Retrieving Soil Moisture from Simulated Brightness Temperatures by a Neural Network

Yuei-An Liou, Senior Member, IEEE, Shou-Fang Liu, and Wen-June Wang

Abstract—We present the retrievals of surface soil moisture (SM) from simulated brightness temperatures by a newly developed error propagation learning back propagation (EPLBP) neural network. The frequencies of interest include 6.9 and 10.7 GHz of the advanced microwave scanning radiometer (AMSR) and 1.4 GHz (L-band) of the soil moisture and ocean salinity (SMOS) sensor. The land surface process/radiobrightness (LSP/R) model is used to provide time series of both SM and brightness temperatures at 6.9 and 10.7 GHz for AMSRs viewing angle of 55°, and at L-band for SMOS’s multiple viewing angles of 0°, 10°, 20°, 30°, 40°, and 50° for prairie grassland with a column density of 3.7 km/m². These multiple frequencies and viewing angles allow us to design a variety of observation modes to examine their sensitivity to SM. For example, L-band brightness temperature at any single look angle is regarded as an L-band one-dimensional (1-D) observation mode. Meanwhile, it can be combined with either observation at the other angles to become an L-band two-dimensional (2-D) or a multiple dimensional observation mode, or with the observation at 6.9 or 10.7 GHz to become a multiple frequency/dimensional observation mode. In this paper, it is shown that the sensitivity of radiobrightness at AMSR channels to SM is increased by incorporating L-band radiobrightness. In addition, the advantage of an L-band 2-D or a multiple dimensional observation mode over an L-band 1-D observation mode is demonstrated.

Index Terms—Brightness temperature, neural network, soil moisture.

I. INTRODUCTION

Soil moisture (SM) dominates the partitioning of net radiation energy into sensible and latent heat fluxes and rainfall into runoff and root-zone storage at the land-air interface. Hence, it plays a crucial role in current hydrologic, climatic, agricultural, and biogeochemical models and becomes a parameter of great interest in the field of remote sensing. It is linked to radiometric signatures through its influence on microwave emission of the land surfaces [3], [4], [13], [20], [22].

Over bare fields, Wang [29] has shown a linear dependence of measured microwave emissivity on moisture content of a soil layer whose thickness ranges from about 1 cm at 5 GHz to 5 cm at 1.4 GHz. Over vegetated areas, the vegetation that links the soil and the air is not only to attenuate microwave signals emitted by the soil but also to add its own contribution to the emitted emission [27]. Therefore, the problem of SM sensing by radiometry becomes more complicated for vegetated than bare fields. However, it is possible to simultaneously measure SM and vegetation variables using microwave emission [4], [30]. Since emission at a given microwave frequency from the soil decreases exponentially with increasing vegetation biomass, it is less likely to obtain a good SM estimate as the vegetation cover becomes optically thick. To obtain adequate electrical signals from vegetation-covered soil for sensing its parameters, it is a general agreement in the literature to utilize radiometers with lower frequencies such as L-band [18], [21], [25]. In addition, knowledge of microwave emission from the vegetation to some extent is required to monitor moisture content of the underlying soil.

Kerr and Wigneron [5] reviewed microwave emission models for vegetated fields. A two-parameter model was proposed to characterize the emission of the vegetated fields. The two parameters consist of the optical thickness of the vegetation layer τ and the single scattering albedo ω. This τ-ω model is essentially a zeroth-order solution to the radiative transfer equation within the land-air system since the phase matrix addressing the effects of multiple scattering is neglected. Hence, it should be kept in mind that the τ-ω model is only valid in a low-frequency range where scattering effects inside the vegetation are considerably low. Recently, a simple algorithm based on the τ-ω model was presented to simultaneously retrieve SM and canopy biomass based on measurements collected over a soybean and a wheat crop [31]. The measurements were acquired during a three-month entire growth cycle so that a large range of SM and vegetation density conditions can be studied. It was shown that the best retrieval accuracy for the moisture content of the topmost 3-cm soil is with errors as low as 5.3% (by volume) over the wheat field when a configuration with both two frequencies and four incident angles (8°, 18°, 28°, and 38°) is adopted. However, surface temperature and crop type are the auxiliary information of the algorithm.

In light of the crucial role of SM in many scientific and applied fields and the tremendous potential of microwave radiometers in sensing SM, it is a goal shared by many in the field of remote sensing by spaceborne sensors such as AMSR, and SMOS [6]. Among these sensors, AMSR is developed by NASDA to be loaded on ADEOS-II for launching in November 2001 [26]. Its frequencies include 6.9, 10.7, 18.7, 23.8, 36.5, and 89.0 GHz with both horizontal and vertical polarizations, and 50.3 and 52.8 GHz with vertical polarization. It scans conically at an incident angle of 55°. SMOS, on the other hand, is based on an
innovative, bidimensional (2-D) aperture synthesis concept promoted by LeVine et al. [7], [8]. The multi-angular viewing capability of a 2-D interferometric sensor enables the availability of radiometric signatures of a specific target from a wide range of incident angles. That is, geophysical parameters of interest on the spot of observation can be inferred from the radiometric signatures acquired at multiple look angles.

In this study, simulated brightness temperatures at L-band, 6.9, and 10.7 GHz are utilized to retrieve surface SM. They are allocated into various groups of which correspond to certain specific observation mode. They are added by Gaussian distributed noises with standard deviation as large as 2 K to simulate instrumental noises. Our objectives are to examine the sensitivity of radiobrightnesses at the two lowest AMSR channels and L-band, and their combinations to SM, and to characterize the sensitivity using the error propagation learning back propagation (EPLBP) neural network [17]. We first briefly review the LSP/R model to produce paired time series of SM and brightness temperatures for grass with a column density of 3.7 km/m² at AMSR channels and L-band, and the EPLBP neural network to handle the nonlinear mapping from brightness temperatures to SM. We then analyze the retrieved SM by comparing with its reference. A variety of frequency combinations, i.e., observation modes with 1-D, 2-D, and multiple dimensional viewing configurations, are considered.

II. LSP/R Model and the EPLBP Neural Network

A. LSP/R Model

We have studied radiometric characteristics of land surfaces for the purpose of sensing surface parameters by microwave radiometry for many years. Our approach is to improve the understanding and capability by incorporating land surface processes into microwave emission models. As a consequence, a series of LSP/R models for bare soils and prairie grassland have been developed [9]–[11], [13]. Each of these LSP/R models consists of two modules, an LSP module and an R module. The LSP module simulates land-air exchange of energy and moisture to predict temperature and moisture profiles of soil and, if any, vegetation. The R module uses predictions of temperature and moisture fields from the LSP module to compute brightness temperatures of the terrain.

The current study utilizes the LSP/R model developed and validated by Liou et al. [13] for prairie grassland in South Dakota. In the LSP module, the soil is divided into root zone and nonroot zone. The amount of water extracted from the root zone due to transpiration is governed by the depth-dependent distribution of roots and the surrounding moisture profile. The thickness of the first layer is 5 mm, and the thicknesses of the other layers increase exponentially with depth. Heat and moisture transport within soil layers is handled using the approach of Philip and deVries [23] and deVries [1] with various enhancements by adopting temperature-suction relation [32] for freeze/thaw modeling, a closed-form equation of Mualem [19] for predicting the relative hydraulic conductivity, the improved Brooks and Corey water retention model developed by Rossi and Nimmo [24], etc. Its further details are referred to Liou and England [10], [11] for bare soils and Liou et al. [13] for vegetated terrain. Vegetation coverage may vary from 0% to 100%. Energy and moisture exchanges between air and bare or vegetated land are treated as linearly dependent on the vegetation coverage. For the prairie vegetation, it is modeled as a two-layer medium, an upper canopy layer and a thermally insulating lower thatch layer. Transfer of shortwave radiation through the canopy is dependent on the leaf area index (LAI). For dry-down simulation, shortwave radiation and weather forcing follow England [2]. Sensible heat exchange between the air and the vegetation is modeled with the bulk aerodynamic approach. Transpiration is characterized by incoming insolation, air vapor pressure deficit, soil moisture, and air temperature.

For the R module, the outputs of the LSP module are used as its inputs to determine the microwave emission from soil and vegetation. The brightness of the vegetated terrain is comprised of four components, the soil brightness attenuated by one trip through the canopy, the down-welling canopy brightness reflected by the soil and attenuated by one trip through the canopy, the upwelling canopy brightness, and the sky brightness reflected by the soil and attenuated by two trips through the canopy [13]. The moist soils are treated as a five-component mixture material, soil solids, air, free water, bound water, and ice when their dielectric properties are computed. The relative permittivity of a wet canopy is found using the dual-dispersion model of Ulaby and El-Rayes [28]. The soil surface is assumed to be specular for the determination of emissivity. More details about the LSP/R models are referred to Liou et al. [13].

The LSP/R model was previously integrated into a dynamic learning neural network to demonstrate the ability of L-band radiometers to sense SM [14]. SSM/I frequencies were used in the two studies to contrast the strength of the L-band microwave radiometry, while the viewing angle is fixed at the SSM/Is incident angle. Since L- and X-band spaceborne radiometers are likely to co-exist in the foreseeable future, and since the viewing angles at the L-band would be designed to acquire radiometric signatures at a wide range of angles, the use of their radiometric signatures to measure SM becomes of great interest, and hence, the focus of this presentation.

B. The EPLBP Neural Network

Radiometric signatures of a vegetation-covered field reflect an integrated response of the soil and vegetation system to the observing microwave system. This allows one to link surface parameters to the radiometric signatures by [15]

$$\mathbf{f} = f(\mathbf{x})$$  \hspace{1cm} (1)

where

- $\mathbf{f}$ feature vector of surface parameters (variables of interest);
- $\mathbf{x}$ observation vector of radiometric signatures;
- $f$ mapping function.

Traditionally, $f$ is treated as an explicit function so that it can be described by simple schemes such as multiple linear regression and the $\tau$-$\omega$ model. However, these simple schemes are in general inadequate to well resolve the nonlinear relationship between the variables of interest and the radiometric observations.
since the relationship is determined by soil temperature and moisture profiles, and vegetation temperature and water content profiles [13]. Besides, most of these simple schemes are subject to certain restrictions such as their use to a specific type of vegetation with auxiliary information about the surface temperature [31]. Hence, more elegant schemes are required to eliminate the restrictions. Neural networks that can characterize the \( f \) function without knowing its explicit forms and the restrictions become one of the best choices to resolve the nonlinear mapping problems of our interest. For example, one could ignore the dependence of radiometric signatures on the surface temperature while retrieving the SM by a neural network.

In this study, the newly developed EPLBP neural network is used to handle nonlinear mappings from microwave emissions to the parameter of interest, SM. It is improved upon a modified back propagation neural network developed by Liu and Yao [16] in that it is not only to correlate the errors associated with individual network via adjustable penalty parameters but also to allow the penalty parameter to be distance dependent [17]. Fig. 1(a) shows a lattice of cells with a circular neighborhood around each cell to limit the correlation range. The correlation function (or penalty parameter) is variable (decreased) with distance from the center of the indicated circle. Networks outside the circle of concern are considered as uncorrelated with the individual network located at the center.

Fig. 1(b) shows the input–output (I-O) configuration of the EPLBP, consisting of three layers: an input layer with a certain number of nodes determined by the observation mode, a hidden layer with three nodes, and an output layer of five nodes. This simple I-O configuration is aimed at saving the computation time although the number of the modes for the input, hidden, and output layers may be tunable. The inputs are composed of brightness temperatures associated with each observation mode. For example, the numbers of the input nodes are two for an L-band 1-D observation mode (horizontal and vertical polarization), and four for an L-band 2-D observation mode or a “combined” or “integrated” 6.9 GHz and L-band 1-D observation mode. The five outputs are simply averaged to obtain SM. During the training process, they are correlated with distance-dependent penalty parameters imposed upon the weight updating. The training process is regarded as complete either when 100 epoch are finished or when the difference (error) between the predicted SM and the reference is smaller than a certain given threshold. Specifically, we use a simple step-function to describe the penalty parameter so that its value is one for the neural network of concern, 0.5 for the neural network next to the neural network of concern, and zero for the other neural networks. This simple architecture of the EPLBP algorithm handles the nonlinear mapping of our interest very well to be shown later in this paper so that no further investigations are conducted by using more complicated architectures.

C. The Training and Testing Data

In the current study, the training and testing data are obtained from outputs of the LSP/R model of Liou et al. [13]. The LSP/R model is used to produce paired brightness temperatures-SM (TB-SM) time series (once per 10 min) during a two-month dry-down of prairie grassland. At this stage, a silt loam with vertically homogeneous texture is adopted [11]. In addition, vegetation biomass of 3.7 kg/m² is used due to the constraint of the current LSP/R model incapable of simulating the growth of the prairie. However, the model does allow vegetation temperature and soil temperature vary with time. Under the assumption of biomass, it is estimated that about 75% of the total observed brightness is from the soil at an incident angle of 53° (SSM/I incident angle) for L-band, about 10% for 19 GHz, and less than 5% for 37 GHz [13]. In contrast, given the similar condition it is found that 6.9 and 10.7 GHz are moderately sensitive to SM with about 50% and 35% brightness of their total observed brightness from the soils, respectively.

The total number of paired TB-SM data is 8640 from each LSP/R model simulation run. As in a common practice, a training data set that is representative is adequate for the neural networks. Since radiometric signatures of the prairie show periodically diurnal variations, 5% of outputs from the LSP/R model that can properly define the TB-SM relationship are randomly used to train the EPLBP. Similarly, 5% of the paired TB-SM data are randomly chosen from the LSP/R model outputs for testing. Fig. 2 shows SM time series of the two-month dry-down simulations for both training and testing. Note that none of the testing data is same as any of the training data although both SM time series show similar patterns. It is observable that SM decreases from 38% to 26% (by volume, throughout the whole paper) in response to the dry-down simulations. The SM appears to be large at the end of the simulation.
possibly due to three reasons. First, weather forcing is mild at middle latitudes. Second, soil moisture can be unlimitedly supplied from the deeper soils. Third, a vegetation-covered silt loam with porosity of 48% can hold more water.

Unlike the SM time series, the TB time series are not unique since each observation mode has its own signatures. Fig. 3(a) shows TB with vertical polarization TBV, and Fig. 3(b) horizontal polarization TBH time series for the testing process under no noise condition. Note that the scale for Fig. 3(a) TBV is offset by 20 K with respect to that for Fig. 3(b) TBH. The term “no noise” is used relative to the Gaussian distributed noises with standard deviations of “1 K” and “2 K” added to the brightness temperatures. The numbers at the ends of the curves indicate the incident angle of concern in degrees, and the corresponding frequency in parenthesis in GHz. L-band brightness temperatures at 10°, 20°, and 40° are not shown. The magnitudes of TB are higher for the AMSR channels than for L-band since the vegetation appears optically thicker for the former than the latter.

Fig. 4 shows TBH time series for the testing process under Fig. 4(a) 1 K and Fig. 4(b) 2 K noise conditions. The patterns of the TBV time series are similar to those of the TBH time series so that the TBV time series are not presented. Compared to Fig. 3(a), it is evident that the noise level is increased with the added noise. The behavior of the consequent time series after noises are added to the brightness temperatures is more like that of the measurements. Note that TB time series for the training process are similar to those for the testing process under no noise condition so that they are not presented. For a similar reason, TB time series for the training process under 1 K and 2 K noise conditions are not shown.

III. RETRIEVAL ANALYSIS

A. Observation Modes

In total, 49 observation modes are analyzed.

1) One 2-AMSR channel observation mode. The radiometric signatures at both 6.9 and 10.7 GHz channels of the AMSR are used simultaneously to become an integrated 2-AMSR frequency observation mode. Either 6.9 or 10.7 GHz alone will not provide better SM retrievals than their integration so that no related simulation is performed.

2) Six L-band 1-D observation modes. The radiometric signatures at each single angle of either 0, 10, 20, 30°, 40°, or 50° at L-band is regarded as an L-band 1-D observation mode.

3) Nine L-band 2-D observation modes. The radiometric signatures at two angles with an angular difference of 10° (five modes), 30° (three modes), or 50° (one mode) at L-band represent an L-band 2-D observation mode.

4) One L-band 6-D observation mode. The radiometric signatures acquired at all of the six look angles at L-band are integrated into an L-band six-dimensional (6-D) observation mode.

5) Thirty-two integrated AMSR and L-band observation modes. The radiometric signatures at each of the 6.9 and 10.7 GHz channels are combined with those associated
with all of the two, three, and four steps to become integrated AMSR and L-band multiple dimensional observation modes. Since there are too many observation modes considered, it is impossible to show all of the results here. Instead, we show and analyze some representative results in figures and tables.
B. Results from Single Satellite Observations

1) By AMSR Observation Alone: Fig. 5 compares the retrieved SM from the 2-AMSR frequency observation mode for the (a) no noise, (b) 1 K noise, and (c) 2 K noise cases with the corresponding reference. The correlation coefficient ($R$) between the retrieved SM and the reference, and the corresponding root mean squared error (RMSE) in SM are also given. Overall,
the retrieved SM falls onto or near the 1:1 line, especially for the no noise case with \( R = 1 \) and RMSE less than 0.1%. This indicates that the EPLBP algorithm manages the mapping of microwave signatures to SM very well. Errors that might be introduced into the retrieved SM from the EPLBP algorithm can be neglected. For realization of the concerned problem, Gaussian distributed noises with standard deviations of 1 K and 2 K are added to the inputs of the retrieval algorithm, i.e., the brightness temperatures, as shown in Fig. 4. The quality of the retrieved SM is expectedly degraded as the noise level is increased. The Rs (RMSE’s) are reduced to 0.927 (1.13%) for the 1 K noise case, and 0.813 (1.76%) for the 2 K noise case from 1 (0.094%) for the no noise case. The RMSE’s are smaller than that one might expect possibly because the TB-SM relationship is well defined and because the biomass is fixed in the LSP/R model, which ignores surface heterogeneity due to differential vegetation or wetness. Liou et al. [12] examined the effect of scaling upon the interpretability of mixed pixel radiobrightness. It was found that subpixel variation in canopy density is a significant factor in the quantitative interpretation of the 19 GHz brightness of prairie grassland but is not a factor in the interpretation of the L-band brightness. Subpixel variation in canopy density would have a gentle influence on the X-band brightness of a mixed pixel. It should be of great interest to quantitatively study the scaling effect on the mixed pixel radiobrightness through further theoretical and experimental analysis for future investigations on the radiometric sensing of SM over a terrain of surface heterogeneity.

2) By L-Band Observation Alone: Fig. 6 compares the retrieved SM from L-band 1-D observation mode at (a) 0°, (b) 30°, and (c) 50° with the corresponding reference for the no noise case. In general, the retrieved SM matches the reference very well for all angles although the Rs (RMSE’s) are decreased (increased) slightly compared to the 2-AMSR frequency observation mode [Fig. 5(a)]. We observe that the largest deviations from the 1:1 line occur for the 0 degree mode when horizontally- and vertically-polarized TBs are essentially the same, and for the 50° mode when the vegetation becomes relatively optically thick.

Fig. 7 presents the retrieved SM from L-band 2-D observation mode at 0° and 10° (0°–10°) versus the corresponding reference for the no noise case. Comparisons for the other observation modes with a constant angular difference of 10° are not shown. It is found that the Rs between the retrieved SM and the refer-
Fig. 6. Retrieved SM from L-band 1-D observation mode at (a) 0°, (b) 30°, and (c) 50° with the corresponding reference for the no noise case.

Fig. 7. Retrieved SM from L-band 2-D observation mode at 0° and 10° (0° – 10°) versus the corresponding reference for the no noise case.

ence are all 1 except for the 0°–10° mode with $R = 0.999$. A comparison between Figs. 6 and 7 clearly shows the advantage of a 2-D mode over a 1-D mode since the RMSE’s are reduced significantly. When the angular difference between the two observation modes is either 30° or 50°, the corresponding Rs are 1 or 0.999 with RMSE smaller than 0.1% (not shown). It is not surprising that the $R$ between the retrieved SM and the corresponding reference is 1 with RMSE as small as 0.015% for the L-band 6-D observation mode.

Fig. 8 compares the retrieved SM from L-band 1-D observation mode at 0 degree with the corresponding reference for (a) the 1 K, and (b) the 2 K noise cases. It is clear that $R$ (RMSE) is slightly decreased (increased) when the noise level is increased from 1 K to 2 K noise. In addition, the $R$ between the retrieved SM and the reference for the six L-band 1-D observation modes (0°, 10°, 20°, 30°, 40°, and 50°) ranges from 0.975 to 0.979 for the 1 K noise case, and from 0.955 to 0.966 for the 2 K noise case (not shown in figures), which are expectedly smaller than those for the no noise case. It is worthy to mention that the quality of the retrieved SM is not worsened much when the Gaussian distributed noises are doubled. This could be an indication that the proposed retrieval algorithm is robust.

The root mean square errors (RMSEs) of concern can be improved (decreased) when the L-band 2-D observation modes with an angular difference of 10° are utilized, ranging from 0.978
TABLE I
CORRELATION COEFFICIENTS BETWEEN THE RETRIEVED SM AND THE REFERENCE AND THE CORRESPONDING RMSEs FOR THE L-BAND 2-D OBSERVATION MODES WITH ANGULAR DIFFERENCES OF 30° AND 50° AND FOR THE L-BAND 6-D OBSERVATION MODE FOR THE 1 K NOISE CASE

<table>
<thead>
<tr>
<th>Obs. Modes (1K noise)</th>
<th>R</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>L-band 0-30</td>
<td>0.978</td>
<td>0.630%</td>
</tr>
<tr>
<td>L-band 10-40</td>
<td>0.980</td>
<td>0.592%</td>
</tr>
<tr>
<td>L-band 20-50</td>
<td>0.982</td>
<td>0.574%</td>
</tr>
<tr>
<td>L-band 0-50</td>
<td>0.980</td>
<td>0.594%</td>
</tr>
<tr>
<td>L-band 6D</td>
<td>0.982</td>
<td>0.573%</td>
</tr>
</tbody>
</table>

TABLE II
CORRELATION COEFFICIENTS BETWEEN THE RETRIEVED SM AND THE REFERENCE AND THE CORRESPONDING RMSEs FOR THE L-BAND 2-D OBSERVATION MODES WITH ANGULAR DIFFERENCES OF 30° AND 50° AND FOR THE L-BAND 6-D OBSERVATION MODE FOR THE 2 K NOISE CASE

<table>
<thead>
<tr>
<th>Obs. Modes (2K noise)</th>
<th>R</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>L-band 0-30</td>
<td>0.972</td>
<td>0.709%</td>
</tr>
<tr>
<td>L-band 10-40</td>
<td>0.971</td>
<td>0.726%</td>
</tr>
<tr>
<td>L-band 20-50</td>
<td>0.969</td>
<td>0.747%</td>
</tr>
<tr>
<td>L-band 0-50</td>
<td>0.967</td>
<td>0.763%</td>
</tr>
<tr>
<td>L-band 6D</td>
<td>0.977</td>
<td>0.648%</td>
</tr>
</tbody>
</table>

(0.624%) to 0.98 (0.601%) for the 1 K noise cases, and from 0.967 (0.762%) to 0.973 (0.703%) for the 2 K noise cases. The corresponding results for the cases of angular differences of 30° and 50°, and the 6-D case are listed in Table I for the 1 K noise case and Table II for the 2 K noise case. The capability of L-band 2-D and multiple dimensional radiometry in sensing SM, and their advantage over the L-band 1-D observation mode is evident.

C. By Combined AMSR and L-Band Observations

From the results shown in the previous subsections, the RMSEs are in general lower for the no-noise and 1 K cases than for the 2 K case. It is redundant to repeatedly show the very good matching between the retrieved SM and the reference so that in the following, we only present the results from the other observation modes for the 2 K noise case.

Fig. 9 compares the retrieved SM from the combined 6.9 GHz observation and L-band 1-D observation at 0° versus the corresponding reference for the 2 K noise case. Retrievals from the combined 6.9 GHz and L-band 1-D observations at the other viewing angles are not shown for simplicity. Similarly, the corresponding results from the combined 10.7 GHz and L-band 1-D observations are not presented. We found that the 6.9 and 10.7 GHz observations add about equal values on the L-band 1-D observation for sensing SM. This statement remains effective when we combine either 6.9 or 10.7 GHz observation with L-band 2-D observations with angular differences of 10°, or with angular differences...
and the 6-D case (Tables III and IV). In general, the use of L-band 2-D or 6-D observation increases (reduces) \( \bar{R} \) (RMSE) of concern by 0.01 (0.1%) compared to the case when the L-band 1-D observation is used.

### IV. Conclusion

The SMOS and the AMSR may co-exist in the space in the foreseeable future. It is interesting to examine the sensitivity of the channels of the SMOS and the AMSR to SM. The sensitivity has been studied in this paper by incorporating LSP/R model into the newly developed EPLBP algorithm. For realization of the concerned problem, the simulated brightness temperatures are added by Gaussian-distributed noises with 1 K and 2 K standard deviations. We have shown that the EPLBP algorithm can manage the nonlinear mapping from microwave brightness temperatures to SM very well. The algorithm introduces negligible errors to the retrievals, less than 0.1% SM for the 2-AMSR frequency mode with zero noise imposed upon its inputs and about 1.76% for the 2 K noise case. The error associated with the 2 K noise case does not appear as large as one might expect possibly because of a fixed biomass, and of a well defined TB-SM relationship in the model in addition to the ignorance of surface heterogeneity due to differential vegetation or wetness.

In addition, it is shown that the L-band 1-D radiometric observation is sensitive to SM. RMSEs between the retrieved SM and the reference are as low as 0.412% for the no-noise case at an incident angle of 10°, 0.614% for the 1 K noise case at an incident angle of 20°, and 0.955% for the 2 K noise case at an incident angle of 50° (not shown in the figures). The sensitivity can be increased by incorporating radiometric observation either from a second angle, or from multiple look angles, or from any of the two lowest AMSR channels. For example, the corresponding RMSEs are reduced to near 0.7% for the L-band 2-D observation modes and to less than 0.6% for the observation modes of combined L-band 2-D and one of the two lowest AMSR channels for the 2 K noise case. These results imply that the EPLBP algorithm is robust since the quality of the retrieved SM remains high when the Gaussian distributed noise with 1 K standard deviation is increased to 2 K.

While the results of the current study are based on the “simulations” of a validated LSP/R model, they do show us a promising approach to further investigate the sensing of the SM by space-based microwave radiometers such as the AMSR and the SMOS. For example, we may study the impact of varying vegetation biomass on the sensing capability. In any case, we do impose noises on the input nodes of the retrieval algorithm in this study to increase the similarity between the setup problem and the reality. In addition, a further study on radiometric sensing of SM and biomass by a neural network approach based on the field measurements from PORTOS-93 and -96 is being conducted [33].

### Acknowledgment

The authors wish to thank the anonymous reviewers for their useful comments to the original manuscript.

### References


---

**TABLE III**

<table>
<thead>
<tr>
<th>Obs. Modes (2K noise)</th>
<th>R</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>L-band 0-30 + 6.9GHz</td>
<td>0.982</td>
<td>0.572%</td>
</tr>
<tr>
<td>L-band 10-40 + 6.9GHz</td>
<td>0.980</td>
<td>0.602%</td>
</tr>
<tr>
<td>L-band 20-50 + 6.9GHz</td>
<td>0.981</td>
<td>0.590%</td>
</tr>
<tr>
<td>L-band 0-50 + 6.9GHz</td>
<td>0.979</td>
<td>0.611%</td>
</tr>
<tr>
<td>L-band 6D + 6.9GHz</td>
<td>0.984</td>
<td>0.541%</td>
</tr>
</tbody>
</table>

**TABLE IV**

<table>
<thead>
<tr>
<th>Obs. Modes (2K noise)</th>
<th>R</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>L-band 0-30 + 10.7GHz</td>
<td>0.981</td>
<td>0.583%</td>
</tr>
<tr>
<td>L-band 10-40 + 10.7GHz</td>
<td>0.981</td>
<td>0.587%</td>
</tr>
<tr>
<td>L-band 20-50 + 10.7GHz</td>
<td>0.981</td>
<td>0.594%</td>
</tr>
<tr>
<td>L-band 0-50 + 10.7GHz</td>
<td>0.967</td>
<td>0.772%</td>
</tr>
<tr>
<td>L-band 6D + 10.7GHz</td>
<td>0.985</td>
<td>0.524%</td>
</tr>
</tbody>
</table>


