P- AND L-BAND RETRIEVAL OF SUBSURFACE SOIL MOISTURE AND TEMPERATURE PROFILES AS FIRST-ORDER POLYNOMIAL FUNCTION

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ABSTRACT

This paper demonstrates the potential use of P and L band passive measurements to determine root zone soil moisture (SM) and soil temperature (ST). SM and ST data have been taken as a function of depth during the NASA GSFC PLEX19 experiment in the summer of 2019 at Beltsville, MD, USA. Using these data, a coherent model has been used to compute H and V brightness temperatures at frequencies of 0.8 and 1.4 GHz with an observation angle of 35 degrees. These synthetic brightness data are then used to estimate the SM and ST profiles which are represented by linear polynomials. The inversion problem is formulated as a least square problem that is solved by a global optimization method known as the Adaptive Simulated Annealing (ASA) method. Four inversion examples having different SM and ST profiles are presented. Selected results show that the standard deviation between the retrieved and measured data is less than 0.077 cm^3/cm^3 for SM, and 2.245 °C for ST.

Index Terms— Root zone soil moisture, soil temperature, brightness temperature, P and L bands, adaptive simulated annealing

1. INTRODUCTION

Soil moisture (SM) and soil temperature (ST) are two variables of interest to agriculture (food production) and hydrology (floods and droughts). These applications need SM and ST data in the root zone to the depth of 40 cm. Current satellite sensing [1]-[2] at 1.4 GHz (L band), however, generally provides the estimation of average values of SM and ST over the top 5 cm. Direct measurement of SM and ST in the root zone is required to be developed at P band region so that electromagnetic wave can penetrate into the soil deeply enough. The NASA Goddard Space Flight Center (GSFC) experiment PLEX19 has made H and V brightness temperature measurements sensitive to the root zone area of vegetated fields (corn) and bare fields (short grass) at P and L band [3,4]. *In situ* SM and ST have been measured at the depths of 5, 10, 20, 40 and 60 cm in each field.

The P-band radiometric data from PLEX19 are presently unavailable. The experiment encountered high RFI (radio frequency interference) in the P band region and a redesigned receiver is under consideration. In this paper only *in situ* SM and ST data is utilized and made as a function of depth to calculate H and V synthetic brightness temperatures. Because of the preliminary nature of this calculation, the being used *in situ* SM and ST data will be considered only at 5, 10 and 20 cm for the synthetic brightness temperatures at a P band frequency of 0.8 GHz and the L band frequency of 1.4 GHz. Lower P band frequencies can penetrate more deeply, so that the retrieval of SM and ST at depths larger than 20 cm will be a subject of future investigation.

There have been several studies on the retrieval of SM and ST profiles from passive remote sensing observations. These studies have either been limited to retrieval of SM and ST of the first few centimeters of soil [5] or to retrieval of the SM and ST profiles from surface SM and ST using sequential data-assimilation techniques [6]. A previous study [7] considered the same two frequencies but it used hypothetical soil data. To our knowledge, direct retrieval of root zone SM and ST using passive remote sensing data at P-band has not been studied, although it has been shown that deeper soil moisture can impact the radiometric response significantly. Therefore, the study aims to use the synthetic brightness temperatures at P- and L- bands to estimate the SM and ST profiles that are represented as first-order polynomial functions.

This paper is organized as follows. Section II describes the coherent model that is used to generate the synthetic brightness temperature at P- and L-bands. Section III introduces the Adaptive Simulated Annealing method that is used to retrieve both SM and ST profiles as a first-order polynomial function. Section IV presents inversion results and its analysis. Section V draw a conclusion.

2. DATA ACQUISITION

In situ SM and ST had been collected hourly from 3 test sites in a corn field (Sites 1-3) and 3 test sites (Sites 4-6) in an adjacent field of short grass during the PLEX19 experiment. The experimental sites are marked in Fig.1. The measurements lasted from June 5, 2019 to November 15,

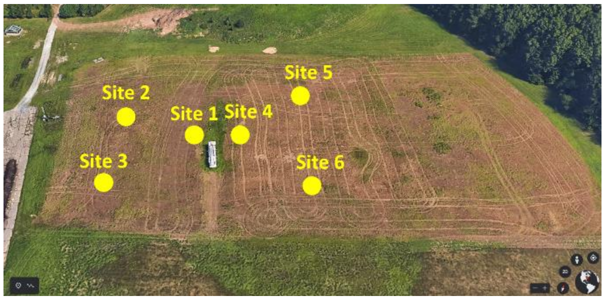

Fig. 1 NASA GSFC PLEX19 experimental site in the summer of 2019 at Beltsville, MD, USA. Sites 1-3 were corn fields and Sites 4-6 were short grass fields.

2019. SM and ST have been measured by Stevens Water Hydra probes in the root zone at 5 soil depths (5, 10, 20, 40, and 60 cm) at all 6 sites.

Since a P band frequency of 0.8 GHz is being employed, only SM and ST data at 5, 10 and 20 cm can be sensed. Remote sensing of SM and ST at deeper depths will require much lower frequencies in the P band region (0.50-0.85 GHz) to penetrate deeply enough into the soil, which will be future subjects. During the experimental period, the grass was relatively short and had remained sparse. It has been assumed that the grass field is essentially bare soil for the microwave frequencies being studied, and SM and ST data from the short grass field will be used in this paper. Sites 4-6 in the short grass field have similar SM and ST profiles to each other, thus only values of SM and ST from Site 4 will be employed. The soil at Site 4 is sandy loam with 52.5% sand, 35.1% silt, and 13.4% clay.

Radiometric response is significantly affected by the air-soil surface data much than the soil data below the surface. To investigate the impacts, four cases are considered and shown in Table I for discussion in this paper. They are the lowest and highest surface values of SM and ST during the experiment: CASE 1 -- the lowest surface value of SM; CASE 2 – the highest surface value of SM; CASE 3 -- the lowest surface value of ST; CASE 4 – the highest surface value of ST. The SM and ST at the air-soil surface are estimated by fitting the measured data with a quadratic function. The SM or ST between two adjacent sampled depths, in addition, has been obtained by linearly interpreting the measured data.

Table I. The *in situ* SM and ST profiles at short grass field during the PLEX 19 experiment.

	CASE 1		CASE 2	
Depth (cm)	SM (cm^3/cm^3)	ST (°C)	SM (cm^3/cm^3)	ST (°C)
0	0.08	25.8	0.51	29.20
5	0.14	25.9	0.49	28.30
10	0.19	26.9	0.43	26.20
20	0.22	27.2	0.38	25.40
	CASE 3		CASE 4	
Depth (cm)	SM (cm^3/cm^3)	ST (°C)	SM (cm^3/cm^3)	ST (°C)
0	0.26	1.5	0.18	42.90
5	0.27	2.8	0.23	39.60
10	0.29	4.7	0.29	34.20
20	0.27	6.7	0.31	30.10

Note that CASE 1 is measured on July 8, 2019 at 16:00; CASE 2 measured on July 20, 2019 at 14:00; CASE 3 measured on November 12, 2019 at 23:00; CASE 4 measured on Aug 1, 2019 at 16:00.

3. MODEL DESCRIPTION

3.1. Forward Model

A coherent model [8] is used to compute the brightness temperatures from the SM and ST profiles of the four cases above. The final algorithm is generated by discretizing the continuous SM and ST profiles by a stack of finely layered medium. In the model, SM is related to the complex dielectric constant based on Mironov's model [9] that is a linear function at the studied site [10].

3.2. Inversion Model

In this paper, the brightness temperature is used to estimate both SM and ST profiles. The profiles are approximated by linear functions of the depth z. The linear functions are written in the form of

$$m_v(z) = a_m + b_m z \tag{1-1}$$

$$T(z) = a_t + b_t z \tag{1-2}$$

where z denotes depth; a_m , b_m and a_t , b_t are the unknown coefficients for the estimated SM and ST profiles.

To estimate the unknown coefficients a_m , b_m and a_t , b_t , we use the following cost function that is based on the difference between estimated and synthetic brightness temperatures:

$$L(\mathbf{X}) = \sum_{p=h,v} \sum_{i=1}^{N_f} \left(\frac{T_B^p(\mathbf{X}, f_i) - d^p(f_i)}{d^p(f_i)} \right)^2 \tag{2}$$

where $d^p(f_i)$ denotes the synthetic brightness temperature which is obtained from soil with *in situ* SM and ST profiles at frequencies of 0.8 and 1.4 GHz with an incidence angle of 35°; $T_B^p(\mathbf{X}, f_i)$ denotes the estimated brightness temperature which is obtained from soil with linear SM and ST variations; p denotes polarization; N_f is the number of frequencies used; vector $\mathbf{X}$ contains the unknown coefficients a_m , b_m and a_t , b_t .

To find the global minimum of the cost function, we employ Adaptive Simulated Annealing (ASA) method [11], which is developed based on the Simulated Annealing (SA) method. The ASA method considers the determination of the unknown parameters of an optimization problem as an analogy with the particles in the annealing process of solids. Compared to the classical SA method, ASA can give unknowns in individual ranges which benefits finding the

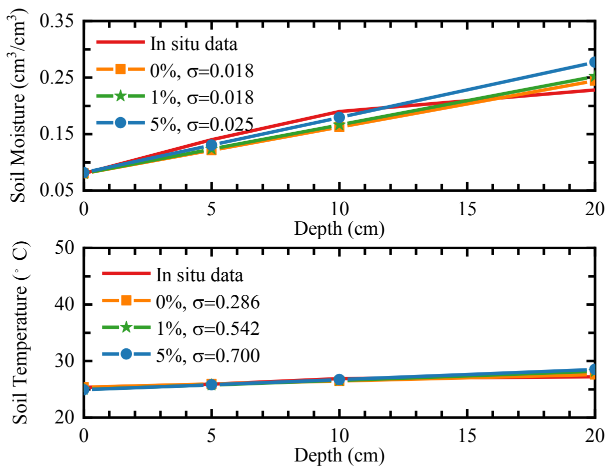

Fig. 2 Comparison between in situ SM and ST data and retrieved profiles T_B perturbed by noises of 0%, 1%, and 5% where *in situ* SM and ST data are CASE 1 in Table I.

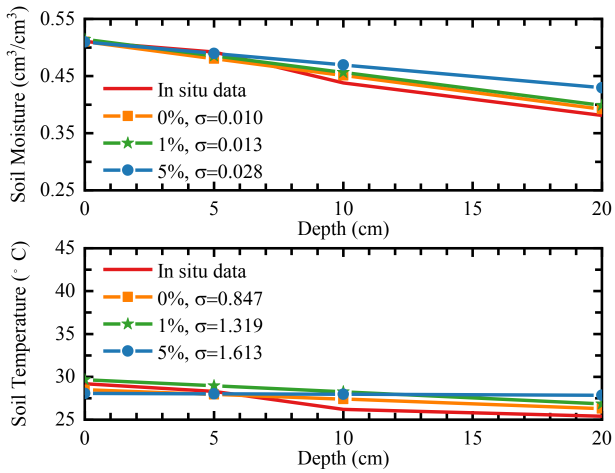

Fig. 3 Comparison between in situ SM and ST data and retrieved profiles T_B perturbed by noises of 0%, 1%, and 5% where *in situ* SM and ST data are CASE 2 in Table I.

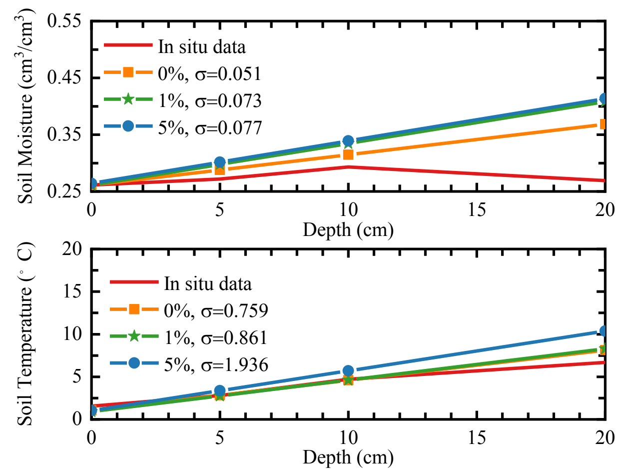

Fig. 4 Comparison between in situ SM and ST data and retrieved profiles T_B perturbed by noises of 0%, 1%, and 5% where *in situ* SM and ST data are CASE 3 in Table I.

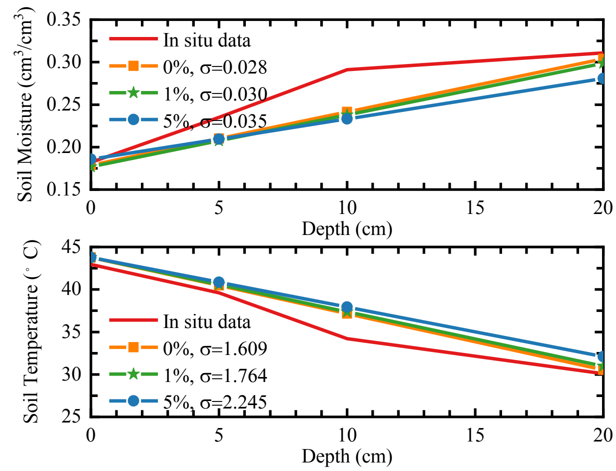

Fig. 5 Comparison between in situ SM and ST data and retrieved profiles T_B perturbed by noises of 0%, 1%, and 5% where *in situ* SM and ST data are CASE 4 in Table I.

global optimum solution with less computational time and power.

To test the stability of our solutions, we use a noise analysis to analyze the sensitivity of the inversion method to measurement noise. The noise is modeled as

$$d_n^p = d^p + \delta_n N(0,1) d^p \tag{3}$$

where d^p is the noise-free brightness temperature; d_n^p denotes the synthetic brightness temperature perturbed by noise with the amplitude of δ_n; the quantity $N(0,1)$ is a normally distributed random number. The noise can be added in the inversion model by replacing d^p by d_n^p in eq. (2).

4. Inversion Results

To study the sensitivity of P- and L-bands passive observations to SM and ST over depths of 20 cm, we employ 0.8 and 1.4 GHz brightness temperatures with an incidence angle of 35° at both polarizations. The synthetic brightness temperatures d_n^p are obtained by perturbing the noise-free brightness temperature d^p with a noise of δ_n=0%, 1%, and 5%. Both SM and ST profiles are inverted as a linear function. Guided by the available *in situ* SM and ST data given in Table I, the unknown coefficients have been constrained as $0 \le a_m \le 0.52$, $-1.5 \le b_m \le 1.5$ and $0 \le a_t \le 45$, $-100 \le b_t \le 100$. The inversion algorithm runs 200 times in each case, the average value is then calculated.

To evaluate the accuracy of inversion results, the standard deviation, σ, of difference between the retrieved and *in situ* SM or ST is evaluated below

$$\sigma = \sqrt{\frac{\sum_{i=1}^{N_p}\left[\hat{Y}_i - Y_i\right]^2}{N_p}} \tag{4}$$

where N_p is the number of depths at which the SM and ST are measured (equal to 4 in this paper); $\hat{Y}$ is the retrieved SM or ST, Y is the *in situ* SM or ST.

Comparisons between in the *situ* SM and ST data and the inverted profiles as function of depths are shown in Figs. 2-5 with different added noise values. The results show a good accuracy even for 5% noise in brightness temperature. Some deterioration occurs at large depths, however, even in the noisiest case it is clearly possible to distinguish these cases. The inversion accuracy is summarized in Table 2 for brightness temperature perturbed by 5% noise.

Further important findings from the series of examples are as follows. First, the ASA method is capable of inverting SM and ST from brightness temperature with varying amounts of noise. Second, the range of microwave frequencies between L band and P band are best suited for the retrieval of SM and ST along depths of 0-20 cm. Third, the worst inversion of SM at the depth of 20 cm is CASE 3. The is because brightness temperature has low response to soil having a low temperature. In this case the range of unknowns needs further to be restricted with a consideration of the interaction between brightness temperature and soil temperature, which will be discussed in a future paper. Finally, the inversion model in this paper estimates SM and ST profiles to be linear functions. Use of a quadratic estimation function and more frequencies may improve the retrieval accuracy, which will be another discussion in the future paper.

5. CONCLUSIONS

We presented the application of P and L band brightness temperature to the inversion of first-order polynomial functions representing SM and ST profiles. Four inversion examples are given for soils having low and high surface moisture and temperature, respectively. The results showed that the ASA method is a powerful tool, which is capable of giving RMSE less than 0.077 cm^3/cm^3 for inverting SM profile and 2.245 ℃ for inverting ST profile. The inversion accuracy could be improved by estimating SM and ST profiles to higher-order polynomial functions and by using more frequencies of brightness temperatures. They will be presented in a future paper.

Table 2. NRMSE for T_B perturbed by noise of 5%

	CASE 1	CASE 2	CASE 3	CASE 4
SM (cm^3/cm^3)	0.025	0.028	0.077	0.035
ST (℃)	0.700	1.613	1.936	2.245

6. REFERENCES

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