Evaluation of the Tau–Omega Model for Passive Microwave Soil Moisture Retrieval Using SMAPEx Datasets

Ying Gao, *Member, IEEE*, Jeffrey P. Walker, *Member, IEEE*, Nan Ye, Rocco Panciera, Alessandra Monerris, Dongryeol Ryu, *Member, IEEE*, Christoph Rüdiger, *Senior Member, IEEE*, and Thomas J. Jackson, *Fellow, IEEE*

***Abstract*—The parameters used for passive soil moisture retrieval algorithms reported in the literature encompass a wide range, leading to a large uncertainty in the applicability of those values. This paper presents an evaluation of the proposed parameterizations of the tau–omega model from 1) the soil moisture active passive (SMAP) algorithm theoretical basis document (ATBD) for global condition and 2) calibrated parameters from the National Airborne Field Experiment (NAFE'05) for Australian conditions, with special focus on the vegetation parameter *b* and roughness parameter H_R. This study uses airborne *L*-band data and field observations from the SMAP experiments conducted in south-eastern Australia. Results show that the accuracy with the proposed parameterizations from SMAP ATBD was satisfactory at 100-m spatial resolution for maize (0.07 m^3/m^3) and pasture (0.07 m^3/m^3), while it decreased to 0.19 m^3/m^3 for wheat. Calibrated parameters from the NAFE'05 did not provide better results, with the accuracy of wheat degrading to 0.23 m^3/m^3. After a comprehensive site-specific calibration and validation at 100-m spatial resolution, this result was improved to 0.10 m^3/m^3. Further calibration and validation were performed at 1-km resolution against intensive ground sampling and at 3-km against *in situ* monitoring stations. Results showed an accuracy over grassland and cropland of 0.04 m^3/m^3 and 0.05 m^3/m^3, respectively. This study also suggests that the parameters from SMAP ATBD show an underestimation of soil moisture, with the roughness parameter H_R being too low for south-eastern Australian condition. Therefore, a new set of *b* and H_R parameters for ten different land cover types was proposed in this study.**

***Index Terms*—Calibration, passive microwave, retrieval, soil moisture, validation.**

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Y. Gao, J. P. Walker, N. Ye, and C. Rüdiger are with the Department of Civil Engineering, Monash University, Clayton, VIC 3800, Australia (e-mail: ying.gao@monash.edu; jeff.walker@monash.edu; nan.ye@monash.edu; chris.rudiger@monash.edu).

R. Panciera was with the Cooperative Research Centre for Spatial Information, Carlton, VIC 3053, Australia, and is now with United Nation Children's Fund (UNICEF), New York, NY 10038, United States (e-mail: pancerarocco@gmail.com).

A. Monerris and D. Ryu are with the Department of Infrastructure Engineering, University of Melbourne, Parkville, VIC 3010, Australia (e-mail: alessandra.monerris@unimelb.edu.au; dryu@unimelb.edu.au).

T. J. Jackson is with the U.S. Department of Agriculture ARS Hydrology and Remote Sensing Laboratory, Beltsville, MD 20705 USA (e-mail: tom.jackson@ars.usda.gov).

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I. Introduction

RESEARCH activities carried out worldwide over the past three decades have demonstrated that microwave radiometry at *L*-band (1–2 GHz) is the most suitable remote sensing technique for measuring surface soil moisture at the global scale [1], [2]. Both the Soil Moisture and Ocean Salinity (SMOS) [3] and the Soil Moisture Active Passive (SMAP) [4] missions are dedicated to enhanced global soil moisture mapping using *L*-band microwave radiometry. Current algorithms for passive microwave soil moisture retrieval are based on the inversion of radiative transfer models that simulate the passive microwave emission from the land surface using ancillary information such as vegetation-related indices, soil surface roughness, and soil temperature [5]–[17]. For the SMOS mission, an operational SMOS Level 2 soil moisture algorithm, called the *L*-band microwave emission of the biosphere (L-MEB) model, was developed based on an extensive review of the past knowledge of the microwave emission of various land covers [1]. The core of this model is based on the well-known *tau–omega* model in the passive microwave soil moisture community [15]. This model is also being applied in the SMAP Level 2 passive microwave soil moisture algorithm [18].

The tau–omega model has been evaluated with both tower- and airborne-based campaigns over various surface conditions in Europe and America [19]–[22]. In 2007, a summary of model parameters used for a variety of land cover types was proposed in [1]. In Australia, Panciera *et al.* [23]–[25] have previously tested the tau–omega model with the parameters suggested in [1] using experimental data from the National Airborne Field Experiments (NAFE'05, NAFE'06) and the first soil moisture active passive experiment (SMAPEx-1). The results showed mixed quality soil moisture retrieval accuracy using these parameters, with grassland performing better than crops (RMSE ranged from 0.02 to 0.07 m^3/m^3 for grassland, and from 0.06 to up to 0.3 m^3/m^3 for crops). In addition, Panciera *et al.* [23] and Mialon *et al.* [26] assessed the tau–omega model by calibrating vegetation- and roughness-related parameters with data from NAFE'05 and the surface monitoring of soil reservoir experiment, respectively, with significantly improved retrieval accuracy (RMSE smaller than 0.04 m^3/m^3 for both grassland and crop fields). It is the variation in ancillary information (e.g., vegetation opacity, single scattering albedo,

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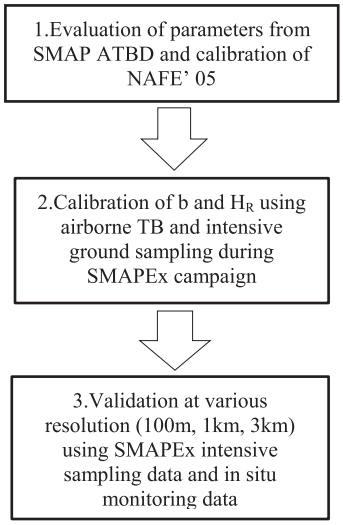

Fig. 1. Flowchart of the evaluation, calibration, and validation procedures in this study.

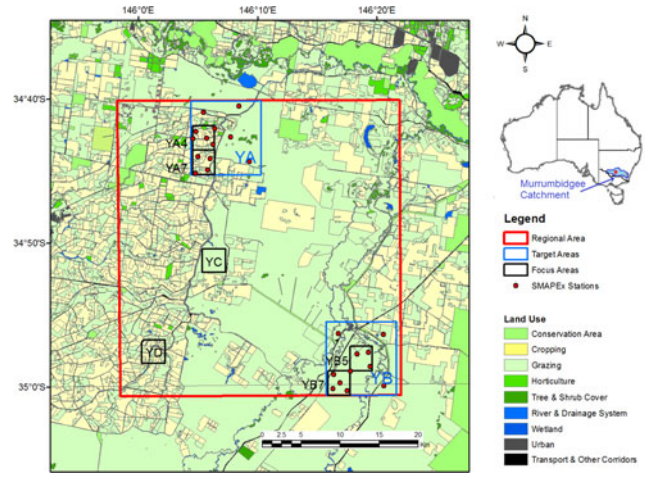

Fig. 2. Layout of the SMAPEx study area.

surface roughness, etc.) from place to place that has made the model parameterization difficult to be specified globally. Therefore, there is a strong need for ongoing evaluation of the tau–omega model across a diverse range of land surface types and conditions.

The aim of this paper can be summarized in three parts. First, it performs an evaluation of the model parameters from 1) the SMAP algorithm theoretical basis documents (ATBD) [18], which was proposed for global application, and 2) the NAFE'05, which was calibrated to Australian surface conditions [23]. The evaluation is done using *L*-band airborne data from the three soil moisture active passive experiments (SMAPEx) [27] conducted prior to the launch of SMAP. Second, a calibration and independent validation under the SMAPEx land cover conditions are performed at a 100-m spatial resolution. The calibration and validation were based on the SMAPEx-1 and -2 high-resolution datasets. Calibration was focused on the vegetation parameter *b* and the surface roughness parameter H_R, the two parameters which have been shown to have the largest impact on the soil moisture retrieval accuracy [23]. Third, the calibrated model parameters from the previous step were applied in independent soil moisture retrieval for SMAPEx-3 using the airborne observations at 1-km resolution, providing a further validation opportunity against ground soil moisture samplings (aggregated to 1-km resolution) and continuous *in situ* monitoring stations (aggregated to 3-km resolution). A further calibration on the 1-km data was then performed to see if better results were achievable. This series of steps has allowed a comprehensive assessment of the tau–omega model accuracy at 100-m, 1-km, and 3-km resolutions. Moreover, the retrieved SMAPEx-3 soil moisture maps from this study are being used as the basis for a range of further studies, including the combined active–passive soil moisture retrieval and downscaling. A flowchart of the study is shown in Fig. 1. It should be noted that this paper is also a part of the author Gao's doctoral thesis [28].

II. Datasets

The three SMAPEx campaigns were conducted during various stages of the crop growing season and covered a range of climatic conditions: SMAPEx-1 on July 5–10, 2010; SMAPEx-2 on December 4–8, 2010; and SMAPEx-3 on September 5–23, 2011. These three campaigns correspond to the southern hemisphere winter, summer, and spring, respectively. The SMAPEx study site is a semiarid cropping and grazing area near Yanco, New South Wales, located in the center of the Murrumbidgee River catchment (see Fig. 2). The main passive airborne instruments used were the polarimetric *L*-band multibeam radiometer (PLMR). Flights carrying PLMR were conducted at both 100-m and 1-km resolutions during SMAPEx-1 and -2, but only at 1-km resolution during SMAPEx-3. Ground sampling was undertaken concurrently with each flight across local focus farms. Ancillary information on vegetation water content (VWC) and surface roughness were also collected for each dominant vegetation type. More details about the airborne and ground data utilized in this study are described in [27] and available at www.smapex.monash.edu

Two types of airborne data were analyzed in this study: 1) T_B at 100-m resolution from the SMAPEx-1 and -2 "Target Flights," which focused on target areas YA and/or YB; and 2) T_B at 1-km resolution from the SMAPEx-3 "Regional Flights," which covered the entire SMAPEx area (see Fig. 2). The SMAPEx-1 Target Flights were conducted on July 7th and 9th, 2010, covering the YB and YA, respectively, while the SMAPEx-2 Target Flights were restricted to the YA area only (on December 5th, 2010) due to extremely wet conditions in YB with some surface ponding. The SMAPEx-3 Regional Flights were conducted on nine days (5th, 7th, 10th, 13th, 15th, 18th, 19th, 21st, and 23rd) of September 2011 at an altitude of 3000 m, providing 1-km resolution T_B over the entire SMAPEx area. It should be noted that since each Regional Flight and Target Flight was conducted over a time span of approximately 5–7 h, all the T_B data have been standardized to the soil temperature at the middle of the flight period [29]. The soil temperature used for the standardization was the effective soil temperature (T_{EFF}) calculated from

a near-surface temperature at 2.5 cm (T_{SURF}) and a deep temperature at 40 cm (T_{DEPTH}), which were obtained from the *in situ* ground monitoring stations.

Three types of ground-based soil moisture data were used in this study: 1) intensive sampling data over target areas YA and YB from SMAPEx-1 and -2 (at 50 m spacing); 2) intensive sampling data over all six focus areas from SMAPEx-3 (at 250 m spacing); and 3) data from SMAPEx *in situ* monitoring stations during SMAPEx-3 (see Fig. 2 for locations of the focus areas and monitoring stations). Details on ground soil moisture sampling strategy and monitoring stations can be found in [27].

For all three campaigns, up to five destructive vegetation samples for biomass and water content determination were collected for each major vegetation type over the focus areas. At each sample location, the vegetation height, crop row spacing, and direction were recorded. Surface roughness height and correlation length were measured at up to three locations per major vegetation type using two perpendicular 3-m long profiles (E–W and N–S directions). A land surface classification map was also developed for the entire study site for SMAPEx-3 using Landsat images. This map (together with MODIS surface reflectance data, refer to Section IV-C for details) was used to develop land cover based VWC maps, parameter *b* maps, and parameter H_R maps, as inputs for the soil moisture retrieval of the regional area for SMAPEx-3.

III. Model

The tau–omega model requires two main parameters: the optical depth of the canopy τ and the single-scattering albedo ω, which are used to parameterize the vegetation attenuation properties and the scattering effects within the canopy layer. The basic concept of the tau–omega model has been illustrated in [15] and the detailed description of the model equations used in this study can be found in both [1] and [18]. Apart from τ and ω, other model parameters include soil roughness parameters H_R (–) vegetation parameter *b* (–). The optical depth τ was found to be linearly related to the VWC using the *b* parameter through $\tau = b^{*}\mathrm{VWC}$ [12], [30]. The effective soil temperature required in the model can be calculated using near-surface (2–5 cm) temperature T_{SURF} and deep-soil temperature (~50 cm) T_{DEEP} from $T_{\mathrm{EFF}} = T_{\mathrm{DEEP}} + (T_{\mathrm{SURF}} - T_{\mathrm{DEEP}})^{*}(\theta/w_0)\,b_0$. θ here is the surface soil moisture, and w_0 and b_0 are semiempirical parameters depending on specific soil characteristics. Parameters $w_0 = 0.398$ and $b_0 = 0.181$ were applied in this study, being values that were calibrated by Wigneron *et al.* [17] and shown to be suitable for all types of soil varying from sandy loam to silty clay for a T_{SURF} of 2 cm and T_{DEEP} of 50 cm. The vegetation temperature T_{VEG} required in the model was considered to be equal to T_{SURF} based on the data availability.

IV. Model Evaluation and Calibration

A. Evaluation of the ATBD and NAFE'05 Parameters

The accuracy of the tau–omega soil moisture retrieval using SMAP ATBD parameters and NAFE'05 calibrated parameters was evaluated using the SMAPEx-1 and -2 high-resolution airborne observations at 100-m resolution over the target YA and YB areas, where all the factors known to affect the microwave emission at these sites were well monitored, and the spatial variability of soil moisture within the aircraft footprint known in great detail. Therefore, a comparison of the tau–omega model retrieval with ground measured soil moisture at these locations allowed detailed evaluation of the effectiveness of the model physics and parameterization with minimum uncertainty on the ancillary data used and on the soil moisture heterogeneity within each pixel.

The soil moisture retrieval was evaluated using the vegetation parameter *b* and roughness parameter H_R from 1) the SMAP ATBD proposed for global application, and 2) the calibrated parameters from NAFE'05, conducted also in Australia. The parameters ω_V and ω_H were assigned with 0.05 suggested in the ATBD for both cropland and grassland. Soil moisture was retrieved using a two-channel retrieval (H-pol and V-pol) on each T_B observation and the resulting soil moisture compared with the mean ground observed soil moisture within each 100-m pixel. The values of soil temperature at 2.5 cm and 40 cm depth from the nearest *in situ* monitoring station at the time of T_B acquisition were used by the direct emission model to calculate the effective temperature. The value of the VWC estimated daily from the biomass samples collected at the high-resolution site was used to characterize the contribution of the vegetation to the emission. The model inputs and the RMSE of the soil moisture retrieval are summarized in Table I. It can be seen that the soil moisture retrieval accuracy when using the parameterizations from the ATBD was satisfactory only for maize (0.07 m^3/m^3) and pasture (0.07 m^3/m^3), with RMSE reaching to 0.13 m^3/m^3 over barley and 0.19 m^3/m^3 over wheat. The biases for the four types of land cover were all negative, indicating that the soil moisture values were underestimated. In comparison, the soil moisture–related roughness parameterizations developed from NAFE'05 overestimated the soil moisture (i.e., positive bias), with RMSE also far from satisfactory (0.12–0.23 m^3/m^3).

B. Calibration and Validation at 100 m

Site-specific calibration was subsequently performed at the same spatial resolution (100 m). Data from three Target Flights were available at this resolution: two over the YA area (mostly crop fields) from SMAPEx-1 and -2, and one over the YB area (grassland) from SMAPEx-1 only. In order to achieve the most accurate calibration, ground measurements of soil moisture, roughness, and VWC should all be known. Therefore, only those pixels with concurrent measurements of these three variables were used for calibration (see locations of ground measurements in Fig. 1). Although the number of these pixels is very limited, it guarantees that the model is calibrated with the most accurate ancillary information.

The calibration process was focused on the vegetation parameter *b* and roughness parameter H_R. They were calibrated simultaneously by minimizing the sum of the squares of the errors between the function and the measured data points. The calibration was conducted within preset ranges of 0–1 for *b* and 0–1.5 for H_R, being their common ranges. The following two

TABLE I
MODEL INPUTS AND RETRIEVAL STATISTICS FOR EVALUATION

Land cover	b		H_R		ω	VWC (kg/m^2) min–max	Retrieval RMSE		Retrieval Bias	
	SMAP ATBD	NAFE' 05	SMAP ATBD	NAFE' 05			SMAP ATBD	NAFE' 05	SMAP ATBD	NAFE' 05
Barley	0.11	0.08	0.108	1.5–1.6θ	0.05	0.10–0.56	0.13	0.12	–0.12	0.01
Maize	0.11	NA	0.094	NA	0.05	1.20–1.73	0.07	NA	–0.06	NA
Wheat	0.11	0.08	0.083	1.5–1.6θ	0.05	0.04–0.36	0.19	0.23	–0.06	0.12
Pasture	0.13	0.15	0.156	0.50	0.05	0.12–1.02	0.07	0.15	–0.05	0.13

TABLE II
LAND COVER SPECIFIC CALIBRATION OF PARAMETER b AND H_R, TOGETHER WITH RESULTING SOIL MOISTURE RMSE FOR BOTH CALIBRATION AND VALIDATION OVER THE TARGET AREAS OF SMAPEX-1 AND SMAPEX-2 (VAL1), AND VALIDATION OVER THE REGIONAL AREA OF SMAPEX-3 (VAL2)

Calibration and Validation over SMAPEx-1 and -2 target areas (100 m pixels)									Validation over SMAPEx-3 regional area (1 km pixels)			
Land cover	No. of pixels	Calibration method	b_{ini}	$H_{R\,ini}$	b	H_R	$RMSE_{SM}$ CAL	$RMSE_{SM}$ VAL1	Land cover	No. of pixels	Calibration method	$RMSE_{SM}$ VAL2
Barley	8	'Unconstrained'			**0.02**	**0.31**	0.08	0.13	Cropland	81	'Unconstrained'	0.08
		'Constrained'	0.08	0.15	0.06	0.13	0.14	0.18				
Maize	4	'Unconstrained'			**0.05**	**0.38**	0.01	0.03			'Constrained'	0.09
		'Constrained'	0.08	0.30	0.05	0.24	0.04	0.03				
Wheat	2	'Unconstrained'			**0.03**	**0.39**	0.02	0.10				
		'Constrained'	0.08	0.09	0.06	0.12	0.10	0.12				
Pasture	4	'Unconstrained'			**0.22**	**0.23**	0.02	0.06	Grassland	81	'Unconstrained'	0.05
		'Constrained'	0.15	0.20	0.12	0.22	0.04	0.06			'Constrained'	0.06

*Values of b and H_R in bold are optimum values considering their overall performance of calibration and validation, i.e. relatively lower $RMSE_{SM}$ for CAL, VAL1 and VAL2, shaded in grey.

alternate objective functions (OF) were used for calibration:

$$\mathrm{OF}_1 = \frac{\sum(\mathrm{TB}_{\mathrm{obs}} - \mathrm{TB}_{\mathrm{sim}})^2}{\sigma(\mathrm{TB})^2} \tag{1}$$

$$\mathrm{OF}_2 = \frac{\sum(\mathrm{TB}_{\mathrm{obs}} - \mathrm{TB}_{\mathrm{sim}})^2}{\sigma(\mathrm{TB})^2} + \frac{\sum(b - b_{\mathrm{ini}})^2}{{\sigma_b}^2} + \frac{\sum(H_R - H_{R\mathrm{ini}})^2}{{\sigma_{H_R}}^2} \tag{2}$$

where $\mathrm{TB}_{\mathrm{obs}}$ and $\mathrm{TB}_{\mathrm{sim}}$ are the observed and simulated brightness temperature, respectively. The σ_{TB}, σ_{b}, and σ_{HR} are the standard deviation of brightness temperature, b, and H_{R}, respectively, allowed in the calibration. The b_{ini} and $H_{R\mathrm{ini}}$ are the initial guesses for b and H_R, respectively, which provide a constraint on these parameters during the calibration. Here, b_{ini} is assigned using value suggested in the previous literature (see Table II), while $H_{R\mathrm{ini}}$ is calculated from ground-sampled surface roughness using the relationship provided by [31]

$$H_R = [0.9437^{*}\mathrm{RMS}/(0.8865^{*}\mathrm{RMS} + 2.2913)]^6 \tag{3}$$

where RMS indicates the root mean square of the ground-sampled surface height. The values of $H_{R\mathrm{ini}}$ for different types of land cover are also listed in Table II. The calibration using OF_1 is referred to herein as "unconstrained calibration," because it optimizes the two parameters only by minimizing the difference between the observed and simulated brightness temperature without constraining b and H_R, thus finding the values that provide the best model performance. The calibration using OF_2 is referred to herein as "constrained calibration," since b and H_R are constrained using the initial guesses. Thus, the calibration is looking for a compromise between minimizing the error of brightness temperature and the deviation of b and H_R from their initial guesses. It should be noted that attempts were also made to calibrate polarization-specific b parameter, but the results did not show any significant improvement in terms of soil moisture accuracy. Therefore, only a single b value for both polarizations was used in this study.

The resultant parameters of this comprehensive calibration are given in Table II. It is seen that the "unconstrained" calibration method yielded superior results to the "constrained" method. Plots of the calibration results shown in Fig. 3 suggest that for calibration with data from both SMAPEx-1 and -2, a discrepancy exists between the scatters from SMAPEx-1 and SMAPEx-2, especially for barley and wheat. This suggests that the parameter b and/or H_R may vary in different seasons. While it is possible to calibrate b and H_R for winter (SMAPEx-1) and summer (SMAPEx-2) separately, deriving one single set of parameters is more practical in terms of global satellite applications. Therefore, both datasets are combined together for calibration purposes.

The remaining pixels of the Target Flight for SMAPEx-1 and -2 were used for the first step of validation. Since the VWC is unknown for these pixels, the average of all VWC samples for each type of vegetation was assigned to these pixels. These validation results are also shown in Fig. 3. Maize performed the best (RMSE = 0.03 m^3/m^3) compared with other crops (RMSE = 0.10–0.13 m^3/m^3 for barley and wheat) and grassland (RMSE

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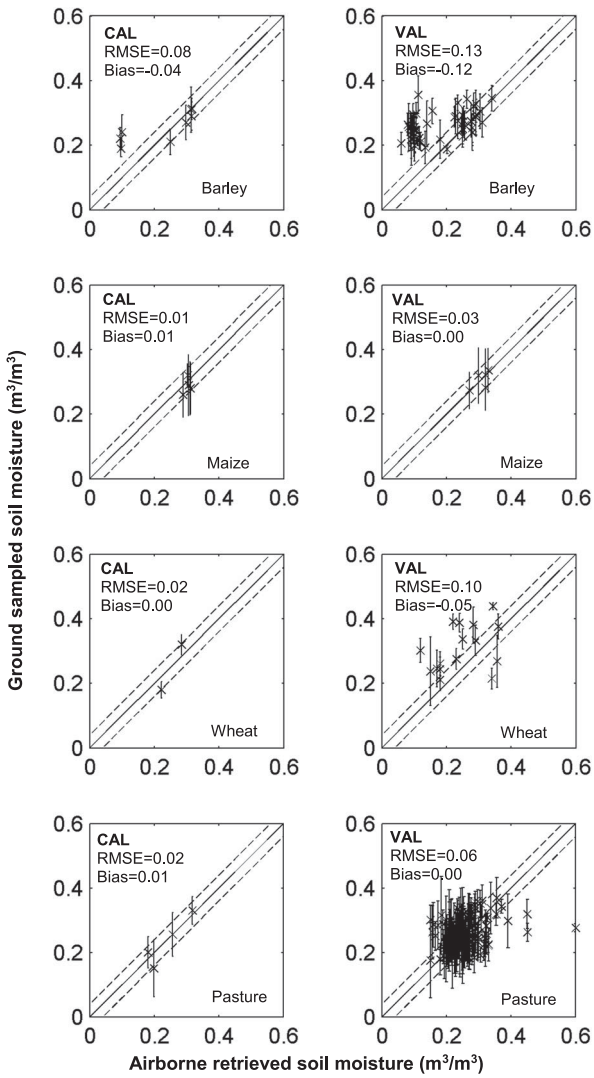

Fig. 3. Observed versus retrieved soil moisture for 100-m pixels of SMAPEx-1 and -2 for both calibration and validation. Whiskers indicate soil moisture sampling standard deviation within a 100-m pixel.

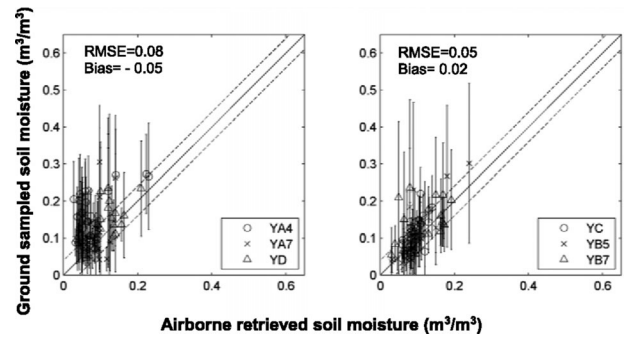

Fig. 4. Soil moisture retrieval validation (with calibrated parameters from SMAPEx-1 and -2) at 1-km resolution for the six focus areas of SMAPEx-3: YA4, YA7, and YD represent cropland (left) and YC, YB5, and YB7 represent grassland (right). Whiskers indicate soil moisture samping standard deviation within the 1-km pixel.

TABLE III
B AND H_R VALUES CALIBRATED TO SMAPEX-3 DATASETS

Parameter	Wheat	Pasture	Fallow	Lynseed	Canola	Bare	Woodland	Lucerne
b	0.03	0.14	0.05	0.09	0.13	0	0.06	0.09
H_R	0.68	0.35	0.26	0.33	0.35	0.88	0.15	0.17

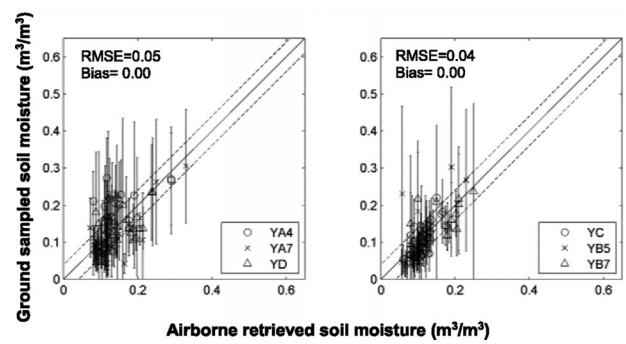

Fig. 5. As for Fig. 4 but with calibrated parameters from SMAPex-3 datasets.

$= 0.06$ m^3/m^3). Compared with the parameters suggested by the SMAP ATBD and NAFE'05, apart from barlsfig4ey in which the NAFE'05 parameters perform slightly better than this study (RMSE $= 0.12$ versus 0.13 m^3/m^3), the soil moisture retrieval accuracy of the remainder of the land cover types has been improved considerably.

C. Retrieval, Validation, and Further Calibration at 1 km

Using the calibrated parameters from Section IV-B, soil moisture maps for the nine flight days of SMAPEx-3 were derived from the regional brightness temperature data, allowing for additional validation at 1-km resolution. These soil moisture maps are also potentially of great value for related studies, as a benchmark for high-resolution land surface modeling, active–passive downscaling algorithm developments, assessment of the most representative stations within the monitoring network, and so on. In order to perform the soil moisture retrieval for the entire experiment area, a land cover classification map at 30-m resolution was developed from Landsat 5 images (work performed by G. Satalino and delivered through personal communication). This map was used to extrapolate the maps of VWC, H_R, and b parameters over the SMAPEx-3 regional area according to the spatial variation in land cover type. The VWC datasets were calculated from the normalized difference vegetation index (NDVI) through the individual regression models recommended by Gao *et al.* [32] for different land cover types. The NDVI datasets were derived from the MODIS daily surface reflectance data (Product MYD09GQ) at 250-m resolution for each of the nine flight days. For those days on which clouds were observed, a linear interpolation was performed using the data of the adjacent cloud-free days. The H_R and b maps were interpolated by different vegetation types according to the land classification map at 30-m resolution, and aggregated to 1-km resolution through linear averaging. VWC maps were also extrapolated using the same method.

Additional validation of the tau–omega model was performed with the nine days of regional soil moisture maps from SMAPEx-3 using ground-sampled soil moisture from the six focus areas at 1-km resolution. While the retrieval results (shown

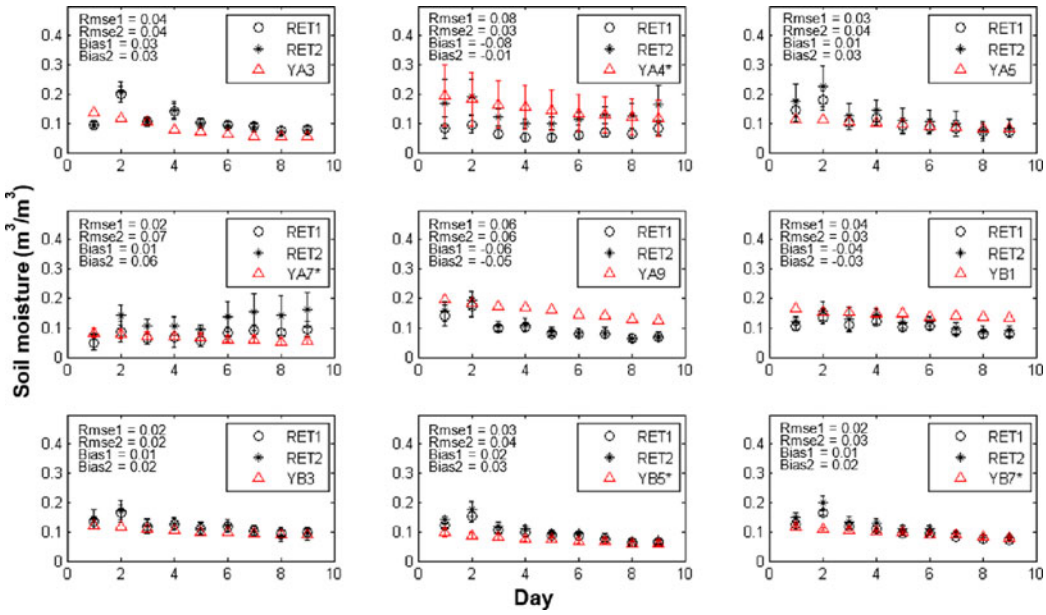

Fig. 6. Soil moisture retrieval validation at 3-km resolution with the YA and YB *in situ* monitoring stations of SMAPEx-3, using both calibrated parameters from SMAPEx-1 and -2 (RET1) and the updated calibration from SMAPEx-3 (RET2). Whiskers indicate soil moisture standard deviation of the 1-km retrievals and the cases with multiple stations within a 3-km pixel.

in Fig. 4) are generally dry biased compared with the observed soil moisture for both cropland and grassland, grassland still shows higher retrieval accuracy (RMSE $= 0.05$ m^3/m^3) than cropland (RMSE $= 0.08$ m^3/m^3). This is likely due to the greater homogeneity in grasslands as compared with crop fields. As the retrieval result for both land cover types did not achieve the SMAP target accuracy (0.04 m^3/m^3), attempts were made to identify the maximum accuracy achievable by further calibrating parameters b and H_R based on the 1-km pixels from SMAPEx-3. Since the land cover type is generally not homogenous within a 1-km cropland pixel, the calibration was based on the following: For a mixed land cover of a 1-km pixel with n types and the area percentage of each type of x, the brightness temperature of the whole pixel was approximated as $T_B = \sum_i^n x_i\, T_{Bi}$. The calibration algorithm used is the same as described in Part Section IV-B, with the unconstrained calibration method (OF_1) for optimization, since it provided better accuracy based on the previous analysis. The resultant parameters are shown in Table III with the soil moisture retrieval results using this updated calibration plotted in Fig. 5. The retrieval accuracy of cropland improved to an RMSE of 0.05 m^3/m^3 while grassland was improved to 0.04 m^3/m^3. Meanwhile, the biases for both crop and grassland were eliminated after the calibration. The new calibration provides b and H_R parameters for eight different land cover types: wheat, pasture, fallow, linseed, canola, bare, woodland, and Lucerne.

Comparing parameters of wheat and pasture with the previously calibrated values in Part Section IV-B, it can be seen that while b did not change much, H_R was significantly increased (0.68 compared with 0.39 for wheat, and 0.35 compared with 0.23 for pasture). The reason why there are two different groups of b and H_R for wheat and pasture is that the brightness temperature and soil moisture sampling datasets used for calibration at 100 m and 1 km are different. Also, the 100-m data were collected in summer and winter 2010, while the 1-km data were collected in spring 2011, during which the land cover classification (crop types) is different. Therefore, it is reasonable to have different b and H_R calibrated to fit data at different scale and/or different seasons. Nevertheless, the issue of scale dependence of model parameters still worth further investigation in the future research. Apart from wheat and pasture, the remaining land covers also obtained higher roughness parameters (0.15–0.35 for vegetated land) compared with what was suggested in the SMAP ATBD.

D. Validation at 3 km With In Situ Monitoring Stations

An additional validation was undertaken with the nine days of retrieved soil moisture maps from SMAPEx-3 based on a comparison against monitoring stations at 3-km resolution. The validation was done using both calibrated prameters from SMAPEx-1 and -2 (shown as RET1 in Fig. 6) and the updated calibration from SMAPEx-3 (RET2 in Fig. 6). For most 3-km pixels within YA and YB areas, there was only one *in situ* monitoring station, which was used for comparing with the retrieval. However, for YA4, YA7, YB5, and YB7, there are multiple monitoring stations. In this case, an average value was calculated for these stations and then compared with the retrieval. The validation results show that the soil moisture retrieved from grasslands (YB sites) is highly consistent with the station data. The RMSE ranges from 0.02 to 0.04 m^3/m^3, which falls within the SMAP target accuracy. For crop sites, YA3 and YA5 are also performing well, with RMSE for both RET1 and RET2 equal or smaller than 0.04 m^3/m^3. However, for YA9, the retrieved soil moisture is significantly dry biased (–0.05 to –0.06 m^3/m^3) compared to the station data. While for YA4 and YA7, RET1 and RET2 are

either a lot dry biased or wet biased. This is because YA4, YA7, and YA9 sites are highly heterogeneous, i.e., within the 3-km pixel, they all have a mixed land cover consisting of bare, fallow, wheat, and pasture. This may contribute to the station-only records of soil moisture for a specific type of land cover, failing to represent the soil moisture condition of its larger surrounding area. This problem does not exist in YB area, therefore it is providing more satisfying results.

V. Conclusion

In summary, the key parameters used by the tau–omega model, which is the basis for the passive soil moisture retrieval algorithms for both SMOS and SMAP, were assessed using airborne *L*-band passive microwave observations and ground sampling information during SMAPEx-1, -2, and -3. The evaluation of the SMAP ATBD parameters saw an underestimation of soil moisture in general, while the parameters calibrated from the NAFE'05 (soil-moisture-dependent roughness parameterization) yielded an overestimation. Compared with the calibration in this study, it is suggested that the parameter H_R from SMAP ATBD is too low for the south-eastern Australian condition. While Fung and Chen [9] tried to improve the roughness parameterization for cropland through establishing a relationship with soil moisture, this relationship did not perform well in the SMAPEx study area. Consequently, this study provides a new set of b and H_R parameters for ten different land covers (eight from SMAPEx-3 and two from SMAPEx-1 and -2) that meet the accuracy requirements, and a validated set of soil moisture maps that will be used in further studies.

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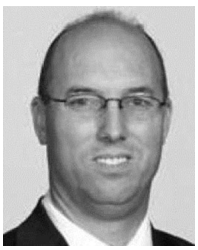
Ying Gao (S'13–M'16) received the B.E. degree (Hons. 1) in civil engineering from Monash University, Melbourne, VIC, Australia, and Central South University, Changsha, China, in 2010, and the Ph.D. degree in civil engineering from Monash University in 2016.

Since 2016, she has been with Monash University as a Research Fellow. Her research interests include active and passive microwave remote sensing, optical sensing of vegetation, and surface roughness parameterization.



Jeffrey P. Walker (M'13) received the B.E. degree in civil engineering and the Bachelor of Surveying (Hons. 1 and University Medal) degree from the University of Newcastle, Callaghan, NSW, Australia, in 1995, and the Ph.D. degree in water resources engineering from the University of Newcastle, in 1999.

He then joined NASA Goddard Space Flight Centre to implement his soil moisture work globally. In 2001, he moved to the Department of Civil and Environmental Engineering, University of Melbourne, Melbourne, VIC, Australia, as a Lecturer. Since 2010, he has been a Professor with the Department of Civil Engineering, Monash University, Melbourne, VIC, Australia, where he is continuing his research. He is contributing to soil moisture satellite missions at NASA, ESA, and JAXA, as a Science Team Member for the Soil Moisture Active Passive mission and Cal/Val Team Member for the Soil Moisture and Ocean Salinity and Global Change Observation Mission—Water, respectively.

Nan Ye received the B.E. degree in hydraulic and hydropower engineering from Tsinghua University, Beijing, China, in 2006, and the Ph.D. degree in civil engineering from Monash University, Melbourne, VIC, Australia, in 2014.

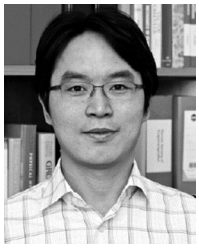
In 2013, he joined the Department of Geographic Information Science, Nanjing University, Nanjing, China, and worked on snow properties retrievals from optical and synthetic aperture radar data. Then, in 2014, he returned to Monash University where he coordinated a number of airborne field experiments for the in-orbit calibration/validation of the Soil Moisture Active Passive mission in the Murrumbidgee River catchment, southeast of Australia. He is currently a Senior Research Fellow with Monash University working on *P*-band passive microwave remote sensing of soil moisture.

Rocco Panciera received the M.S. degree in environmental engineering from the University of Trento, Trento, Italy, in 2003, and the Ph.D. degree in environmental engineering with a thesis on the effect of land surface heterogeneity on the accuracy of spaceborne soil moisture retrieval using passive microwave techniques from the University of Melbourne, Melbourne, VIC, Australia, in 2009.

He was with the University of Melbourne as a Research Fellow within the Soil Moisture Active Passive project for algorithm development for NASA's SMAP mission. In this role, he conducted two large-scale field experiments in South-Eastern Australia, including airborne active and passive microwave sensors. Since January 2011, he has been with the Cooperative Research Centre for Spatial Information, Melbourne, VIC, Australia, where he is working under the Superscience Fellowship from the Australian Research Council. In this role, he has been working on techniques to estimate the fine-resolution soil moisture by use of *L*-band and *X*-band synthetic aperture radar measurements. He is currently with the United Nation Children's Fund New York headquarters on supporting application of geospatial technologies in global health program.

Alessandra Monerris received the B.E. degree in electrical engineering from the Universitat Politècnica de València, València, Spain, and the Ph.D. degree in remote sensing from the Universitat Politècnica de Catalunya, Barcelona, Spain.

She has extensive experience in field experiments for the validation of soil moisture products derived from proximal and remote sensing data, and has been involved in Cal/Val activities for ESA, NASA, and JAXA satellite missions. She has been responsible for several *in situ* monitoring systems in Australia such as OzNet and CosmOz (Yanco). Her research interests include microwave radiometry, cosmic-ray probes, and global navigation satellite systems reflectometry applications for agriculture and water management.



Dongryeol Ryu (M'05) received the B.S. and M.S. degrees in geology from Seoul National University, Seoul, South Korea, in 1997 and 2000, respectively, and the Ph.D. degree in earth system science from the University of California, Irvine, CA, USA, in 2006.

He is currently an Associate Professor with the Department of Infrastructure Engineering, Melbourne School of Engineering, University of Melbourne, Melbourne, VIC, Australia. His research interests include hydrological modeling, remote sensing of land surface variables such as soil moisture and vegetation characteristics, their spatial and temporal variability, and hydrologic application of the remotely sensed land surface properties.

Christoph Rüdiger (M'10–SM'15) received the B.E. degree in civil engineering from the University of Applied Sciences, Wiesbaden (now Rhein-Main), Germany, in 2002, and the Ph.D. degree in environmental engineering from the University of Melbourne, Melbourne, VIC, Australia, in 2008, with a focus on the potential to assimilate streamflow data into land surface models for soil moisture prediction. His undergraduate thesis covered the topic of groundwater and contaminant flow around submerged building structures.

In 2006, he joined the Centre National de Recherches Météorologiques, Météo France, Toulouse, France, where he is focusing on the performance analysis and data assimilation of surface soil moisture and LAI within the French land surface model ISBA. This was followed by a postdoctoral position financed by the French Space Agency (CNES) on the validation of different passive and active microwave satellite products over France, with a particular focus on ESA's SMOS mission. He returned to Australia in 2008, on a position to coordinate and lead a number of Cal/Val campaigns for the Australian land validation segment of the SMOS mission in the Australian arid zone and the Murrumbidgee River catchment. Since 2011, he has been a faculty member with the Department of Civil Engineering, Monash University, Melbourne, VIC, Australia. Since then, he has participated in the Australian Cal/Val segments for NASA's SMAP and Aquarius missions, and is a PI on JAXA's GCOM-C mission. His current research interests include the remote sensing of vegetation dynamics and landscape water content at high resolution for drought monitoring and wildfire predictions, and the development of low-cost environmental monitoring networks.

Thomas J. Jackson (SM'96–F'02) received the Ph.D. degree from the University of Maryland in 1976.

He is a Research Hydrologist with the U.S. Department of Agriculture, Agricultural Research Service, Hydrology and Remote Sensing Lab, Beltsville, MD, USA. He is or has been a member of the science and validation teams of the Aqua, ADEOS-II, Radarsat, Oceansat-1, Envisat, ALOS, SMOS, Aquarius, GCOM-W, and SMAP remote sensing satellites. His research interests include the application and development of remote sensing technology in hydrology and agriculture, primarily microwave measurement of soil moisture.

Dr. Jackson was the recipient of the William T. Pecora Award (NASA and Department of Interior) in 2003 for outstanding contributions toward understanding the Earth by means of remote sensing, the AGU Hydrologic Sciences Award for outstanding contributions to the science of hydrology, and the IEEE Geoscience and Remote Sensing Society Distinguished Achievement Award in 2011. He is a Fellow of the Society of Photo-Optical Instrumentation Engineers, the American Meteorological Society, and the American Geophysical Union.