An Empirical Relationship of Bare Soil Microwave Emissions Between Vertical and Horizontal Polarization at 10.65 GHz

Zeng-Lin Liu, Hua Wu, Bo-Hui Tang, Shi Qiu, and Zhao-Liang Li

***Abstract*—Land surface microwave emission is mainly a function of soil moisture and surface roughness. However, the relationship between vertical and horizontal polarization land surface emissivities is not fully understood. This study attempts to develop a parameterized relationship to relate the emissivities at different polarizations for bare surfaces. A microwave emission database is simulated for bare surfaces with a wide range of surface roughness and dielectric properties using the Dobson model and the Advanced Integral Equation Model (AIEM) at 10.65 GHz under the configuration of the Advanced Microwave Scanning Radiometer-Earth Observing System (AMSR-E). By analyzing the factors that influence microwave emission, parameterized relationships between vertical and horizontal polarization emissivities are established. With the proposed relationships, the effects of soil moisture and surface roughness on the soil microwave emission signal can be separated. Simulated results using the proposed relationships are compared with those of the AIEM. These results show that the proposed relationships are accurate, with absolute root mean square errors (RMSEs) of 0.0025, and they can be used as a reliable boundary condition to retrieve other surface geophysical parameters. Combining this relationship with the calculated soil moisture, the RMSE of the estimated soil moisture is 0.44% using simulated data. As an example, observations of AMSR-E are used to estimate the variation in soil moisture in Saharan Africa in 2004. By comparing with independent soil moisture data, the result shows that the proposed relationship is promising for retrieving surface geophysical parameters from microwave observations.**

***Index Terms*—Microwave emissivity, passive microwave remote sensing, soil moisture.**

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I. INTRODUCTION

LAND surface emissivity and reflectivity are essential for deriving land surface geophysical parameters using remote sensing data. In many applications, the uncertainty in land surface emissivity or reflectivity directly affects the accuracies of the calculated parameters, such as land surface temperature and soil moisture. In reality, it is difficult to obtain land surface emissivity from passive radiometers because the number of measurements is always less than the number of unknowns [1], [2]. Although more accurate physics-based models have been developed in the past decades [3]–[7], their complexity often makes them difficult to use for retrieving geophysical parameters. To make the solutions deterministic, additional assumptions, semiempirical relationships, and extra constraints have been used in previous studies [8]–[14]. In this letter, we develop a parameterized relationship between the vertical and horizontal polarization emissivities, which is helpful in understanding the emission of a natural surface and can be easily used for land surface emissivity retrievals. Section II gives a brief description of the simulated database used in this work and describes the modeling of the parameterized relationships. Section III evaluates the proposed parameterized relationship using both simulated and actual data, and it presents an application of the proposed relationships. Conclusions are summarized in Section IV.

II. DATA AND METHOD

A. Reference Data Set

To develop parameterized relationships between emissivity at different frequencies, a soil emission database for bare surfaces was simulated for the configuration of the Advanced Microwave Scanning Radiometer-Earth Observing System (AMSR-E) at 10.65 GHz. The soil surface dielectric constants are described by volumetric soil moisture (sm), which is varied from 2% to 44% at 2% intervals by Dobson's dielectric mixing model [15], for a given soil texture (i.e., the volumetric fraction of sand is 30%, the volumetric fraction of clay is 30%, and the volumetric fraction of solid material is 50%). For a rough surface, the Advanced Integral Equation Model (AIEM) [7] is used to simulate bare surface emissivity, and the Gaussian correlation function was used in the simulation, which is a better approximation for high-frequency microwave measurements

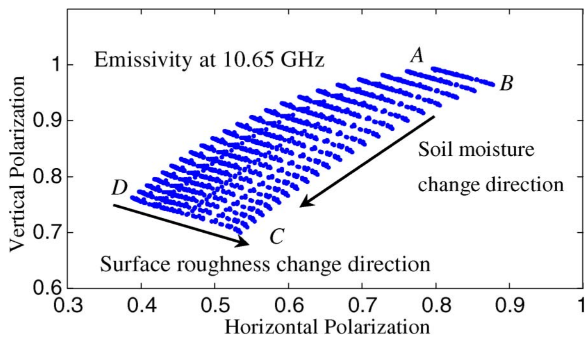

Fig. 1. Relationship between e_v and e_h at 10.65 GHz.

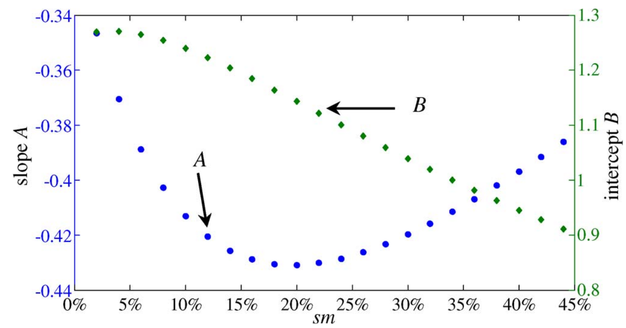

Fig. 2. Coefficients A and B versus sm.

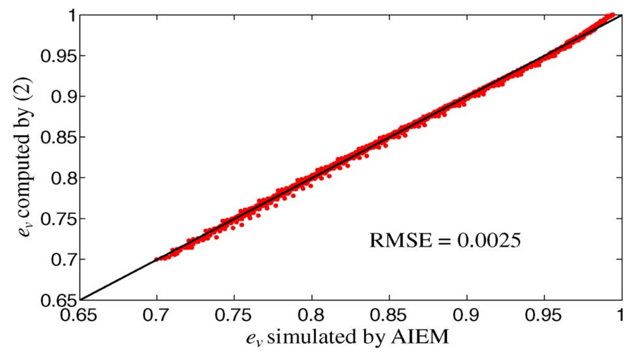

Fig. 3. Comparison between the AIEM simulated e_v and the corresponding e_v computed by using (2).

than an exponential correlation function [11]. The applicability of the AIEM has been proven by comparing the simulation of the AIEM with simulated data of a 3-D Monte Carlo model and field data [7], [11], [16]. The surface roughness parameters, which are also necessary input parameters of the AIEM, are set with a root-mean-square height (s) from 0.25 to 3.0 cm at a 0.25-cm interval and a correlation length (l) from 5 to 30 cm at a 2.5-cm interval [11]. The selected range of s here can meet the condition $(s = 0.1\lambda - \lambda)$. A ratio of s to l (s/l) that is positively correlated with the surface roughness condition is used to describe surface roughness in the following analysis. The simulated database was randomly divided into two groups. One group was used to parameterize the relationships, and the other was used to independently validate those parameterized relationships in Section III.

Based on the simulated database, the effect of sm and surface roughness on the bare surface emission and the relationship between vertical (e_v) and horizontal polarization (e_h) emissivity at 10.65 GHz were analyzed. Fig. 1 shows the scatterplot of e_v versus e_h at 10.65 GHz.

There are two clear trends. From points A to B, the value of s/l changes from 0.055 to 0.333, whereas sm remains unchanged at 2%. From B to C, sm increases to 44%, whereas the value of s/l is unchanged. From C to D, the value of s/l decreases from 0.333 to 0.055, whereas sm is constant at 44%. For a given sm condition and in the direction of varying surface roughness, e_v and e_h are negatively correlated, and their relationship is almost linear. The slope and intercept of the linear function may depend on sm. For a given surface roughness and in the direction of varying sm, e_v and e_h are positively correlated, and their relationship is weakly nonlinear over the full range of emissivities for a given surface roughness condition. However, there is a nearly linear relationship between e_v and e_h when e_h is larger than 0.6. The slope and intercept are thought to be a function of s/l.

B. Method

Considering the different effects of sm and surface roughness on emissivity, two empirical parameterized relationship models are developed to characterize the relationship between e_v and e_h. The relationship between e_h and sm is also analyzed.

1) Parameterized Relationship Between e_h and e_v Using sm: As shown in Fig. 1, a linear function can be established between e_v and e_h in the direction of varying surface roughness for a given sm. The slopes and intercepts of the function vary with sm, i.e.,

$$e_v = A(sm)e_h + B(sm). \tag{1}$$

Fig. 2 shows A and B versus sm, which can be expressed by quadratic functions of sm.

After further analysis, a simpler form of the relationship is developed, which may be more convenient for application. In this simpler relationship, slope A is set to be a constant, and B is a quadratic function of sm. Then, (1) can be rewritten as

$$e_v = Ce_h + p_1 sm^2 + p_2 sm + p_3 \tag{2}$$

where $C = -0.414$, $p_1 = 0.505$, $p_2 = -1.204$, and $p_3 = 1.354$, which were determined using the simulated data. The AIEM simulated e_v versus corresponding calculated e_v by using (2) are shown in Fig. 3. The root mean square error (RMSE) of the calculated e_v by using (2) is 0.0025, which is sufficient for some applications.

2) Parameterized Relationship Between e_h and e_v Using s/l: The direction in which sm varies is also important. Although the relationship between e_v and e_h is weakly nonlinear for a varying sm within the full range of emissivities, a linear relationship can also be established under certain conditions analyzed above (e.g., e_h is larger than 0.6). The linear relationship can be written as

$$e_v = E(s/l)e_h + F(s/l) \tag{3}$$

where E and F are linear functions of s/l. The RMSE of the estimated e_v using (3) is 0.0037. Based on the relationship

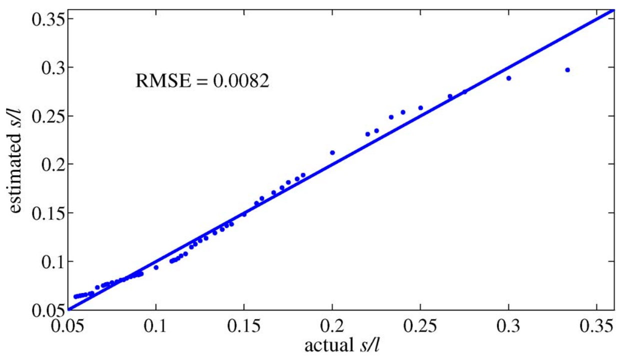

Fig. 4. Comparison of the estimated and actual s/l.

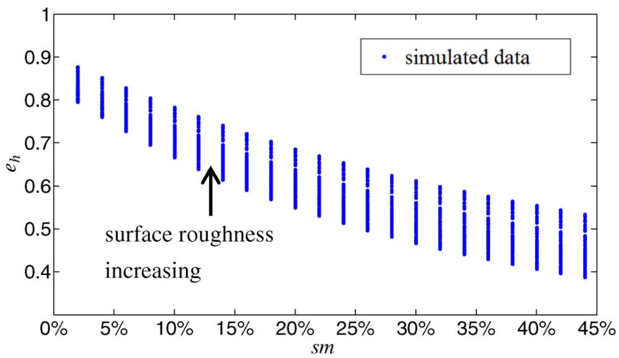

Fig. 5. Variation of e_h versus sm at 10.65 GHz.

between s/l and E (or F), s/l can be estimated from E and F. Specifically, s/l can be expressed as

$$s/l = q_1E + q_2F + q_3 \tag{4}$$

where $q_1 = -1.193$, $q_2 = -1.780$, and $q_3 = 1.796$, which were determined using the simulated data. Fig. 4 shows comparison between the estimated s/l by (4) and actual s/l.

3) Parameterized Relationship Between e_h and sm: A scatterplot of e_h versus sm is shown in Fig. 5. It can be seen that the relationship between e_h and sm can also be thought of as a quadratic function.

It is notable that this relationship becomes linear when e_h is larger than 0.6 or sm is lower than 15%, which may be more important because sm is often monitored in drought-prone regions where sm is generally lower. During a drought, the slope and intercept of this linear relationship also depend on s/l. This linear relationship can be written as

$$e_h = M(s/l)sm + N(s/l), \text{ for } sm < 15\% \tag{5}$$

where M and N are functions of the surface roughness condition, i.e.,

$$M = 2.765s/l - 1.846, \text{ RMSE} = 0.0396 \text{ and } r^2 = 0.96 \tag{6}$$

$$N = 0.293s/l + 0.813, \text{ RMSE} = 0.0035 \text{ and } r^2 = 0.97. \tag{7}$$

The RMSE of e_h estimated using (5) is 0.0083.

III. Application

Soil moisture is important in understanding the interactions between the atmosphere and land surface, and it is useful in the study of weather and climate change. Microwave remote sensing is advantageous for the estimation of sm due to the sharp contrast between the dielectric constant of soil particles (< 4) and that of water (80) [15] and the sensibility of microwave measurements to change of dielectric constant. Here, we demonstrate how to estimate sm using the proposed relationships and show the capability of the proposed soil emission relationship for the retrieval of geophysical parameters.

Because changes in sm vary more than surface roughness for a given location on the earth, particularly for bare surfaces, it is reasonable to assume that the surface roughness may be constant over a period of time and that the variation in emissivity is mainly due to changes in sm. Therefore, the parameterized models that describe the relationships between e_h and e_v using s/l in the direction of varying sm and between e_h and sm can be used to estimate sm. Microwave data (AE_Land3) from AMSR-E at 10.65 GHz are used to show how to estimate sm using the proposed empirical relationships. Due to the transparency of the atmosphere, the atmospheric effect was neglected. According to (3)–(5), sm for a bare surface can be estimated from the slope and intercept of the linear relationship between e_h and e_v, i.e.,

$$sm = \frac{e_h - N(s/l)}{M(s/l)} = \frac{e_h + k_1E + k_2F + k_3}{k_4E + k_5F + k_6} \tag{8}$$

where k_1 to k_6 are the retrieval coefficients ($k_1 = 0.346$, $k_2 = 0.522$, $k_3 = -1.339$, $k_4 = -3.299$, $k_5 = -4.922$, and $k_6 = 3.120$), and E and F are the slope and intercept in (3).

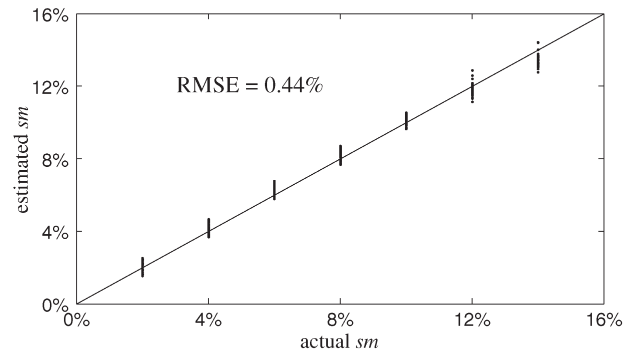

Fig. 6. Comparison of the estimated and actual sm.

A. Evaluation and Application of the Relationships Using Independent Simulation Data

Using independent simulation data that are different to the data used to establish the relationships, sm was estimated by (8). The results have an RMSE of 0.44% and are shown in Fig. 6. The proposed method is accurate for low sm (<15%) when there are no measurement errors.

B. Evaluation and Application of the Relationships Using Actual AMSR-E Data

Neglecting atmospheric effects, the daytime land surface e_v and e_h at 10.65 GHz under a clear-sky condition were computed by combining microwave brightness temperature

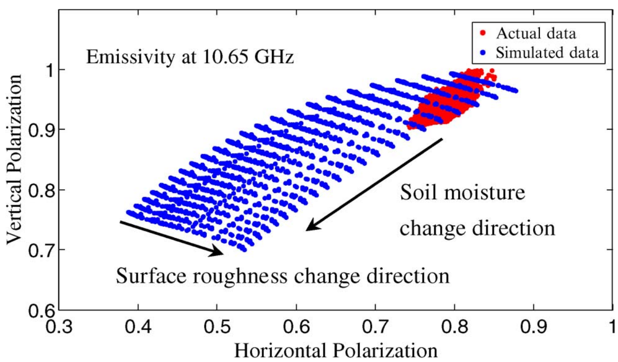

Fig. 7. Both simulated and calculated e_v versus e_h at 10.65 GHz.

from AE_Land3 and land surface temperature (LST) data (MYD11B1) of the Moderate Resolution Imaging Spectroradiometer (MODIS) as

$$e_p = T_{B_P}/T_s \tag{9}$$

where e_p is the land surface emissivity at polarization p (v or h). T_{Bp} is the brightness temperature from AMSR-E, and T_s is the LST from MODIS data. In this letter, cloud mask product (MYD35) was used to determinate whether it was clear day or not.

A study area in Saharan Africa spanning from 24.89° N to 29.27° N and 9.89° E to 28.11° E is considered. The e_v and e_h at 10.65 GHz in 2004 were calculated. The calculated e_p values are plotted together with the simulated data in Fig. 7.

Because surface roughness is less variable than soil moisture at a given place for a period, e_p may be described by an approximate linear relationship, as in (3). To further illustrate these phenomena, six sites with predominantly bare soils are chosen and labeled A through F. The calculated e_p for these sites for all clear days in 2004 are shown in Fig. 8. Clear linear relationships can be seen between e_v and e_h, which agree well with the analysis above. Regression lines and values of s/l estimated by (4) are also shown in Fig. 8.

The estimated values of s/l are largely consistent. However, the absolute values of the estimated s/l are near the maximum used in the simulated data, which is inconsistent with the fact that the surface should be relatively smooth in the study area. This inconsistency may attribute to the difference between the simulated and actual data, the fact that volumetric roughness increases with penetration depth increasing due to dielectric heterogeneities [10] or the discrepancy between the scale of modeling and that of observation [17].

To overcome the impact of the difference, $ratio_x$ (soil moisture (sm_x) with respect to a reference soil moisture (sm_0)) is estimated, rather than the absolute soil moisture, using the following comparison at two observation times:

$$ratio_x = \frac{sm_x}{sm_0} = \frac{e_{h,x} - N}{e_{h,0} - N} = \frac{e_{h,x} + k_1E + k_2F + k_3}{e_{h,0} + k_1E + k_2F + k_3} \tag{10}$$

where subscripts x and 0 denote the observation times, one of which corresponds to the time when sm_x is estimated and the other to the time when the reference soil moisture sm_0 is measured. Because the k_i $(i = 1, 2, 3)$, E and F are in both the numerator and denominator, their uncertainties affect less the accuracy of the retrieved $ratio_x$ compared with the impact on the retrieved sm in (8). According to sensitivity analysis, an error of 0.1 is estimated for s/l, mainly leads to a 0.05 error on the estimated $ratio_x$.

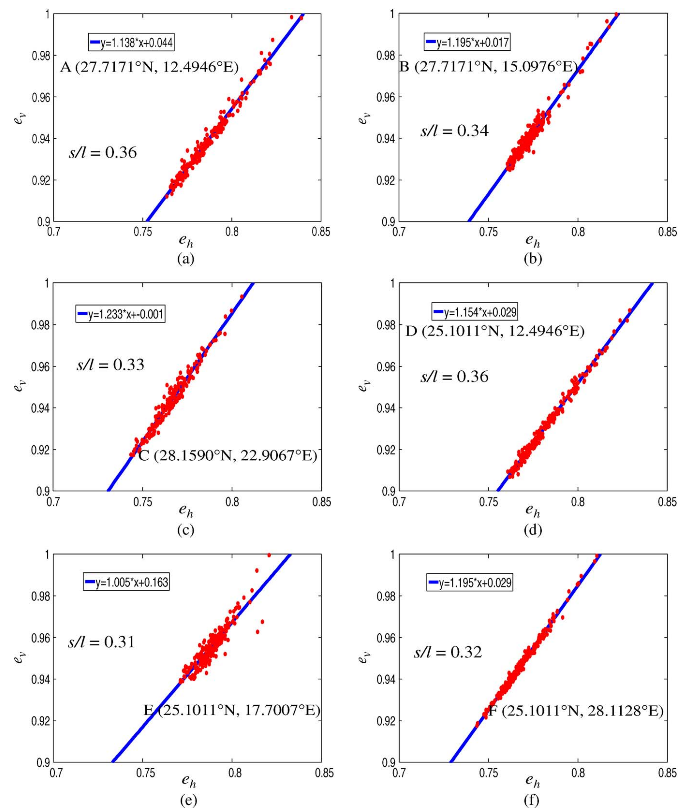

Fig. 8. Scatterplots of vertical and horizontal polarization emissivities for the six sites in the Sahara Desert.

Using the soil moisture on the first clear day of 2004 as a reference, the corresponding relative soil moisture for other days can be estimated from (10). The estimated $ratio_x$ values of sites A through F are shown in Fig. 9. As a comparison, $ratio_x$ values were also computed from the independent soil moisture product provided by Jones and John [18]. This product has been validated using WMO daily surface station summary of the day precipitation for the Northern Hemisphere and TRMM data. Correlation with station precipitation is typically between 0.2 and 0.8 with antecedent precipitation for areas where 18.7 GHz vegetation optical depth < 1.2 and open water fraction < 0.5.

Fig. 9 shows the comparison results. It can be seen that there are similar trends between the two results in most cases. Some sudden drop points and opposite tendencies points may attribute to the abnormal values of e_h mainly caused by the existence of undetected clouds in the LST product and the difference between the determinations of T_s. Jones and John took physical near-surface air temperature as T_s and computed land emissivity from it.

From (10), the partial differential equation can be calculated as

$$\Delta ratio_x = [ratio_x + N/(e_{h,0} - N)]\, \Delta e_{h,x}/e_{h,x}. \tag{11}$$

It can be found that 1% error of T_{Bp} or T_s leads to 1% error on estimated e_p. According to the calculated value of $\Delta ratio_x = [ratio_x + N/(e_{h,0} - N)]\Delta e_{h,x}/e_{h,x}$ with the

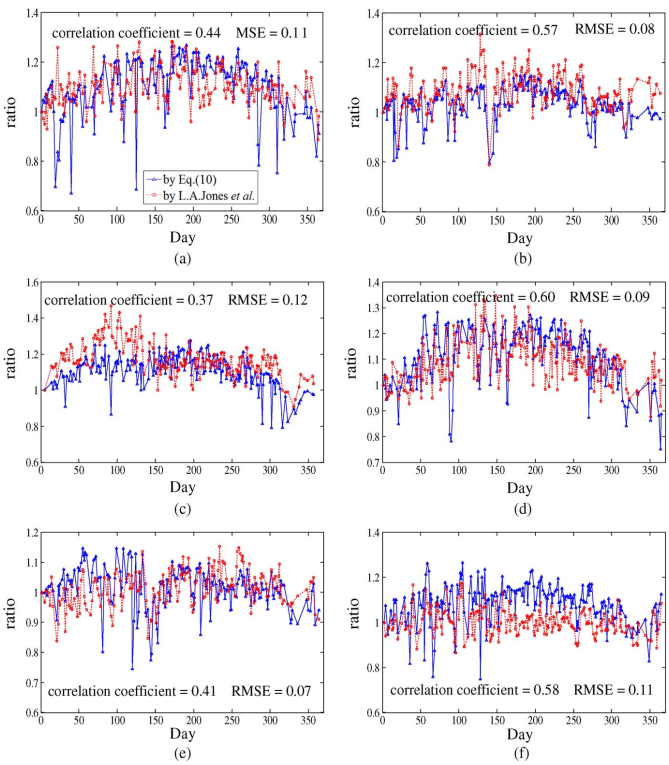

Fig. 9. Variation of sm relative to the reference values at sites A through F in 2004.

simulated data, for rough surface and drought-prone regions, 1% error of T_{Bp} or T_s can generate about 0.1–0.15 error on $ratio_x$. The result shows that accurate measurements of T_{Bp} and T_s can improve the accuracy of $ratio_x$ estimation.

IV. Conclusion

In this letter, a simulated soil microwave emissivity database covering a wide range of soil moisture and surface roughness conditions was generated using the Dobson model and the AIEM. Then, the effects of soil moisture and surface roughness on soil emission were analyzed, and several empirical parameterized relationships were developed. With the proposed relationships, the differing effects of soil moisture and surface roughness on the microwave emission of bare surfaces can be efficiently separated. Estimations of soil moisture were used to show the application of the proposed relationship. Using the simulated data, the volumetric soil moisture was estimated with an RMSE of 0.44%. Using actual data, the variations in soil moisture were also computed. Independent soil moisture data were used as a comparison. The compared results show that the proposed method is useful for estimating variations in soil moisture, and the proposed relationships are helpful in understanding the effects of soil moisture and surface roughness on the microwave emissions of bare surfaces and useful for estimating soil moisture. The parameterized relationships link soil moisture, surface roughness, and LST, and they provide a new way and possibility of retrieving these quantities simultaneously.

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