

# Soil moisture inversion from aircraft passive microwave observations during SMEX04 using a single-frequency algorithm

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**Abstract.** Soil moisture plays a key role in global water cycles. In the study, soil moisture retrievals from airborne microwave radiometer observations using a single-frequency algorithm were presented. The algorithm is based on a simplified radiative transfer (tau-omega) model and the influence of both the roughness and vegetation is combined into a single parameter in the algorithm. The microwave polarization difference index (MPDI) is used to eliminate the effects of temperature. Then soil moisture is obtained through a nonlinear iterative procedure by making the absolute value of the differences between the simulated and observed MPDI minimum. The algorithm was validated with aircraft passive microwave data from the Polarimetric Scanning Radiometer (PSR) at the Arizona during the Soil Moisture Experiment 2004 (SMEX04). The results show that the soil moisture retrieved by the algorithm is in good agreement with ground measurements with a small bias and an overall accuracy of  $0.037\text{m}^3\text{m}^{-3}$ .

## 1. Introduction

Land surface soil moisture is not only a very important part of the earth ecosystem, but also a key state variable in hydrological and meteorological modeling [1]. Passive microwave signals have the advantage of being less affected by atmospheric conditions and directly related to soil moisture through the soil dielectric constant. Thus, the passive microwave remote sensing technology has become one of the most effective tools for soil moisture monitoring at large scales [2-4].

In the past decades, several space-borne passive microwave radiometers, such as the Special Sensor Microwave/Imager (SSM/I), the Scanning Multichannel Microwave Radiometer (SSMR), the Tropical Rainfall Measuring Mission (TRMM) Microwave Imager (TMI), the Advanced Microwave Scanning Radiometer (AMSR-E) and the Microwave Imaging Radiometer with Aperture Synthesis (MIRAS) mounted on the Soil Moisture and Ocean Salinity (SMOS) satellite, have been widely used for soil moisture detection. However, the verification of space-borne remotely sensed soil moisture is still not well resolved. The main reason is that soil moisture always exhibits tremendous spatial heterogeneity and the observing scales of the point-based ground measurements and space-borne measurements are quite different. Furthermore, the lack of measured data is also a critical issue for both the development and validation of retrieval algorithm [5]. To solve these issues, scientists have conducted a series of field experiments in support of remote sensing, hydrology and climate [5-6], such as the Southern Great Plains 1997 (SGP97), SGP99, the Soil Moisture Experiment 2002 (SMEX02), SMEX03 and SMXE04. One purpose of these experiments is to assess and refine the performance of soil moisture retrieval algorithm [5]. These experimentation areas are relatively

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homogeneous and have abundant in-situ data, thus very suitable for the validation of soil moisture retrieval algorithm. Additionally, the airborne radiometers have higher spatial resolution than satellite radiometers, which can reduce the scale differences between ground measurements and remotely sensed retrievals to a certain extent.

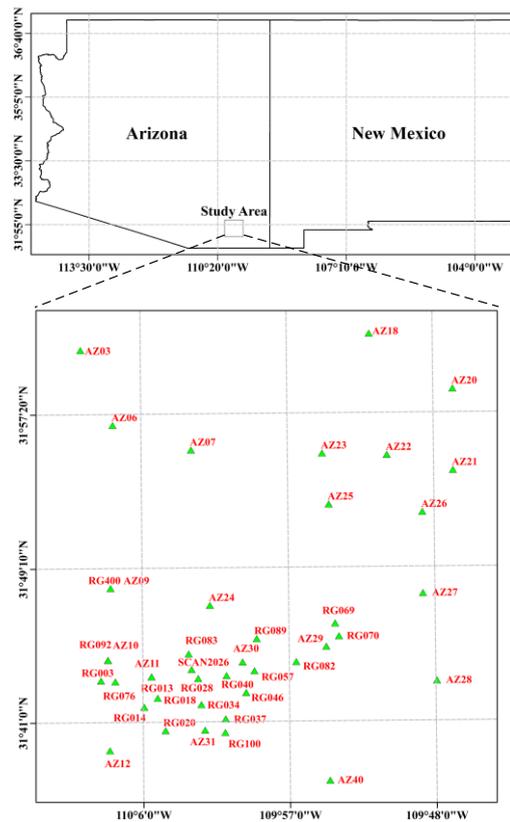
This paper focuses on the development and validation of the soil moisture retrieval algorithm using the experiment data during SMEX04. The algorithm is based on a simplified radiative transfer (tau-omega) model and the effects of both the roughness and vegetation are grouped into a single parameter in the algorithm. It uses the microwave polarization difference index (MPDI) to remove the temperature dependence of the emitting layer. Then soil moisture is obtained through a nonlinear iterative procedure by making the absolute value of the differences between the simulated and observed MPDI minimum. Finally, the C-band dual-polarized brightness temperature data from the Polarimetric Scanning Radiometer (PSR) at the Arizona during SMEX04 were used for soil moisture estimation and the soil moisture retrievals were validated by in-situ data from 42 sites in the Arizona.

## 2. Data and method

### 2.1. Experiment data

SMEX04 provides an excellent opportunity for development and verification of soil moisture retrieval algorithm owing to the relatively sparse vegetation in the region. It was conducted over two regions: Arizona and Sonora. Since Sonora has strong topographic gradients, Arizona was selected as the study area.

The experiment area is located at the southeast of Arizona in the United States. The soil moisture field observations are very abundant at Arizona during SMEX04. There are three soil moisture field observation networks, namely the AZ (Arizona Regional site), RG (Walnut Gulch Watershed Rain Gage Site) and SCAN (Soil Climate Analysis Network), in the study area with a total of 42 soil moisture observation sites, shown in figure 1. The records of each site nearest to the passing time of PSR were averaged as an in-situ soil moisture measurement. Then the average value of all soil moisture measurements of the 42 sites was used for validation of the soil moisture retrieved by the present algorithm. Additionally, the PSR with polarimetric channels of C-band (7.32 GHz) and X-band (10.7 GHz) obtained brightness temperature data of the experiment area for nine days, which were 5 August, 8-10 August, 12-13 August and 24-26 August, respectively. The PSR has a footprint size of 800 m×800 m with dual-polarized polarizations, and its incident angle is 55°. Due to the ability to maximize vegetation and soil penetration than higher frequencies, the dual-polarized brightness temperatures at 7.32 GHz were used for soil moisture inversion in the study. The retrieved soil moisture of all the grids was also averaged for comparison with the averaged in-situ data. The soil texture data was determined by the CONUS-SOIL database built by the United States Department of Agriculture. These data were projected to the same coordinate system, and resampled to the same resolution of 800 m×800 m.



**Figure 1.** The location of the experiment area and the distribution of all soil moisture observation sites.

## 2.2. Method

The algorithm is based on a simplified radiative transfer model, usually called tau-omega model [7], which can be expressed as:

$$T_{Bp} = (1 - r_{sp})T_s \exp(-\tau_p) + (1 - \omega)T_c [1 - \exp(-\tau_p)] [1 + r_{sp} \exp(-\tau_p)] \quad (1)$$

Where the subscript  $p$  denotes the vertical or horizontal polarization,  $T_{Bp}$  is the brightness temperature,  $r_{sp}$  is the effective reflectivity of rough surface,  $T_s$  and  $T_c$  are the thermodynamic temperatures of the soil and vegetation canopy, respectively,  $\omega$  is the single scattering albedo of the vegetation, and  $\tau_p$  is the vegetation optical depth along the observation path.

The soil and vegetation temperatures are usually assumed to be equal and represented as  $T$  for simplicity. Moreover,  $\omega$  is assumed to be equal to zero [8], which is more reasonable at low frequency and under light-vegetation conditions.  $\tau_p$  is also supposed to be polarization independent, which is widely accepted at satellite scales [4][9]. Thus equation (1) can be simplified as:

$$T_{Bp} = T[1 - r_{sp} \exp(-2\tau)] \quad (2)$$

The effective reflectivity from rough soil surface ( $r_{sp}$ ) can be empirically obtained from the equivalent smooth surface using the Q/H model [10]:

$$r_{sp} = [(1 - Q)r_{op} + Qr_{oq}] \exp(-h) \quad (3)$$

Where  $p$  and  $q$  represent orthogonal polarizations, the parameter  $Q$  describes the energy emitted in the orthogonal polarization on account of the surface roughness effect,  $h$  describes the effect of surface roughness, leading to a decrease in the effective reflectivity. By inserting equation (3) into equation (2) and then combining the coefficients, equation (4) can be obtained:

$$T_{Bp} = T[1 - r'_{sp} \exp(-2\tau - h)] \quad (4)$$

Where  $r'_{sp} = (1 - Q)r_{op} + Qr_{oq}$ . In this study, the same value of  $Q$  (0.174) at 6.9 GHz which was calibrated at global scale by Njoku and Chan [9] was adopted as a fixed parameter. The parameter  $h$  was left to incorporate the roughness spatial variability. Hence,  $r'_{sp}$  is only related to the soil dielectric properties at a specific frequency and incidence angle according to the Fresnel equations. The Hallikainen empirical model [11] is used to convert soil dielectric constant into soil moisture. Therefore, if the soil texture data are known,  $r'_{sp}$  can be expressed as a function of soil moisture (i.e.,  $r'_{sp} = f(sm)$ ). In equation (4), the exponential attenuation effects of vegetation and roughness are combined into a single parameter (i.e.,  $\exp(-2\tau - h)$ ). In addition, let  $\exp(-2\tau - h) = B$ , then at a given frequency with H and V polarization, equation (4) can be expressed as:

$$T_{Bh} = T(1 - r'_{sh} B) \quad (5)$$

$$T_{Bv} = T(1 - r'_{sv} B) \quad (6)$$

Combining equation (5) and equation (6), the single parameter  $B$  can be derived:

$$B = \frac{T_{Bv} - T_{Bh}}{T_{Bv}r'_{sh} - T_{Bh}r'_{sv}} \quad (7)$$

Furthermore, inserting equation (7) into equation (5) and (6), then the H and V polarization brightness temperature at a given frequency can be obtained:

$$T_{Bh} = T \left( 1 - r'_{sh} \frac{T_{Bv} - T_{Bh}}{T_{Bv}r'_{sh} - T_{Bh}r'_{sv}} \right) \quad (8)$$

$$T_{Bv} = T \left( 1 - r'_{sv} \frac{T_{Bv} - T_{Bh}}{T_{Bv}r'_{sh} - T_{Bh}r'_{sv}} \right) \quad (9)$$

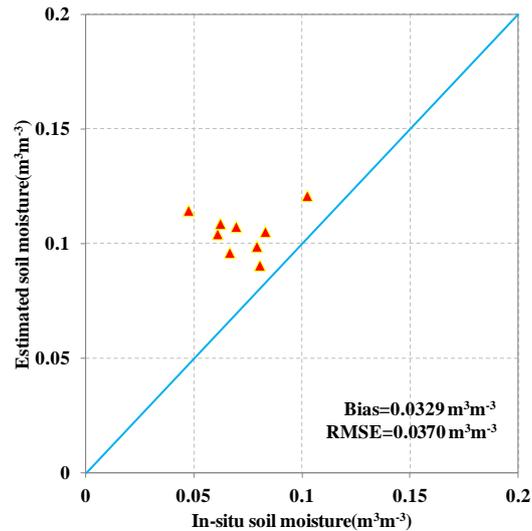
Thus, the H and V polarized brightness temperatures are only influenced by soil moisture and surface temperature. Additionally, the MPDI [12] is often used to eliminate the effects of surface temperature. The MPDI is defined as:

$$MPDI = \frac{T_{Bv} - T_{Bh}}{T_{Bv} + T_{Bh}} \quad (10)$$

By inserting equation (8) and equation (9) into equation (10), the simulated MPDI (i.e.,  $MPDI_{sim}$ ) which is only related to  $r'_{sp}$  can be obtained. Thus,  $MPDI_{sim}$  can be expressed as a function of soil moisture with known soil texture at a given frequency. Finally, a nonlinear iterative procedure is performed to make the absolute value of the differences between the simulated and observed MPDI minimum (i.e.,  $abs(MPDI_{obs} - MPDI_{sim}) = min$ ) to obtain surface soil moisture.

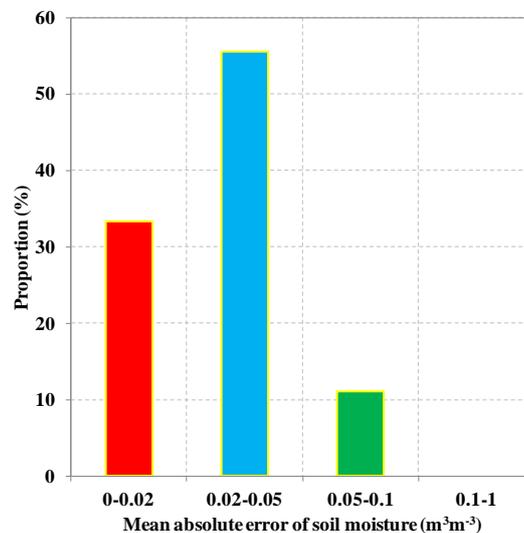
### 3. Results and discussions

To validate the feasibility of the proposed algorithm, we compared the soil moisture retrieved by the algorithm and the ground soil moisture during the SMEX04. Figure 2 shows the scatter plots comparison between soil moisture retrievals and in-situ average soil moisture, and the root mean square error (RMSE) and Bias were also displayed in this figure. It is clearly shown that the soil moisture retrieved by the proposed algorithm is very close to the in-situ soil moisture, except only one point which is relatively far away from the 1:1 line. The overall RMSE is  $0.0370 \text{ m}^3 \text{ m}^{-3}$  and the Bias is  $0.0329 \text{ m}^3 \text{ m}^{-3}$ . These two statistical parameters further indicate that the algorithm can estimate the soil moisture with a high accuracy.



**Figure 2.** Scatter plots comparison between soil moisture retrieved by the present algorithm and in-situ average soil moisture during SMEX04.

Figure 3 demonstrates the histogram of the distribution of mean absolute error (MAE) between in-situ soil moisture and retrieved soil moisture. It shows that about one third of the values of the MAE between retrievals and measurements are less than  $0.02 \text{ m}^3 \text{ m}^{-3}$ . Nearly 90% values of the MAE are less than  $0.05 \text{ m}^3 \text{ m}^{-3}$ . Thus, conclusion can be drawn that the proposed algorithm is an effective method for surface soil moisture estimation which uses only one frequency brightness temperature observations and needs no filed observations of surface roughness, soil moisture, or canopy biophysical data as calibration parameters.



**Figure 3.** Histogram of the distribution of mean absolute error between in-situ soil moisture and estimated soil moisture.

#### 4. Conclusions

In this study, a single-frequency algorithm for surface soil moisture retrieval from passive microwave radiometer data was developed. The algorithm is based on the tau-omega model and the assumption that the vegetation optical depth is polarization independent. The influence of both the roughness and vegetation is combined into a single parameter in the algorithm. The microwave polarization difference index (MPDI) is used to eliminate the effects of temperature. Then soil moisture is obtained through a nonlinear iterative procedure by making the absolute value of the differences between the simulated and observed MPDI minimum, so the algorithm does not require thermal infrared sensor or Ka-band passive microwave observations to obtain surface temperature. To verify

the present algorithm, the C-band dual-polarized brightness temperature data from the Polarimetric Scanning Radiometer (PSR) at the Arizona during the Soil Moisture Experiment 2004 (SMEX04) were used for soil moisture estimation. Then the soil moisture retrievals were validated by in-situ data from 42 sites in the Arizona. The results show that the soil moisture retrieved by the algorithm agrees well with ground measurements. The advantage of the the proposed algorithm is that it uses only one frequency brightness temperature observations and uses the least auxiliary data, namely soil texture, during the whole soil moisture retrieval process.

### Acknowledgments

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