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Radar Remote Sensing of Soil Moisture and Surface Roughness for Vegetated Surfaces

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Abstract : This paper presents radar remote sensing of soil moisture and surface roughness for vegetated surfaces. A precise volume scattering model for a vegetated surface is derived based on the first-order radiative transfer technique. At first, the scattering mechanisms of the scattering model are analyzed for various conditions of the vegetation canopies. Then, the scattering model is simplified step by step for developing an appropriate inversion algorithm. For verifying the scattering model and the inversion algorithm, the polarimetric backscattering coefficients at 1.85 GHz, as well as the ground truth data, of a tall-grass field are measured for various soil moisture conditions. The genetic algorithm is employed in the inversion algorithm for retrieving soil moisture and surface roughness from the radar measurements. It is found that the scattering model agrees quite well with the measurements. It is also found that the retrieved soil moisture and surface roughness parameters agree well with the field-measured ground truth data.

Key Words : Scattering model, inversion algorithm, soil moisture, surface roughness, vegetated surfaces, genetic algorithm.

1. Introduction

Remote sensing of soil moisture is essential in agriculture, global change monitoring, and other hydrological process. Since the sensitivity of the radar response on surface roughness is comparable to or even higher than that on soil moisture, the surface roughness might be considered in the soil moisture estimation (Ulaby *et al.*, 1982). Radar scattering from bare surfaces depends on only soil moisture and surface roughness, and the polarimetric radar response can be modeled quite accurately for bare surfaces (Oh *et al.*, 2002). Based on the accurate scattering model, both the soil moisture and surface roughness can be retrieved from the polarimetric backscatter measurements with a good accuracy for bare-soil surfaces (Oh, 2004: Oh 2006). However, for vegetation-covered surfaces, the soil moisture retrieval is a challenging problem because of complicate scattering mechanisms in the vegetation canopy.

The most popular scattering model for vegetated surfaces is the radiative transfer model (Tsang *et al.*, 1985). This scattering model, however, is too complicate to be used for the inversion algorithm. Therefore, simplified scattering models are usually

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employed for soil moisture estimation. Regression models for the backscattering coefficients of a specific vegetation canopy can be used to get soil moisture from radar response as in (De Roo *et al.*, 2001). The ratios of different radar channels (polarization or frequency) can be regressed against the soil moisture content. Then, the regression curve can be used to retrieve the soil moisture contents from the radar measurements. In this approach the vegetation biomass and surface roughness are ignored. The other approach would be an inversion of a simplified scattering model, so-called water-cloud model, which represents the vegetation canopy as uniformly distributed water particles like a cloud. The parameters of the water-cloud model are derived by fitting the model with experimental data as in Bindlish and Barros (2001) and Sikdar *et al.* (2005). The model parameters are dependant on the vegetation type and the polarization.

In this paper, at first, the radiative transfer model is formulated, analyzed and simplified for computing the radar backscattering coefficients of vegetated surfaces. The backscattering coefficients for a tall-grass field are measured with a polarimetric L-band scatterometer during two months, and at the same time, the biomasses, leaf moisture contents, and soil moisture contents are also measured. Then the measurement data are used to estimate the model parameters for vv-, hh-, and vh-polarizations. The scattering model for tall-grass-covered surfaces is used as the cost function of a genetic algorithm to retrieve the soil moisture content and the surface roughness from the radar measurements.

2. Radiative Transfer Scattering Model

The radiative transfer scattering model is to compute polarimetric microwave scattering from

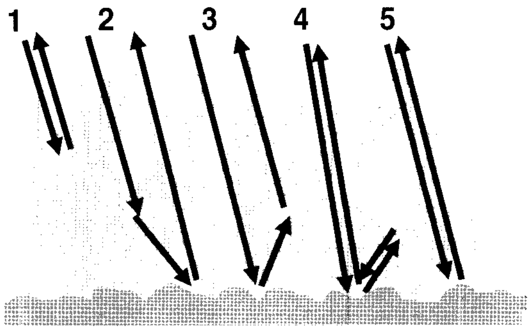


Fig. 1. Five different scattering mechanisms.

randomly distributed scatterers which is a heuristic treatment of multiple scattering by assuming no correlation between multiple scattered fields so that the addition of intensity terms, instead of the addition of fields, is appropriate. The first-order radiative transfer scattering model includes five basic scattering mechanisms as shown in Fig. 1; *i.e.*, (1) directly backscattering from the vegetation canopy, (2) forward-scattering from the vegetation layer and then reflecting from the soil surface, (3) reflecting from the soil surface and then forward-scattering from the vegetation layer, (4) reflecting from the soil surface, then backscattering from the vegetation layer, and reflecting again from the soil surface, and (5) direct backscatter contribution of the underlying soil surface with two-way attenuations through the vegetation layer.

The backscattering coefficients can be obtained by multiplying $4\pi \cos\theta_0$ to the transformation matrix elements,

$$\begin{aligned}\overline{\overline{T}} = \sec\theta_0[&\overline{\overline{E}}_4\overline{\overline{A}}_{41}\overline{\overline{E}}_1^{-1} \\ &+ \{\overline{\overline{E}}_4\overline{\overline{D}}_4\overline{\overline{E}}_4^{-1}\}\overline{\overline{R}}\,\overline{\overline{E}}_3\overline{\overline{A}}_{31}\overline{\overline{E}}_1^{-1} \\ &+ \overline{\overline{E}}_4\overline{\overline{A}}_{42}\overline{\overline{E}}_2^{-1}\overline{\overline{R}}\{\overline{\overline{E}}_1\overline{\overline{D}}_1\overline{\overline{E}}_1^{-1}\} \\ &+ \{\overline{\overline{E}}_4\overline{\overline{D}}_4\overline{\overline{E}}_4^{-1}\}\overline{\overline{R}}\,\overline{\overline{E}}_3\overline{\overline{A}}_{32}\overline{\overline{E}}_2^{-1}\overline{\overline{R}}\{\overline{\overline{E}}_1\overline{\overline{D}}_1\overline{\overline{E}}_1^{-1}\} \\ &+ \{\overline{\overline{E}}_4\overline{\overline{D}}_4\overline{\overline{E}}_4^{-1}\}\overline{\overline{M}}\{\overline{\overline{E}}_1\overline{\overline{D}}_1\overline{\overline{E}}_1^{-1}\}]\end{aligned} \quad (1)$$

$$\text{with } [\overline{\overline{A}}_{kl}]_{ij} = [\overline{\overline{E}}_k^{-1}\overline{\overline{P}}_{kl}\overline{\overline{E}}_l]_{ij}\, C_{kl,ij}. \quad (2)$$

The first, second, third, fourth, and fifth terms of above equation correspond to the scattering mechanism (1), (2), (3), (4) and (5), respectively. The subscripts 1, 2, 3, and 4 correspond to the wave directions of ↘, ↗, ↙, and ↖, respectively. As shown in the above equation, the 4 × 4 transformation matrix $\overline{\overline{T}}$ can be computed using the phase matrices $\overline{\overline{P}}$, the eigen matrices $\overline{\overline{E}}$, the reflectivity matrices $\overline{\overline{R}}$, the diagonal extinction matrices $\overline{\overline{D}}$, and the Stokes' scattering operator matrix $\overline{\overline{L}}$ (Ulaby and Elachi, 1990).

The wave attenuation through the vegetation canopy is accounted using the Foldy's approximation (Tsang *et al.*, 1985). The diagonal terms of the diagonal matrices $\overline{\overline{D}}$ can be obtained from the eigen values of coherent propagation β_i.

$$D_{ii} = e^{\beta_i(\theta,\phi)z\sec\theta} \tag{3}$$

where

$$\beta_i = -(\mathrm{Re}\,M_{vv} + \mathrm{Re}\,M_{hh}) + 0.5\,m_i \tag{4}$$

and $m_1 = -r - r^*$, $m_2 = -r + r^*$, $m_3 = r - r^*$, $m_4 = r + r^*$, and

$$r = \{(M_{vv} + M_{hh})^2 + 4M_{hv}M_{vh}\}^{1/2}. \tag{5}$$

The elements of the averaged scattering matrix $\overline{\overline{M}}$ can be obtained by averaging the scattering matrix over the orientation and size distribution of the rice leaves;

$$\overline{\overline{M}} = <\overline{\overline{S}}(\theta,\phi;\theta,\phi)> i2\pi N/k. \tag{6}$$

The elements of the associate eigen matrix $\overline{\overline{E}}$ can also be computed from the averaged scattering matrix,

$$\overline{\overline{E}} = \begin{pmatrix} 1 & b_2^* & b_2 & |b_2|^2 \\ |b_1|^2 & b_1 & b_1^* & 1 \\ 2\mathrm{Re}(b_1) & 1 + b_1 b_2^* & 1 + b_1^* b_2 & 2\mathrm{Re}(b_2) \\ -2\mathrm{Im}(b_1) & -i(1 - b_1 b_2^*) & i(1 - b_1^* b_2) & 2\mathrm{Im}(b_2) \end{pmatrix} \tag{7}$$

where

$$b_1 = \frac{2M_{hv}}{M_{vv} - M_{hh} + r},\; b_2 = \frac{2M_{hv}}{-M_{vv} + M_{hh} - r}. \tag{8}$$

The reflectivity matrix can be computed using the Fresnel reflection coefficients.

$$\overline{\overline{R}} = \begin{pmatrix} |R_v|^2 & 0 & 0 & 0 \\ 0 & |R_v|^2 & 0 & 0 \\ 0 & 0 & \mathrm{Re}(R_v R_h^*) & -\mathrm{Im}(R_v R_h^*) \\ 0 & 0 & \mathrm{Im}(R_v R_h^*) & \mathrm{Re}(R_v R_h^*) \end{pmatrix} \tag{9}$$

The subscripts k and l of (2) denote the wave directions, and the subscripts i and j denote the ij^{th} element of the matrix. The phase matrix $\overline{\overline{P}}$ is the average of the Mueller matrix over the distribution of particles in terms of size, shape, and orientation, where the Mueller matrix elements are the covariance between the scattering matrix elements (Ulaby and Elachi, 1990).

$$\overline{\overline{P}} = \int_a\int_b\int_{\theta_j}\int_{\phi_j} \overline{\overline{L}}(\theta_i,\phi_i;\theta_s,\phi_s)p(a,b,\theta_j,\phi_j)da\,db\,d\theta_j\,d\phi_j \tag{10}$$

where $\overline{\overline{L}}$ is the Mueller matrix as in Tsang *et al.* (1985) and Ulaby and Elachi (1990) and p is the probability density function for four random variables; *e.g.*, size and shape ($a \times b$), and horizontal and vertical angles. The constant $C_{kl,ij}$ for each scattering mechanism can be summarized as

$$\begin{aligned} C_{41,ij} &= \frac{1 - e^{[\{\beta_i(\theta_s,\phi_s)\sec\theta_s + \beta_j(\pi-\theta_0,\phi_i)\sec\theta_0\}d]}}{\beta_i(\theta_s,\phi_s)\sec\theta_s + \beta_j(\pi-\theta_0,\phi_i)\sec\theta_0}, \\ C_{31,ij} &= \frac{e^{[-\beta_i(\pi-\theta_s,\phi_s)d\sec\theta_s]} - e^{[-\beta_j(\pi-\theta_0,\phi_i)d\sec\theta_0]}}{-\beta_i(\pi-\theta_s,\phi_s)\sec\theta_s + \beta_j(\pi-\theta_0,\phi_i)\sec\theta_0}, \\ C_{42,ij} &= \frac{e^{[\beta_i(\theta_s,\phi_s)d\sec\theta_s]} - e^{[-\beta_j(\theta_0,\phi_i)d\sec\theta_0]}}{-\beta_i(\theta_s,\phi_s)\sec\theta_s + \beta_j(\theta_0,\phi_i)\sec\theta_0}, \\ C_{31,ij} &= \frac{1 - e^{[\{\beta_i(\pi-\theta_s,\phi_s)\sec\theta_s + \beta_j(\theta_0,\phi_i)\sec\theta_0\}d]}}{\beta_i(\pi-\theta_s,\phi_s)\sec\theta_s + \beta_j(\theta_0,\phi_i)\sec\theta_0}. \end{aligned} \tag{11}$$

The scattering matrix is the basis for the computation of the scattering coefficients of any vegetated surfaces. The scattering matrix element for pq-polarization S_{pq} is $\hat{p}_s \cdot \overline{\overline{S}} \cdot \hat{q}_i$ where the scattering matrix field $\overline{\overline{S}}$ is defined as

$$\bar{E}_s(\bar{r}) = \frac{e^{ikr}}{r}\overline{\overline{S}}(\hat{k}_s,\hat{k}_i)\cdot\hat{q}_i E_0. \tag{12}$$

The computation of the scattering matrix is quite complicate for vegetation particles such as leaves and branches. A leaf can be modeled as a lossy dielectric thin disk. It was shown that the RCS of a thin leaf can be computed alternatively by either the physical optics (PO) model or the generalized Rayleigh-Gans (GRG) model at microwave frequencies in (Oh and Hong, 2007). The scattering matrices for the leaves, for example, can be computed from the equivalent current distribution induced on the leavers, which can be obtained using the PO and resistive sheet approximation. The equivalent current $\bar{J}(\bar{r}')$ can be approximated to a surface current distribution $\bar{J}_s^R(\bar{r}')$ on the resistive sheet lying on x-y plane as

$$\bar{J}_s^R(\bar{r}') = \bar{J}_s^{pc}(\bar{r}')\Gamma_q, \tag{13}$$

where $\bar{J}_s^{pc}(\bar{r}')$ is the PO surface current on a perfect conductor, Γ_q is the reflection coefficients for a resistive sheet at q-polarization as

$$\Gamma_h = \left[1 + \frac{2R\cos\theta_0}{\eta_0}\right]^{-1} \text{ and } \Gamma_v = \left[1 + \frac{2R}{\eta_0\cos\theta_0}\right]^{-1}, \tag{14}$$

with $R = \frac{i\eta_0}{k_0 t(\varepsilon_r - 1)}$, where R is the resistivity of the leaf, $\theta_0 = \pi - \theta_i$, and t is the leaf thickness. The relative permittivity ε_r of a leaf can be computed by the empirical formula in (Hallikainen *et al.*, 1985) using the gravimetric water content of the leaf. A branch can be modeled as a lossy dielectric cylinder for simplicity, and the scattering matrix of an arbitrarily oriented lossy dielectric cylinder can be computed as follows;

$$\begin{bmatrix} S_{vv} & S_{vh} \\ S_{hv} & S_{hh} \end{bmatrix} = \begin{bmatrix} \hat{v}_s\cdot\hat{v}_s' & \hat{v}_s\cdot\hat{h}_s' \\ \hat{h}_s\cdot\hat{v}_s' & \hat{h}_s\cdot\hat{h}_s' \end{bmatrix} \begin{bmatrix} S'_{vv} & S'_{vh} \\ S'_{hv} & S'_{hh} \end{bmatrix} \begin{bmatrix} \hat{v}_i'\cdot\hat{v}_i & \hat{v}_i'\cdot\hat{h}_i \\ \hat{h}_i'\cdot\hat{v}_i & \hat{h}_i'\cdot\hat{h}_i \end{bmatrix} \tag{15}$$

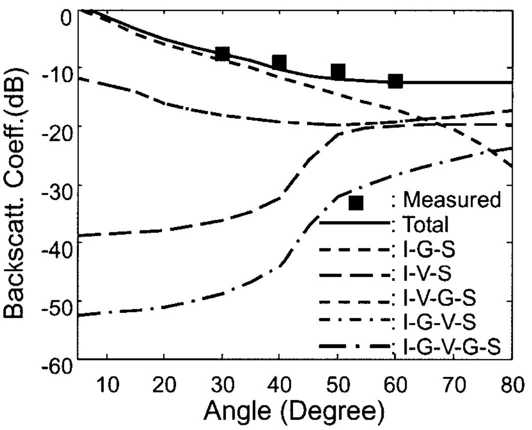
where the primed terms denote the local coordinate scattering from a vertical cylinder with a diameter d and a length l.

$$S'_{pq} = \frac{k_0 d}{4} l \frac{\sin V}{v} (\hat{v}_i'\cdot\hat{z}') \,|\hat{z}'\times\hat{k}_s|\, p_{pq} \tag{16}$$

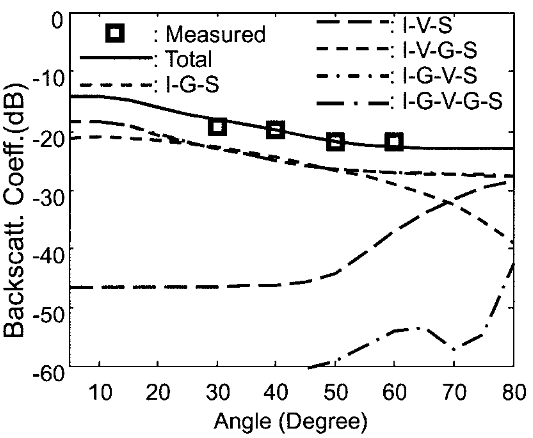
where V can be computed from the incident and scattered wave directions and the cylinder length in wavelength, and P_{pq} can be computed using Bessel functions, for example, for the vv-polarized wave the term P_{vv} can be computed by

$$\begin{aligned} P_{vv} = \sum_{m=-\infty}^{\infty} [\{ & J'_m(x_0)J_m(y_0)/\sin\beta - J_m(x_0)J'_m(y_0)/B\} \\ & + C_m^{TM}\{H_m^{(2)\prime}(x_0)J_m(y_0)/\sin\beta - H_m^{(2)}(x_0)J'_m(y_0)/B\} \\ & + \bar{C}_m m\left\{\frac{\cos\beta}{x_0\sin\beta} - \frac{\hat{k}_s\cdot\hat{z}'}{B y_0}\right\} H_m^{(2)}(x_0)J'_m(y_0)](-1)^m e^{-jm\phi} \end{aligned} \tag{17}$$

where C_m^{TM} and $\bar{C}_m$ are another complicate functions of the Bessel functions, J_m, J'_m, $H_m^{(2)}$, $H_m^{(2)\prime}$ with arguments such as $x_0 = k_0 a \sin\beta$ and $x_1 = k_0 a\sqrt{\varepsilon_r - \cos^2\beta}$. For other polarization combinations, P_{vh}, P_{hv}, P_{hh} can also be computed similarly with complicate functions.



(a)



(b)

Fig. 2. Contributions of scattering mechanisms on the backscattering coefficients for (a) hh- and (b) hv-polarizations.

Fig. 2 shows the contributions of scattering mechanisms on the backscattering coefficients for co- and cross-polarized waves for a vegetated surface with vegetation height h=72 cm, averaged leaf length L_{leaf}=60 cm, averaged leaf width W_{leaf}=2 cm, leaf density N_{leaf} =800 m^{-2}, soil moisture m_v=0.21 cm^3/cm^3, surface RMS height s=2.35 cm, and surface correlation length l=34.5 cm. The scattering model agrees quite well with the radar measurements as shown in Fig. 2.

Fig. 2 also shows that the direct backscatter from ground (5; I-G-S) is dominant while the ground double-bounce (4; I-G-V-G-S) affects least on the backscattering coefficients for co-polarization. For the cross-polarization, however, the ground single-bounce terms (2 and 3; I-G-V-S and I-V-G-S) are comparable with the direct surface backscatter (5; I-G-S) as shown in Fig. 2(b).

3. Simplification of the Scattering Model

Considering the complexity of the radiative transfer scattering model, it might be very difficult to invert the RT scattering model for the retrieval of soil moisture and surface roughness from the radar measurements of a vegetated surface, unless the RT scattering model is simplified enough for the inversion of the model. For this purpose, the complicate RT scattering model can be simplified as in De Roo *et al.* (2001).

$$\sigma_{pq}^0 = \sigma_{pq1}^0 + \sigma_{pq2}^0 + \sigma_{pq3}^0 + \sigma_{pq4}^0 \qquad (18)$$

with

$$\begin{aligned}
\sigma_{pq1}^0 &= \sigma_{pq1}\cos\theta(1 - T_pT_q)/(\kappa_p + \kappa_q) \\
\sigma_{pq2}^0 &= 2T_pT_q(R_p + R_q)h\sigma_{pq2} \\
\sigma_{pq3}^0 &= \sigma_{pq1}^0 T_pT_qR_pR_q \\
\sigma_{pq4}^0 &= \sigma_{s,pq}^0 T_pT_q
\end{aligned} \qquad (19)$$

where σ_{pq1} and σ_{pq2} are the backward and forward radar cross section (RCS) per unit volume of scatterers in the canopy, κ is the extinction coefficient of vegetation canopy, T is the transmissivity of the canopy, h is canopy height, R is the reflectivity of soil surface, and σ_s^0 is the backscattering coefficient of the soil surface.

The second term of (18) represents sum of the second and third terms of (1), and the third and fourth equations in (19) represent the fourth and fifth terms of (1), respectively. For a dense vegetation canopy the σ_{pq1}^0 will be dominant, while the σ_{pq4}^0 is dominant for a sparse vegetation canopy. The σ_{pq3}^0 term usually gives minimal effect on total backscatter as shown in Fig. 2, because of the combination of the reflection, attenuation and the backscattering mechanism; *i.e.*, usually $T_pT_qR_pR_q \ll 1$ for a dense canopy, and $\sigma_{pq1}^0 \rightarrow 0$ for a sparse canopy. Therefore the term σ_{pq3}^0 can be ignored without a considerable loss of accuracy. The σ_{pq2}^0 may not be negligible especially for the cross-polarization, because the forward scattering RCS σ_2 of a particle included in this term is much higher than the backscatter RCS σ_1 in other terms for the cross-polarization as shown in Fig. 2 (b).

For the retrieval of soil moisture form radar measurements, the backscattering coefficient σ_s^0 need to be extracted from the RT scattering model, which seems still very complicate. In order to further simplify the scattering model, at first, we can assume a uniform distribution for the orientation angles of the scatterers in the vegetation canopy, such that $\kappa_p = \kappa_q$, consequently, $T_p = T_q$. Then the radar backscatter can be approximated ignoring the ground-crown-ground term as

$$\sigma_{pq}^0 \cong \sigma_{pq1}^0 \frac{\cos\theta}{2\kappa}(1 - T^2) + 2T^2(R_p + R_q)h\sigma_{pq2} = \sigma_{s,pq}^0 T^2 \qquad (20)$$

Above equation is still not simple enough to be inverted because the computation of the RCS per unit volume, σ_{pq1} or σ_{pq2}, is very complicate as in (12)-(17). It was reported in De Roo *et al.* (2001) that the RCS per unit volume is proportional to the area density of the vegetation water mass m_w (kg/m^2) and the extinction coefficient is proportional to the square-root of m_w. The relations were derived from the analysis of the precise RT scattering model for various conditions. Therefore, the RCS and the extinction coefficient can be empirically expressed with unknown constants.

$$\sigma_{pq1} = a_1 m_w/h \qquad \sigma_{pq2} = a_2 m_w/h \qquad \kappa = a_3\sqrt{m_w/h} \tag{21}$$

with the reflectivity and transmissivity of

$$R_p = \Gamma_p \exp[-(2ks\cos\theta)^2] \qquad T = \exp[-\kappa h \sec\theta) \tag{22}$$

where Γ_p is the Fresnel reflectivity, k is wave number, and θ is incidence angle. The constants a_1, a_2, a_3, as well as the height h, the vegetation water mass m_w for the canopy, the rms height s, the dielectric constant ε_r of the soil surface, in addition to the radar parameters such as wave number k and incidence angle θ, should be known to retrieve the backscatter of the soil surface from the radar measurement of a vegetation-covered surface.

The well-known 'water-cloud' model is the simplest scattering model for estimation of the radar backscatter of a vegetated surface. If all canopy-ground interactions are ignored from (20), then the water-cloud model can be expressed in the following form.

$$\sigma^0_{pq} = \sigma^0_{pq1} + T^2\sigma^0_{s,pq} \tag{23}$$

where the first term is the direct backscatter from a vegetation canopy, which can be written as

$$\sigma^0_{pq1} \cong a_1\frac{m_w}{h}\frac{\cos\theta}{2a_3\sqrt{m_w/h}}(1-T^2) \tag{24}$$

Above equation may not be valid for the cross-polarization because the canopy-ground interaction usually can not be ignored for cross-polarization. The canopy height may also be considered as an unknown constant, because it is not usually known in advance. Therefore above equation can be rewritten with an unknown constant A.

$$\sigma^0_{pq1} = A\sqrt{m_w}\cos\theta(1-T^2) \tag{25}$$

where the transmissivity of a canopy can be represented with an unknown constant B.

$$T = \exp[-B\sqrt{m_w}\sec\theta] \tag{26}$$

The simplest scattering model with (23), (25) and (26) has only three parameters for vegetation; i.e., the unknown constants A and B, and the vegetation water mass m_w. The unknown constant A and B should be determined for a specific vegetation canopy, and the vegetation water mass should be provided as well for the retrieval of the backscatter of a soil surface.

4. Inversion Algorithms

The simplified scattering model can be used for an inversion algorithm of soil moisture and surface roughness with determined unknown constants for vegetation characteristics. One of robust optimization techniques would be the genetic algorithm (GA) (Oh, 2006). The GA is a global numerical-optimization process, patterned after the natural processes of genetic recombination and evolution, which has advantages over other traditional optimization techniques, because they are simple to program, and don't get stuck in local minima. The algorithm begins with binary encoding of input parameters, *e.g.*, the surface rms height s and the soil moisture content m_v. The random binary bits for the initial 120 chromosomes are generated using the sequential random numbers. Then, an optimum chromosome is obtained from the initial chromosomes by an iterative computation; (1)

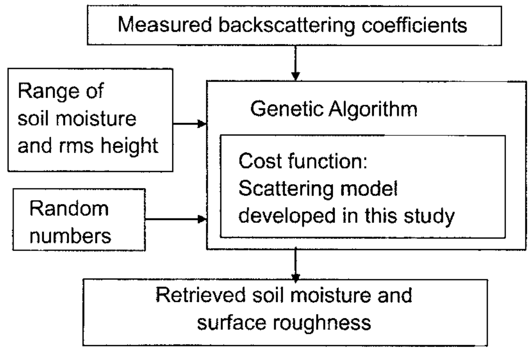


Fig. 3. Flow chart for the GA-based inversion algorithm.

assigning merit to those chromosomes by a cost function (a scattering model), (2) ranking the chromosomes and discarding the inferior ones, (3) mating the superior chromosomes, and (4) mutating a small portion of the chromosomes to avoid getting stuck in local minima. Fig. 3 shows the flow chart of the GA-based inversion algorithm.

Each binary-encoded chromosome is decoded by the formula

$$p = \sum_{i=1}^{N} b_i 2^{N-i} \frac{p_{\max} - p_{\min}}{2^N - 1}, \qquad (27)$$

where p is one of the surface parameters (s or m_v), b_i is the i^{th} binary bit ('0' or '1'), N is the number of binary bits, p_{max} and p_{min} are the maximum and the minimum values of the parameter. The number of bits N for each input parameter is 6, which gives the quantization error smaller than 1%.

The cost function for each chromosome is evaluated using the scattering model described in the previous section. At first, the polarimetric backscattering coefficients corresponding to the decoded surface parameter values of each chromosome are computed by the model. Then, the estimated backscattering coefficients are compared with the measurements. The cost function is defined as a summation of the weighted difference between the measured and the estimated vv-, hh-, and hv-polarized backscattering coefficients. The chromosomes are ranked from the most-fit to the least-fit, according to their respective costs using a data-sorting program. Then, 50% of the inferior chromosomes are discarded and the remaining superior chromosomes mate each other. Finally, about 1% of the bits in the list of all chromosomes is chosen randomly and reversed a binary bit; "1" to "0" or visa versa, to increase the algorithm's freedom to search outside the current region of parameter space to avoid getting stuck in local minima. Then, the cost functions are computed again, and iterate this process for convergence.

The scattering model as the cost function is summarized as in (23), (25), (26), and the following surface scattering model (Oh *et al*, 2002: Oh, 2004).

$$\sigma^0_{s,vv} = \sigma^0_{s,vh}/q \qquad (28)$$

$$\sigma^0_{s,hh} = \sigma^0_{s,vv} p \qquad (29)$$

$$\sigma^0_{s,vh} = 0.11 m_v^{0.7} \cos\theta^{2.2}[1 - \exp(-0.32(ks)^{1.8})] \qquad (30)$$

$$q = 0.095(0.13 + \sin(1.5\theta))^{1.4}[1 - \exp(-1.3(ks)^{0.9})] \qquad (31)$$

$$p = 1 - (\theta/90^0)^{0.35 m_v^{-0.65}} \cdot \exp[-0.4(ks)^{1.4}] \qquad (32)$$

where m_v denotes volumetric soil moisture, k is wave number, s is surface RMS height, and θ is incidence angle.

5. Inversion Results

A set of polarimetric measurement data was acquired using the Hongik Polarimetric Scatterometer system at 1.85 GHz from a tall-grass field at an incidence angle of 40^0 for a period of two months in 2006 with various soil moisture conditions and a fixed surface roughness. The rms height and the volumetric soil moisture contents m_v (cm³/cm³) of the soil surface, and the vegetation water mass m_w (kg/m²) and the gravimetric moisture content m_g (g/cm³) of the tall-grass were measured. The measured ground-truth data have the following values; the vegetation height h=72 cm, averaged leaf length L_{leaf}=60 cm, averaged leaf width W_{leaf}=2 cm, leaf density N_{leaf} =800 m^{-2}, surface RMS height s=2.35 cm, and surface correlation length l=34.5 cm. The measured volumetric soil moisture contents m_v have a range from 0.17 cm^3/cm^3 to 0.38 cm^3/cm^3 during the experiment period.

The unknown constants A and B in (25) and (26) were determined by comparison between the scattering model and the measurements using the minimum mean square error (MMSE) technique. It was shown that B is not sensitive on polarization. The estimated values of A_{vv}, A_{hh}, A_{vh}, and B are 0.0977, 0.1328, 0.0117, and 7.5, respectively. The scattering model with the estimated constants agrees quite well with the measured backscattering coefficients as shown in Fig. 4.

The vegetation water mass will change depending on the seasonal variation of the vegetation canopy and also on the soil moisture content. After analyzing the two-month measurements of the vegetation water mass, at first, we selected a functional form for the annual change of the m_w and the soil moisture change. Then, the unknown constants of the functional form were determined by data-fitting with *in-situ* measurements as follows;

$$m_w = 0.03(328 - t)e^{-\left(\frac{t-328}{100}\right)^2} + 0.6(m_v - \langle m_v \rangle). \quad (33)$$

where t is day of year (DOY), m_v is the soil moisture, and <···> denotes the mean value.

The scattering model is now a function of only two parameters; the soil moisture content m_v and the surface rms height s, which can be retrieved together from the measurements using the genetic algorithm. The measured co-polarized ratio $p=\sigma^0_{hh}/\sigma^0_{vv}$ and cross-

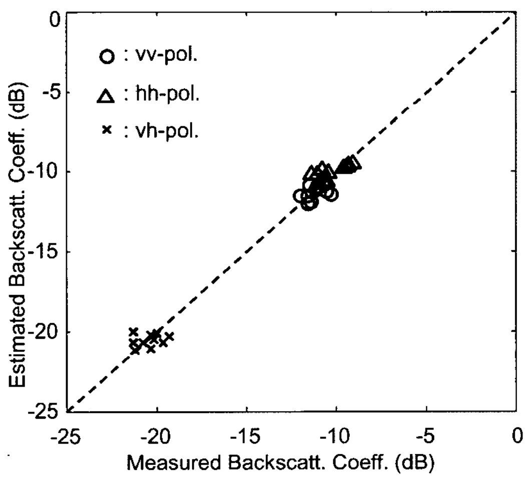
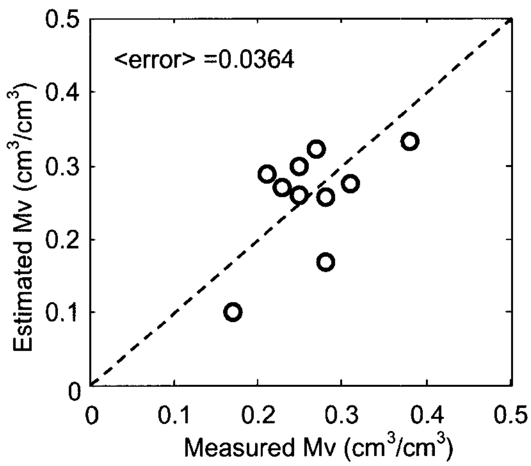
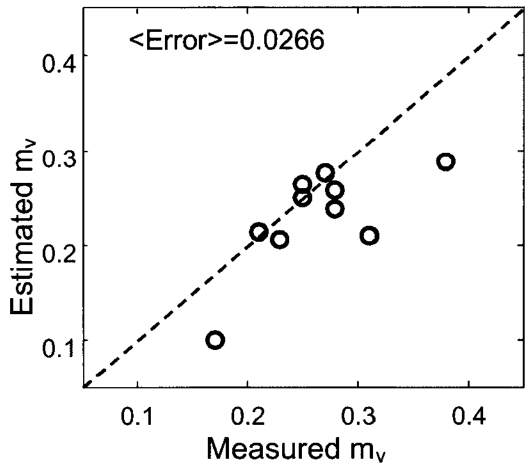


Fig. 4. Comparison between the radar measurements and the scattering model.



(a)



(b)

Fig. 5. Comparison between the estimated and measured soil moisture contents using (a) co- and cross-polarized measurements and (b) only co-polarized measurements.

polarized ratio $q=\sigma^0_{hv}/\sigma^0_{vv}$ of the tall-grass field, as well as the vv-, hh-, and hv-polarized backscattering coefficients (σ^0_{vv}, σ^0_{hh}, and σ^0_{hv}), were used to retrieve the soil moisture and surface roughness using the GA-based inversion algorithm. The inversion results which are obtained from each of the measured σ^0_{vv}, σ^0_{hh}, σ^0_{hv}, p, and q, are combined to get averaged values. Fig. 5 shows the comparison between the estimated and in-situ measured soil moisture contents. Results of Fig. 5(a) were obtained using all data (σ^0_{vv}, σ^0_{hh}, σ^0_{hv}, p, and q) resulting an RMS error of 0.0364, while only the co-polarized data (σ^0_{vv}, σ^0_{hh}, and p) were used for Fig 5 (b) resulting an RMS error of 0.0266.

Since the simplified scattering model is not valid for cross-polarization, the cross-polarization data (σ^0_{hv} and q) does not help at all as shown in Fig. 5 (a) and (b). It is recommended to use only co-polarization measurements when the simplified scattering model of (23) is employed for the GA-based inversion algorithm. The averaged value of ten estimated surface heights was 2.38 cm, which agrees quite well with the measured surface RMS height s=2.35 cm. In Fig. 5 (b), three measurements show large discrepancies between the measurements and the estimations. We can consider various sources of errors affecting soil moisture retrieval, such as imperfection of the scattering model, inaccurate radar measurements, and inaccurate in situ measurements of the soil moisture.

6. Conclusions

A simple scattering model for vegetated surfaces was derived by analysis and simplification of the precise radiative transfer model. The backscattering coefficients for a tall-grass field were measured with a polarimetric L-band scatterometer for various conditions of soil moisture at a fixed surface roughness. The ground truth data including the biomass, leaf moisture content, and soil moisture content were also collected *in situ* for every measurement. Unknown parameters of the scattering model were determined based on the measurements of the vegetation canopy. An inversion technique was developed based on the genetic algorithm using the scattering model as a costing function. The accuracy of the inversion algorithm was verified by comparisons between the measurements and the estimations of the soil moisture and surface roughness.

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