Analysis and Reduction of the Uncertainties in Soil Moisture Estimation With the L-MEB Model Using EFAST and Ensemble Retrieval

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***Abstract*—This letter quantitatively analyzes and reduces the uncertainties of soil moisture retrieval using the L-band microwave brightness temperatures and the L-band Microwave Emission of the Biosphere model. Through a global sensitivity analysis using the method of extended Fourier amplitude sensitivity testing, the crucial parameters are identified at different polarizations and incidence angles. The retrieval uncertainties of soil moisture caused by the observation error, parameter uncertainty, and retrieval strategy are then studied based on an ensemble retrieval and Polarimetric L-band Multibeam Radiometer flight data. The results show that soil moisture retrieval accuracy is determined by both the total sensitivity of each model parameter and the coupling effect between soil moisture and other parameters. Consequently, three-parameter retrieval, including soil moisture, optical depth, and roughness, is recommended. During three-parameter retrieval using observations at three angles, H-polarization is doing better than V-polarization due to its higher sensitivity to the optical depth; a good pre-estimation and lower standard deviation of optical depth will improve the soil moisture retrieval results. Increasing the number of brightness temperature observations by using multiangle and dual-polarized radiometer can obviously reduce the uncertainties caused by observation error, parameter uncertainties, and inversion method.**

***Index Terms*—Ensemble retrieval, global sensitivity analysis (SA), soil moisture, uncertainty.**

I. Introduction

SOIL moisture is an important variable in climate and hydrology research. Microwave remote sensing is the recommended technique to estimate the soil moisture distribution, and L-band is most suitable due to its longer wavelength and stronger penetration ability. Soil Moisture and Ocean Salinity (SMOS) [1]–[4] now provides multiangle and dual-polarized brightness temperatures of the land surface at the L-band with the aim to estimate global surface soil moisture with an error of less than 0.04 cm^3/cm^3.

Because of the coarse resolution of SMOS, it is difficult to evaluate the soil moisture retrieval algorithm based on the current observation networks. Therefore an airborne simulator of SMOS is useful, e.g., Polarimetric L-band Multibeam Radiometer (PLMR) [5], [6], which can measure the passive microwave radiation of the land surface with dual-polarization and three incidence angles (7°, 21.5°, and 38.5°). Due to its higher spatial resolution of hundreds of meters, the uncertainty of SMOS-derived soil moisture can be quantitatively analyzed in a specific region based on calibration of the airborne soil moisture retrieved to precise ground measurements.

The retrieval accuracy of soil moisture product is affected not only by the uncertainty of the radiative transfer model due to the model structure and parameter setting but also by the observation error of the radiometer and the uncertainty of the inversion strategy. Therefore, this letter quantitatively analyzes the contribution of model parameters and their coupling effect to the brightness temperature output by the L-band Microwave Emission of the Biosphere (L-MEB) model using a global sensitivity analysis (SA). The uncertainties due to observation error, parameter uncertainty, and inversion strategy are then evaluated using ensemble retrieval. Finally, some suggestions to reduce the uncertainties are proposed.

II. Method

A. Microwave Radiative Transfer Model

The L-MEB model is used by the SMOS soil moisture inversion algorithm, based on the zero-order form of radiative transfer equation [7], [8]. In this letter, two layers are considered, i.e., the vegetation and the soil layers. The main parameters of the L-MEB model are shown in Table I.

In Heihe Watershed Allied Telemetry Experimental Research (HiWATER), there were several PLMR flights and an intensive wireless sensor network that conducted synchronized soil moisture observations [9], [10]. By using the PLMR multiangle observations at 700-m resolution, the model parameters were accurately calibrated (see Table I) [11]. The PLMR multiangle data are also used to test the parameter retrieval method.

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TABLE I
CALIBRATED VALUE AND RANGE OF THE L-MEB MODEL PARAMETERS

Parameter	SM (cm^3/cm^3)	N_{RH}	N_{RV}	tt_H	tt_V	ω_H	ω_V	Sand (%)	Clay (%)	T_e (K)	H_r	τ_{NAD}
Value	0.24	0	-2	2	5	0.05	0	28.72	5.27	300	0.6	0.35
Range	0–0.5	-2–2	-2–2	1–10	1–10	0–0.1	0–0.1	0–50	0–50	280–320	0–1.5	0–0.7

B. Global SA

To quantitatively analyze the contribution of each model parameter to the L-MEB output, a global SA method, i.e., extended Fourier amplitude sensitivity testing (EFAST) [12], was used to evaluate the sensitivity of model parameters under different angles and polarizations. EFAST is a variance-based global SA method that combines the Fourier Amplitude Sensitivity Testing and Sobol methods, with the advantage that EFAST can handle nonlinear problems quantitatively at a rather small computation cost.

Many studies have performed sensitivity analyses of microwave radiative transfer models, but most studies only consider several major parameters independently by changing one parameter at a time [13], [14]. However, the interaction between parameters cannot be neglected, particularly when the number of model parameters is large. EFAST can estimate both the total and the first-order sensitivity index of each parameter. The total sensitivity index is the total contribution of each input parameter to the variance of the model output, including the parameter's main effect (first-order sensitivity index) and all the interaction terms [12]. The sum of each first-order sensitivity index is close to 1.

In this letter, L-MEB is assumed to be sufficiently accurate to model the microwave radiative transfer process over the vegetated land; the sensitivity of all major parameters listed in Table I is analyzed. It is assumed that each parameter has a uniform distribution, with the range provided in Table I. The sample size is assigned as 5000.

The parameters that dominate the model output are distinguished based on the SA, which impacts parameter selection during soil moisture retrieval.

C. Ensemble Retrieval

To optimize the soil moisture during retrieval process, a cost function was minimized using the Levenberg–Marquardt iterative algorithm

$$\text{cost} = \sum \frac{(T_{B\_\text{obs}} - T_{B\_\text{sim}})}{\sigma(T_{B\_\text{obs}})} + \sum \frac{(P^{\text{ini}} - P^{*})}{\sigma(P_i)} \qquad (1)$$

where T_{B_sim} is the simulated brightness temperature, T_{B_obs} is the observed brightness temperature, and $\sigma(T_{B\_\text{obs}})$ is the standard deviation (STD) of the observation. P_i^{ini} is a vector consisting of the first guess for the parameters to be retrieved, and $\sigma(P_i)$ is the STD of this initial estimate. An ensemble retrieval method is used to quantitatively analyze the uncertainties caused by observation, parameters, and retrieval process and to find some treatments to reduce these uncertainties.

To create an ensemble data set of brightness temperatures at three incidence angles and dual-polarization consistent with PLMR, different combinations of three model parameters were used, including soil moisture (SM), optical depth (τ), and roughness parameter (H_r). The ranges of three parameters were divided into ten subranges with the minimum (SM: 0.05; τ: 0.07; and H_r: 0.15). These minimums were then accumulated with the step (SM: 0.05; τ: 0.07; and H_r: 0.15) until the upper bounds of the ranges, ending up with ten levels of each parameter. Then, 1000 kinds of different parameter combinations were produced. Effective soil temperature T_{e} is set to 300 K during SA, which is the average of the changing range; other parameters are from the calibration results in Table I.

1) Observation Uncertainty: To understand the uncertainty of the retrieved soil moisture due to the observation error of the microwave radiometer, brightness temperatures are first simulated using the 1000 different combinations of the three major model parameters of L-MEB and the other calibrated parameters in Table I.

Different levels of Gaussian-distributed noise (1–3 K) [15], representing the observation errors, were then randomly added to the modeled brightness temperatures to produce an ensemble with a size of 1000. Finally, the single parameter (soil moisture) retrieval was undertaken on this ensemble data set to obtain the root-mean-square error (RMSE) of retrieved soil moisture.

2) Parameter Uncertainty: The errors of the model parameters play an important role in the soil moisture retrieval. Using the ensemble data set of brightness temperatures produced in the same way but without observation errors, the influences of τ and H_r were evaluated based on the ensemble retrieval of soil moisture. To depict the model parameter uncertainty, the input parameter ensembles, including parameter errors, were produced by adding different levels of Gaussian noise, τ (0.02, 0.07, 0.15, 0.3) and H_r (0.05, 0.15, 0.3, 0.6), to the calibration value of τ and H_r, respectively. The ensemble retrieval of soil moisture was then performed on the simulated brightness temperature data set using the input parameter data set with different levels of uncertainties to estimate the response of soil moisture retrieval RMSE to the parameter error.

3) Retrieval Uncertainty: If the number of parameters to be retrieved is greater than that of the remote sensing observations, an ill-posed inversion problem arises. This problem is common in quantitative remote sensing, particularly when focusing on the soil moisture. To overcome this challenge, an experiment was designed to test the utility of multiangle remote sensing observations and pre-estimation information of model parameters to reduce the inversion error.

In the soil moisture inversion process, the initial estimate and STD of the retrieved parameters should be provided in (1), and their errors would contribute to the uncertainty of the soil

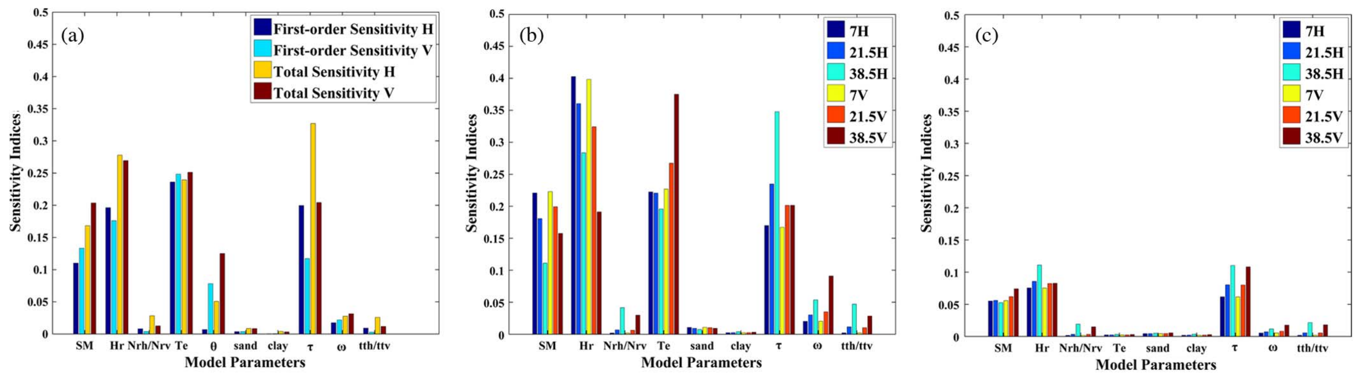

Fig. 1. Global SA of the L-MEB model: first-order and total sensitivity at (a) dual-polarization, (b) total sensitivity, and (c) interaction term at different incidence angles.

moisture retrieval. A smaller STD indicates that the confidence in the estimated value is higher, which mainly depends on the prior knowledge of model parameters. Similarly, using the same ensemble of brightness temperatures produced without observation error, different levels of Gaussian noise were added to the initial estimates to test the three-parameter ensemble retrieval. The real PLMR data were then used to conduct soil moisture retrieval with different STDs of the retrieved parameters; the retrieval result is verified by the observations of 50 ground-based wireless sensor network nodes [9], [10].

III. Results

A. SA of L-MEB

The SA in Fig. 1 shows that the parameters of the L-MEB model have different degrees of contribution to the output brightness temperature at different polarizations and incidence angles. Fig. 1(a) reveals that SM, H_r, T_e, τ, and incidence angle θ together account for more than 90% of the L-MEB output. The total sensitivity index of each parameter was found to be always higher than its first-order sensitivity index because the former includes the interactions among parameters. However, both indexes exhibit similar trends, indicating that the first-order sensitivity accounts for most of the total sensitivity.

At the small incidence angle [see Fig. 1(b)], the most dominant parameter is H_r; other important parameters, in decreasing order of influence, are SM, T_e, and τ. At the larger incidence angle, the dominant parameter is τ; other important parameters, in decreasing order of influence, are H_r, T_e, and SM. In general, the sensitivity of SM, H_r and T_e is lower under H-polarization than under V-polarization. In contrast, the optical depth is more sensitive under H-polarization.

With increasing incidence angle, the first-order and total sensitivities of SM and H_r decrease. The sensitivity of the optical depth τ increases with the incidence angle, and its effect under H-polarization is greater than under V-polarization. The sensitivity of T_e does not change appreciably with the incidence angle under H-polarization. However, T_e exhibits an increasing trend under V-polarization and is much greater than it is under H-polarization [see Fig. 1(b)].

As demonstrated in Fig. 1(c), all the parameters' interaction sensitivity terms increase with incidence angle, with the exception of the SM parameter under H-polarization. Because the incidence angle can be obtained during radiometer measurement, the four most sensitive parameters are τ, H_r, T_e, and SM. Furthermore, the land surface temperature can be operationally obtained by infrared remote sensing with satisfactory accuracy, e.g., Moderate Resolution Imaging Spectroradiometer (MODIS) land surface temperature product, whereas the parameterization of τ and H_r is difficult; therefore, τ and H_r should be retrieved along with SM.

B. Observation Uncertainty Analysis

Fig. 2(a) illustrates that the soil moisture retrieval accuracy values at different incidence angles and polarizations have different responses to the observation error. The most influenced incidence angle is 38.5°, whereas the least influenced one is 7°. This pattern is similar to the interaction sensitivity term of SM in Fig. 1(c). It shows that the larger interaction of SM with other parameters will increase the uncertainty in soil moisture retrieval. The result also shows that, to achieve a retrieval error of less than 0.04 cm^3/cm^3 for soil moisture, which is the goal of the SMOS soil moisture product, the observation error should be less than 2 K. When using all the available remote sensing observations, the effect of the observation error can be significantly reduced.

C. Parameter Uncertainty Analysis

Two sensitive parameters (τ and H_r) in the L-MEB model were selected to test the influence of parameter uncertainty on the soil moisture retrieval. The error (RMSE) of τ below 0.07, which is 10% of the parameter range, can ensure 0.04 cm^3/cm^3 soil moisture retrieval accuracy at smaller incidence angles and V-polarization. The error of τ has a greater impact on the SM retrieval at larger angles under H-polarization [see Fig. 2(b)].

The same relation is presented with the roughness parameter; the acceptable error of H_r was found to be below 0.05, which is less than 5% of the H_r range [see Fig. 2(c)]. The uncertainty of SM retrieval increases with the total sensitivity of τ. However, the result of H_r parameter exhibits a trend more similar to that of the interaction sensitivity term [see Fig. 1(c)]. It suggests that H_r may have more interaction with SM compared with τ.

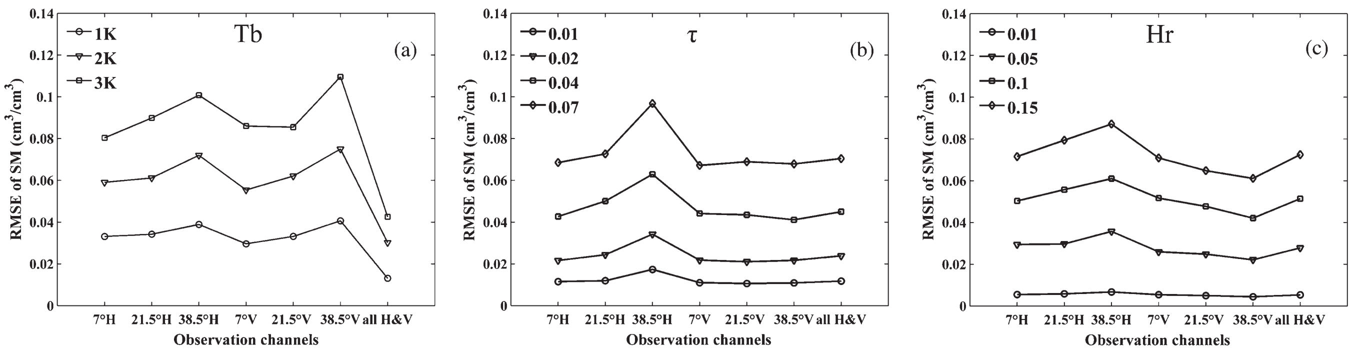

Fig. 2. Responses of soil moisture retrieval RMSE to the errors of (a) observation T_b, (b) optical depth τ, and (c) roughness parameter H_r.

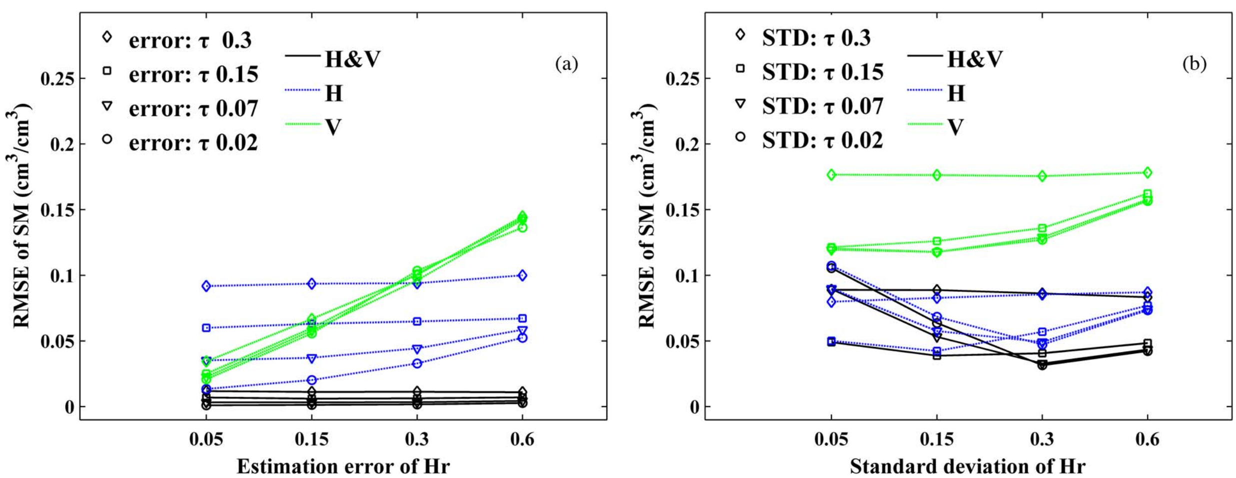

Fig. 3. Three-parameter retrieval using (a) simulated and (b) real PLMR observations at three angles and dual-polarization.

D. Retrieval Uncertainty Analysis

The three-parameter retrieval method (3-P), which simultaneously retrieves SM, τ, and H_r, has been used with the simulated brightness temperatures and PLMR data for the following three combinations of observations: dual-polarization at three angles (six channels), H-polarization at three angles (three channels), and V-polarization at three angles (three channels). The simulated brightness temperatures can give different scenarios on the estimation errors of retrieved parameters. In addition, when using real PLMR data, with the calibration values as pre-estimations, the influence of STDs on soil moisture retrieval can be tested.

Except for considering the soil moisture as a free parameter, different levels of Gaussian noise (error) are added on the initial guess of both τ and H_r: τ (0.02, 0.07, 0.15, 0.3) and H_r (0.05, 0.15, 0.3, 0.6). The STDs of τ and H_r are set to 0.7 and 1.5, which is the upper bound of parameters' range during retrieval, aiming to reduce the effect of STD as far as possible.

Fig. 3(a) demonstrates that using all six observation channels reduces the uncertainties caused by parameter estimation error; the estimation error of τ dominates the RMSE of retrieved soil moisture under H-polarization, whereas the estimation error of H_r has significant influence on the RMSE under V-polarization. During three-parameter retrieval using V-polarization, because of the low sensitive to τ, the model output is mostly determined by H_r and SM; thus, the estimation error and free change (higher STD) of H_r cause a huge error in the soil moisture retrieval.

The PLMR observation on July 10, 2012 was used to explore the effect of STDs of retrieved parameters on soil moisture inversion. The initial guesses of parameters came from the calibration results in Table I [11], the STDs for each parameter are as follows: τ (0.02, 0.07, 0.15, 0.3) and H_r (0.05, 0.15, 0.3, 0.6).

Fig. 3(b) shows that, except for the situation of V-polarization, as long as the STD of τ is above 0.15 and the STD of H_r is under 0.3, being about 50% of the calibrated values, the RMSE of soil moisture retrieval can be fewer than 0.05 cm^3/cm^3.

No matter using simulated or real PLMR data, the overall RMSE of using dual-polarization observations at all angles is lower than that of using only H- or V-polarization observations.

IV. Conclusion

The EFAST analysis shows that only certain parameters play important roles in the radiative transfer model, which have different contributions depending on the polarizations and incidence angles.

Using simulated brightness temperatures with different observation errors, the single-parameter retrieval results showed that, at large incidence angle, the RMSE of soil moisture is more sensitive to the brightness temperature noise, mainly due to the larger interaction of soil moisture with other model parameters.

The parameter uncertainty also leads to different levels of influence at different incidence angles and polarizations. H-polarization, particularly at large incidence angle, is more likely impacted by the uncertainty of τ and H_r due to high total sensitivity or interaction of the parameters. The higher sensitivity of input parameter generally increases the soil moisture retrieval uncertainty, but when the parameter has a strong interaction with soil moisture, the interaction term dominates the source of uncertainty.

The use of auxiliary data to predefine the model parameter is the ideal way to reduce the parameter uncertainty. However, when the precise value of a model parameter cannot be estimated, the multiparameter retrieval should be used.

During the 3-P soil moisture retrieval, if the observation channels are noisy or deficient, for example, caused by the radio-frequency interference (RFI), it is better to choose the H-polarization observations rather than V-polarization observations because of the lower sensitivity of V-polarization to τ. A good pre-estimation of τ is more important than that of H_r when 3-P retrieval is conducted on the vegetation-covered surface.

If there is a pre-estimation of the τ such as from a leaf area index remote sensing product, it is better not to give a high STD. The more precise estimation of τ, the lower the STD of τ that should be specified. Using H-polarization or dual-polarization, giving an STD on H_r close to half of its pre-estimation will reduce the uncertainty of soil moisture retrieval in some degree.

Because multiple brightness temperature observations have a major influence on reducing the uncertainty during soil moisture retrieval, it is important to use as many observation channels as possible.

REFERENCES

[1] Y. H. Kerr *et al.*, “The SMOS mission: New tool for monitoring key elements of the global water cycle,” *Proc. IEEE*, vol. 98, no. 5, pp. 666–687, May 2010.

[2] S. Pinori, R. Crapolicchio, and S. Mecklenburg, “Preparing the ESA-SMOS (Soil Moisture and Ocean Salinity) mission—Overview of the user data products and data distribution strategy,” in *Proc. Microw. Radiometry Remote Sens. Environ.*, Firenze, Italy, Mar. 11–14, 2008, pp. 1–4.

[3] Y. H. Kerr *et al.*, “The SMOS soil moisture retrieval algorithm,” *IEEE Trans. Geosci. Remote Sens.*, vol. 50, no. 5, pp. 1384–1403, May 2012.

[4] T. J. Jackson *et al.*, “Validation of Soil Moisture and Ocean Salinity (SMOS) soil moisture over watershed networks in the U.S.,” *IEEE Trans. Geosci. Remote Sens.*, vol. 50, no. 5, pp. 1530–1543, May 2012.

[5] S. Peischl, N. Ye, J. P. Walker, D. Ryu and Y. H. Kerr, “Soil moisture retrieval from multi-incidence angle observations at L-band,” in *Proc. 19th Int. Congr. Model. Simul.*, Perth, WA, Australia, Dec. 12–16, 2011, pp. 1987–1993.

[6] R. Panciera *et al.*, “The NAFE’05/CoSMOS data set: Toward SMOS soil moisture retrieval, downscaling, and assimilation,” *IEEE Trans. Geosci. Remote Sens.*, vol. 46, no. 3, pp. 736–745, Mar. 2008.

[7] J. P. Wigneron *et al.*, “L-band Microwave Emission of the Biosphere (L-MEB) model: Description and calibration against experimental data sets over crop fields,” *Remote Sens. Environ.*, vol. 107, no. 4, pp. 639–655, Apr. 2007

[8] T. Mo, B. Choudhury, T. Schmugge, J. Wang, and T. Jackson, “A model for microwave emission from vegetation-covered fields,” *J. Geophys. Res., Oceans*, vol. 87, no. C13, pp. 11229–11237, Dec. 1982.

[9] X. Li *et al.*, “Heihe Watershed Allied Telemetry Experimental Research (HiWATER): Scientific objectives and experimental design,” *Bull. Amer. Meteor. Soc.*, vol. 94, no. 8, pp. 1145–1160, Aug. 2013.

[10] R. Jin *et al.*, “A Nested Ecohydrological Wireless Sensor Network for Capturing the Surface Heterogeneity in the Midstream Areas of the Heihe River Basin, China,” *IEEE Geosci. Remote Sens. Lett.*, vol. 11, no. 11, pp. 2015–2019, Nov. 2014.

[11] D. Li *et al.*, “Soil moisture retrieval from airborne PLMR and MODIS products in the Zhangye Oasis of middle stream of Heihe River Basin, China,” *Adv. Earth Sci.*, vol. 29, no. 2, pp. 295–305, Feb. 2014.

[12] A. Saltelli, S. Tarantola, and K. S. Chan, “A quantitative model-independent method for global sensitivity analysis of model output,” *Technometrics*, vol. 41, no. 1, pp. 39–56, Feb. 1999.

[13] A. G. Konings, D. Entekhabi, S. K. Chan, and E. G. Njoku, “Effect of radiative transfer uncertainty on L-band radiometric soil moisture retrieval,” *IEEE Trans. Geosci. Remote Sens.*, vol. 49, no. 7, pp. 2686–2698, Jul. 2011.

[14] I. J. Davenport, J. Fernández-Gálvez, and R. J. Gurney, “A sensitivity analysis of soil moisture retrieval from the tau–omega microwave emission model,” *IEEE Trans. Geosci. Remote Sens.*, vol. 43, no. 6, pp. 1304–1316, Jun. 2005.

[15] M. Pardé *et al.*, “N-parameter retrievals from L-band microwave observations acquired over a variety of crop fields,” *IEEE Trans. Geosci. Remote Sens.*, vol. 42, no. 6, pp. 1168–1178, Jun. 2004.