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Algorithm for the retrieval of soil moisture from the radar backscattering coefficient

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An algorithm based on a fit to the small perturbation method (SPM) was developed so that soil moisture can be derived directly from radar backscattering coefficient data. Using the genetic algorithm with a simulated data set generated from the original SPM model, this algorithm is developed to derive the dielectric constant and then the soil moisture of bare soil surfaces. The fitting algorithm is tested against the original SPM model for incidence angles between 10° and 60°, soil dielectric constants between 3 and 41, and the surface root mean square height between 1 and 20 mm. The fitting algorithm has the same frequency range as the original SPM model. The fitting algorithm computes the backscattering coefficients with an average error of 0.05 dB for horizontal horizontal (HH)-polarisation and 0.15 dB for vertical vertical (VV)-polarisation, where the backscattering observations are taken from the literature. Comparison of the soil moisture derived from the radar backscattering coefficient using the inversion algorithm with the simultaneous measurement shows that the soil moisture retrieved from the inversion algorithm agrees very well for VV-copolarisation ($R = 0.89$, in contrast with $R = 1$ for perfect agreement) and agreement between the calculation and measurement is significant only at the 90% significance level for HH-copolarisation.

Keywords: algorithm; soil moisture; retrieval; radar; backscattering coefficient; microwave remote sensing

1. Introduction

The soil moisture content is one of the important parameters in a number of disciplines, including hydrology, agriculture, and environmental sciences. Operational large-scale soil moisture products would likely enhance the accuracy of numerical weather prediction, hydrological flood forecasting, agricultural irrigation management and drought monitoring, as well as water cycle research related to climate studies. The significance of soil moisture content is its role in the partition of energy at the ground surface into sensible and latent heat exchange with the atmosphere, and the partition of precipitation into infiltration and runoff. Therefore, various methods of assessing and monitoring soil moisture have been developed, and retrieval of this parameter from ground-base or space-borne radar measurements has been actively investigated.[1–19] The retrieval of soil moisture has been implemented over bare soils from synthetic aperture radar (SAR) data in the literature.[8,9,20,21] The multi-incidence SAR data have been used to improve the estimation of soil moisture.[8,13,14,20] The sensitivity of advanced SAR data to soil surface parameters (surface roughness and soil moisture) has been investigated over bare fields at various polarisations (horizontal horizontal (HH), horizontal vertical (HV), and vertical vertical (VV)) and incidence angles in Holah et al.[5]

Analytical models based on physical approximation such as the physical optics, the geometrical optics, the first-order small perturbation method (SPM),[22] and integral equation method (IEM) [4] offer approaches to simulate the backscattering coefficient. Moreover, various parameters, such as surface root mean square (RMS) height, correlation length, incidence angle, and dielectric constant of soil, are model input parameters. Soil is a mixture of various minerals, organic materials, liquid water, and air pores. However, its mixing dielectric constant is not simply a linear mixing of the dielectric constants of all constitutive components but rather a nonlinear mixing. The complexity of these methods and nonlinearity in the mixing of constitutive dielectric constants make it very difficult to derive soil moisture using these models directly from the SAR backscattering data measured from natural surfaces. Many empirical and semi-empirical models have been developed to establish the relationships between backscattering coefficient with soil moisture and surface roughness,[23–25] and the empirical models derived from in situ data sets can fit their data well. These empirical models may be very suitable under similar soil surface

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conditions and SAR system parameters as those on which the empirical models were developed.

The first-order SPM [22] 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 addition, the average slope of the surface should be of the same order of magnitude as the wave number times the surface RMS height. Mathematically, the above two conditions are [22]

$$ks < 0.3, \tag{1}$$

$$\frac{\sqrt{2}s}{l} < 0.3, \tag{2}$$

where k is the wave number, s is the surface RMS height, and l is the surface correlation length. The SPM model has been applied to the bare soils, snow, and sea ice.[21,27–33] In addition, the IEM model can be applied over a wider range of soil surface roughness conditions than the SPM model. However, it is still an open question if the IEM model can perform equally well as or even better than the SPM model for cases such as monitoring sporadic rainfalls in desert, measurement of soil moisture in flat bare soils, and liquid water content in snow. Compared with the IEM model, the analytical formulation of the SPM model is simpler and fewer computer resources may be required if it is applicable for retrieval of soil moisture or liquid water content in snow. On the other hand, as the soil or snow dielectric constant is implicitly imbedded in the original SPM, inversion of soil moisture or liquid water content in snow is often accomplished through iterations till convergence is reached. This is computationally expensive and can cause accumulated round-off errors in the final retrieved soil moisture, especially when it is applied to retrieve soil moisture or snow liquid water content from active microwave remote sensing data on a large scale. Parameterisation of SPM is useful in order to obtain a manageable inversion algorithm that can handle a large volume of SAR backscattering data.

The objective of this paper is to develop and test an inversion algorithm for direct soil moisture retrieval from radar backscattering coefficient through parameterisation of the SPM model for a wide range of soil dielectric constant, incidence angle, RMS height, and surface correlation length, which also include the effect of surface power spectrum. In the following sections, the fitting algorithm will be developed using the generic algorithm (GA) through parameterisation of the SPM model and the fidelity to the original SPM model is assessed. Then the algorithm is tested with in situ measurement of radar backscattering coefficients.[4] Lastly, the inversion algorithm is derived from the fitting algorithm and then used to derive soil moisture and tested with in situ soil moisture and radar backscattering coefficient measurement collected simultaneously [2,8] and the difference between derived and measured soil moisture is assessed. Compared with the previous inversion algorithm, the inversion algorithm presented in this paper is simple. The retrieval of soil moisture is direct and can be a useful tool for retrieving soil moisture of bare soil surfaces from both ground-based and space-borne radar backscattering coefficient data.

2. Development of an statistic algorithm based on a GA approach

The backscattering coefficients of bare soil surfaces depend on its dielectric constant, surface roughness, incidence angle, and frequency. The dielectric constant of soil is the parameter sensitive to volumetric soil moisture due to the large difference in dielectric constant between dry soil (typical dielectric constants of 2–3) and water (dielectric constant of approximately 80), and the surface roughness is generally described by an autocorrelation function depending on the surface RMS and the correlation length. The radar backscattering coefficients from the SPM model are given by [22]

$$\sigma_{\mathrm{pp}} = 8k^4 s^2 |\alpha_{\mathrm{pp}} \cos^2\theta|^2 W(2k\sin\theta, 0), \tag{3}$$

where $p = h$ (horizontal) or v (vertical) polarisation and

$$\alpha_{\mathrm{hh}} = \frac{(\cos\theta - \sqrt{\varepsilon_{\mathrm{r}} - \sin^2\theta})}{(\cos\theta + \sqrt{\varepsilon_{\mathrm{r}} - \sin^2\theta})}, \tag{4}$$

$$\alpha_{\mathrm{vv}} = \frac{(\varepsilon_{\mathrm{r}} - 1)[\sin^2\theta - \varepsilon_{\mathrm{r}}(1 + \sin^2\theta)]}{[\varepsilon_{\mathrm{r}}\cos\theta + (\varepsilon_{\mathrm{r}} - \sin^2\theta)^{1/2}]^2}. \tag{5}$$

In the above equations, $k = 2\pi f/c$ is the wave number, f the operating frequency, c the light velocity in the free space, s is the RMS height, θ is the incidence angle, ε_{r} is the soil relative dielectric constant, and $\mathrm{W}_{(2k\sin\theta,0)}$ is the Fourier transform of a known surface correlation function which can be calculated by

$$W(2k\sin\theta, 0) = \frac{1}{2\pi}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\rho(x,y) \times \exp(-j2kx\sin\theta)\,\mathrm{d}x\,\mathrm{d}y, \tag{6}$$

where $\rho_{(x,y)}$ is the surface correlation function, taking either the exponential form or Gaussian form.

From the above equations, it is shown that the soil dielectric constant ε_r only appears in α_{pp}, which is a nonlinear function of ε_{r} and θ. To retrieve the soil moisture, ε_{r} has to be inverted from α_{pp}, which is usually impossible analytically. Based on this observation, α_{pp} can be fit by using the basic mathematical functions so that ε_{r} can be derived, directly from the equations of backscattering coefficients, and soil moisture can be subsequently retrieved.

To fit α_{pp} by using the basic mathematical functions of ε_r and θ, the variation trend of α_{pp} with respect to variables ε_r and θ must be obtained first. By setting the value of incidence angle θ to specific values, α_{pp} has been computed with ε_r values changed. The basic mathematical functions to fit Equations (4) and (5) are chosen by observing the mathematical function scheme of Equations (4) and (5), the variation trend of the simulated curves from original SPM model, and the fitting error between the inversion algorithm and the original SPM model. In addition, the simple mathematical functions have been used to realise minimum fitting error by using an optimisation method. After the type of the basic mathematical functions for fitting Equations (4) and (5) are chosen, the coefficients of the basic mathematical functions are optimised by using the GA to get a minimum error between the original SPM model and the optimised fitting algorithm. According to the simulated results, it was found that a power function of ε_r as a basic function for fitting is optimal for the horizontally and vertically polarised backscattering. Similarly, the cosine functions of θ are optimal for the horizontally polarised backscattering, while a polynomial function of θ for the vertically polarised backscattering.

After optimising the basic mathematical functions as the building blocks, the fitting is then performed using GA. The ranges of soil dielectric constant ε_r, incidence angle θ, RMS height s, the correlation length L, and their incremental steps are listed in Table 1. These ranges are used for computation of σ_{hh} and σ_{vv}. The GA is a global numerical optimisation method which is patterned after the natural processes of genetic recombination and evolution. Moreover, the GA is simple to programme and does not get stuck in the local minima, so it has advantages over other traditional optimisation techniques.[34–36] GA can also be used as an inversion technique in retrieving soil moisture.[37,38] The algorithm begins with a binary encoding of the input parameters, i.e. the coefficients of basic mathematical functions selected. The random binary bits for the initial chromosomes are generated using the sequential random numbers. Then an optimum chromosome is obtained from the initial chromosomes by an iterative computation, and these chromosomes undergo an iterative natural selection using a cost function to get an optimal solution. The cost function is the absolute errors of backscattering coefficients between the original SPM model and the optimised fitting algorithm, which is given as

$$c_{pp} = \sum_{\theta,\varepsilon_r} |\sigma_{pp}(\theta,\varepsilon_r) - \sigma^F_{pp}(\theta,\varepsilon_r)|, \tag{7}$$

where σ_{pp} and σ^F_{pp} are the backscattering coefficients calculated by the original SPM model and the fitting algorithm, respectively. Summation $\sum_{\theta,\varepsilon_r}$ is over all data points of (θ,ε_r). c_{pp} is the horizontally ($p = h$) or vertically ($p = v$) co-polarised cost function. Our purpose is to find the exact form of σ^F_{pp} by minimising c_{pp} through numerical fitting. To ensure the fidelity of the statistic algorithm to the original SPM model, more than 1000 samples (data points) were generated with the original SPM model followed by multivariate linear regression analysis to obtain the statistic soil moisture algorithm. The exact forms of the fitting functions of the horizontally and vertically co-polarised backscatter coefficients that minimise the cost function are given as in Equations (8) and (9), where θ is in radian and other parameters in SI units.

$$\sigma^F_{hh} = 17k^4s^2\left[\frac{\cos 0.6\theta}{4.056}\mathrm{e}^{1.51/\varepsilon_r^{0.2}} - 1\right]^2 \times W(2k\sin\theta,0)\cos^4\theta, \tag{8}$$

$$\sigma^F_{vv} = 8k^4s^2\left[6.7\sin^{2.8}\theta - 9.2\sin^{1.2}\theta + 3.68\sin 2\theta + \frac{0.396(\varepsilon_r - 2.7)^{0.3}}{(1.585-\theta)^2}\right]^2 \times W(2k\sin\theta,0)\cos^4\theta. \tag{9}$$

Table 1. Model parameters.

Model parameters	Minimum	Maximum	Interval	Unit
Dielectric constant	3	41	2	
Incidence angle	10	60	1	degree
RMS height	1	20	1	mm
Correlation length	10	100	10	mm
Correlation functions	Gaussian, Exponential			

3. Comparison of the fitting algorithm and original SPM model

Before application of the fitting algorithm to retrieve soil moisture, the fidelity of the fitting algorithm to the original SPM model needs to be assessed. Figure 1(a) and 1(b) shows the histograms of the absolute errors in dB between the original SPM model and the SPM fitting algorithm σ_{hh} (Equation (8)) and σ_{vv} (Equation (9)), respectively, using soil model parameter values listed in Table 1. Comparing the original SPM model (Equations (3)–(5)) with the SPM fitting algorithm σ_{hh} (Equation (8)) and σ_{vv} (Equation (9)), it can be seen that they all include "$k^4W(2k\sin\theta,0)$" and the operating frequency is only included in "$k^4W(2k\sin\theta,0)$". So, the fitting algorithm has the same frequency range as the original SPM model. That is to say, any frequency can be chosen to assess the fidelity of the fitting algorithm to the original SPM, and the difference (absolute error) between the fitting algorithm and the original SPM model is independent of the operating frequency.

Comparison was performed separately for HH (Figure 1(a)) and VV (Figure 1(b)) co-polarisation cases.

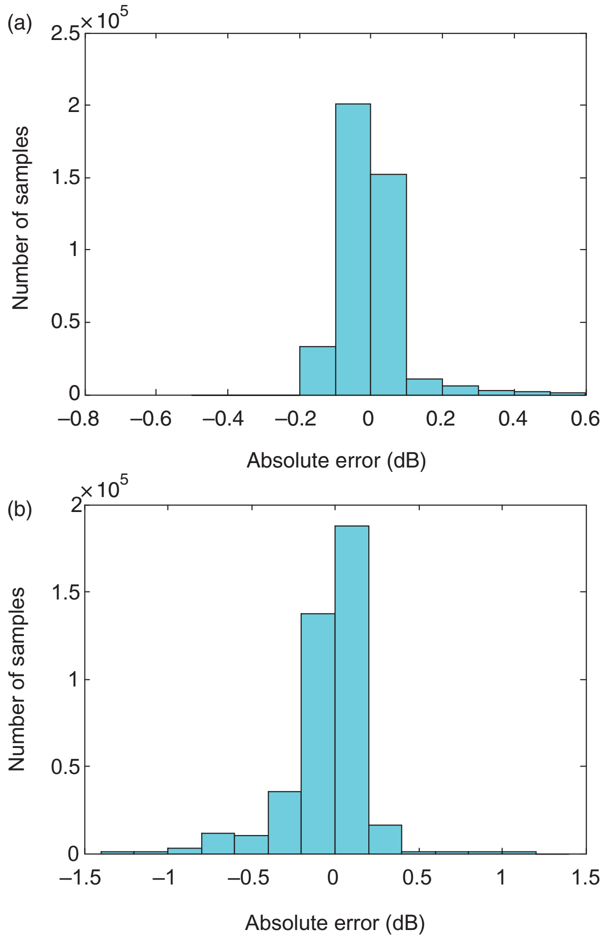

Figure 1. Histogram of absolute error in dB between the SPM model and the SPM fitting algorithm for (a) σ_{hh}; and (b) σ_{vv}. The total number of samples is 408,000.

For each case, a specific set of values for the model parameters given in Table 1 is a sample for either Gaussian or exponential correlation functions. Based on the minimum, maximum, and interval for each model parameter and two correlation functions, there are totally 4.08×10^5 samples for the calculation of the radar backscattering coefficient. For each sample, calculation was performed for the radar backscattering coefficient using both the fitting algorithm and the original SPM model and the difference between them (absolute error) is tracked down. For the HH case, since the maximum difference (error) is 0.53 dB, the absolute errors from -0.8 to 0.6 were subdivided into 14 bins, each covering a range of 0.2 dB. The absolute error for each sample falls into one of these bins. The number of samples fallen in each bin was tracked down and shown in Figure 1(a). Similar process was performed for the VV-polarisation case and was shown in Figure 1(b). From Figure 1(a), it is shown that the majority of the sample calculations fall within the two error bins close to 0. This means that for most of the samples, the absolute error is within 0.2 dB. Similar results are for the VV-polarisation case. A comparison between the fitting algorithm developed and the original SPM model shows that the fitting algorithm computes the backscattering coefficients with an average error of 0.05 dB for HH-polarisation and 0.15 dB for VV-polarisation. The maximum absolute error between the original SPM model and the fitting algorithm (Equation (8)) is 0.53 dB for the HH-polarisation, while that between the SPM model and the fitting algorithm (Equation (9)) is 1.23 dB for the VV-polarisation. For σ_{vv}^{F}, the largest error of 1.23 dB occurs when $\theta = 11°$ and $\varepsilon_{\mathrm{r}} = 3$. These comparisons indicate that the backscattering coefficients calculated by the optimal fitting algorithm agree with those from the original SPM model with errors being within an error envelop of 0.53 dB for HH-polarisation and of 1.23 dB for VV-polarisation.

4. Algorithm assessment through comparison with in situ measurement

4.1. Backscattering coefficient comparison

Comparison with in situ measurement is the best way for algorithm assessment. However, simultaneous in situ measurements of both radar backscattering coefficients and soil surface conditions are scare due to the sophistication of a radar system and difficulty in soil surface characterisation. The limited data sets available in the literature were used for this task.

The set of data was from Fung et al.[4] A comparison between the calculated and measured values of the backscattering coefficients from a bare soil surface over the incident angle range from 10° to 70° under two soil surface conditions at frequencies 1.515 and 4.725 GHz is shown in Figures 2 and 3. In Figure 2, the RMS height is 4 mm, the correlation length is 84 mm, and the soil dielectric constant is about 8. In Figure 3, the RMS height is 3.2 mm, the correlation length is 99 mm, and the soil dielectric constant is about 16. It is noted that the difference between the algorithm results and the measured values were found to become larger when the incidence angle increases, especially for HH-polarisation. For VV-polarisation, the difference is smaller than 4 dB for the range of θ (10°–70°), except for the frequency 1.515 GHz and $\theta = 10°$. The difference is more than 10 dB at the frequency 1.515 GHz and $\theta = 10°$ for both VV- and HH-polarisation, which is compatible with [4] and may be caused by the measurement error or the original SPM model. On the other hand, the difference is more than 5 dB over the incidence angle of 50°–70° for HH-polarisation, which is also observed in Fung et al.[4] Overall, the average absolute error of the backscattering coefficients between the algorithm developed and measurements is 3.3 dB over the incident angle ranging from 10° to 70°.

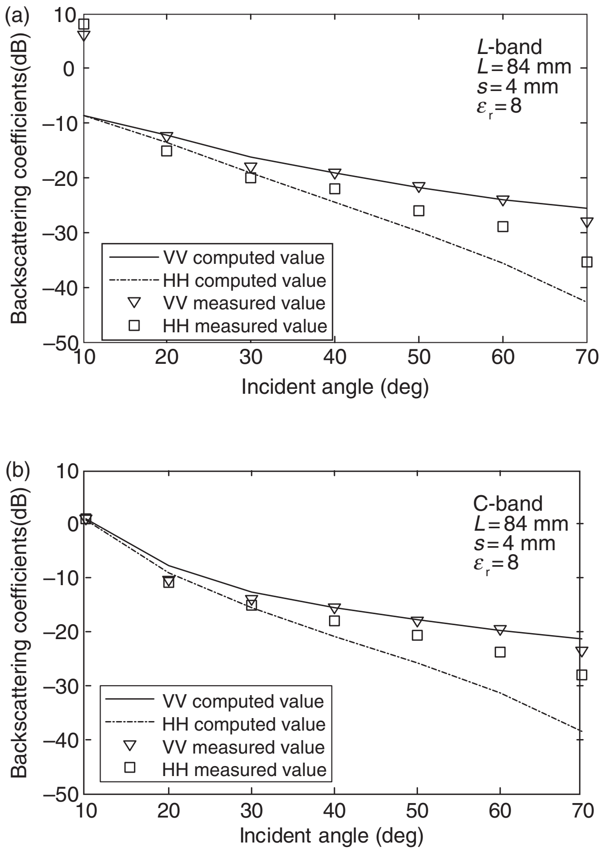

Figure 2. Comparisons of the algorithm predictions (lines) with measurements (symbols) from a bare soil surface 14% surface moisture content at (a) 1.515 GHz and (b) 4.725 GHz.

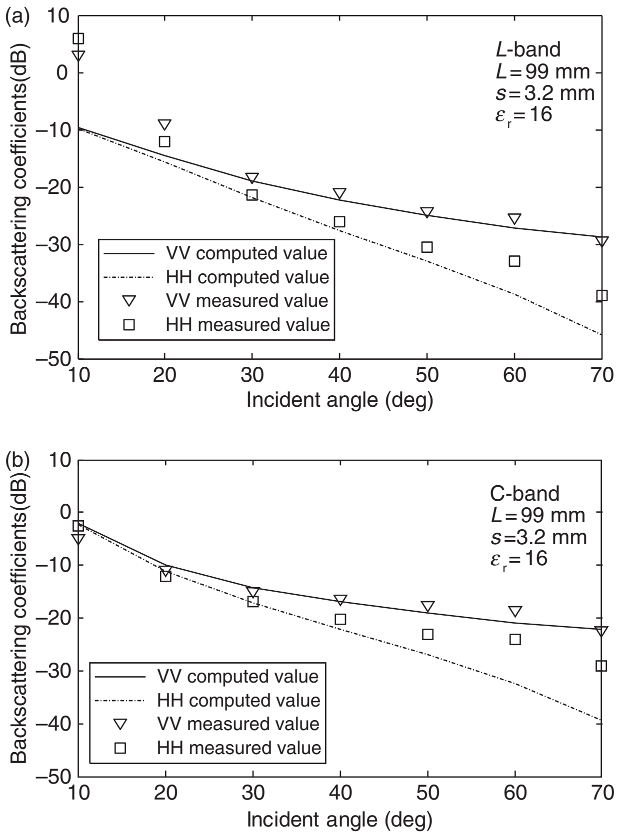

Figure 3. Comparisons of the model predictions (lines) with measurements (symbols) from a bare soil surface 30% surface moisture at (a) 1.515 GHz and (b) 4.725 GHz.

4.2. *Inversion algorithm and soil moisture comparison*

To assess the appropriateness of the developed algorithm to estimate soil moisture content, the soil dielectric constant is inverted from the measured backscattering coefficients firstly. According to Equations (8) and (9), the inversion algorithm can be obtained as follows:

$$\varepsilon_{\mathrm{rhh}} = 7.85\left\{\ln\left|\frac{4.056}{\cos 0.6\theta}\left(1-\frac{0.2425\sqrt{\sigma_{\mathrm{hh}}^{F}}}{k^{2}s\cos^{2}\theta\sqrt{W(2k\sin\theta,0)}}\right)\right|\right\}^{-5}, \tag{10}$$

$$\varepsilon_{\mathrm{rvv}} = \frac{(1.585-\theta)^{6.67}}{0.0456}\left(\frac{\sqrt{\sigma_{\mathrm{vv}}^{F}/2W(2k\sin\theta,0)}}{2k^{2}s\cos^{2}\theta} + 9.2\sin^{1.2}\theta - 6.7\sin^{2.8}\theta - 3.68\sin 2\theta\right)^{3.334} + 2.7. \tag{11}$$

Equation (10) describes the soil dielectric constant as an explicit function of backscattering coefficient, incidence angle, and surface roughness parameters for HH-polarisation, while Equation (11) describes the soil dielectric constant for VV-polarisation.

The above inversion algorithm is applied to inferring the moisture content from experimental radar backscattering coefficient data obtained from literatures [2,8] over soil surfaces with different roughness and wetness conditions. The soil dielectric constant has been retrieved from the measured backscattering coefficient using Equations (10) and (11). Then, the soil moisture content is inferred from soil dielectric constant using a set of empirical formulae.[39] According to these empirical formulae, the soil moisture content is dependent on the soil dielectric constant. For the data set from Bolten et al. [2] the soil surface roughness parameters, the soil moisture, and other parameters are given in Table 2. The gravimetric soil moisture of the 0–5 cm depth is used exclusively (instead of volumetric soil moisture) due to possible error in the in situ measured bulk density, and the soil moisture content were measured at low-vegetated fields. Table 3 shows the surface roughness, moisture, and other parameters for the

Table 2. Soil roughness, moisture, and other parameters from Bolten et al.[2].

s (mm)	θ (degree)	Freq (GHz)	Soil moisture (%)	Vegetation (kg/m^2)	Soil density (g/cm^3)
2	39	1.26	6.1	<0.25	1.28
2	39	1.26	8.0	<0.25	1.28
2	39	1.26	8.4	<0.25	1.28
2	39	1.26	9.0	<0.25	1.28
2	39	1.26	9.9	<0.25	1.28
2	39	1.26	11.2	<0.25	1.28
2	39	1.26	11.6	<0.25	1.28
2	39	1.26	13.8	<0.25	1.28
2	39	1.26	15.3	<0.25	1.28
2	39	1.26	17.0	<0.25	1.28
2	39	1.26	19.7	<0.25	1.28
2	39	1.26	20.6	<0.25	1.28
2	39	1.26	23.4	<0.25	1.28

Table 3. Soil roughness, moisture, and other parameters from Sano et al.[8].

s (mm)	θ (degree)	Freq. (GHz)	Soil moisture (%)	Crop cover	Soil density (g/cm^3)
3	23	5.3	36	Wheat (<5%)	1.4
3	23	5.3	35	Wheat (<5%)	1.4
2	23	5.3	13	Wheat (<5%)	1.4
3	23	5.3	10	Wheat (<5%)	1.4
2	23	5.3	24	Wheat (<1%)	1.4
3	23	5.3	20	Wheat (<1%)	1.4
4	23	5.3	15	Wheat (<1%)	1.4
3	23	5.3	15	Wheat (<1%)	1.4
2	23	5.3	15	Wheat (<1%)	1.4
3	23	5.3	14	Wheat (<1%)	1.4
3	23	5.3	14	Wheat (<1%)	1.4
2	23	5.3	20	Wheat (<1%)	1.4
2	23	5.3	20	Wheat (<1%)	1.4
4	23	5.3	24	Wheat (<1%)	1.4
3	23	5.3	29	Wheat (<1%)	1.4
3	23	5.3	31	Wheat (<1%)	1.4
5	23	5.3	36	Wheat (<1%)	1.4
3	23	5.3	34	Wheat (<1%)	1.4
3	23	5.3	32	Wheat (<1%)	1.4
3	23	5.3	35	Wheat (<1%)	1.4

data set from Sano et al.[8] The correlation function for the data set of Sano et al. [8] was chosen to be the exponential function.

The correlations between the calculated and measured values of soil moisture content for HH mode and VV-mode from Bolten et al.,[2] VV-mode from Sano et al.[8] are shown in Figure 4, where "Linear" means linear fit. The dashed line is the linear regression line for the calculated soil moisture versus the measured by Bolten et al. [2] (open triangles) for HH-polarisation. The dotted line is the linear regression line for the calculated soil moisture versus the measured by Bolten et al. [2] (filled squares) for VV-polarisation. The dash-dot line is the linear regression line for the calculated soil moisture versus the measured by Sano et al. [8] (filled circles) for VV-polarisation. The dashed double dot line is the linear regression line for all the calculated soil moisture versus the measured by both Bolten et al. [2] and Sano et al. [8] for VV-polarisation (filled squares plus filled circles). The thick solid line is the linear regression line for all the calculated soil moisture versus the measured for both HH and VV-polarisations (filled squares and filled circles plus open triangles). The root-mean-square deviation (RMSD) and correlation between the calculated and all VV-mode measurements and overall measurements are also shown in Figure 4. The number (n) of samples (measurements), correlation coefficient R, significance of the correlation, and RMSD are summarised in Table 4. Here, significance is defined as $S_0 = (1 - p) \times 100\%$, where p is the level of probability for the rejection of the null hypothesis with correlation coefficient $R = 0$. Perfect agreement between the calculation and measurement is characterised by $R = 1$. Values of S_0 given in Table 4 are for one-tailed test. Analyses were focused first on the impact of polarisation because the model equations for VV and HH are different. Then the impact of frequency was considered.

From the results shown in Figure 4 and Table 4, the best agreement between the calculation and measurement is found for all VV-copolarisation data from both [2,8] data sets. For each individual VV-mode data set, the correlation coefficient is 0.81 for [2] and 0.87 for [8], both are statistically significant taking $S_0 = 95\%$ as the threshold. For the HH-mode data set, the correlation coefficient is 0.44, which is statistically significant taking $S_0 = 90\%$ as the threshold but not so taking $S_0 = 95\%$ as the threshold. Since the measurements in Bolten et al. [2] were carried out at low soil moisture content region (6.1–23.4%) and only limited HH-mode measurements ($n = 13$) were obtained, the results for HH-mode is thus compromised and not conclusive. For VV-mode, however, the measurements in Sano et al. [8] were carried out over soil moisture conditions between 10% and 36%, in combination with the soil moisture conditions in Bolten et al. [2] between 6.2% and 23.4%, the soil moisture spectrum covers from 6.2% to 36%. The agreement between calculation using the fitting algorithm (Equations (10)–(11)) and the measurement is reasonably well with $R = 0.89$, in comparison with $R = 1$ for perfect agreement. It should be noted that the low-vegetated fields include bare fields and low-vegetated fields,[8] but it still gives a good response when applied to the bare-surface algorithm. The RMSDs of soil moisture are similar for these data sets, varying from 5.67% to 7.18%. Figure 4 also shows the analyses for different frequencies. Consider the VV mode for the two different frequencies. The correlation coefficient for 1.26 GHz is 0.81, comparable to 0.87 for 5.3 GHz, both correlations are significant at a level of >99.9%. This

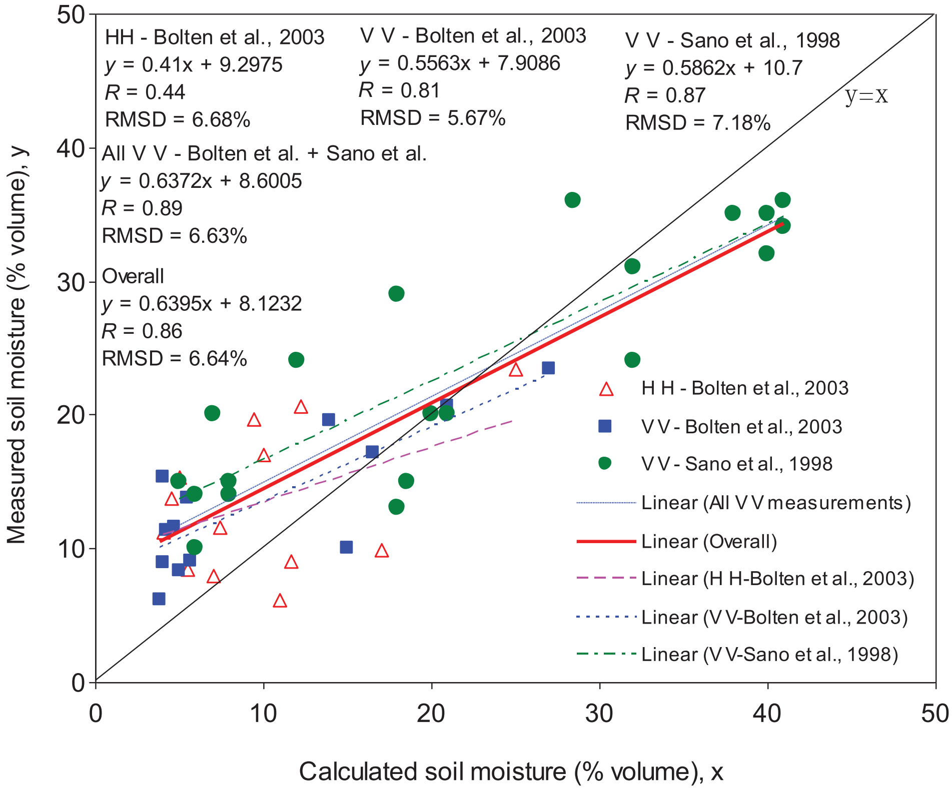

Figure 4. Correlation between the soil moisture contents calculated by the inversion algorithm and those measured by Bolten et al.[2] and Sano et al.[8].

Table 4. Correlation between calculated soil moisture and in situ measurement.

	Number of samples, n	Correlation coefficient, R	Significance, S_0	RMSD
HH – Bolten et al.	13	0.44	93.38%	6.68%
VV – Bolten et al.	13	0.81	99.96%	5.67%
VV – Sano et al.	20	0.87	>99.99%	7.18%
All VV measurements	33	0.89	>99.99%	6.63%
All measurements	46	0.86	>99.99%	6.64%

indicates that the parameterised SPM works equally well for the two frequencies.

5. Conclusions

An analytic inversion algorithm based on the SPM model has been developed to retrieve soil moisture from radar backscattering coefficient data over bare soil surfaces using two co-polarised radar measurement data. Based on the GA, a fitting algorithm has been derived from parameterisation of the SPM model for a wide range of soil dielectric constant, incidence angle, RMS height, and surface correlation length. More than 1000 samples were generated with the original SPM model followed by multivariate linear regression analysis to obtain the statistic soil moisture algorithm. This inversion algorithm describes the correlation between the backscattering coefficients and soil dielectric constant, and is used to retrieve the soil moisture content from the measured backscattering coefficients.

Numerical comparisons were made to illustrate the fidelity of the fitting algorithm to the original SPM model. Results show that the fitting algorithm computes the backscattering coefficients with an average error of 0.05 dB for HH-polarisation and 0.15 dB for VV-polarisation. Comparison of the inversion algorithm with in situ measurement of soil dielectric constants and backscattering coefficient measurements reported by Fung et al. [4] shows that the average absolute error of the backscattering coefficients is 3.3 dB over the incident angle ranging from 10° to 70°. Comparison of the soil moisture derived from the inversion algorithm with simultaneous measurement of soil surface conditions and radar backscattering coefficients [2,8] shows that: (1) The soil moisture retrieved from the inversion algorithm agrees very well for VV-copolarisation ($R = 0.89$, in contrast with $R = 1$ for perfect agreement); (2) For HH-copolarisation, agreement between the calculation and measurement is significant only at 90% significance level. Due to the limited HH-mode measurements ($n = 13$), the agreement is not conclusive for HH-mode. These results show that the inversion algorithm works fine at least for the VV-mode.

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