Semi-analytical Soil Moisture Retrieval Using PolSAR Imagery

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ABSTRACT

Precise evaluation of spatial and temporal changes in soil moisture is critical for environmental studies. In this regard, Synthetic Aperture Radar (SAR), providing multi-channel dataset with wide coverage, is a reliable tool for monitoring this parameter. This study proposes Modified Improved Water Cloud Model (MIWCM) as semi-analytical method for predicting soil moisture. C, L and P-band data were obtained in 2003 by Airborne Synthetic Aperture Radar (AIRSAR). Results clearly shows superiority of the proposed method comparing to previous models, with R^2 in the 95%-98% range and RMSE in the 0.00012-0.0016 range.

1. INTRODUCTION

Soil moisture is a component of attainable water taken up by plants and it is measured in 200 centimeters above the soil surface [1]. This small amount of water might be considered insignificant comparing to the amount of water in our globe, however it is of precious importance in many hydrological, biological, and environmental processes [1], and it is proven that there is a strong relation between soil moisture anomaly and local weather condition [2]. Therefore, providing precise soil moisture products give us better understanding of the local weather conditions. SAR distinguishing qualities in broad spectral evaluation and in high degree of local resolution has made it a perfect tool for evaluating soil moisture comparing to multispectral and hyperspectral image datasets. Active data signal is influenced heavily by the effects of maximal vegetation-covered area and soil surface roughness [3]. Backscattering analysis from ground state is an essential phenomenon in remote sensing and monitoring, since there is a potential for regenerating physical surface parameters such as moisture and surface roughness [4]. The aim of this study is utilizing PolSAR data to identify roughness parameter and estimate soil moisture.

2. STUDY AREA AND DATASETS

The study area is located in south of Oklahoma in the United States (Figure 1). Data obtained over these areas are gathered from airborne platform and in-situ during soil moisture test in 2003. For incorporating in-situ data in this study, information was gathered from SMEX03 campaign on July 10, 2003 [5]. Amount of soil moisture was measured and analyzed in fourteen locations in Oklahoma. Also, PolSAR dataset was acquired by AIRSAR instrument over this area. This dataset has a resolution of 6.6 meters in angular direction. Every pixel in AIRSAR shows radar backscattering for every obtained vertical and horizontal polarizations (VV, HH, VH and HV). Each pixel includes backscattering information in three channels, C, L, and P.

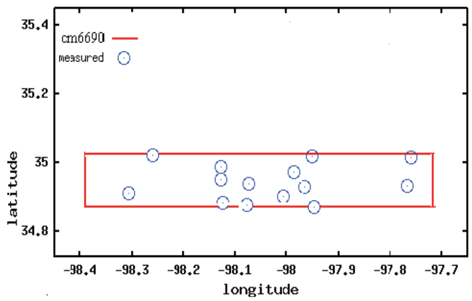

Figure 1. Location of in-situ data points (in south Oklahoma) and their distribution in AIRSAR scene.

3. SOIL MOISTURE RETRIEVAL METHODS

Most semi-analytical models that have been proposed so far only apply to bare soil surfaces, and with using a simple linear equation, the soil moisture can be estimated [4], [6]. In 1978, Ulaby *et al.* modeled the soil moisture with a simple linear equation as [6]

$$\sigma^0 = A + B \times SM \tag{1}$$

where σ^0 is the radar backscattering coefficient and *SM* is soil moisture. In this equation, A and B are constant parameters. In 1995, the Ulaby model was improved by Ji et *al.* In addition to the effect of moisture on distribution of radar, the effects of roughness were taken into account according to the following equation [7]:

$$\sigma^0 = A + B \times SM + C \times S \tag{2}$$

where σ^0 is the radar backscattering coefficient, *SM* is soil moisture, S is the root mean square error (RMSE) of surface height, and A, B, and C are constant parameters. The Improved Water Cloud Model (IWCM) is used as semi-analytical method in some researches that considered soil surface roughness backscattering, soil moisture surface backscattering and vegetation backscattering [6], [8]. In this model, total radar backscattering (σ^0) equals combination of grass backscattering (σ^0_{Veg}), soil backscattering (σ^0_{Soil}), and two side grass layer intensity (τ^2). For a special descending angle, backscattering is

$$\sigma^0 = \sigma^0_{Veg} + \tau^2(\sigma_{Soil,Sm} + \sigma_{Soil,S}) \tag{3}$$

where σ^0 is the total backscattering, σ^0_{Veg} is the vegetation contribution, $\sigma_{Soil,Sm}$ is backscattering coefficient for soil moisture, $\sigma_{Soil,S}$ is backscattering coefficient for soil surface roughness, and τ^2 is double-faced vegetation effect. Roughness is one of the effective factors in active microwave backscattering. Ulaby *et al.* [6] found that for incidence angles over 10 degrees, the amount of returned energy is increased with increase in surface roughness. Determining this parameter and separating its contribution from total backscattering is considered as an effective factor in calculating soil moisture by means of active microwave. Dubois was utilized in order to calculate RMSE of surface height [9].

$$K \times S = \frac{10^{\frac{2.75}{1.4}} \sigma^0_{hh}{}^{\frac{1}{1.4}} \sin(\Theta)^{2.57} \lambda^{-0.5}}{10^{0.02\varepsilon' \tan(\Theta)} \cos(\Theta)^{1.07}} \tag{4}$$

where S is RMSE of surface height, σ^0_{hh} is the total horizontal backscattering, Θ is incidence angle, ε' is dielectric constant, λ is wavelength, and K is wave number ($K = 2\pi/\lambda$). Many studies have shown that microwave and light waves are sensitive to soil dielectric constant [4], [10]. Microwave methods for calculating soil moisture is based on the differences in water dielectric properties and soil contents. Dielectric constant ε' model used in this work is based on the work by Hallikainen *et al.* [11]. As mentioned before, there are a number of theoretical models for calculating soil moisture in infertile lands, however the existing models in calculating soil moisture in fertile lands and vegetated areas are limited. In this study to define the degree of statistical disorder of each distinct scatter type within the ensemble, the polarimetric entropy *H* [12], provides an efficient and suitable basis-invariant parameter, and is given by

$$H = -\sum_{i=1}^{3} P_i \log_3(P_i) \tag{5}$$

where P_i correspond to the pseudo-probabilities obtained from the eigenvalues ($P_i = \lambda_i / \sum_{k=1}^{3} \lambda_k$) of coherency matrix (*T*). It is possible to measure mechanism through *H*, when *H=0* then we have pure target with these eigenvalues $\lambda_1 = span$, $\lambda_2 = 0$ and $\lambda_3 = 0$. If *H=1*, we have distributed target with $\lambda_1 = \lambda_2 = \lambda_3 = span/3$. On the other hand, *H=0* shows that depolarization has not occurred in the region and it appears in smooth surface and if *H=1* shows random value which indicated that different mechanism occurred in that area. In areas with dense vegetation coverage, volume scattering is dominant. Based on entropic values, study area covers 80% through 90% with grass. In this study, MIWCM model is proposed as semi-theoretical in which soil moisture is a function of grass formation, surface roughness, and surface temperature.

$$\sigma_{Veg}^0 = A \times entropy(1 - \tau^2) \tag{6}$$

$$\tau^2 = \exp(-2 \times B \times \ entropy \times \sec(\Theta)) \tag{7}$$

$$\sigma^0 = \frac{-20 \times B \times entropy}{\ln(10) \times \cos(\Theta)} + \mathrm{C} + \mathrm{D} \times \mathrm{SM} + \mathrm{E} \times \mathrm{S} \times \cos(\Theta) + F \times T \tag{8}$$

where σ^0 is the backscattering coefficient, *B, C, D, E* and *F* are model parameters that are calculated by the least square, Θ is incidence angle, *SM* is soil moisture, *S* is RMSE for surface height, and *T* is field surface temperature. For more accurate evaluation, it is necessary to check the accuracy of different models through check points. In this study, among surface points, eight points were chosen randomly for model training, and testing was done for remaining points. The accuracy of the model for three polarizations (HH, VV and VH) and three bands (L, C and P) in AIRSAR data was compared with previous semi-analytical models (Ulaby *et al.*, Ji *et al.*, and Hosseini *et al.*) [7], [13].

As expected, the results extracted from MIWCM model shows a small decrease in terms of RMSE. The accuracy of the proposed model is higher than IWCM model, which considers the effects of soil moisture, surface roughness, and vegetation. Also the accuracy of IWCM is higher comparing to Ji's model and Ulaby's model in which soil moisture effects and surface roughness effects are considered. The HH polarization in the P band in AIRSAR has made estimation of soil moisture more accurate. The results are summarized in Table 1.

4. CONCLUSIONS

The advantages of microwave remote sensing compared to optical and thermal imaging for calculating soil moisture is related to the minimal effects of cloud covering and no atmospheric attenuation. Also, microwave scattering sensitivity to dielectric properties and geometrical structure of soil surface has led to widespread usage especially estimation of soil parameters. Some of these parameters include soil moisture, surface roughness, and grass formation. One of the main challenges estimating soil moisture using PolSAR images is the effect of vegetation cover on the backscattering signal. Regardless of these issues, incorporating multi-channel PolSAR instrument with L, C, and P band provides more precise estimation of soil moisture in temporal and spatial settings.

5. REFERENCES

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Table 1: Evaluation of semi-analytical soil moisture models

band	model	pol	R^2	RMSE	SSE
C	IWCM	HH	0.9674	0.0107	0.0016
		VH	0.4876	0.0489	0.0334
		VV	0.3764	0.0381	0.0203
	MIWCM	HH	0.9800	0.0091	0.0012
		VH	0.4317	0.0632	0.0559
		VV	0.3515	0.0406	0.0231
	Ulaby	HH	0.4823	0.0416	0.0242
		VH	0.2142	0.1040	0.1516
		VV	0.2808	0.0642	0.0577
	Ji	HH	0.9671	0.0109	0.0017
		VH	0.4383	0.0559	0.0438
		VV	0.3741	0.0379	0.0201
L	IWCM	HH	0.9748	0.0139	0.0027
		VH	0.3053	0.0600	0.0504
		VV	0.6430	0.0249	0.0087
	MIWCM	HH	0.9840	0.0068	0.0063
		VH	0.4306	0.0506	0.0359
		VV	0.4954	0.0254	0.0090
	Ulaby	HH	0.3812	0.1527	0.3264
		VH	0.1250	0.2836	1.1262
		VV	0.2345	0.1278	0.2288
	Ji	HH	0.9623	0.0106	0.0016
		VH	0.3765	0.0574	0.0461
		VV	0.6661	0.0241	0.0082
P	IWCM	HH	0.9751	0.0084	0.00098
		VH	0.3894	0.1038	0.1507
		VV	0.4397	0.0345	0.0167
	MIWCM	HH	0.9841	0.0081	0.00091
		VH	0.4056	0.1463	0.2996
		VV	0.1943	0.0570	0.0455
	Ulaby	HH	0.4209	0.1539	0.3317
		VH	0.3206	0.5326	3.9715
		VV	0.3466	0.0736	0.0758
	Ji	HH	0.9854	0.0065	0.00058
		VH	0.3887	0.1654	0.3830
		VV	0.2723	0.0387	0.0210