Development of a Soil Moisture Retrieval Algorithm for Spaceborne Passive Microwave Radiometers and Its Application to AMSR-E and SSM/I

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Abstract— **This paper reports the development of a soil moisture retrieval algorithm for spaceborne passive microwave radiometers. The algorithm is based on a modified radiative transfer model, so-called DMRT-AIEM model. The implementation of this algorithm consists of three steps: 1) forward model parameters optimization; 2) lookup table generation and 3) lookup table reversion and soil moisture estimation. The algorithm was tested at a CEOP (Coordinate Enhanced Observing Period) reference site on the Mongolia Gobi. The retrieved soil moisture data was compared with the in situ observations. The comparison results show that the performance of the new algorithm is good, giving a Standard Error of the Estimate (SEE) of 3.8% and R-square of 0.4. Moreover, a successful TB validation on SSM/I low frequencies was achieved by the RTM used in this algorithm. It means this algorithm provides a possibility to retrieval around 20 years' soil moisture data from SSM/I observations.**

Keywords- remote sensing; soil moisture; satellite; passive microwave measurement; brightness temperature; AMSR-E; SSM/I

I. INTRODUCTION

Soil moisture patterns, both spatial and temporal, are the key to understanding the spatial variability and scale problems that are paramount in scientific hydrology, meteorology and climatology. Soil moisture controls the ratio of runoff and infiltration, decides the energy flux and influents vegetation development and then carbon cycle. A long term soil moisture data set on a region scale therefore could provide valuable information for researches such as climate change and global warming, and then improve the weather forecasting and water resources management. But, due to its large variability, it is extremely difficult to observe the spatial and temporal distribution of soil moisture in a large scale with traditional measurement methods. As a result, in recent 30 years, much effort has been directed towards observing soil moisture by satellite remote sensing approaches.

Passive microwave remote sensing has been recognized as a potential method for measuring soil moisture with a large spatial coverage, while the sensors operated at low frequencies have been acknowledged to be capable to estimate soil moisture reliably[1-4]. For instant, the Advanced Microwave Scanning Radiometer for the Earth Observing System (AMSR-E) is believed to offer state of the art soil moisture estimation through the combination of low frequency observations at 6.9, 10.65 and 18.7 GHz[5-7]. In terms of soil moisture temporal distribution, the Special Sensor Microwave/Imager (SSM/I) equipped on Defense Meteorological Satellite Program (DMSP) satellites, measuring the brightness temperature of the earth at 19, 22, 37 and 85 GHz with a history around 20 years, is highly expected to provide long-term global soil moisture estimation[8-10].

In this study, we present a new soil moisture retrieval algorithm developed at the University of Tokyo. This algorithm is based on a modified radiative transfer model[11], in which the volume scattering inside soil layers is calculated through dense media radiative transfer theory (DMRT)[12] and the surface roughness effect is simulated by Advanced Integration Equation Model (AIEM)[13]. The optimal values of forward model parameters are estimated using in situ observation data and lower frequency brightness temperature data. And with those optimized parameters, we run the forward model to generate a lookup table, which relates the variables of interest, such as soil moisture content, soil physical temperature, vegetation water content and atmosphere optical thickness, to the brightness temperature or some indexes calculated from brightness temperature data. Finally, soil moisture content is estimated by linearly interpolating the brightness temperature or index into the inversed lookup table. The algorithm was tested with AMSR-E match up data set at Mongolia region. And the forward model was also validated for SSM/I brightness temperature data at same region.

II. THE ALGORITHM

The objective of our research is to develop a physically-based soil moisture retrieval algorithm, which should be able to estimate soil moisture content from low frequency passive microwave remote sensing data at spare vegetation region.

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A. The Forward Model

In our forward model, the downward radiation from vegetation and rainfall, which are reflected by soil surface, is neglected with considering the fact that the reflection at soil surface is much smaller than the emission from the surface. The brightness temperature observed by spaceborne sensors is then expressed as:

$$T_b = T_{bs} e^{-\tau_c} e^{-\tau_r} + (1-\omega_c)(1-e^{-\tau_c}) T_c e^{-\tau_r} + \int (1-\omega_r(R))(1-e^{-\tau_r(R)}) T_r(R) dR \quad (1)$$

where T_{bs} is the emission of soil layer, T_c is the vegetation temperature, T_r is the temperature of rainfall, τ_c and ω_c are the vegetation opacity and single scattering albedo, τ_r and ω_r are the opacity and single scattering albedo of rainfall.

The emission from soil is controlled by the soil properties and land surface roughness. Soil properties, such as soil temperature, moisture content, and texture profiles, are taken into account through dielectric constant models and radiative transfer process inside the soil media. In our model, the Dobson model[14] is used to calculate the dielectric constant of soil; while the radiative transfer process inside the soil is simulated by a discrete ordinate method and the scattering and emission effects of soil particles are calculated by DMRT. Land surface roughness effect is simulated by a physically based model, AIEM. By coupling AIEM with DMRT, this radiative transfer model for soil media is a fully physically based model, hereinafter termed as DMRT-AIEM model.

As a fully physically based radiative transfer model, the parameters of DMRT-AIEM, such as the RMS height, correlation length and soil particle size, have clearly physical meaning and their values can be obtained from field measurement or theoretical calculation.

B. The Algorithm

The most notable advantage of our algorithm is the parameters used in it have clear physical meanings. This is inherited from the strength of the forward radiative transfer model. The parameters of forward RTM therefore should be optimized before the algorithm application. In detail, the implementation of our algorithm consists of three steps as following:

Step 1. Forward model parameters optimization. The parameters to be optimized include RMS height (*h*), correlation length (*l*), soil particle sizes (*r*) and vegetation parameter such as χ and *b'*. These parameters are optimized by minimizing the cost function expressed as:

$$J(h,l,r,b',\chi,\ldots) = \sum_{i=1}^{n}\sum_{f}\sum_{p=H,V} ABS[TB_{sim}(i,f,p) - TB_{obs}(i,f,p)] \quad (2)$$

where the subscript *sim* denotes the model simulated value and *obs* is the observed value. *n* is the number of samples used in the optimization. *p* denotes the polarization status: *H* for horizontal polarization and *V* for vertical. *f* is the frequency operated by sensors in the long wavelength region where the atmosphere effect could be ignored, such as the 6.9, 10.7 and 18.7 GHz of AMSR-E, 1.4 GHz of SMOS and 19GHz of SSM/I.

As done in former paper of authors[15], the observation conducted in wet days is used to estimate RMS height and correlation length firstly, with considering the fact that there is no volume scattering effect in wet soil. And then observation done in dry days is used to estimate particle size.

Step 2. Lookup table generation. When we finished step 1, the optimal parameter values are then stored in the forward RTM. And then we run the forward model by inputting all possible values of variables which are considered in equation (1), such as soil moisture content, soil temperature, vegetation water content and atmosphere optical thickness. As a result, a family of brightness temperature is then generated. Based on this brightness temperature database, brightness temperature of special frequencies and polarization are selected to composite a lookup table or to calculate some indexes to composite a lookup table.

Step 3. Lookup table reversion and soil moisture estimation. The lookup table generated in step 2 is reversed to give a relationship which mapping the brightness temperature or indexes obtained from satellite remote sensing data to the variables of interest. Finally, soil moisture content is estimated by linearly interpolating the brightness temperature or indexes into the inversed lookup table.

III. APPLICATION

The presented algorithm was tested at a CEOP (Coordinate Enhanced Observing Period)[16] reference site on the Mongolia Gobi. The information about this site and AMSR-E match up data set can be found from [15] and from the web site of Hiroshima University[17].

A. Best-fitting Parameters for AMSR-E

For the AMSR-E data, observation obtained from low frequency channels (6.925, 10.65 and 18.7 GHz) is used to optimize model parameters. Since the wavelength of those channels is generally much larger than the diameter of atmospheric particles, the atmosphere effect is negligible for the data measured with those channels.

According to the in situ observation done in June and August, 2003, the vegetation water content (VWC) in this region is generally smaller than 0.1 kg/m^2. Following the research done by Jackson et al. [18, 19], vegetation effect is also negligible. The equation (1) is therefore simplified as:

$$T_b = T_{bs} \quad (3)$$

It means the radiative transfer model for AMSR-E in Mongolia site is simplified to the soil RTM, DMRT-AIEM. And the optimizing parameters are only those three parameters related to soil media: RMS height (*h*), correlation length (*l*) and soil particle sizes (*r*). The complexity of our RTM and the computation cost are also reduced.

With the optimized parameters, we first run the forward model to simulate brightness temperature from 6.9GHz up to 36GHz with using in situ observation soil moisture and temperature data as input. The brightness temperature validation result is shown in **figure 1**, where the x axis is the AMSR-E observation and the y axis is our model output.

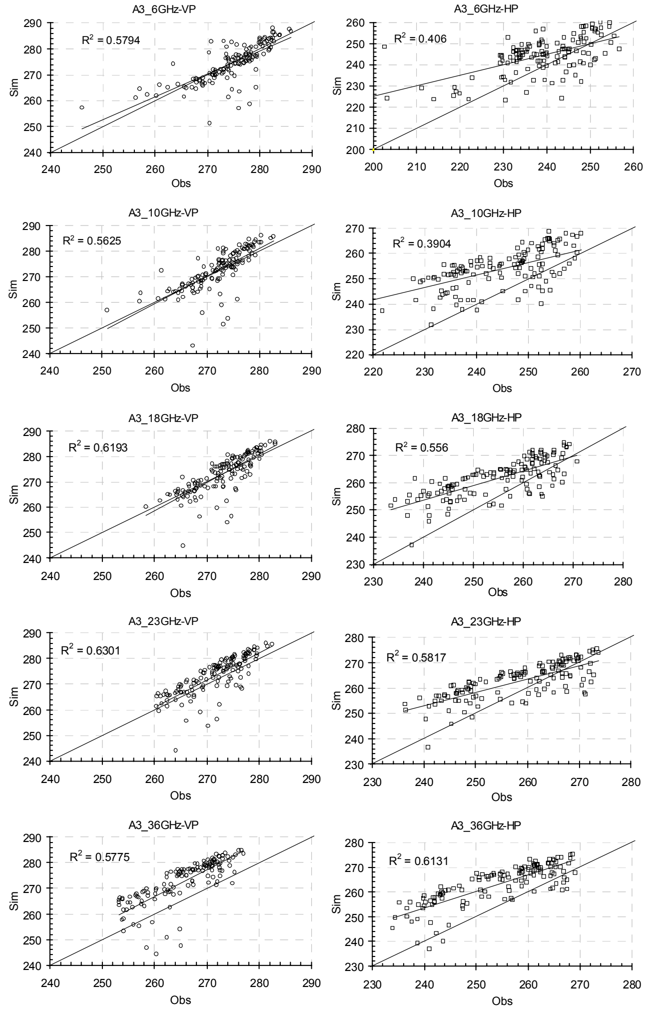


Figure 1. Comparasion of simulated brightness temperature with the ones observed by AMSR-E

B. *Retrieval Soil Moisture from AMSR-E*

As shown in **figure 1**, the simulation result of DMRT-AIEM is generally good, with better result for vertical polarization than for horizontal polarization. And the model overestimates brightness temperature at horizontal polarization n for all frequencies, while the bias values for each frequency are almost same. With those findings, we build a lookup table which composed by the soil physical temperature, soil moisture content, brightness temperature at 10.65GHz vertical polarization and an index named *dTB* calculated as following:

$$dTB = TB(18.7,H) - TB(10.65,H) \tag{4}$$

The lookup table of our AMSR-E algorithm is shown in **figure 2**. As we can see from this figure, the lookup table is covering a region in which soil moisture content is varying from 2% to 40% and soil physical temperature is varying from 270K to 303K. Compared with in situ observation values, this range is large enough for including all of the actual soil moisture and temperature status at Mongolia.

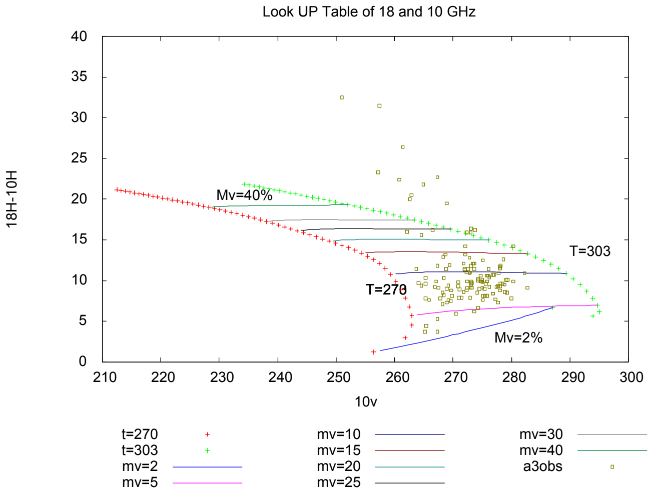
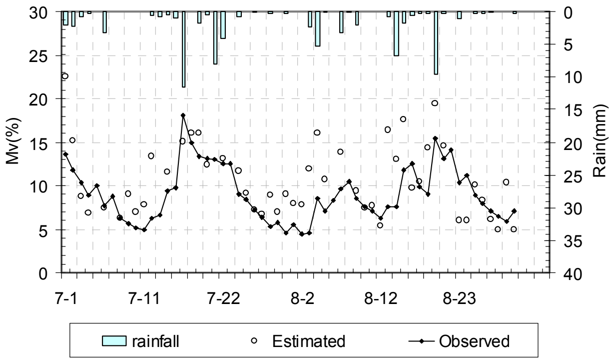


Figure 2. Lookup table for the AMSR-E soil moisture retrieval algorithm

Since the one-to-one relationship in our lookup table is very clear, it get much simple to reverse the lookup table. With the reversion of lookup table, soil moisture can be easily estimated from AMSR-E data set. In this study, we retrieved soil moisture data from July to August, 2003. The estimation results are shown in **figure 3** for (a) time variation and (b) accuracy comparison.

(a) Time variation of soil moisture (ASSH stations' average)



(b) Comparison of SMC estimation (ASSH stations' average)

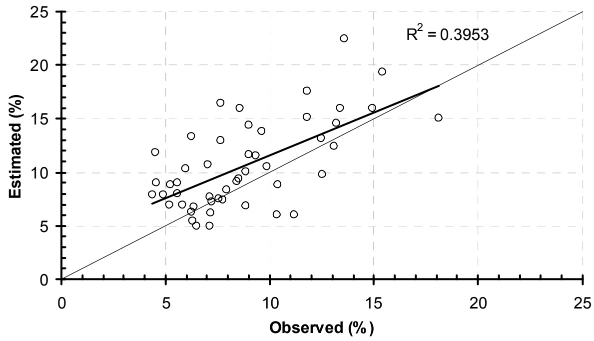


Figure 3. Comparation of retrieval results with in situ observation

It is clear from **figure 3** that the algorithm gives a reliable soil moisture content estimation, in both the tendency and

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quantity. The value of R-square is 0.3953, and the value of Standard Error of the Estimate (SEE) is 3.8%.

C. TB Simulation for SSM/I

After get the success from AMSR-E, we tried to simulate brightness temperature of SSM/I with using same parameters in same location. Here, SSM/I match-up data also is for A3 station, and the time range is from Jul. 1st to Jul. 30th, 2003. The brightness temperature simulation results are shown in **figure 4**. The R-square between observed brightness temperature and simulated one are also shown in this figure.

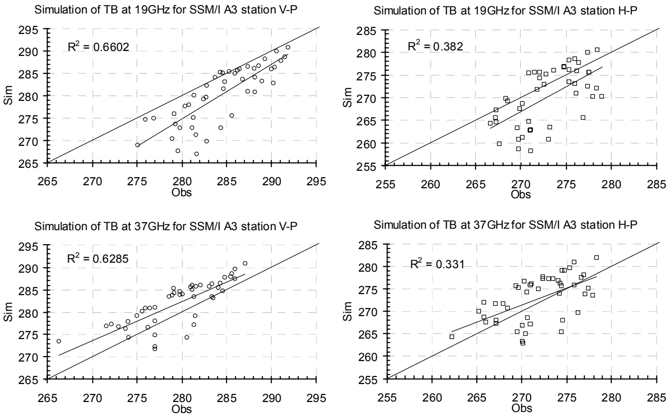

Figure 4. Simulation Results of SSM/I

It is clear that DMRT-AIEM estimate SSM/I brightness temperature in a good quality, showing the values of R-square is comparable to the results of AMSR-E comparison. Since there is only one lower frequency onboard SSM/I, our algorithm can not directly use to estimate soil moisture content from SSM/I. For the observation at 37GHz, the atmosphere effect should be included.

IV. CONCLUSION

Spatial distributed soil moisture information is an essential parameter for hydrological, meteorological and ecological studies. This paper presents a simple soil moisture retrieval algorithm which successful estimates reliable soil moisture content from AMSR-E data at CEOP Mongolia reference site. Moreover, it was demonstrated that the forward RTM of this algorithm was capable to represent the SSM/I brightness temperature data only after the parameters were calibrated by AMSR-E data set. Therefore, we have built a bridge between the parameters retrieved from AMSR-E and those for SSM/I. With some further consideration about the difference between AMSR-E and SSM/I, e.g. the footprint size and the observation patterns, it is believed that our algorithm could provide a possibility to use the long historical global data observed by SSM/I.

ACKNOWLEDGMENT

This study was carried out as a part of Coordinated Enhanced Observing Period (CEOP) project funded by the Japan Science and Technology Agency and the Special Coordination Funds for Promoting Science and Technology. The authors express their so deep gratitude to them.

Furthermore we would like to thank the Japan Aerospace Exploration Agency (JAXA) for their support in providing the necessary data set.

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