Retrieval of Crop Biomass and Soil Moisture From Measured 1.4 and 10.65 GHz Brightness Temperatures

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***Abstract*—Physically based land surface process/radiobrightness (LSP/R) models may characterize well the relationship between radiometric signatures and surface parameters. They can be used to develop and improve the means of sensing surface parameters by microwave radiometry. However, due to a lack in the skill to properly understand the behavior of the data, a statistical approach is often adopted. In this paper, we present the retrieval of wheat plant water content (PWC) and soil moisture content (SMC) profiles from the measured H-polarized and V-polarized brightness temperatures at 1.4 (L-band), and 10.65 (X-band) GHz by an error propagation learning back propagation (EPLBP) neural network. The PWC is defined as the total water content in the vegetation. The brightness temperatures were taken by the PORTOS radiometer over wheat fields through three month growth cycles in 1993 (PORTOS-93) and 1996 (PORTOS-96). Note that, through the neural network, there is no requirement of ancillary information on the complex surface parameters such as vegetation biomass, surface temperature, and surface roughness, etc. During both field campaigns, the L-band radiometer was used to measure brightness temperatures at incident angles from 0 to 50° at L-band and at an incident angle of 50° at X-band. The SMC profiles were measured to the depths of 10 cm in 1993 and 5 cm in 1996. The wheat was sampled approximately once a week in 1993 and 1996 to obtain its dry and wet biomass (i.e., PWC). The EPLBP neural network was trained with observations randomly chosen from the PORTOS-93 data, and evaluated by the remaining data from the same set. The trained neural network is further evaluated with the PORTOS-96 data.**

***Index Terms*—Neural network, plant water content, soil moisture.**

I. Introduction

Soil moisture plays a crucial role in hydrology, agronomy, and meteorology [1]. In hydrology, it governs the redistribution of precipitation between infiltration and runoff. In agronomy, it affects the development of crops through its dominance on regulating water-uptake by the plants. In meteorology, it manages the partitioning of energy and water through evaporation and transpiration at the lower boundary of the atmosphere. Hence, it has been a parameter of great interest in the field of microwave remote sensing for decades.

Microwave radiometry is the most successful of the remote sensing approaches for sensing soil moisture. Over bare soils, radiobrightness at nearly all microwave frequencies are sensitive to soil moisture content (SMC) and its state. Wang [2] proposed a linear relationship between microwave emissivity and the effective thickness of the emitting soil layer of about 1 cm at 5 GHz and 5 cm at 1.4 GHz. Liou and England [3] used a physically based model to show the sensitivity of radiometric signatures to soil moisture at microwave frequencies from 19 to 85 GHz, and to demonstrate how radiometric signatures are affected by the state of soil moisture [4].

Lower microwave frequencies must be used to observe SMC in vegetated areas [5], [6] because the optical thickness of the vegetation increases with increasing frequency. Over grassland of 3.7 kg/m^2 biomass it was shown that the vegetation radiobrightness weightings are approximately 25% at L-band, 90% at 19 GHz, and 97% at 37 GHz [7], and 50% at C-band and 65% at X-band [8]. Liou *et al.* [9] also used an LSP/R model of prairie grassland to show that a 19 GHz pixel having a homogeneously distributed 50% canopy cover is 40 to 50 K brighter than a 50% tiled pixel for a 60-day summer dry-down simulation, and that the L-band brightness is essentially identical for homogeneous and tiled pixels. Hence, the quality of the SMC retrievals from C- and X-band channels of the Advanced Microwave Scanning Radiometer (AMSR) onboard the Japanese Advanced Earth Observing Satellite (ADEOS)-II and Earth Observing System (EOS) PM platforms will suffer relative to an L-band retrieval as canopies thicken. Njoku and Li [10] expect AMSR retrieval accuracies of 0.06 g/cm^3 (roughly equal to 8% by volume) for SMC and 0.15 kg/m^2 for plant water content (PWC) in regions of PWC less than approximately 1.5 kg/m^2. These relatively low standards of the retrieved SMC and PWC are a result of the relatively weak sensitivity to SMC in vegetated areas at the higher microwave frequencies.

The masking effects of the vegetation are often managed through simplifying assumptions. Wigneron *et al.* [11], [12] adopted a two-parameter (optical thickness of the vegetation layer, τ_0, and single scattering albedo, ω) model to describe the emission of the vegetated fields. Since the model is essentially a zeroth-order solution to the radiative transfer equation within

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the land-air system, it is valid only at low frequencies where scattering within the vegetation is low. For example, SMC of the topmost 3 cm of soil was retrieved with errors 5.3% (by volume) from PORTOS-93 data and PWC was also retrieved with errors 0.242 kg/m^2 [11]. These retrievals used prior knowledge of surface temperature and crop type as well as brightness temperature measurements at L-band and C-band data at incident angles of 8, 18, 28, and 38°. Wigneron *et al.* [12] further investigated the potential of an L-band 2-D microwave interferometric radiometer to monitor SMC, PWC, and surface temperature for the Soil Moisture and Ocean Salinity (SMOS) mission [13] that is based on an innovative two-dimensional aperture synthesis concept. The objective of the latter study was to optimize the SMOS mission scenario—to meet both the scientific requirements and technical constraints of the mission. Apparently, retrieval algorithms that do not require prior information would be a significantly simplification.

This study differs from the Wigneron *et al.* [11], [12] retrieval of SMC and PWC from radiobrightness in three aspects. First, no auxiliary information about surface temperature is required. Second, no consideration of vegetation scattering is needed. These are possible because vegetation is treated as a black box in the error propagation learning back propagation (EPLBP) neural network approach [8]. Since the physics of the problem is ignored, the information is statistical in nature. Statistical treatments require a large number of data to cover all possible situations that might occur. Hence, it is necessary to consider the range of the parameters in the input data. A neural network approach may not properly extract values of the parameters beyond the range that served as the input. That is, the quality of the extract values may be reduced if the input data do not probably represent the problem of interest. Third, the proposed PORTOS-93 data trained algorithm is also applied to the PORTOS-96 data, while the study of Wigneron *et al.* [11] was only based on PORTOS-93 data.

II. Retrieval Description

A. The Physical System

The SMC profile is a result of the balance in moisture and energy budgets at the land–air interface and within the soil. It can be characterized by a land surface process (LSP) module that solves coupled differential equations of moisture and energy conservation. The LSP module must account for the energy and moisture interactions among the air, the soil, and the canopy if vegetation is present. The consequent soil and canopy radiobrightness for p polarization can be found by [9]

$$T_{b,p} = T_{s,e}(1 - R_p(\mu))e^{-\tau_0/\mu} + T_{c,e}\left(1 - e^{-\tau_0/\mu}\right)\left(1 + R_p(\mu)e^{-\tau_0/\mu}\right) \quad (1)$$

where $T_{s,e}$ is the effective emitting temperature of the soil, K; R_p is the Fresnel reflectivity of the moist soil for polarization p; τ_0 is the optical thickness of the canopy, nepers (Np); μ is the cosine of the incident angle, degrees; and $T_{c,e}$ is the effective emitting temperature of the canopy, K. The effective emitting temperatures of the soil and canopy, the reflectivity of the soil, and the optical thickness of the canopy are all functions of the physical temperature and moisture content of the soil and canopy. Brightness temperatures of the vegetated terrain are hence nonlinearly dependent on SMC and PWC in addition to their dependence on the other factors, such as soil and canopy temperatures, surface scattering from the soil, and volume scattering from the canopy …, etc. Note that improper handling of these factors would potentially degrade the recovery of SMC and PWC from radiobrightness. For example, the ignorance of surface scattering from the vegetation–soil interface resulted in underestimate of brightness temperatures at H-polarized, L-band at an incident angle of 53° over prairie grasslands by 12 K [14].

B. Field Measurements

Field measurements used in this study have been applied in previous studies [11], [15], [16]. Inevitably, for the convenience of reading this article, this subsection duplicates some materials from the previous studies.

The field campaigns were conducted over wheat fields through three-month growth cycles at the Institut National de Recherches Agronomiques (INRA) Avignon Remote Sensing test site (43°55 N, 4°53 E) in 1993 (PORTOS-93) and 1996 (PORTOS-96). It was manufactured by the Centre National d'Etudes Spatiales of France and Matra Marconi Space in 1990. Its operating frequencies include 1.4 (L-band), 5.05, 10.65 (X-band), 23.8, 36.5, and 90 GHz. Its 3-dB and the 20-dB beamwidth were 12.5° and 30°, respectively. Its calibrations were made over calm water surfaces and "eccosorb" slabs either at ambient temperature or immersed in liquid nitrogen. The calibrations showed that the measured brightness temperature could be expressed as a linear function of the radiometer output and the coefficients of this function could be kept constant during the whole experiment. Based on this simple calibration approach, the radiometer absolute accuracy was about 5 K and 3 K at 1.4 and 10.5 GHz, respectively. Both H- and V-polarized brightness temperatures were measured, while the microwave data used in this study only include L-band brightness temperatures at viewing angles common both to the 1993 and the 1996 data and X-band brightness temperatures measured in 1993 as shown in Fig. 1. The reasons are threefold. First, brightness temperatures at 23.8 and 36.5 GHz are insensitive to soil moisture over the wheat field. Second, brightness temperatures at C-band are unavailable in 1996. Third, the X-band radiometer appears to be instable for about 5% of the measurements. Hence, nothing is presented latter using the X-band measurements in 1996.

Note that there is difference in mounting the radiometer in 1993 and 1996. In 1993, the radiometer was mounted on a 20-meter crane boom and observations were carried out at different incidence angles (from 0° to 60° over a large 40 × 60 m wheat field). The look direction of the radiometer was parallel or orthogonal to the tillage direction of the bare field plots. In 1996, the radiometer was installed on a cross-bar system at a height of about five meters. To avoid measuring the instrument self-emission at low incidence angles, the measurements were obtained over a limited range of incidence angles (30 to 55°).

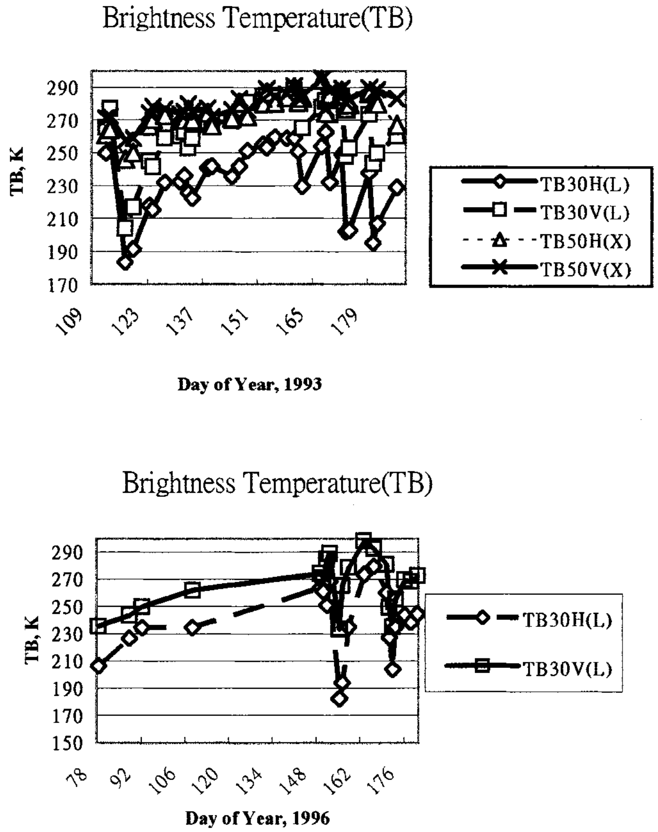
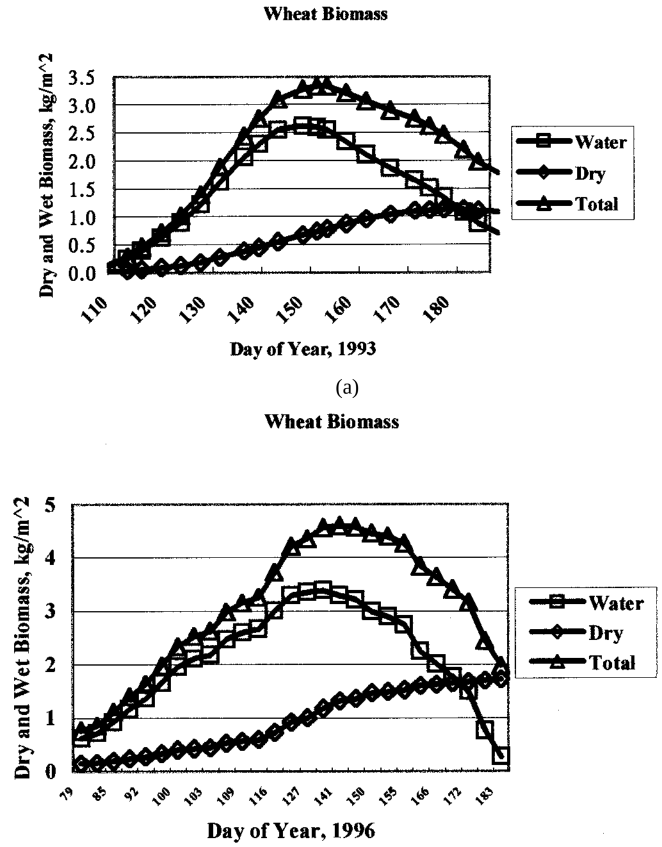


Fig. 1. L-band and X-band brightness temperatures measured in (a) 1993 and (b) 1996. The numbers 30 and 50 are the viewing angles in degrees.



(b)

Fig. 2. Total fresh biomass, water content, and dry biomass of the wheat vegetation through three month growth cycles in (a) 1993 and (b) 1996.

The field plot consists of silty clay loam soil with 62% silt, 11% sand and 27% clay. A large range of SMC conditions were obtained by irrigating the field and, then, letting it dry out (dry and sunny conditions occurred during the experiment). However, the surface SMC conditions were spatially rather heterogeneous over the fields especially during extreme conditions (i.e., very dry and very wet) [17]. It was observed that moist spots remained in dry conditions and puddles occurred just after rainfall or irrigation events. Hence, gravimetric moisture sampling may not be representative of the actual SMC conditions at the field scale during extreme conditions. The accuracy in volumetric SMC measurements was estimated to be about 4% during the whole experiment. The soil variables were sampled regularly during the campaign. Concurrently with the radiometric observations, SMC profiles were obtained from gravimetric measurements (3 to 5 replications) at several depth intervals (0–0.5 cm, 0–1 cm, 1–2 cm, 2–3 cm, 3–4 cm, 4–5 cm, 5–7 cm and 7–10 cm in 1993 and 0–0.5 cm, 0–1 cm, 1–2 cm, 2–3 cm, 3–5 cm in 1996). These gravimetric measurements were converted into volumetric soil moisture using the measured dry bulk density ρ_b for each field plot. Vertical profiles of ρ_b were obtained from a transmission gamma-ray technique [18] at different depths in soil [19]. The value of ρ_b at the soil surface (mean value over the 2–4 cm depth interval) is about 1.35 g/cm^3 in 1993 and 1.27 g/cm^3 in 1996.

Additional measurements of SMC were obtained for all measurement dates using the time domain reflectrometry (TDR) method [20]. Six TDR probes were installed in the wheat field at a depth of about 3 cm. Their measurements provide an estimate of the volumetric SMC of top 0–5 cm layer. Soil temperature was automatically measured with platinum resistance temperature probes or thermocouples. Ten probes were installed in the soil at different depths from about 0.5 cm to 1 meter at depth. The soil temperature was measured continuously and averaged every 10 min. Vegetation was sampled approximately weekly both in 1993 and in 1996 to obtain dry and wet biomass, water content, height, volume fraction, and geometry of the vegetation canopy. In addition, a thermal infrared radiometer (8–14 μm) was mounted on the crane boom to monitor the surface temperature concurrently with the radiometric measurements.

Fig. 2(a) shows the total fresh biomass, PWC, and dry biomass of the wheat from day of year (DoY) 110 to 190 in 1993 (seeding was performed on DoY 78 and harvest was done shortly after DoY 190). Fig. 2(b) shows total fresh biomass, PWC, and dry biomass of the wheat from DoY 79 to 183 in 1996. Fig. 2(a) and (b) show that the wheat biomass is much heavier in 1996 than in 1993. The maximum total fresh biomass (PWC) is 3.33 (2.61) kg/m^2 in 1993, and 4.60 (3.38) kg/m^2 in 1996. While the PORTOS-96 data could have extended the PORTOS-93 data to a larger range of vegetation biomass, there were no radiometric observations over a significant portion of the PORTOS-96 experiment (from DoY 109 to 144).

C. Neural Network

Neural networks are known for their ability to handle nonlinear mapping problems. Liou *et al.* [21] applied a dynamic learning neural network to demonstrate the capability of the L-band radiometry in sensing soil moisture based on the LSP/R model simulations for the HYDROSTAR mission proposed by England *et al.* [22]. Recently, the EPLBP neural network was used to retrieve surface soil moisture from simulated brightness temperatures for a variety of frequency and viewing angle combinations [8]. The combinations consist of AMSR's two lowest channels for a viewing angle of 55° and L-band for multiple viewing angles of 0, 10, 20, 30, 40, and 50°. It was shown that the sensitivity of the AMSR channels to soil moisture is increased by incorporating L-band signal, and that an L-band 2-D (two look angles) or a multiple dimensional observation mode is superior to an L-band 1-D (one look angle) observation mode for sensing SMC. The maximum retrieval error is only 1.76% (by volume) for all of the studied cases even though Gaussian distributed noises with standard deviation as large as 2 K are added to the simulated instrumental noises. The retrieval error is relatively low because model simulations present well-defined relationship between soil moisture and brightness temperatures. Since the correlation relationship of concern in nature cannot be completely defined by physical modeling, it is of great interest to reexamine the radiometric sensing of soil moisture based on field measurements.

In this paper, the EPLBP neural network is used not only to retrieve SMC from the observed brightness temperatures based on the similar observing configurations studied by Liou *et al.* [8], but also to infer PWC. More details about the implementation of the EPLBP neural network are referred to Liou *et al.* [8]. We use some of the PORTOS-93 data to train and "validate" (to be explained in the next subsection) the neural network and apply it to the remaining PORTOS-93 data as representative of wheat biomass less than 3.33 kg/m^2. The measurements are managed as follows.

1) Obtain the measured brightness temperatures (Tb), SMC, and PWC.
2) Form a data set to be further processed and analyzed. The measurements of Tb, SMC, and PWC that are simultaneously available in the same day are chosen. The measurement time was typically between 12:00 and 17:00.
3) Normalize the data to fall into the range between 0 and 1. The data are assumed to be Gaussian distributed and offset by their average.
4) Allocate the observed data randomly into three groups, namely training, "validation," and testing, with approximately one half, one quarter, and one quarter of the data, respectively, but for SMC retrievals the data used for validation are also used in testing due to relatively limited numbers of the data. Note that only PORTOS-93 data are used in training and "validation," but both PORTOS-93 and -96 data are used in testing. The term "validation" is used since the scheme of "early stopping with validation" is adopted to avoid over-training of the neural network. The training process is stopped if any of the following five conditions exists [23]. First, the maximum number 100 of training epochs (repetitions) is reached. This condition is rarely applied in this study. Second, the gradient of the training performance falls bellow 10^{-10}. Third, over-training occurs. This is recognized when validation errors increase for a specified number of iterations. Fourth, the training performance has been minimized to zero. Fifth, the tuning index of Levenberg–Marquardt optimization exceeds 10^{10}.
5) Apply the EPLBP neural network to the testing data and record the results or retrievals. The retrievals are then analyzed and used to provide the statistics (RMSE and weighted RMSE) presented in the following.

As a practical extension, the trained neural network is also used to recover SMC and PWC from the PORTOS-96 data. It is found that the accuracy of the retrievals is low with errors around 0.6 to 0.8 kg/m^2 on average if we do not filter all data in 1996 with a biomass larger than in 1993. The associated low-quality retrievals are not further presented. Results presented in the following are obtained after performing the filtering.

D. Observation Modes

Based on the data management addressed in the previous subsection, there are in total 13 observation (i.e., input-data) modes. Note that both horizontal and vertical brightness temperatures are used in the retrieval.

1) One X-band observation mode—Radiometric measurements at X-band at an incident angle of 50°.
2) Three L-band 1-D (one look angle) observation modes—Radiometric observations at L-band at angles of either 30, or 40, or 50°. Each angle corresponds to one L-band 1-D observation mode.
3) Three L-band 2-D (two look angles) observation modes—Radiometric observations at L-band at two angles of either 30 and 40°, or 40 and 50°, or 30 and 50°. Each combination of two angles corresponds to one L-band 2-D observation mode.
4) Six integrated X- and L-band observation modes—Radiometric observations at X-band combined with those prepared in steps 2, and 3 to become integrated X-band and L-band multiple dimensional observation modes.

III. Results and Discussion

A. Correlation Between Brightness Temperatures and Surface Parameters

The observed brightness temperatures are used to infer SMC and PWC. Their correlation with surface parameters indicates to some degree how good the retrieval quality can be achieved. Table I compares the correlation coefficients between brightness temperatures at L- and X-band and SMC in the topmost 5 cm of soil layers. Three major features are observable. First, X-band is less sensitive to SMC than L-band because wheat canopy appears to be optically thick. The correlation coefficients are low, -0.222 and -0.272, for the X-band cases, but higher than -0.615 for the L-band cases. Second, the correlation coefficients are slightly higher in 1996 than in 1993 by 0.1 or so. Note that the measurements were taken during the whole

TABLE I
CORRELATION COEFFICIENT BETWEEN BRIGHTNESS TEMPERATURES AT L- AND X-BAND AND SMC IN THE TOPMOST 5 cm OF SOIL LAYERS

Frequency		L-BAND						X-band	
Polarization		V			H			V	H
Year	Depth\angle	30°	40°	50°	30°	40°	50°	50°	50°
1993	0-5	-0.768	-0.761	-0.615	-0.764	-0.777	-0.731	-0.272	-0.222
1996	0-5	-0.864	-0.791	-0.753	-0.919	-0.905	-0.773	NA	NA

TABLE II
CORRELATION COEFFICIENT BETWEEN BRIGHTNESS TEMPERATURES AT L- AND X-BAND AND VEGETATION BIOMASS

Frequency		L-BAND						X-band	
Polarization		V			H			V	H
Year	Angle	30°	40°	50°	30°	40°	50°	50°	50°
	Total	0.647	0.739	0.731	0.469	0.543	0.565	0.671	0.760
1993	Water	0.611	0.701	0.669	0.511	0.584	0.578	0.475	0.585
	Dry	0.533	0.598	0.627	0.219	0.286	0.360	0.816	0.836
	Total	0.192	0.479	0.366	0.327	0.186	0.197	NA	NA
1996	Water	0.267	0.560	0.405	0.377	0.275	0.429	NA	NA
	Dry	0.062	0.266	0.218	0.185	0.045	-0.102	NA	NA

growth cycle of the wheat in 1993 but not in 1996. As mentioned, brightness temperatures are unavailable from DoY 109 to 144 in 1996 during which period the wheat is growing and healthy, and appears to have higher masking effect on the transmission of microwave emissions from soil to the radiometer. Third, the higher the viewing angle, the lower the correlation between L-band brightness and SMC. For example, the correlation coefficients are -0.919 at 30°, -0.905 at 40°, and -0.773 at 50° for the H-polarized L-band cases.

Table II shows correlation coefficients between brightness temperatures at L- and X-band and vegetation biomass. Note that microwave emission from wheat is information here but noise for the problem of sensing SMC. Consequently, compared to Table I, Table II shows three similar but opposite characteristics. First, X-band is more correlated with vegetation biomass than L-band. Second, the correlation coefficients are lower in 1996 than in 1993. Third, the higher the viewing angle, the higher the correlation between L-band brightness and vegetation biomass.

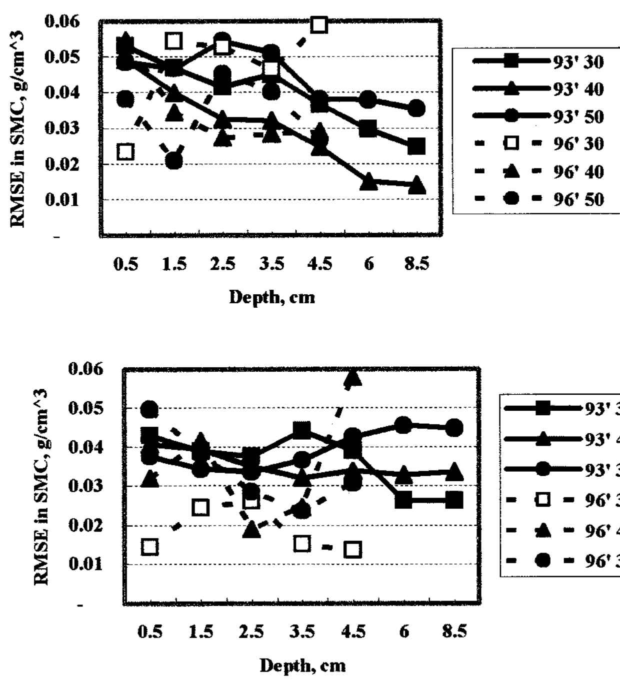


Fig. 3. The rms errors (RMSEs) in the retrieved SMC versus depth for the L-band: (a) one-dimensional (1-D) and (b) two-dimensional (2-D) observation modes. The numbers 30, 40, and 50 are the viewing angles in degrees with that 93′ and 96′represent the years of 1993 and 1996, respectively.

B. Retrieval of Soil Moisture Content

The rms errors (RMSEs) in the retrieved SMC versus depth are shown in Fig. 3 for the L-band (a) 1-D and (b) 2-D observation modes. Two characteristics are observed. First, RMSEs scatter over a larger range for 1996 than 1993 possibly because the neural network is trained with the 1993 data only. Second, RMSEs locate in the regions with larger magnitudes for the L-band 1-D than 2-D observation modes between depths 0 and 5 cm. The only outlier is that the RMSE at the depth of 4.5 cm (4–5 cm) for the L-band 2-D observation mode is relatively high. These results indicate that the quality of the retrieval is higher for the L-band 2-D than 1-D observation modes. Such a finding is consistent with that observed by Liou *et al.* [8] based on predictions from theoretical models. Note that the RMSEs at the depths below 5 cm for the L-band 2-D observation mode are relatively high since L-band is essentially losing sensitivity to SMC, and hence associated measurements are not further considered.

The RMSEs are then used to compute weighted RMSE (WRMSE) with weighting linearly dependent on the thickness of each soil layer. Fig. 4 shows the WRMSEs for the L-band

TABLE III
NUMBERS OF MEASUREMENTS USED TO TRAIN, VALIDATE, AND TEST THE EPLBP NEURAL NETWORK FOR SMC RETRIEVALS

Frequency		L- BAND						X-band
Mode		1D			2D			1D
Year	Angle	30°	40°	50°	30°-40°	40°-50°	30°-50°	50°
1993	Train	8	10	7	5	6	5	5
	Test[a]	7	6	4	8	3	5	5
1996	Test	3	4	4	3	3	2	NA

[a]ROUGHLY HALF OF THE "TEST" DATA ARE USED IN VALIDATION.

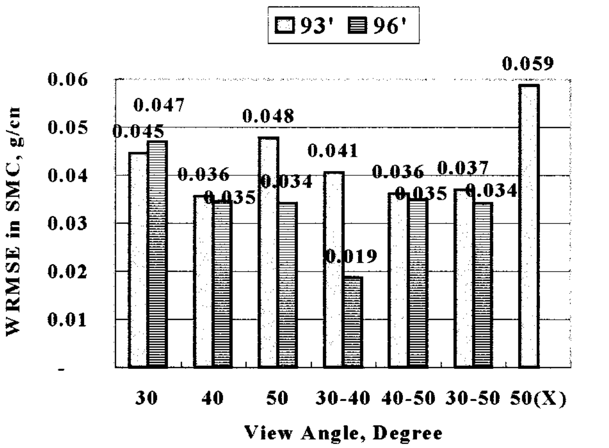


Fig. 4. WRMSEs in the retrieved SMC for the L-band 1-D and 2-D, and X-band 1-D observation modes. The numbers indicate the magnitudes of the WRMSEs.

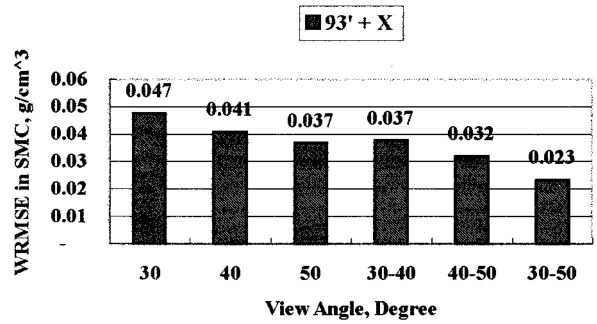


Fig. 5. WRMSE in the retrieved SMC for the integrated X-band and L-band 1-D/2-D observation modes in 1993. The numbers indicate the magnitudes of the WRMSEs.

1-D and X-band observation modes, and the L-band 2-D observation modes. The numbers indicate the magnitudes of the WRMSEs. RMSEs for the topmost 5 cm soil layers (0–1 cm, 1–2 cm, 2–3 cm, 3–4 cm, 4–5 cm in 1993 and 0–1 cm, 1–2 cm, 2–3 cm, 3–5 cm in 1996) are used to compute the WRMSEs since L-band becomes less sensitive to SMC at depths between 5 and 10 cm. Generally speaking, there is no specific look angle of concern found to be the best for sensing SMC. Table III shows the numbers of measurements used to train, validate, and test the EPLBP neural network for SMC retrievals. The numbers are not too many since tremendous work is required to collect all the parameters of interest. They are relatively small in 1996 due to the above-mentioned data filtering and unavailable data for a significant portion of field campaign. Three encouraging characteristics are observed. First, the largest WRMSE of 0.059 g/cm^3 occurs for the X-band observation mode because of its insensitivity to SMC over vegetated terrains. Second, WRMSEs are larger for the L-band 1-D (from 0.034 to 0.048 g/cm^3, average 0.041 g/cm^3 or 5% by volume) than 2-D (from 0.019 to 0.041 g/cm^3, average 0.034 g/cm^3 or 4% by volume) observation modes. Third, but not least important, the accuracy in the retrieved SMC is good not only for the 1993 cases, but also for the 1996 cases. The averages of the errors are about 0.041 g/cm^3 or 5% by volume for all cases in 1993, and about 0.034 g/cm^3 or 4% by volume in 1996. These inter-comparison results are consistent with those found by Liou *et al.* [8]. Note that while results from the neural network vary from one test to another, the results presented in Figs. 3 and 4 are typical and represent a general trend for the performance of the neural network.

Fig. 5 shows WRMSE in the retrieved SMC for the integrated X- and L-band 1-D/2-D observation modes in 1993. A comparison between Figs. 4 and 5 shows that the quality of the retrieval is slightly improved for the L-band 1-D observation modes, but considerably for the 2-D observation modes with incorporation of the X-band signals. The mean errors are reduced from 0.043 g/cm^3 to 0.042 g/cm^3 for the L-band 1-D observation modes, and from 0.038 g/cm^3 to 0.031 g/cm^3 for the L-band 2-D observation modes. Although this is not totally same as the previous experience [8] where the X-band signal improved the quality of the retrieval for any specific observation mode of interest, the X-band signal does in general add additional values to L-band 1-D and 2-D radiometry. The reasons for the disagreement are at least twofold. First, biomass varies over a large range in the current study, but constant in Liou *et al.* [8]. Second, X-band is essentially insensitive to SMC under the vegetation in this study as shown in Table I. Apparently, field measurements used to cross check the results from theoretical simulations are crucial. Table IV shows the numbers of measurements used to train, validate, and test the EPLBP neural network with incorporation of X-band signals for SMC retrievals.

C. Retrieval of Vegetation Water Content

RMSE in the retrieved PWC for the L-band 1-D and 2-D, and X-band observation modes are plotted in Fig. 6. It is clearly seen that L-band 2-D radiometry is superior to L-band 1-D radiometry for sensing PWC. For example, the RMSE ranges from 0.233 to 0.313 kg/m^2 for the L-band 1-D observation modes, and from 0.095 to 0.224 kg/m^2 for the L-band 2-D observation modes in 1993. The exception is that RMSE is relatively high at

TABLE IV
NUMBERS OF MEASUREMENTS USED TO TRAIN, VALIDATE, AND TEST THE EPLBP NEURAL NETWORK FOR SMC RETRIEVALS WITH INCORPORATION OF X-BAND SIGNALS

Frequency		L-band + X-band					
Mode		1D			2D		
Year	Angle	30°	40°	50°	30°-40°	40°-50°	30°-50°
1993	Train	6	8	5	6	5	5
	Test[a]	8	7	5	6	3	4

TABLE V
NUMBERS OF MEASUREMENTS USED TO TRAIN, VALIDATE, AND TEST THE EPLBP NEURAL NETWORK FOR PWC RETRIEVALS

Frequency		L- BAND						X-band
Mode		1D			2D			1D
Year	Angle	30°	40°	50°	30°-40°	40°-50°	30°-50°	50°
	Train	21	16	13	15	11	13	25
1993	Validate	7	11	7	6	7	5	9
	Test	6	6	7	8	3	6	11
1996	Test	4	5	6	4	4	3	NA

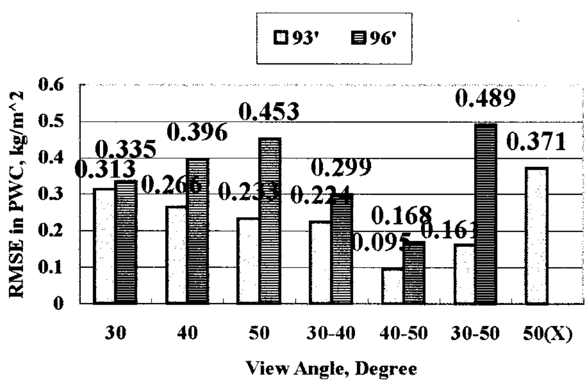


Fig. 6. RMSE in the retrieved PWC for the L-band 1-D and 2-D, and X-band observation modes. The numbers indicate the magnitudes of the RMSEs.

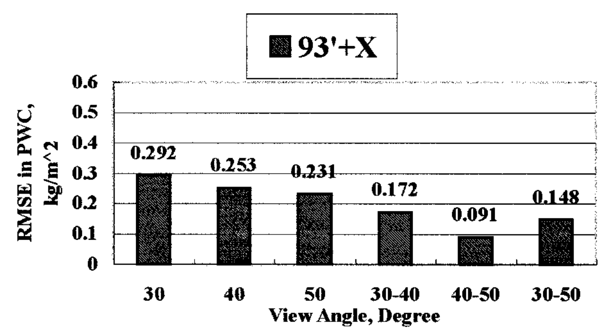


Fig. 7. RMSE in the retrieved PWC for the integrated X-band and L-band 1-D/2-D observation modes in 1993. The numbers indicate the magnitudes of the RMSEs.

0.489 kg/m^2 for the L-band 2-D case in 1996. It is also seen that the quality of retrieval from the L-band 2-D radiometry is rather good in 1993, and satisfactory in 1996 even though the neural network is trained by the PORTOS-93 data only. The average errors on PWC were only about 0.239 kg/m^2—0.160 kg/m^2 in 1993 and 0.319 kg/m^2 in 1996. The errors are the largest for the X-band observation mode because the brightness temperatures are relatively weakly correlated with PWC. The RMSE in the retrieved PWC from X-band data is 0.371 kg/m^2 in 1993. The numbers of measurements used to train, validate, and test the EPLBP neural network for PWC retrievals are listed in Table V. Reasonable numbers of observations are used in 1993 although there are fewer measurements in 1996.

Fig. 7 shows RMSE in the retrieved PWC for the integrated X-band and L-band 1-D/2-D observation modes in 1993. Overall speaking, the quality of the retrieved PWC is very good. In addition, as expected, the errors are smaller for the integrated X-band L-band 2-D than 1-D observation modes. The average errors were 0.259 kg/m^2 for the integrated X-band and L-band 1-D observation modes and 0.137 kg/m^2 for the integrated X-band and L-band 2-D observation modes. A comparison between Fig. 6 and 7 shows that X-band adds additional values to L-band 1-D and 2-D radiometry for sensing PWC for all observation modes. Table VI lists the numbers of measurements used to train, validate, and test the EPLBP neural network for PWC retrievals with incorporation of X-band signals.

IV. CONCLUSIONS

This paper investigates the retrieval of SMC and PWC from the brightness temperatures at L-band and X-band, and their combination based on the measurements taken during the PORTOS-93 and -96 field campaigns. There are in total 13 observation modes considered. We find that rather good retrievals can be obtained for both SMC and PWC if L-band 2-D radiometry is utilized. It has been shown the average errors

TABLE VI
NUMBERS OF MEASUREMENTS USED TO TRAIN, VALIDATE, AND TEST THE EPLBP NEURAL NETWORK FOR PWC RETRIEVALS WITH INCORPORATION OF X-BAND SIGNALS

Frequency		L-band + X-band					
Mode		1D			2D		
Year	Angle	30°	40°	50°	30°-40°	40°-50°	30°-50°
	Train	16	16	7	15	10	12
1993	Validate	13	8	13	7	6	4
	Test	4	8	6	6	4	7

are about 4% by volume for the retrieved SMC and 0.239 kg/m^2 for the retrieved PWC (0.160 kg/m^2 in 1993 and 0.319 kg/m^2 in 1996). These retrievals are especially satisfactory and convincing on the 1996 cases even though the neural network is trained by the 1993 data only, and hence make us feel confident in the retrievals through the neural network approach.

In addition, results demonstrate that the L-band 2-D radiometry provides higher quality retrieval of SMC and PWC than the L-band 1-D radiometry as proved in a previous study by Liou *et al.* [8] who utilized simulated brightness temperatures and SMC predicted by the LSP/R models. It is further shown that the X-band signals are in general helpful to improve the quality of the retrieved SMC and PWC from L-band radiometry.

Furthermore, it is shown that the vegetation has a larger masking effect on the X-band's sensitivity to SMC than the L-band. Among the thirteen studied observation modes the maximum WRMSEs/RMSEs in the retrieved SMC and PWC occur for the X-band observation mode. The associated errors are 0.059 g/cm^3 for SMC, and 0.371 kg/m^2 PWC in 1993. In contrast, the WRMSEs/RMSEs may be minimized when the L-band 2-D observation modes (with or without incorporation of X-band signals) are utilized. They are only 0.031 g/cm^3 or 4% by volume for SMC, and 0.137 kg/m^2 for PWC for the integrated X-band and L-band 2-D observation modes.

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