the backscattering measurements and soil physical properties. However, in attempting to relate the polarization ratio or difference to the physical properties of soils, the volume scattering contribution becomes significant even if it only contributes a small portion in the observed backscattering returns. This effect is also expected when using long-wavelength sensors because of deeper penetration.

Figure 1 shows that the measured degree of polarization of vertical incident wave from the dry fields. The degree of polarization is defined as the ratio of purely polarized power to the total power in the scattered wave for a given polarization status of incident wave [8]. Both the first-order surface and volume scattering models predicate that the degree of polarizations of co-polarization signals are unit. The departures of measured degree of polarization indicate the effects of higher-order scattering and the system noise. The measurements show a significant departure from unit at smaller incidence angles but rather close to unit at large incidence angles. This indicates that the measured co-polarization ratio (in Figure 1) at small incidence angles smaller than the predictions by the first-order surface scattering model is mainly due to the higher-order surface scattering. However, it is resulted from the first-order volume scattering contribution from soil at large incidence angles. To overcome the volume scattering effect on estimation of soil moisture, we propose an algorithm which is based on the first-order scattering model considering both the surface and volume scattering contributions.

III. ALGORITHM DEVELOPMENT

As we have discussed in the last section, the volume scattering affects the co-polarization ratio measurements, especially at longer wavelengths and high incidence angles when soil moisture is low. To minimize this effect, we construct a more general inversion model by considering both surface and volume backscattering

$$\sigma_t^{pp} = \sigma_v^{pp} + \sigma_s^{pp} \quad (1)$$

where pp indicates either vv or hh polarizations. σ_t is the total backscattering coefficient. σ_s is the surface backscattering from air-soil interface and σ_v is the volume backscattering from soil.

The surface backscattering is a function of the permittivity of soil and the roughness of the air-soil interface which is described by the auto-correlation function of random surface height, the standard deviation of the surface height, and the correlation length. When the multi-scattering is not significant, the single surface backscattering can be represented as a product of dielectric and surface roughness functions. The relationship of the surface backscatterings between VV and HH polarization signals can be derived

$$D_R(\theta_i, \epsilon_r) = \frac{\sigma_s^{vv}}{\sigma_s^{hh}} = \frac{|\alpha_{vv}|^2}{|\alpha_{hh}|^2} \quad (2)$$

where α_{vv} and α_{hh} for small perturbation model are given by [7]. Here, we simply denote D_R as the surface backscattering ratio of VV and HH polarizations, which is only a function of incidence angle, θ_i , and the permittivity, ϵ_r , of soil.

Similarly, the volume backscattering coefficient is a function of the permittivity, incidence angle, volume scattering albedo, and surface roughness. Under the spherical particle assumption, the relationship for the first-order volume backscattering signals of VV and HH polarizations can be also obtained

$$D_T(\theta_i, \epsilon_r) = \frac{\sigma_v^{vv}}{\sigma_v^{hh}} = \frac{T_{vv}^2(\theta_i, \epsilon_r)}{T_{hh}^2(\theta_i, \epsilon_r)} \quad (3)$$

where T_{vv} and T_{hh} are *fresnel* transmissivity of a plane interface for vertical and horizontal polarization, respectively. We simply denote D_T as the volume backscattering ratio of VV and HH polarizations, which is also a function of incidence angle and permittivity of soil only. Notice that transmissivity of a rough surface is a product of the transmissivity of a plane interface and a correction factor as give in [9]. However, the ratio of T_{vv} to T_{hh} is independent of the surface roughness because the correction factor is independent of polarization.

As predicated by the first-order small perturbation model, the surface backscattering signals in co-polarization channels is perfectly correlated. In other word, the correlation coefficient, ρ_s , is

$$\rho_s = \frac{|S_s^{vv} S_s^{hh*}|}{|S_s^{vv}| |S_s^{hh}|} = 1 \quad (4)$$

However, the volume backscattering in co-polarization channels can be either perfectly correlated or un-correlated depending on incidence angle. The correlation coefficient for volume scattering is

$$\rho_v = \frac{|S_v^{vv} S_v^{hh*}|}{|S_v^{vv}| |S_v^{hh}|} = \begin{cases} 1 & \text{if } \theta_i < \text{critical angle;} \\ 0 & \text{if } \theta_i \geq \text{critical angle.} \end{cases} \quad (5)$$

To further reduce the number of unknowns in order to measure soil moisture, we introduce the volume to surface backscattering ratio

$$C_{pp} = \frac{\sigma_v^{pp}}{\sigma_s^{pp}} \quad (6)$$

Using Equations (1) to (6), two measurements, the co-polarization ratio $\sigma_t^{vv}/\sigma_t^{hh}$ and correlation coefficient ρ_t can be represented as

$$\frac{\sigma_t^{vv}}{\sigma_t^{hh}} = \frac{D_T(\theta_i, \epsilon_r) C_{hh} + D_R(\theta_i, \epsilon_r)}{1 + C_{hh}} \quad (6)$$

and

$$\rho_t = \frac{\sqrt{D_T(\theta_i, \epsilon_r) C_{hh}} + \sqrt{D_R(\theta_i, \epsilon_r)}}{\sqrt{D_R(\theta_i, \epsilon_r) + C_{hh} [D_R(\theta_i, \epsilon_r) + D_T(\theta_i, \epsilon_r)] + D_T(\theta_i, \epsilon_r) C_{hh}^2}} \quad (7)$$

for $\theta_i < \text{critical angle}$,

$$\rho_t = \frac{\sqrt{D_R(\theta_i, \epsilon_r)}}{\sqrt{D_R(\theta_i, \epsilon_r) + C_{hh} [D_R(\theta_i, \epsilon_r) + D_T(\theta_i, \epsilon_r)] + D_T(\theta_i, \epsilon_r) C_{hh}^2}} \quad (8)$$

for $\theta_i \geq \text{critical angle}$. >From these two measurements, the two unknowns, ϵ_r and C_{hh} , can be solved.

The algorithm derived above does not require any information about the surface roughness and the volume scattering albedo. It only involves the calculation of soil permittivity.

IV. RESULTS AND DISCUSSIONS

To test the algorithms for measuring soil moisture over a large areas, a field map was first obtained by performing the supervised bayes classification and the vegetation covered fields were masked. Secondly, the backscattering coefficients of VV and HH polarizations for a given pixel were determined from an average Stokes matrix within a 5 by 5 window to reduce the effect of image speckle. To reduce the effect of system noise, we approximate

$$\sigma^{vv} = \sigma^{vv'} d_v \quad (9)$$

and

$$\sigma^{hh} = \sigma^{hh'} d_h \quad (10)$$

where d_v and d_h are the degree of polarization of vertical and horizontal incident wave, respectively. Then the algorithm was applied.

Figure 3(A) shows an image of the inferred soil moisture map of the study sites from SAR data. This map was produced using an

first-order surface scattering model only. The soil moisture map shown in (B) was derived by the algorithm which includes both surface and volume scattering of soil. The image brightness is proportion to the soil moisture in both images and ranges from 2 to 30 percent by volume. The black regions are vegetation covered fields. When applying the first-order surface scattering algorithm, only about 20 to 30 percent pixels were within the possible physical conditions predicted by the first-order surface scattering model. As shown in Figure 3(A), there are many pixels with missing values even after post-processing. It is especially evident at large incidence angles. However, applying the algorithm with both surface and volume scattering considerations, about 80 percent of the pixels were within the physical limits. During the SAR flights, the volumetric soil moisture for the sampled dry fields varied between 3 and 10 percent. Most bare fields were dry because none of them had been irrigated for at least several weeks. The inferred soil moisture from SAR data agrees well with the field measurements and values ranges from 2 to 14 percent were inferred.

Figure 4. shows the comparisons between the field measurements and the SAR derived soil moisture for the locations where the field measurements were available. The line indicates where the soil moistures are exactly same from the field and SAR derived measurements. The measurements above and below this line indicate an over-estimation and underestimation, respectively. The maximum relative error can reach about 100 percent but most of the measurements have relative errors smaller than 25 percent. The average error was about 30 percent from all measurements. Both regional and point measurement comparisons between the field and SAR derived measurements indicates that the algorithm performs very well.

V. CONCLUSIONS

This paper reports a study of algorithms development and testing for soil moisture retrieval for bare fields using L-band SAR imagery. The effect of volume scattering contribution from soil can result in an underestimate soil moisture, especially at large incidence angles when soil is dry. An algorithm which includes both the surface and volume scattering has been developed and tested on JPL AIRSAR system. The results show that the algorithm performed well and should be useful for repetitive, large-area soil moisture monitoring, without requiring surface roughness measurements.

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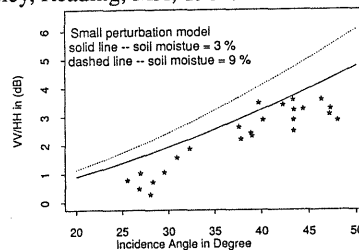


Figure 1. The sampled measurements of σ^{vu}/σ^{hh} from dry bare fields. The solid and dashed lines are the predictions by the first-order small perturbation model for soil moisture at 3 and 9 percent, respectively.

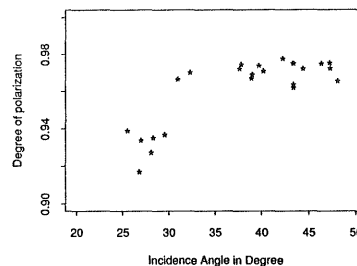


Figure 2. The degree of polarization measurements of vertical incident wave from dry bare fields.

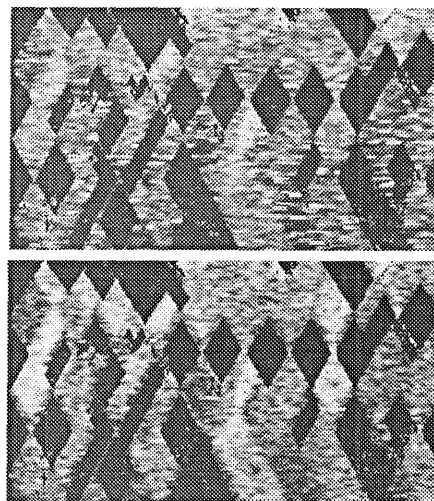


Figure 3. Comparison of inferred soil moisture map by using the first-order surface scattering model in (A) at top with the map derived by the algorithm which includes both surface and volume scattering at bottom in (B).

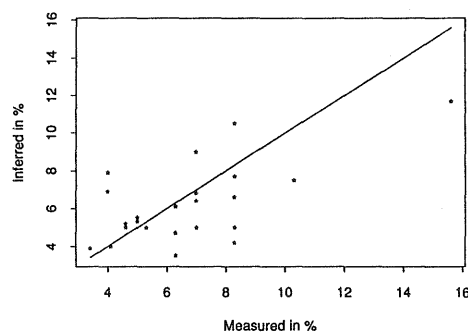


Figure 4. Comparison the field soil moisture measurements with the inferred by SAR data.