A Modified Empirical Model for Soil Moisture Estimation in Vegetated Areas Using SAR Data

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Abstract— **Among the major models developed for soil moisture retrieval, the empirical model developed by Dubois et al. in 1995 proves to be a good choice, because of its accuracy and simplicity of implementation. The model provides quite good results for the estimation in bare soil areas. However, it does not explicitly incorporate vegetation backscatter effects and does not provide good results for vegetated areas with a cross-polarization ratio greater than -11dB. A modified empirical model is developed to address this concern. The water-cloud model is used to introduce vegetation effects into the VV backscatter coefficient, which is further used in the inversion model. The modified model is applied to the Washita 1994 SIR-C data and a correlation of 0.81 is obtained between the ground based measurements and the soil moisture estimated from radar data.**

I. Introduction

The moisture content of the soil plays an important role in the estimation and modelling of various large-scale ecological processes such as climate change, agriculture, evaporation, transpiration, flood forecasting, surface run-off and ground water replenishment. Several approaches for soil moisture retrieval for both active and passive remote sensing instruments have been developed over the last two decades. Research in this area still continues, as drawbacks have been present in all the models proposed. One of the challenges presented by the originally developed models, is their ineffectiveness in accurately estimating the soil moisture content for vegetated regions.

This paper addresses the aforementioned concern and proposes to introduce the vegetation effects into an existing empirical model, developed by Dubois et al. [1]. Generally, an empirical model is developed to express the backscattering coefficients in terms of the surface parameters, based on the knowledge of the scattering behavior in limiting cases and on experimental observations.

II. Existing Models for Soil Moisture Retrieval

Developing direct models by simulating the backscattering coefficients in terms of the soil attributes such as the dielectric constant and the surface roughness, for an area with known characteristics, is one of the common approaches used to develop models for soil moisture retrieval. These direct models are subsequently used in the inverse mode to estimate the surface parameters, given the radar measurements. In the following sections we review the approaches which have been proposed in the recent years. The models have been classified into two groups: soil moisture retrieval in bare-soil and in vegetated areas.

A. Models for soil moisture retrieval in bare areas

Models for soil moisture estimation have mostly been developed based on radiometer or SAR measurements. These models were further validated for their performance using one of the two types of data or both.

Among the models used for soil moisture retrieval with polarimetric radar data, the first was an empirical model proposed by Oh et al. [2]. In this model, the co-polarized and cross-polarized ratios of the backscattering coefficients are expressed in terms of the surface parameters. The model was developed from and tested on radiometer data; as a result its estimation accuracy may not be good when SAR data is used. This model was followed by another empirical model suggested by Dubois et al. [1] which employs the co-polarized backscatter only. Radiometric measurements were used to develop this model, with its performance being validated on both radiometer and SAR data. The Shi Model [3] is based on the Integral Equation Method (IEM) [4] and was tested for its performance only on SAR data. The algorithm and its inverse are complex and difficult to implement due to the requirement of several parameters in the computations. It also requires the knowledge of the surface roughness to estimate the soil moisture and vice versa.

All the models mentioned above provide good results in retrieving the soil moisture in areas/sites with bare soil or short vegetation. They, however, produce erroneous results for areas with larger amounts of vegetation.

B. Models for soil moisture retrieval in vegetated areas

In the recent years, many models have been developed for the purpose of soil moisture estimation in vegetated areas. One of the first approaches to be suggested was by Jackson et al. [5] where a quantitative technique for isolating the effect of vegetation was developed using the field normalized brightness temperature. This required the prior knowledge of the brightness temperatures for both soil and vegetation and the technique was applied to radiometer data. Many other models, such as in [6], [7], are based on regression coefficients

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generated by observations over a specific test site. As a result, they may not be suitable for estimation in other test sites.

Certain models were developed by introducing vegetation effects into the existing models. In [8], the vegetation effect is modelled using the brightness temperature of a weakly scattering layer above a semi-definite medium, as given in [9], in conjunction with a vegetation model based on discrete scatter random media techniques. The use of this particular vegetation model requires the knowledge of several vegetation parameters which tends to decrease the simplicity of implementation. [10] proposes an algorithm to introduce vegetation effects into the Oh Model. However, this model tends to have the same limitations as the original model.

In [11] vegetation correction has been successfully incorporated into the Shi Model. Here, the water-cloud model along with a vegetation correlation function is employed to include the vegetation effects. Though, very good results are obtained; this approach retains the complexity of the Shi Model.

Among all the suggested approaches, the empirical model of Dubois et al. [1] tends to be a better choice since it gives good results for both radiometer and SAR data. The backscatter measured by a radar and the emission measured by a radiometer are both very sensitive to the moisture content. However, the soil moisture affects both types of measurements in different ways [12]. As a result, the Dubois model is applicable to different forms of data measured by a variety of sensors and tends to be quite accurate in most cases. The algorithm also seems to be accurate for rough surfaces [13]. Furthermore, the Dubois Model requires fewer measurable parameters for the estimation, presenting lesser complexity in the instrument design and enabling a simpler implementation as compared to most models [2], [3]. Unlike the Shi Model, this empirical model does not require the knowledge of one surface parameter to determine the other. However, like all the models discussed in Section II-A, the Dubois Model also produces good estimation results in areas with bare soil or short vegetation i.e., regions with a cross polarization ratio of less than -11dB, while errors increase of areas with more vegetation.

III. Proposed Modelling Approach

In order to circumvent the problems associated with different models, our goal is to develop a simple yet effective model, based on the Dubois Model, which incorporates the vegetation correction and is as accurate as the models that already include the vegetation effects.

The Water-Cloud Model presents a simple approach to include the contribution of the vegetation as well as the soil in the backscattering coefficient [9], [14]. According to the model, the total power scattered at a co-polarized channel pp, $\sigma^{\mathrm{o}}_{\mathrm{pp}}$, is the incoherent sum of contribution of the vegetation, $\sigma^{\mathrm{o}}_{\mathrm{veg}}$ and that of the underlying soil, $\sigma^{\mathrm{o}}_{\mathrm{soil}}$, which is attenuated by the vegetation layer. For a given incidence angle, the co-polarized backscatter coefficient can be given by the general form:

$$\sigma^{\mathrm{o}}_{\mathrm{pp}} \;=\; \sigma^{\mathrm{o}}_{\mathrm{veg}} \,+\, \sigma^{\mathrm{o}}_{\mathrm{veg+soil}} \,+\, \tau^2\,\sigma^{\mathrm{o}}_{\mathrm{soil}} \tag{1}$$

where τ^2 is the two-way vegetation transmissivity. The second term in (1) represents the *interaction* between the vegetation and underlying soil. Since the interaction term is not a dominant term in the co-polarized returns [15], it can be neglected. Therefore, the water-cloud model uses:

$$\sigma^{\mathrm{o}}_{\mathrm{pp}} \;=\; \sigma^{\mathrm{o}}_{\mathrm{veg}} \,+\, \tau^2\,\sigma^{\mathrm{o}}_{\mathrm{soil}} \tag{2}$$

with

$$\tau^2 = e^{(-2b\mathrm{W_c}\sec\phi)} \tag{3}$$

and

$$\sigma^{\mathrm{o}}_{\mathrm{veg}} \;=\; A\,m_v\,\cos\theta(1-\tau^2) \tag{4}$$

where W_c is the vegetation water content ($\mathrm{kg/m^2}$), θ is the the incidence angle and ϕ is the nadir angle. A and b are parameters that depend on the type of vegetation; A represents the vegetation scattering, b is the attenuation parameter. The type and geometrical structure of the canopy as well as the polarization and wavelength of the sensor are accounted for through these parameters. Both A and b are determined by fitting models against experimental data [16], [17]. It is expected that in future missions, such as the HYDROS mission [18], it will be possible to estimate these vegetation parameters remotely rather than using ground based measurements.

The orientation and geometry of vegetation are key factors in vegetation backscatter. It is possible that when two canopies of different heights are located at the same range, the backscatter from one is affected by the other and vice versa, leading to an over-estimation of the backscatter by the water-cloud model. Bindlish et al. [11] propose an exponential vegetation correlation function to model this geometric effect of the vegetation spacing within the water-cloud model, by introducing the concept of vegetation correlation length:

$$\sigma^{\mathrm{o}*}_{\mathrm{veg}} \;=\; \sigma^{\mathrm{o}}_{\mathrm{veg}}\,(1-e^{-\alpha}) \tag{5}$$

where $\sigma^{\mathrm{o}*}_{\mathrm{veg}}$ is the corrected vegetation contribution and α is a function of the vegetation correlation length and the average distance between the discrete vegetation canopies within a pixel [17]. Thus, (2) is modified to include the corrected vegetation contribution:

$$\sigma^{\mathrm{o}}_{\mathrm{pp}} \;=\; \sigma^{\mathrm{o}*}_{\mathrm{veg}} \,+\, \tau^2\,\sigma^{\mathrm{o}}_{\mathrm{soil}} \tag{6}$$

A Least Mean Squares (LMS) regression analysis provides a linear correlation function between the measured backscatter and the soil moisture content estimated by the original Dubois Model. This linear function is utilized to obtain the backscatter contribution of the underlying soil, $\sigma^{\mathrm{o}}_{\mathrm{soil}}$.

Consequently, both $\sigma^{\mathrm{o}*}_{\mathrm{veg}}$ and $\sigma^{\mathrm{o}}_{\mathrm{soil}}$ are used in (6) to compute the total backscatter, which is then used in the existing inversion model to estimate the soil moisture. The inversion model, however, computes the dielectric constant rather than the volumetric soil moisture. The empirical model proposed in [19] relates m_v to the dielectric constant as well as the soil texture, using which m_v can be determined.

It is important to note that, while the HH and VV backscattering coefficients are used in the inversion model, the HV backscatter is used to obtain the cross-polarization ratio, $\sigma^o_{hv}/\sigma^o_{vv}$, which is used in determining the extent of vegetation in a particular area/site. A ratio greater than -11dB indicates the presence of a larger amount of vegetation [1] and the necessity of the modified model.

IV. Implementation

Based on the methodology discussed in Section III, the vegetation effects are introduced into the empirical model using the water-cloud model, in conjunction with the vegetation correlation function suggested in [11]. The vegetation parameters will, however, depend on the type and geometrical structure of the vegetation in a particular site/scene.

The modified model is applied to C-Band, SIR-C images of the Little Washita Watershed acquired in April 1994, during the Washita'94 campaign. These data sets are provided with good *in-situ* ground measurements for a number of sites with different forms of vegetation [22]. Both the ground and remotely sensed data were measured under different moisture conditions over a duration of 8 days between 11–18 April. The sites which have been used for the proposed model are given in Table I along with their type of land cover and vegetation parameters. The SIR-C data acquisition parameters of each data take such as the incidence and nadir angles are available in [20].

As an initial step, the linear regression analysis is performed on the measured VV backscatter, σ^o_{vv}, and the soil moisture content, m_f, estimated by the existing Dubois Model. This causes σ^o_{vv} to be expressed as a linear function of the m_f values. Fig.1 shows the linear relationship and the equation thus obtained:

$$\sigma^o_{vv} = 0.0041\, m_f - 13.39 \quad \text{dB} \tag{7}$$

We initially introduced the vegetation effects in both the HH and VV backscattering coefficients. Based on our experimental observations, this type of implementation did not seem to provide better results. [21] claims that if the vegetation cover in a given area is uniform, the vegetation effects will be more dominant in the VV backscatter. Consequently, we incorporate the vegetation correction only in the VV polarized backscatter.

TABLE I
Site Characterization for Washita' 94 April Mission, Source: [17], [22]

Site	Land Cover	W_c (kg/m^2)	A	b	α
11	Alfalfa	1.798	0.0012	0.091	2.12
12	Bare Soil	0	0	0	0
13	Winter Wheat	1.386	0.0018	0.138	10.6
14	Rangeland	0.096	0.0009	0.032	1.87
21	Rangeland	0.078	0.0009	0.032	1.87
22	Rangeland	0.107	0.0009	0.032	1.87
23	Rangeland	0.065	0.0009	0.032	1.87
53	Winter Wheat	0.797	0.0018	0.138	10.6
54	Pasture	0.086	0.0014	0.084	1.29
55	Winter Wheat	0.817	0.0018	0.138	10.6

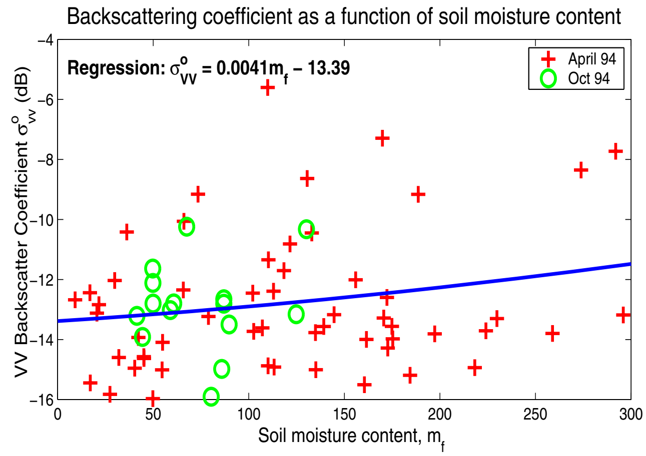

Fig. 1. Measured VV backscattering coefficient as a function of m_f,for all sites and the entire duration of the Washita'94 program

The proposed algorithm can be summarized as follows:

1) The average σ^o_{hh} and σ^o_{vv} are computed for the given site and used in equations of the original inversion model [1] to obtain an initial estimate of the volumetric soil moisture, m_v.
2) The soil moisture content, m_f, is computed from the volumetric soil moisture as follows:
$$m_f = 100 \times \frac{m_v}{\mathrm{FC}_v} \tag{8}$$
where FC_v is the field capacity, as in [9].
3) The soil moisture content is then used in the linear correlation equation (7) to determine σ^o_{soil}.
4) Using the vegetation parameters, A, b and α for the given site in (3), (4) and (5), σ^{o*}_{veg} is obtained.
5) The σ^o_{soil} and σ^{o*}_{veg} determined in Steps 3 & 4, are further employed in (6) to provide the total VV backscatter, σ^o_{vv}.
6) Finally, the full inversion model is run again using σ^o_{vv} computed in Step 5 and σ^o_{hh} from Step 1, to obtain the modified values of m_v.

V. Results

The proposed algorithm is implemented on the C-band Washita'94 data to estimate the soil moisture content for the different sites given in Table I.

Figs. 2 and 3 show the comparison between the measured and retrieved values of volumetric soil moisture for the original empirical model and for the proposed algorithm with vegetation correction, respectively. The correlation has been measured between the estimated soil moisture values and the ground measurements. If there were no errors, the correlation would be unity (R = 1), and the estimated values would all lie on the 45° dashed line. As compared to a correlation of R = 0.58 obtained for the existing model, the introduction of the vegetation effects into the empirical model results in a correlation coefficient of R = 0.81. This indicates a considerable increase in the estimation accuracy in vegetated areas for the empirical model.

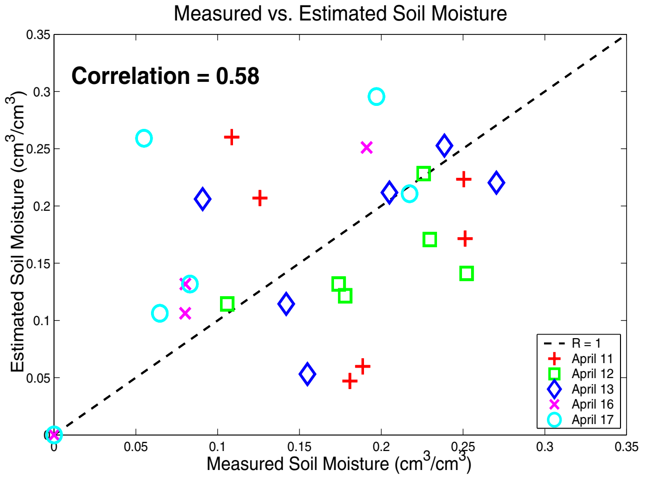

Fig. 2. Scatter plot of measured and estimated volumetric soil moisture for the sites given in Table I for 5 dates in the Washita 94 experiment using the original empirical model without vegetation correction

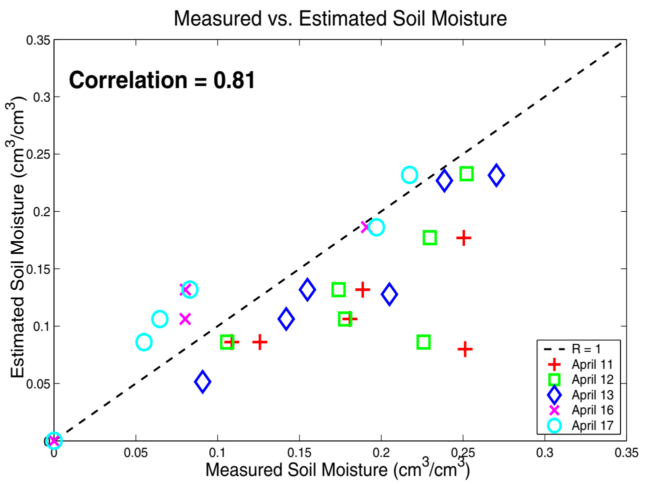

Fig. 3. Scatter plot of measured and estimated volumetric soil moisture for the sites given in Table I for 5 dates in the Washita 94 experiment using the modified empirical model

The proposed model, however, does not yet provide better results as compared to the approach based on the Shi Model in [17] discussed in Section II-B. For the same data set, a correlation of R = 0.87 is obtained using this algorithm.

VI. Conclusions

A modified empirical model for soil moisture retrieval in vegetated areas is presented. The proposed algorithm incorporates vegetation effects into the original empirical model of Dubois et al. and the performance of this model is observed for a well documented SIR-C data set.

An analysis of the results indicates an improvement in the soil moisture estimation from polarimetric radar data when a vegetation term is included in the Dubois Model. We have, however, only partially achieved our objective and hope to obtain better results by further refinement in the model.

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