Estimating the Effective Soil Temperature at L-Band Using Multi-Temporal temperature Data

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Abstract—The effective soil temperature is an essential parameter in the process of the soil moisture retrieval by using the passive microwave remote sensing data. The modeled soil temperature profile data was widely adopted to calculate the soil effective temperature at L-band. Considering that the procedure of using land models to obtain soil temperature profile is cumbersome, this study mainly investigates the effectiveness of using thermal infrared soil surface temperature and air temperature as the input parameters to calculate the soil effective temperature at L-band. The results of this study show that the average value of multi-temporal thermal infrared surface temperature and the monthly mean of air temperature can accurately calculate the soil effective temperature with RMSE=0.57K based on the simulated data of 4 years.

1. Introduction
The soil moisture content is an important parameter in rainfall-runoff prediction, agricultural yield forecasting, and boundary layer heat exchange for meteorological and climatic studies [1-2]. In situ observations of soil moisture, although accurate, is not practical for large areas, particularly when global information is needed. Satellite passive microwave remote sensing, especially at L band (21cm, 1.4GHz), is deemed to be the feasible method for retrieving data on global soil moisture levels [3]. The Soil Moisture and Ocean Salinity (SMOS) and the Soil Moisture Active Passive (SMAP) have already provided the global mapping of surface soil moisture based on radiometric measurements right on L band [4-6].

The brightness temperature observed by passive microwave satellite sensors can be expressed as,

\[ T_u = \varepsilon \cdot T_{\text{eff}} \]  

Where, for the case of the bare soil surface, \( \varepsilon \) is the effective soil emissivity that mainly corresponds to soil moisture and surface roughness, and \( T_{\text{eff}} \) is the effective soil temperature which is influenced by soil moisture, wavelength and soil temperature [7]. In current global operational processors for SMOS and SMAP, the \( T_{\text{eff}} \) in Eq.1 should be was known as a priori in the process of soil moisture retrieval and it was obtained from the modeled soil temperature profile, such as ECMWF (European Centre for Medium-Range Weather Forecasting) and the MERRA (Modern-Era Retrospective analysis for Research and Applications) data product, and so on [8-9].

Under some real-world conditions, obtaining the thermal infrared soil surface temperature \( (T_s) \) and the air temperature \( (T_a) \) is relatively simpler than obtaining the accurate vertical distribution of soil temperature. This paper mainly investigates the effectiveness and method using the \( T_s \) and the \( T_a \) as the input parameters to calculate the \( T_{\text{eff}} \) at L band. Section 2 describes the datasets used in this paper.
and the theoretical calculation method of the $T_{\text{eff}}$. Comparative results among the different schemes for determining the $T_{\text{eff}}$ are presented in section 3. Subsequently, some conclusions are drawn in the last section.

2. Method and materials

2.1 Data set review

The field site of the experimental data used in this paper is located in the Huailai district, Hebei province of China (40.20°N, 115.47°E). The soil is dominated by sandy loam in this area. The observational meteorological data of 4 years (2006–2009) was used to drive the Simultaneous Heat and Water model (SHAW) [10] to simulate soil temperature and moisture profile data at 12 different depths. The meteorological data include the hourly data of wind, air pressure, air temperature, air humidity, precipitation, and solar radiation. To avoid more complex freeze-thaw events, the simulated data from April to October was only used in this paper. Field observation experiments on soil temperature and moisture vertical profile data were carried out in May to June of 2010. The observational data set include the hourly $T_r$, $T_a$ and the soil temperature and moisture profile data measured by a set of temperature and humidity automatic observation system. The soil profile data was interpolated with different intervals, detailed as listed in table 1.

Table 1. An introduction of the Data Set used in this paper and its parameter setting

| Name of Data Set            | parameter                        | Time Span      | Sampling (simulating) Depths/cm | Interpolate Scheme |
|-----------------------------|----------------------------------|----------------|---------------------------------|--------------------|
| Simulate date set (SDS)     | Air temperature, Soil temperature and moisture content | April to October within 2006~2009 | 0, 0.5, 1, 2, 3, 5, 7, 10, 15, 20, 30, 50 | 0.1cm for 0–1cm; 0.2cm for 1~10cm; 0.5cm for 10~50cm |
| Measured Data Set (MDS)     | Air temperature, Soil temperature and moisture content | May to Jun in 2010 | 0, 1, 3, 5, 10, 20, 30, 50 | 0.5cm for 10~50cm |

In the observation data set of MDS, 12 days of data were selected and compared with the SHAW model simulation results and the comparison results are shown in figure 1. The comparison results show that the SHAW model can accurately predict the trend of soil temperature, and the deviation between the simulated value and the observed decreases with the increase of soil depth that made us confident in the simulation accuracy of the SHAW model.

2.2 Theoretical calculation of soil effective temperature

The effective soil temperature $T_{\text{eff}}$ was computed using the radiative transfer theory,
3. Results

Based on the data set of SDS, the \( W_i \) was calculated using the mean volumetric soil moisture within 0–5cm depth and the reference \( T_{air} \) was computed using Eq.2 firstly, then the optimal value of other parameters in the Eq.4 were determined by matching the model results with the reference values by least-squares method. In the process of comparison with the reference value, it is found that the model parameter of \( W_0 \) taking a fixed value of 0.5 has no obvious influence on the simulation accuracy of the Eq.4 and one of the possible reason is that the data used in this paper only cover one type of soil.

### 3.1 Determination of the n

For the data set of SDS, the best fitting of the model can be reached with RMSE=2.61K, \( W_i=0.5 \), and \( b=0.9592 \) when \( n=0 \) (case 1). When the \( n \) is given different values, the results can be significantly improved compared to case 1. Fig.2 shows the different results when \( n \) is given different integers from 0 to 11. For the data set of SDS, the best fitting occurs with RMSE=1.57K when \( n=4 \), \( W_i=0.5 \) and \( b=0.7820 \) (case 2).
The data set of SDS was divided into 24 parts by hour and the optimum value of \( n \) and \( b \) were accounted using the least square method to match the model results and the reference data until the fitting RMSE comes to the minimum at each hour. The accuracy of the model can be met with RMSE=0.5728K (case 3) which was basically the same as the accuracy of the Wigneron’s model. The details about the coefficients were listed in table 2.

### Table 2 The detail of the coefficients of model counted by the data set SDS

| Case 1 n=0 | Case 2 n=4 | Case 3 n with daily variation |
|------------|------------|-----------------------------|
| RMSE=2.61K | RMSE=1.57K | RMSE=0.57K |
| \( W_0=0.5 \) | \( W_0=0.5 \) | \( W_0=0.5 \) |
| \( b=0.9592 \) | \( b=0.7820 \) | \( b=0.7820 \) |
| \( T_{surf}=T^0 \) | \( T_{surf} = \frac{\sum T^e}{5} \) | \( T_{surf} = \frac{\sum T^e}{n+1} \) |
| \( T_{eep}=T_{air} \) | \( T_{eep}=\overline{T_{air}} \) |
| \( T_{surf} = T^0 + \frac{\sum T^e}{5} \) | \( T_{surf} = \frac{\sum T^e}{n+1} \) |
| \( T_{eep}=\overline{T_{air}} \) |

3.2 Validation

The parameters listed in table 2 were validated by using the MDS data set and the results are shown in Figure 3.

Figure 3 shows that the result of Case 3 was significantly improved compared with Cases 1 and Case 2. The verification accuracy of Case 3 in this paper is basically equivalent to the accuracy of the original model. The verification results indicated that the method proposed in this paper could be an effective method to estimate the \( T_{surf} \) at L band when the multi-temporal thermal infrared land temperature data was easier to obtain than the soil temperature profile data. All the coefficients in table 2 are the regression results derived from the data set of SDS from April to October while the verification data are measured in May and June and the significant differences in time will cause the accuracy of the verification results to decrease.
4. Conclusion
Considering that the process of using land models to obtain soil profile temperature at different depths is cumbersome, this study uses thermal infrared soil surface temperature and air temperature to calculate the soil effective temperature at L-band. When the soil temperature profile data is not easy to obtain, the multi-temporal $T_e$ and the monthly mean air temperature can be used as the input parameters of the soil effective temperature model. Based on the data set of SDS, analysis results show that the accuracy of the model can be improved from 2.61K of case 1 to 0.57K of case 3. The verification results based on the field measurement data also confirmed the effectiveness of the method proposed in this paper.

Both the simulated data and the observation data used in this paper were from the same observation site located in Huailai district of Hebei Provence of China, while the optimum value of n in Eq.4 is not only essentially affected by the different hour in a day but also the difference of climate types and soil texture, so the research results are valid only for the areas with the similar climate type and soil texture characteristics as the study area of this paper. Taking into account the diversity of soil texture and climatic conditions, future research will be carried out to further validate the effectiveness of the proposed method.

Acknowledgments
This work was supported by the Shandong Provincial Natural Science Foundation, China under Grant ZR2017MD007, ZR2018BD007 and the National Natural Science Foundation of China under Grant 41971292. We acknowledge the financial support received from the Chinese Scholarship Council (CSC) for Hongzhang Ma. We thank the staff of the Huailai observation station for providing soil texture information.

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