Estimation of Soil Moisture with L-band Multi-polarization Radar

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Abstract

Through analyses of the model simulated data-base, we developed a technique to estimate surface soil moisture under HYDROS radar sensor (L-band multi-polarizations and 40° incidence) configuration. This technique includes two steps. First, it decomposes the total backscattering signals into two components – the surface scattering components (the bare surface backscattering signals attenuated by the overlaying vegetation layer) and the sum of the direct volume scattering components and surface-volume interaction components at different polarizations. From the model simulated data-base, our decomposition technique works quit well in estimation of the surface scattering components with RMSEs of 0.12, 0.25, and 0.55 dB for VV, HH, and VH polarizations, respectively. Then, we use the decomposed surface backscattering signals to estimate the soil moisture and the combined surface roughness and vegetation attenuation correction factors with all three polarizations.

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Abstract - Through analyses of the model simulated data-base, we developed a technique to estimate surface soil moisture under HYDROS radar sensor (L-band multi-polarizations and 40° incidence) configuration. This technique includes two steps. First, it decomposes the total backscattering signals into two components – the surface scattering components (the bare surface backscattering signals attenuated by the overlaying vegetation layer) and the sum of the direct volume scattering components and surface-volume interaction components at different polarizations. From the model simulated data-base, our decomposition technique works quit well in estimation of the surface scattering components with RMSEs of 0.12, 0.25, and 0.55 dB for VV, HH, and VH polarizations, respectively. Then, we use the decomposed surface backscattering signals to estimate the soil moisture and the combined surface roughness and vegetation attenuation correction factors with all three polarizations.

Keywords – soil moisture, L-band multi-polarization radar.

I. INTRODUCTION

During past years, investigations have demonstrated the capability of active microwave instruments in soil moisture mapping. However, the most of investigations are focused on the bare surface cases. Natural variability and the complexity of the vegetation canopy and surface roughness significantly affect the sensitivity of radar backscattering to soil moisture. Backscattering signals from vegetated areas is a function of water content and its spatial distribution as determined by vegetation structure and underlying surface conditions. It is clear that vegetation cover will cause an under-estimation of soil moisture and an over-estimation of surface roughness when we apply the algorithm for bare surface to vegetation covered regions. Due to complexity of natural surface and vegetation structure (unknowns are more than measurements), it is quite difficult to develop a quantitative algorithm to estimate soil moisture in vegetated areas. This study investigates the techniques to estimate surface soil moisture of bare and short vegetated surfaces under HYDROS radar sensor configuration: L-band (1.26 GHz), multi-polarization (VV, HH, and VH), and 40° incidence radar measurements.

We first established a model simulated data-base using a radiative transfer model. For the surface scattering components, it uses the IEM model [1] with the random rough surface assumption to simulate the wide range of soil moisture and roughness conditions for co-polarized signals and the Oh's semi-empirical model [2] to the depolarization factor VH/VV of the surface backscattering, then the cross-polarized signals can be obtained using IEM simulated VV polarization signals. For the vegetation scattering and surface-volume scattering components, we simulated with randomly orientated disk [3] and short cylinders [4] with the maximum of optical thickness and single scattering albedo up to 0.5 and 0.2, respectively. Table 1 summarizes the parameters of vegetation and ground that used to generate the simulated data-base.

Parameters	Minimum	Maximum	Interval
Vegetation fraction	0 %	100 %	20 %
albedo	0.02	0.2	0.02
Optical thickness	0.025	0.5	0.025
Surface rms. height	0.5 cm	3.0 cm	0.25 cm
Correlation length	2.5 cm	25 cm	2.5 cm
moisture	2.5%	45%	2.5%

Table. 1 Vegetation and ground parameters used to generate the data-base for algorithm development.

II. TECHNIQUES TO DECOMPOSE SCATTERING COMPONENT

Commonly, the radar backscattering coefficient from vegetated surfaces can be described as a three components model

$$\sigma_{pq}^{t} = F_V \cdot (\sigma_{pq}^{v} + \sigma_{pq}^{sv}) + (1 - F_V + F_V \cdot L_{pq}) \cdot \sigma_{pq}^{s} \quad (1)$$

where F_v is the vegetation fraction cover. The subscripts *p* and *q* indicate the polarization. The superscripts *t, v, sv*, and *s* indicate the total, volume scattering, surface-volume scattering interaction, and ground surface scattering terms, respectively. $L_{pq} = \exp(-2 \cdot \tau / \cos(\theta_i))$ are the double pass the attenuation factor, respectively. $\tau = \kappa_e \cdot d$ is the optical thickness. κ_e and d are the extinction coefficient and vegetation depth.

Fig 1 shows the histogram of the contributions of the sum of volume and surface-volume interaction terms in total scattering signals - $(\sigma^v_{pq} + \sigma^{sv}_{pq}) / \sigma^t_{pq}$ in the simulated data-base. From top to bottom, they are VV, HH, and VH polarizations, respectively. We can see that the effects of vegetation differ at the different polarization for the same vegetation parameter. From VV, HH to VH polarizations, the vegetation contribution to the total signal increases. In comparison VV and HH polarizations, it is mainly resulted from the surface-volume interaction term that has the characteristics of HH > VV. For VH, it is due to surface scattering does not generate significant cross-polarization signal. VH polarization measurements mainly reflect the vegetation information.

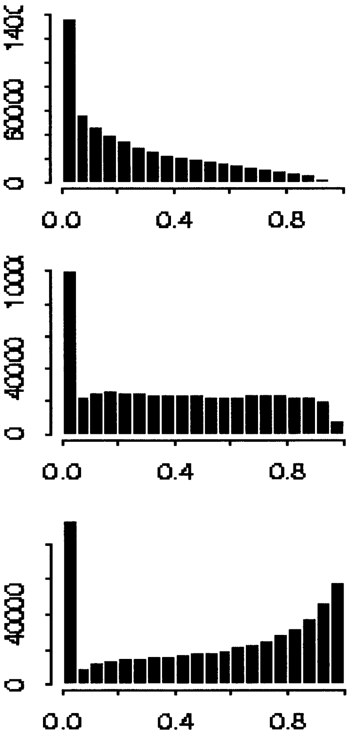

Fig. 1 Histogram of the contributions of the contributions of the sum of volume and surface-volume interaction terms in total scattering signals in the simulated data-base. From top to bottom, they are VV, HH, and VH polarizations, respectively.

In terms of the estimating surface soil moisture, the surface scattering component has the maximum sensitivity to soil moisture and is actually information needed. The signals from the direct volume scattering components and surface-volume interaction components have vegetation information but they are the noise signals for soil moisture estimation.

Fig 2 shows the relationships between the depolarization factor - $\sigma^t_{pq} / \sigma^t_{pp}$ (as x-axis) and the sum of the direct volume and surface-volume interaction contributions - $(\sigma^v_{pp} + \sigma^{sv}_{pp}) / \sigma^t_{pp}$ in VV polarization (top) and HH polarization (bottom). We can see that the depolarization factor is proportional to the sum of the volume scattering and surface-volume scattering contributions and inversely relates the surface scattering contribution. The correlation is better described in VV polarization than that in HH polarization due to the differences in the surface-volume interaction terms in these two polarizations.

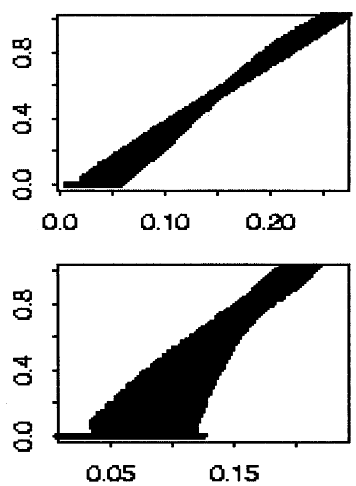

Fig. 2 the relationships between the depolarization factor (as x-axis) and the sum of the direct volume and surface-volume interaction contribution in VV polarization (top) and HH polarization (bottom).

From Fig 2, we can see that the depolarization factor VH/VV < 0.02 (-17 dB) and VH/HH < 0.035 (-14.5 dB) represents the bare surface cases. They may be used to identify the bare surface. In addition, the contributions of the scattering components can be roughly estimated, especially for VV polarization. In order to improve the decomposition accuracy, we carried out the regression analyses using the simulated data-base. We found that the surface scattering contribution can be better estimated by

$$F^s_{pp} = \exp[a_{pp} + b_{pp} \cdot \log(\sigma^t_{pq} / \sigma^t_{pp}) + c_{pp} \cdot \sigma^t_{vv} + d_{pp} \cdot \sigma^t_{hh} + e_{pp} \cdot \sqrt{\sigma^t_{pq}} + f_{pp} \cdot \log(1 - g_{pp} \cdot \sigma^t_{pq} / \sigma^t_{pp}) \quad (2)$$

for the co-polarizations. F^s_{pp} is the surface scattering contribution in the total backscattering signals for polarization pp. The coefficients a, b, c, d, e, f, and g differ for VV and HH. For VH polarization, it is written as

$$
\begin{aligned}
F^s_{pq} = \exp\big[& a_{pq} + b_{pq}\cdot\log(\sigma^t_{vv}) + c_{pq}\cdot\log(\sigma^t_{hh}) \\
& + d_{pq}\cdot\log(\sigma^t_{vh}) + e_{pq}\cdot\log(1 - f_{pq}\cdot\sigma^t_{vh}/\sigma^t_{vv}) \\
& + g_{pq}\cdot\log(1 - h_{pq}\cdot\sigma^t_{vh}/\sigma^t_{hh})\big]
\end{aligned} \tag{3}
$$

Then, the surface backscattering components at each polarization can be obtained by

$$\sigma^s_{pq} = F^s_{pq}\cdot\sigma^t_{pq} \tag{4}$$

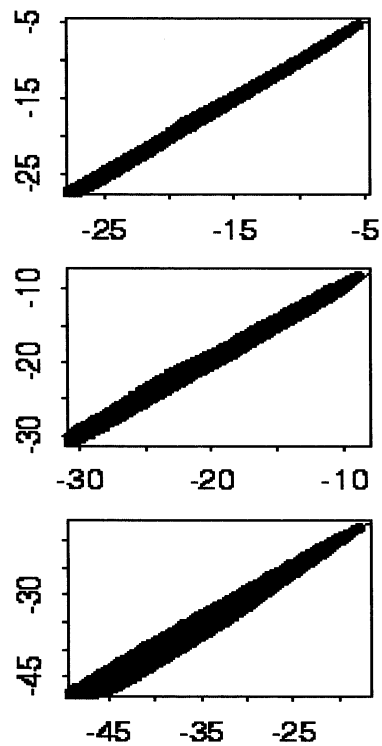

Fig. 3 the comparison of the input surface scattering signals (x-axis) with that the estimated surface scattering signals (y-axis) from the simulated total backscattering coefficients using above technique. From top to bottom of the plots, they represent that in VV, HH, and VH polarizations.

Fig 3 compares the input surface scattering signals (x-axis) with that the estimated surface scattering signals (y-axis) from the simulated total backscattering coefficients using above technique. From top to bottom of the plots, they represent that in VV, HH, and VH polarizations. The corresponding RMSE are 0.12, 0.25, and 0.55 dB for VV, HH, and VH, respectively. They indicate the surface scattering signals can be well estimated for the co-polarizations (VV and HH). However, the less accuracy is expected for VH polarization since its sensitivity to the surface scattering is small in this polarization.

III. Estimation Soil Moisture of Vegetated Surfaces

In our evaluation of the bare surface backscattering coefficients simulated by IEM, we find it can be written as

$$\sigma^s_{pq} = Sr_{pq}\cdot R_{pq}^{B_{pq}} \tag{5}$$

Sr_{pq} is the roughness parameter that depending on the polarization, incidence angle, surface RMS height, correlation length. It represents an overall effect of the surface roughness. B_{pq} is a parameter that mainly depends incidence angle for the incidence < 45°. At 40° incidence, B_{vv}=0.97, B_{hh}=1.1, and B_{vh}=0.8. At higher incidence, the surface roughness start to have a significant effect on the B_{pq} parameter, especially for HH polarization. R_{pq} represents the surface reflectivity and can be written as

$$R_{pq} = \begin{cases} |\alpha_{vv}|^2 & \text{for VV} \\ |\alpha_{hh}|^2 & \text{for HH} \\ |\alpha_{hh}|^2\cdot\Gamma^0 & \text{for VH} \end{cases} \tag{6}$$

where $|\alpha_{pp}|^2$ is the polarization magnitude from the Small Perturbation Model. Γ^0 is the reflectivity for the flat surface at normal incidence. Therefore, $R_{pq}^{B_{pq}}$ is only dependent on the surface dielectric properties and incidence angle for incidence < 45°.

For vegetated surfaces, the surface scattering component can be described as:

$$\sigma^{s'}_{pq} = (1 - F_v + F_v\cdot L_{pq})\cdot\sigma^s_{pq} = R_{pq}^{B_{pq}}\cdot CF_{pq} \tag{7}$$

where $CF_{pq} = Sr_{pq}(1 - F_v + F_v\cdot L_{pq})$ is a combined surface roughness and vegetation correction factor. For soil moisture estimation, the task is how well we can estimate $R_{pq}^{B_{pq}}$ or how well we can minimize the effect of CF_{pq}.

Using the simulated surface backscattering term in Eq (7), we first carried out the regression analysis for estimation of CF_{hh}. It was found that this parameter could be fairly well estimated with the second-order form:

$$CF_{hh} = \exp\Big[a + b\cdot\log(\sigma^{s'}_{vv}) + c\cdot\log(\sigma^{s'}_{hh}) + d\cdot\log(\sigma^{s'}_{vh}) + e\cdot\log^{2}(\sigma^{s'}_{vv}) + f\cdot\log^{2}(\sigma^{s'}_{hh}) + g\cdot\log^{2}(\sigma^{s'}_{vh})\Big] \quad (8)$$

Then, soil moisture can be obtained from the estimation of

$$R^{B_{hh}}_{hh} = \sigma^{s'}_{hh} / CF_{hh} \quad (9)$$

Fig 4 (left) shows Histogram of the relative error in % for the estimated CF_{hh}(top row) and the absolute error in % for estimated volumetric soil moisture (bottom). The inversion is by using the simulated surface component – Eq (7) as the input data. The RMSE are 4.95 % for estimating the relative error of CF_{hh}. It results in 2.68 % in terms of the RMSE in estimating volumetric soil moisture. However, when we use the estimated surface scattering signals by Eqs (2-4) from the total signals, the great error is introduced as shown on the right side of **Fig 4**. The RMSEs are 14.9 % and 5.7 % for estimation of CF_{hh} and soil moisture, respectively. This is because the second-order inversion form is very sensitive the noise. Due the error introduced in the decomposition processes (estimation of the surface scattering signals), it has a significant effect on the soil moisture estimation.

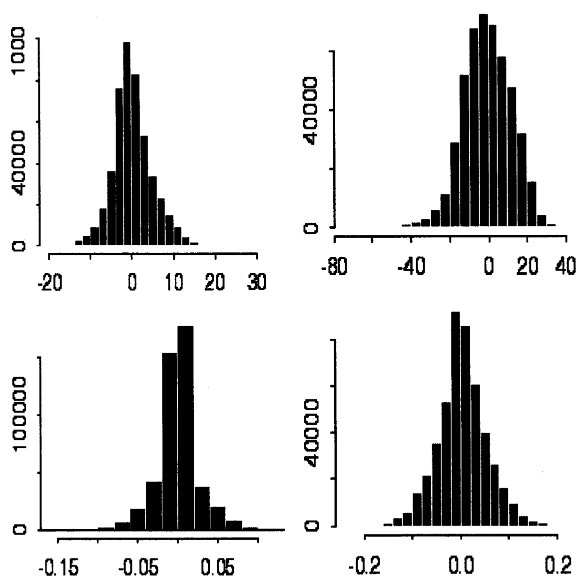

Fig. 4 Histogram of the relative error in % for the estimated CF_{hh}(top row) and the absolute error in % for estimated volumetric soil moisture (bottom). The left side is inversion using the simulated surface component – Eq (7). The right side is inversion using the decomposed surface component.

To further improve the accuracy on estimation of soil moisture, we first use Eq (8) to carry out the initial estimation of CF_{hh}. Then we separated the estimated CF_{hh} to three regions with CF_{hh}<= -20dB, -20dB < CF_{hh}<= -10 dB, and CF_{hh} > -10dB. The parameters a, b, c, d, e, and f are re-determined based on the CF_{hh} region. For the smallest CF_{hh} region, we only used VV and HH polarizations in Eq (8) due to VH signals are very small. For the rest of two regions, the last term in Eq (8) was also excluded since it contains the largest error in the estimated surface scattering components. **Fig 5** shows the histogram of the relative error in % for the estimated CF_{hh}(left) and the absolute error in % for estimated volumetric soil moisture (right) by this improved technique. The RMSEs are 9.5 % and 4.6 % for estimation of CF_{hh} and soil moisture, respectively. It can be see that the accuracies in estimations of the correction factor and soil moisture can be significantly improved.

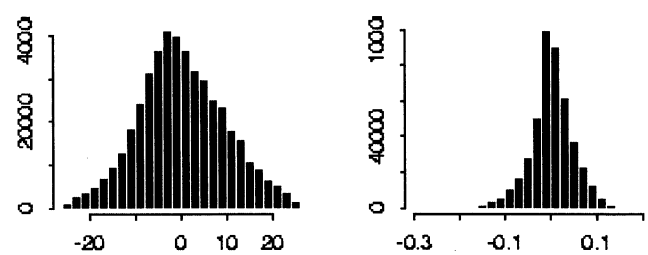

Fig. 5 Histogram of the relative error in % for the estimated CF_{hh}(left) and the absolute error in % for estimated volumetric soil moisture (right).

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