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RETRIEVAL OF SOIL MOISTURE CONTENT FROM MICROWAVE BACKSCATTERING USING A MODIFIED IEM MODEL

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Abstract—A multilayer soil model for retrieving soil moisture content using the Integral Equation Method (IEM) is investigated in this paper. The total reflection coefficients of the natural soil are obtained using the multilayer model, and volumetric scattering is approximated by the internal reflections between layers. The surface reflection terms in IEM model are replaced by the total reflection coefficients from the multilayer soil surface in retrieving the soil moisture content. The original IEM model includes only the surface scattering of the natural bare soil, while the multilayer soil — IEM model (MS-IEM) includes both the surface scattering and the volumetric scattering within the soil. Both the MS-IEM model and the original IEM model are compared in soil moisture retrieval using the experimental Synthetic Aperture Radar (SAR) backscattering coefficient data in the literature. It is noted that the mean square error between the measurement data and

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the values estimated by the modified IEM model is about 7.7%, while that between the measured and the estimated by the original IEM model is about 12%. The accuracy of estimating soil moisture by the IEM model is improved by 4.3%. In addition, the regression analysis between the measured and model-predicted soil moistures has been done.

1. INTRODUCTION

Soil moisture is one of the most important parameters in agricultural and environmental studies. Microwave remote sensing of soil moisture shows a high potential for operational applications because of its all weather, day and night capability. Retrieval of soil moisture content from the radar measurements using an inversion model is possible, and has been extensively investigated [1–3, 20–24, 26]. Many empirical model had been developed to retrieve soil moisture from backscattering coefficient measurement [4–6]. However, these empirical models developed on limited observations are site-dependent due to the nonlinear response of backscattering to the soil moisture and surface roughness parameters. The theoretical method such as the first-order small perturbation method (SPM) [7] can retrieve the soil moisture from SAR data and is valid for surfaces with small roughness parameters. This means that both the surface standard deviation and its correlation length should be small compared with the incident wavelength [26]. In general, SPM requires the surface Root Mean Square (RMS) height to be less than 5 percent of the electromagnetic wavelength. In addition to the RMS height requirement, the average slope of the surface should be of the same order of magnitude as the wave number times the surface RMS height. So, the application of SPM is limited to relatively flat surfaces.

The Integral Equation Model (IEM) developed by Fung et al. [8, 9] offers a promising alternative approach for the retrieval of soil moisture and surface roughness from active microwave data since the model is valid for a wider range of surface roughness conditions when compared to other earlier theoretical models [4, 25]. The active microwave backscattering coefficients from the nature soil is a function of soil texture, structure, density, roughness (surface RMS height), soil moisture, and soil surface conditions that are described by the auto-correlation function of random surface height and correlation length. For natural terrains that have a small RMS slope, only the single scattering is considered in the IEM model. The co-polarization backscattering coefficients given by the IEM can be found in [8, 9]. IEM model outperforms other earlier theoretical models for a wider range of surface roughness conditions. In [27, 28], modified IEM models are proposed to enlarge their applications. To simplify the inversion process of soil moisture directly from the active microwave data, an empirically adopted IEM is presented in [21]. However, since it is a surface scattering model [8–10], the effect of volumetric scattering is ignored. Thus it is expected that it performs well for wet soil where surface effect dominates, but not so for moderate wet soil where volumetric scattering within the active scattering layer plays some role.

To incorporate volumetric scattering in the IEM model, a multilayer soil model is developed in this study. The objective is to improve the accuracy of retrieval of soil moisture content from radar backscattering coefficient. Based on a multilayer soil model, the total reflection coefficients are obtained using ray-tracing technique. The ray-tracing technique is based on the optical principle, which can be used to investigate the reflection and refraction of the incidence electromagnetic wave. The surface reflection coefficients in the IEM model for computing the backscattering coefficients are replaced with the total reflection coefficient from the multilayer soil model that include both the surface reflection and volumetric scattering. For convenience, the modified model is called multilayer soil — IEM (MS-IEM) model. Backscattering coefficients calculated by the original IEM and the MS-IEM models are then compared with *in situ* measurements. In addition, the IEM surface model and the MS-IEM model have been used to retrieve the soil moisture content from radar backscattering coefficient, and compared with the measurements.

2. MULTILAYER SOIL MODEL FOR SURFACE REFLECTION OF RADAR

The natural soil can be viewed as a dense non-tenuous media with multiple species of particles [11], and consists of discrete dielectric soil particles and water with mixing dielectric constant ε_{sw} embedded in air. The different species refers to particles that can be of different shape, size, and permittivity. When only the specified propagation and scattering direction are considered, the propagation and scattering of electromagnetic waves in a discrete random medium can be simplified as those in a multilayer uniform medium. In this case, the non-specular direction is negligible.

A half-space of small soil particles below the ground surface (occupying the region $(z < 0)$) is modeled as a three-layer medium, as shown in Fig. 1, where D and ε_r are the radar penetration depth and the dielectric constant of the natural soil, respectively. Some simplifications are assumed:

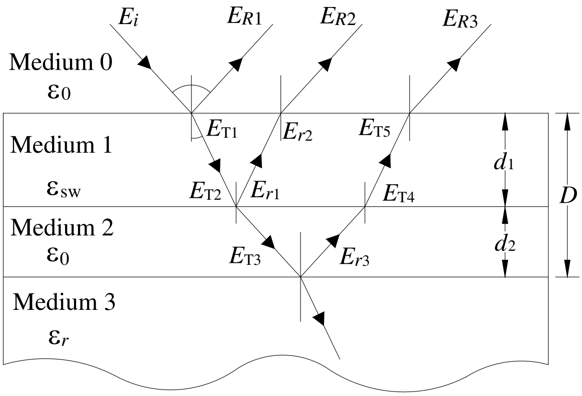


Figure 1. Multilayer medium reflection model of the soil.

1) The mixture of soil particles and liquid water is uniform both horizontally and vertically and thus the distribution of the soil equivalent complex dielectric constant is also uniform;

2) Multiple reflections between different interfaces in the multilayer model are ignorable and thus only single reflection from each interface is considered;

3) The wavelength of the incidence electromagnetic wave is far larger than the size of soil particles. Also, the attenuation of radar beam in air is ignored.

The multilayer soil model for radar reflection coefficient calculation includes three uniform media (layers): The medium 1 with thickness d_1 and permittivity ε_{sw}, representing the mixture of soil particles and liquid water content; the medium 2 with thickness d_2 and permittivity ε_0, representing the air in soil; and medium 3 with permittivity ε_r but any thickness, representing the soil layer that is below the radar penetration depth D. $(d_1 + d_2)$ is the penetration depth of radar in the soil, representing the thickness of active scattering layer. The surface effects can be analyzed according to [29, 30]. Using the ray tracing technique, the incidence and reflective radar rays at air-medium 1 interface can be written as

$$E_i = E_0 e^{-jk_{1z}z} \tag{1}$$

$$E_{R1} = R_a E_0 e^{-jk_{1z}z} \tag{2}$$

$$E_{R2} = T_{10} A R_s A T_{01} E_i \tag{3}$$

$$E_{R3} = T_{10} A T_{21} R_a T_{12} A T_{01} E_i \tag{4}$$

where $k_{1z} = k_1 \cos\theta$, θ and k_1 are the incidence angle and wave number of the incidence wave, respectively; E_0 and $e^{-jk_{1z}z}$ are the amplitude and phase of the incidence wave, respectively; R_a is the specular reflection coefficient of air at air-medium interface; R_s is the reflection coefficient of medium at air-medium interface; T_{mn} is the transmission coefficient from medium m to medium n, and m, $n = 0$, 1, 2, 3; A is the amplitude of attenuation factor [10], which is given as

$$A = e^{-K_e d_1 / \cos\theta_t} \tag{5}$$

where K_e is the extinction coefficient of the medium 1 [10], d_1 is the thickness of the medium 1, and θ_t is the refraction angle at the air-medium 1 interface when the incident radar beam is from air to medium 1. Since medium 2 is air, we have $R_s = -R_a$, $T_{01} = T_{21}$, $T_{12} = T_{10}$. Thus, the reflection coefficient and transmission coefficient are independent of the thickness d_2 of the medium 2 (air).

From Equations (1)–(4), we obtain the total surface reflection coefficient of the multilayer soil as

$$\tilde{R}_a = R_a + R_a T_{01} T_{10} A^2 (T_{01} T_{10} + 1) \tag{6}$$

This model includes two terms: 1) the specular surface reflection term R_a, which corresponds to the surface scattering of the natural soil; 2) the equivalent volumetric scattering term, which is represented by the internal reflections between layers. In this simple multilayer soil model, the thickness d of the medium 1 is a key parameter. In combination with the attenuation factor A and path length, it determines the total attenuation along a single path from one interface to the next in its propagation. Assume the radar penetration depth is D, then

$$D = d_1 + d_2 \tag{7}$$

Since the total volume of the natural soil is equal to the sum of the voids and the mixture of soil particles and liquid water, we have

$$d_1 = D\,(1 - \phi) \tag{8}$$

where ϕ is the soil porosity, which is defined as the volume percentage of voids (air) to the bulk volume of soil.

3. MODIFIED IEM MODEL AND APPLICATIONS

The original IEM model is a surface scattering model without explicit inclusion of volume scattering effect [8, 9]. To take the volume scattering into account, we replace the surface reflection terms in the IEM model with the total reflection coefficient calculated from the multilayer soil model discussed above. Since the total surface reflection coefficient contains internal reflections between internal layers, it contains more or less the contribution of volumetric scattering within the active scattering layer of soil. Two measures are taken to assess if the inclusion of volume scattering improves the performance of IEM model for the soil surface: 1) both models are used to calculate radar backscattering coefficient and then compare with in situ measurements; and 2) both models are used to retrieve soil moisture content and then compare with in situ measurements.

Figure 2 shows the comparison of backscattering coefficients calculated by the IEM model and the MS-IEM model with the measured data. The incident angle ranges from 10° to 70°. The soil surface is characterized by 0.4 cm in the RMS height, 8.4 cm in the correlation length L, and 20% in soil porosity. The surface moisture content was 14% in volume ($M_v = 0.14$ or 14%) when the measurement was carried out. The radar frequency is 1.515 GHz [8] (see Table 1). The dielectric constant is obtained from the following relation [12, 13]

$$M_v = -0.053 + 0.0292\varepsilon_r - 0.00055\varepsilon_r^2 + 0.0000043\varepsilon_r^3 \tag{9}$$

Compared with the IEM surface model, the backscattering coefficients calculated by the MS-IEM model with volume scattering included increase with the incidence angle θ up to 70° for the HH co-polarization. The difference in backscattering coefficients between the modified and MS-IEM model, as an approximate of volume scattering, decreases with increasing incidence angle at VV polarization, while it increases with increasing incidence angle for the HH polarization. The average error in backscattering coefficients between the MS-IEM

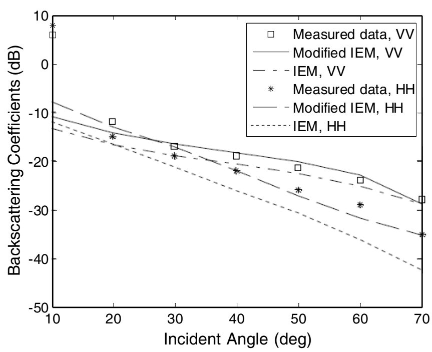


Figure 2. Comparison of backscattering coefficient calculated by IEM model and modified IEM model with measured data obtained from Fung et al., 1992.

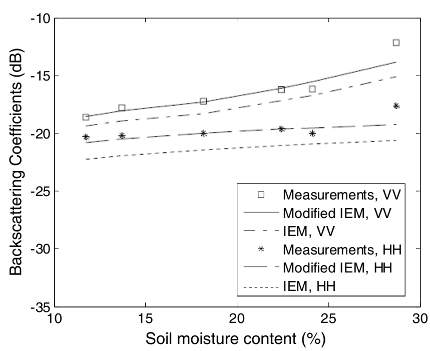


Figure 3. Comparison of backscattering coefficient calculated by the IEM model and the modified IEM model with measurement data obtained from Oh et al., 2002.

Table 1. Soil roughness and moisture parameters.

RMS (cm)	L (cm)	θ	BC (dB)	M_v (%)	Frequency (GHz)	co-polarization
0.4	8.4	10	6	14	1.515	vv
0.4	8.4	20	−12	14	1.515	vv
0.4	8.4	30	−17	14	1.515	vv
0.4	8.4	40	−19	14	1.515	vv
0.4	8.4	50	−21.5	14	1.515	vv
0.4	8.4	60	−24	14	1.515	vv
0.4	8.4	70	−28	14	1.515	vv
0.4	8.4	10	8	14	1.515	hh
0.4	8.4	20	−15	14	1.515	hh
0.4	8.4	30	−19	14	1.515	hh
0.4	8.4	40	−22	14	1.515	hh
0.4	8.4	50	−26	14	1.515	hh
0.4	8.4	60	−29	14	1.515	hh
0.4	8.4	70	−35	14	1.515	hh

model and the measurements is about 3.3 dB, while that between the original IEM model and the measurements is about 5.7 dB. It may indicate that the backscattering coefficient calculated by the MS-IEM model agrees better with the measurement results than the original IEM surface model.

Figure 3 shows a comparison of the radar backscattering coefficients calculated by the MS-IEM model and the original IEM model with measured backscattering coefficients by the JPL AirSAR for a soil surface with $ks = 0.477$, $kl = 4.65$ at about 55° with different wetness [14] (see Table 2). The radar frequency is 1.25 GHz and the radar system operates at both VV and HH polarizations. Results show that both the MS-IEM model and the original IEM model display a similar pattern in the variation of backscattering coefficients with the soil moisture content to that observed with JPL AirSAR. It can be seen that the measured backscattering values are greater than that calculated by the original IEM model, which is because the contribution of volume scattering isn't included in the original IEM model. After including the contribution of volume scattering (namely the MS-IEM model), the backscattering values calculated by the MS-IEM model agree better with the measured results than the original IEM model. Results from Figs. 2 and 3 indicate the contribution of volume scattering should be more or less taken account by the

Table 2. Soil roughness and moisture parameters.

RMS (cm)	L (cm)	θ	BC (dB)	M_v (%)	Frequency (GHz)	co-polarization
1.82	17.75	55	−12.2	28.7	1.25	vv
1.82	17.75	55	−16.2	24.1	1.25	vv
1.82	17.75	55	−16.3	22.4	1.25	vv
1.82	17.75	55	−17.3	18.1	1.25	vv
1.82	17.75	55	−17.8	13.6	1.25	vv
1.82	17.75	55	−18.6	11.6	1.25	vv
1.82	17.75	55	−17.65	28.7	1.25	hh
1.82	17.75	55	−20.07	24.1	1.25	hh
1.82	17.75	55	−19.7	22.4	1.25	hh
1.82	17.75	55	−20.05	18.1	1.25	hh
1.82	17.75	55	−20.25	13.6	1.25	hh
1.82	17.75	55	−20.4	11.6	1.25	hh

technique adopted here.

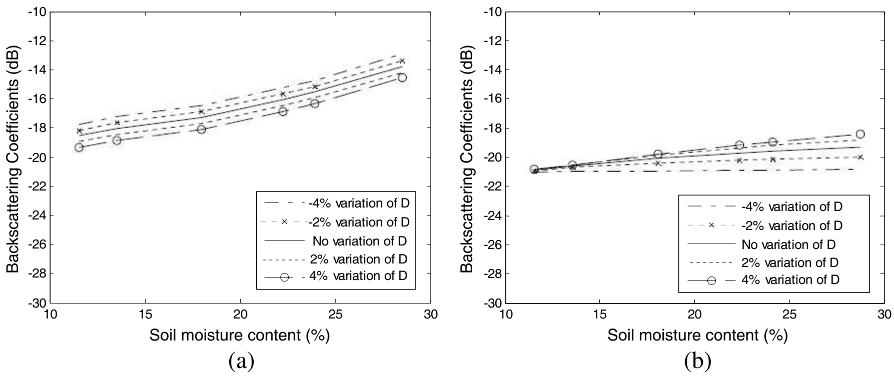


Figure 4. Sensitivity analysis of radar penetration depth D. (a) VV co-polarization, (b) HH co-polarization.

Figures 4(a) and 4(b) show the sensitivity analysis of radar penetration depth D for (a) the VV co-polarization mode and (b) the HH co-polarization mode, respectively. For the VV co-polarization mode (Fig. 4(a)), the influence of the offset of radar penetration depth D is almost uniform for the low and high soil moisture content. However, the backscattering coefficient is more sensitive to the offset of radar penetration depth D at high soil moisture content for the HH

co-polarization mode (Fig. 4(b)).

To evaluate the improvement of soil moisture content retrieval using the MS-IEM model, the inversion procedure was applied to the radar data collected in the literature [15–17]. The genetic algorithm (GA) has been used to retrieve soil moisture from the radar data of natural soil [18, 19]. The cost function for the GA is defined as the absolute errors of backscattering coefficients between the MS-IEM model and the measured data. Firstly, the iterative procedure produces the estimated values of the soil moisture; Secondly, the estimated dielectric constants are derived from the estimated values of the soil moisture using (9); Thirdly, the backscattering coefficients estimated by the MS-IEM model are compared with the measurements; Fourthly, if the difference between the estimated and measured is smaller than a preset criterion, the optimized values of the soil moisture are obtained; otherwise, repeat the above procedure. The accuracy of the estimation is then assessed with a correlation analysis between the measured and the estimated values of the soil moisture.

The data from Sano et al. (1998) are provided by the Sandia National Laboratories (SNL) in Albuquerque, New Mexico. The RMS height is from 0.2 to 0.5 cm, the correlation length is 5–6 cm, and the frequency is 5.3 GHz. The incidence angle is 23°, and the soil moisture content varies from 10% to 36%, corresponding to dielectric constant from 6 to 22 [12, 13] (see Table 3). All of the results are at VV co-polarization. For the data set from Bolten et al. (2003),

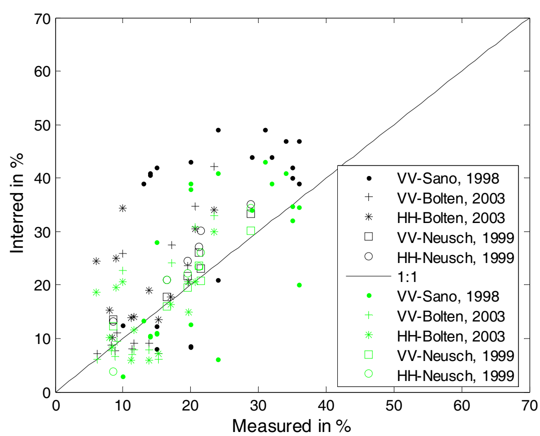
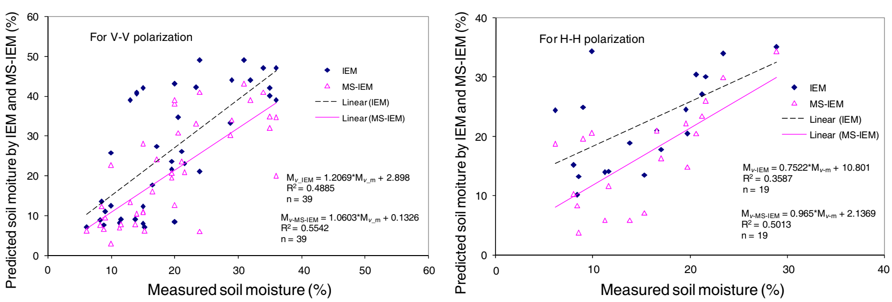


Figure 5. Comparison of the soil moisture content measured and retrieved by the original IEM surface model (black) and by the modified IEM model (MS-IEM model) (green).

the RMS height is 0.2 cm, the correlation length is 7 cm, the incidence angle is 39°, and the frequency is 1.26 GHz (see Table 4). The results are at both VV and HH co-polarizations. For the data set from Neusch and Sties [17], the RMS height is from 1.45 cm to 1.89 cm for several different measured fields, the average correlation length are about 11.1 cm, the incidence angle is 55°, and the frequency is 1.3 GHz (see Table 5). The results are illustrated in Fig. 5. Results show that the mean square errors between the measured data and the soil moisture content retrieved by the modified IEM model from all samples are about 7.7%, while those between the measured and the estimated by the original IEM surface model are about 12%. The overall accuracy of retrieving soil moisture by the IEM model is improved by 4.3% when the surface reflection terms in the IEM model are replaced by the total reflection coefficients derived from the simple multilayer soil model. The mean square error from all samples shown in Fig. 5 is still 7.7%. This may be caused by the radar system noise and the inaccurate surface autocorrelation function adapted for the model calculation that has great influence for the retrieval of the soil moisture content from the radar measurement.

Figures 6(a) and 6(b) show the correlations between the measured and the predicted soil moisture from radar backscattering coefficient by the original IEM and the MS-IEM models for (a) the VV-polarization mode and (b) the HH-polarization mode, respectively. The linear trend line equation for each case is also shown.



(a) (b)

Figure 6. The correlations between the measured soil moisture and model predicted soil moisture by the original IEM model (dashed line and diamond) and by the MS-IEM model (solid line and triangle) for (a) the VV-polarization and (b) the HH-polarization case. The linear equation for the trend lines are also shown, where $M_{v\text{-}m}$ denotes the measured soil moisture, $M_{v\text{-IEM}}$ and $M_{v\text{-MS-IEM}}$ denote the predicted soil moisture by IEM and MS-IEM models.

Table 3. Soil roughness and moisture parameters.

RMS (cm)	L (cm)	θ	BC (dB)	M_v (%)	Frequency (GHz)	co-polarization
0.3	5	23	−7.4	36	5.3	vv
0.3	5	23	−7.5	35	5.3	vv
0.2	5	23	−13.5	13	5.3	vv
0.3	5	23	−13.7	10	5.3	vv
0.2	6	23	−12.5	24	5.3	vv
0.3	6	23	−14	20	5.3	vv
0.4	6	23	−14.2	15	5.3	vv
0.3	6	23	−14.2	15	5.3	vv
0.2	6	23	−14.2	15	5.3	vv
0.3	6	23	−14.3	14	5.3	vv
0.3	6	23	−14.3	14	5.3	vv
0.2	6	23	−14	20	5.3	vv
0.2	6	23	−14	20	5.3	vv
0.4	6	23	−12.5	24	5.3	vv
0.3	6	23	−10.8	29	5.3	vv
0.3	6	23	−9	31	5.3	vv
0.5	6	23	−7.7	36	5.3	vv
0.3	6	23	−7.9	34	5.3	vv
0.3	6	23	−8	32	5.3	vv
0.3	6	23	−8.3	35	5.3	vv

For the VV-polarization mode (Fig. 6(a)), the number of total samples is $n = 39$. For the original IEM model, correlation coefficient is $r = 0.699$, coefficient of determination $R^2 = 0.4885$, and p-vale is $p < 0.001$. The correlation between the predicted soil moisture by the original IEM and the measurement is significant taking $p = 0.05$ as the criterion. For the MS-IEM model, the correlation coefficient $r = 0.744$, coefficient of determination $R^2 = 0.5542$, and p-vale is $p < 0.001$. The correlation between the predicted soil moisture by the MS-IEM model and the measurement is significant and correlation is better than the case of the original IEM. If the prediction by a model is perfect, the slope of the linear equation should be 1, and the offset should be 0. The slope and offset for the original IEM are $S = 1.2069$ and $OS = 2.898$, respectively, while for the MS-IEM model, $S = 1.0603$ ad $OS = 0.1326$. Compared with the original IEM model, the slope and offset for the MS-IEM model are closer to 1 and 0, respectively. These comparisons

Table 4. Soil roughness and moisture parameters.

RMS (cm)	L (cm)	θ	BC (dB)	M_v (%)	Frequency (GHz)	co-polarization
2	7	39	−20.3	6.2	1.26	vv
2	7	39	−19.5	8.3	1.26	vv
2	7	39	−20	8.9	1.26	vv
2	7	39	−18.7	9.1	1.26	vv
2	7	39	−15.7	10	1.26	vv
2	7	39	−19.8	11.3	1.26	vv
2	7	39	−19.4	11.6	1.26	vv
2	7	39	−19.4	13.8	1.26	vv
2	7	39	−20.3	15.3	1.26	vv
2	7	39	−15.5	17.2	1.26	vv
2	7	39	−16	19.6	1.26	vv
2	7	39	−14.7	20.6	1.26	vv
2	7	39	−14	23.4	1.26	vv
2	7	39	−18.7	6.1	1.26	hh
2	7	39	−20.1	8	1.26	hh
2	7	39	−20.6	8.4	1.26	hh
2	7	39	−18.6	9	1.26	hh
2	7	39	−17.7	9.9	1.26	hh
2	7	39	−21.5	11.2	1.26	hh
2	7	39	−19.8	11.6	1.26	hh
2	7	39	−21.5	13.8	1.26	hh
2	7	39	−21	15.3	1.26	hh
2	7	39	−19	17	1.26	hh
2	7	39	−19.2	19.7	1.26	hh
2	7	39	−18.5	20.6	1.26	hh
2	7	39	−16.8	23.4	1.26	hh

demonstrated that for the VV-polarization mode, the predictability of the soil moisture is improved by the MS-IEM model when volume scattering in soil is considered.

For the HH-polarization mode (Fig. 6(b)), the number of total samples analyzed is $n = 19$. For the original IEM model, correlation coefficient is $r = 0.599$, coefficient of determination $R^2 = 0.3587$, and p-vale is $p = 0.0068$. The correlation between the predicted soil moisture by the original IEM and the measurement is still significant. For the

Table 5. Soil roughness and moisture parameters.

RMS (cm)	L (cm)	θ	BC (dB)	M_v (%)	Frequency (GHz)	co-polarization
1.7	11.15	55	−17.7	28.85	1.3	vv
1.78	11.2	55	−18.85	21.57	1.3	vv
1.49	10.8	55	−19.2	21.2	1.3	vv
1.56	11.1	55	−20.36	19.53	1.3	vv
1.45	10.9	55	−21.4	16.52	1.3	vv
1.89	11.6	55	−21.5	8.53	1.3	vv
1.7	11.15	55	−18.4	28.85	1.3	hh
1.78	11.2	55	−18.6	21.57	1.3	hh
1.49	10.8	55	−18.83	21.2	1.3	hh
1.56	11.1	55	−20.5	19.53	1.3	hh
1.45	10.9	55	−21.8	16.52	1.3	hh
1.89	11.6	55	−22.47	8.53	1.3	hh

MS-IEM model, the correlation coefficient $r = 0.708$, coefficient of determination $R^2 = 0.5013$, and p-vale is $p = 0.0007$. The correlation between the predicted soil moisture by the MS-IEM model and the measurement is significant and correlation is better than the case of original IEM. The slope and offset for the original IEM are $S = 0.7522$ ad $OS = 10.801$, respectively, while for the MS-IEM model, $S = 0.965$ and $OS = 2.1369$. Compared with the original IEM model, the slope and offset for the MS-IEM model are closer to 1 and 0, respectively. These comparisons demonstrated that for the HH-polarization mode, the predictability of the soil moisture is also improved by the MS-IEM model when volume scattering is considered.

For the VV-polarization, both models can predict well the soil moisture, while for the HH-polarization; the predictability is not as good as for the VV-polarization. The improvement by the MS-IEM model is even more significant in the HH-polarization mode compared to the VV-polarization mode.

A better agreement between the modified IEM model and in situ measurement in both backscattering coefficient and soil moisture retrieval than the original IEM mode indicates that: 1) the contribution of volume scattering to the total backscattering coefficient should be more or less captured in the total reflection coefficient calculated by the ray-tracing method with a simplified multilayer soil model; and 2) the approach adopted here to replace the surface reflection coefficient with total reflection coefficient in IEM model works well, even though the original development of IEM model only considered the surface scattering.

4. CONCLUSIONS

Based on a multilayer soil model developed, the total surface reflection coefficient has been obtained using ray-tracing technique. The total surface reflection coefficient of radar beam includes both the surface reflection term and the volumetric reflection term, which is simplified as the internal reflections from the interfaces of the multilayer model. The pure surface reflection terms in the IEM model is replaced by the total reflection coefficient. The comparisons of backscattering coefficient simulations using the IEM model and the MS-IEM model were performed for two cases: 1) different incidence angles but constant soil moisture content; 2) different soil moisture contents but at a single incidence angle. Results show that the MS-IEM model shows better agreement with the experimental data than the original IEM model, especially for HH-polarization mode, even though the multi-layer is a simple model and the total surface reflection coefficient is obtained by a simplified ray-tracing method.

The MS-IEM model was also compared with the original IEM surface model in retrieving soil moisture content from radar backscattering coefficients. The MS-IEM model gives comparable soil moisture to the in situ measurements. The mean square error from all samples is about 7.7% for the MS-IEM model, comparing to about 12% for the original IEM model. The predicting capability of IEM model is improved by 4.3% with volumetric scattering being considered with multilayer soil model for radar backscattering. Regression analysis between the measured and model-predicted soil moistures shown that: (1) The correlation coefficient and coefficient of determination are higher for the MS-IEm model than the original model; (2) the slope and offset of the linear regression equation are closer to 1 and 0, respectively, for the MS-IEM than the original IEM model.

All these results indicate that the predictability of soil moisture by the MS-IEM model is improved compared to the original model. In addition, all the terms of Equation (6) can be derived by using the iterative procedure for applications of the MS-IEM model to airborne or Spaceborne SAR. The MS-IEM model can be used to different textured soil. For the partially vegetated fields, it can be further modified by adding a top layer of vegetation to simulate the impact of the vegetation.

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