Medium-Resolution Soil Moisture Retrieval Using the Bayesian Merging Method

Xiaoling Wu, Jeffrey P. Walker, Christoph Rüdiger, *Member, IEEE*, Rocco Panciera, and Ying Gao, *Member, IEEE*

***Abstract*— The National Aeronautics and Space Administration's Soil Moisture Active Passive (SMAP) mission, launched in January 2015, was designed to provide a global soil moisture product at medium resolution (∼9 km), by combining observations from its radar and radiometer. Several downscaling methods have been proposed by the SMAP team for this purpose. This paper evaluates another candidate downscaling method, namely, the Bayesian merging approach. While this has been tested using a synthetic data set across the USA, it is imperative that it can also be tested using the experimental data for a comprehensive range of land surface conditions (i.e., in different hydro-climatic regions) prior to a global application. Consequently, this paper applies this method using the data collected from SMAP experiments field campaigns in southeastern Australia that closely simulated the SMAP data stream for a single SMAP radiometer pixel over a three-week interval. The method studied here differs from the linear downscaling methods of the SMAP mission, in that it uses a nonlinear method based on Bayes' theorem. The medium-resolution soil moisture product is obtained using background soil moisture estimates that are updated according to the difference between the observed and predicted brightness temperatures and backscatter coefficients, relating the high- and low-resolution data. Results were assessed against a reference soil moisture map derived from high-resolution airborne radiometer observations. The root-mean-square-error and R^2 for the Bayesian merging method were found to be 0.02 cm^3/cm^3 and 0.55, respectively, at 9-km resolution, being similar to the SMAP's "optional" downscaling method.**

***Index Terms*— Bayesian, downscaling algorithms, Soil Moisture Active Passive (SMAP), SMAP Experiments (SMAPEx), soil moisture.**

I. Introduction

MEDIUM-resolution (∼9 km) soil moisture products at global scale are a significant contribution for hydrometeorological applications such as regional weather forecasting, flood prediction, drought monitoring, and agricultural activities [1]. The main limitation is the tradeoff between resolution and radiometric accuracy of alternative remote sensing technologies. Microwave radiometry has been considered as the most promising method to retrieve surface soil moisture with high accuracy, however, it suffers from being at a low resolution (∼40 km), which has limited its application at regional scales [2], [3]. Conversely, radar remote sensing, with a resolution of better than 3 km, typically has poor results in retrieving global soil moisture due to the confounding effects of vegetation conditions and surface roughness and the relatively low signal-to-noise-ratio of the sensor [4]. Consequently, the Soil Moisture Active Passive (SMAP) mission launched by the National Aeronautics and Space Administration was designed to overcome the individual disadvantages of radar and radiometer by combining both, and therefore providing an improved soil moisture product at a medium resolution of approximately 9 km [5], [6]. This is achieved by merging observations from both radar and radiometer via a simple downscaling model. Two methods, including the baseline downscaling algorithm and the optional downscaling algorithm, have, in the past, been proposed as operational methods [7], [8]. These two methods, together with a further linear downscaling algorithm known as the change detection method [9], have been evaluated in [10], showing that the optional downscaling algorithm provided the best results in retrieving medium-resolution soil moisture for the Yanco area (a semiarid agricultural and grazing area in southeast Australia). As these three downscaling algorithms are all linear methods based on the assumption of linear relationships between radar and radiometer observations, alternative methods for SMAP such as the Bayesian merging method which retrieves medium-resolution soil moisture in a nonlinear way [11], should be tested within the same experimental framework. According to [11], the Bayesian method showed promising results in retrieving soil moisture at 9 km, with a root-mean-square-error (RMSE) of 0.027 cm^3/cm^3 using low-noise data and 0.044 cm^3/cm^3 using high-noise data. However, there were many poorly justified assumptions in the development and application of this synthetic data. Therefore, the objective of this paper is to test the Bayesian method and the three linear methods in [10] with the same experimental data and framework, and to thus recommend an optimal downscaling method for obtaining a medium-resolution soil moisture product from radar and radiometer observations such as those collected by the SMAP mission.

II. Data Set

Data from the third SMAP experiment (SMAPEx-3) in Australia were used in this paper. The campaign was conducted from September 4–23, 2011. The SMAPEx field

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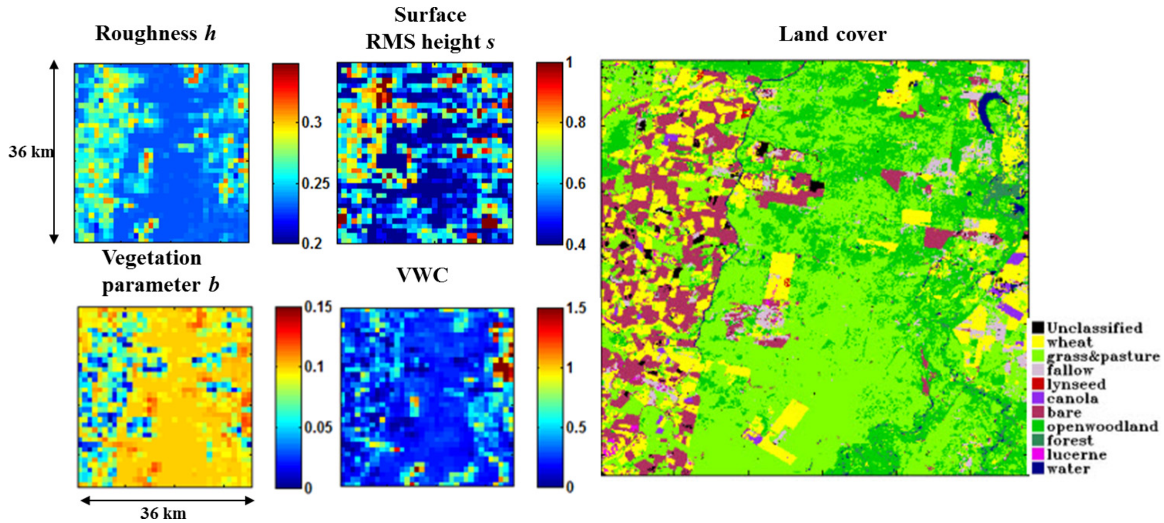

Fig. 1. Spatial distribution of static surface roughness parameter h, surface rms height s and vegetation parameter b; also shown is VWC map on D5 (S eptember 15, 2011) and land cover map of the study area.

campaign was specifically designed to contribute to the development of radar and radiometer soil moisture retrieval algorithms for the SMAP mission. The SMAPEx study site is within a semiarid agricultural and grazing area located in the Murrumbidgee River catchment in South-Eastern Australia (−34.67°N, −35.01°N, 145.97°E, and 146.36°E), and forms part of the greater Murray-Darling basin. A general description of the SMAPEx study area and monitoring activities can be found in [12], with details of the experiments available in the experiment plans on the SMAPEx website (www.smapex.monash.edu.au).

The SMAPEx field site was selected due to its relatively flat topography, widely distributed *in situ* soil moisture monitoring stations, and representation of soil, vegetation, and land-use conditions typically of semiarid environments. The total study area for SMAPEx-3 covered by the airborne observations corresponded in size to an SMAP-sized radiometer footprint (approximately 36 km × 38 km at such latitude).

Data for this paper include: airborne observations, i.e., 1-km resolution brightness temperature (Tb) at h- and v-pol from the Polarimetric L-band Multibeam Radiometer (PLMR), 10-m resolution radar backscatter (σ) at hh-, vv-, and hv-pol from the Polarimetric L-band Imaging SAR (PLIS), and ancillary ground data. The airborne data have been processed in terms of calibration, aggregation, and angle normalization so as to provide a prototype SMAP data set [13]. Ultimately, σ at 1 km was used to downscale Tb at 36- to 9-km medium resolution. The evaluation of the downscaling algorithms was performed over the nine days of airborne observations from SMAPEx-3.

Apart from the airborne data, ground data were used for background soil moisture retrieval from radar and radiometer observations alone, and for forward modeling of backscatter and Tb from a given soil moisture. The ancillary data, mainly, including the surface roughness parameter h, surface root-mean-square (rms) height s, vegetation water content (VWC), vegetation parameter b depending on vegetation type, surface temperature T_{surf}, canopy temperature T_{veg}, sand/clay fraction, soil bulk density, incidence angle, and single scattering albedo ω have been obtained from [14]. Due to the limited ground sampling, those parameters covering the entire 36 km × 36 km SMAPEx site were obtained by aggregating small-scale data resampled to the larger scale, as in [14]. Surface roughness and vegetation parameters were assumed constant through time due to the short period considered here. Although, in reality, those parameters would have varied spatially and temporally, which may affect the accuracy of soil moisture retrievals, however, this is considered marginal in this case, as there was no targeted agricultural activity in the region during this period. Spatial distribution of static surface roughness parameter h, surface rms height s, vegetation parameter b, and an example of VWC on September 15, 2011 are shown in Fig. 1. Other parameters relating to soil moisture retrieval models mainly include: sand fraction = 0.31, clay fraction = 0.25, soil bulk density = 1.3 (g/cm^3), and single scattering albedo $\omega = 0.1$, assuming the same surface conditions across the entire site. Errors involved in aggregating single-point parameters to large scale and the assumption of constant surface conditions may reduce the accuracy of the final downscaled soil moisture products.

Importantly, radiometer and radar retrieval use different roughness parameters, being surface roughness h and rms height s, respectively, as shown in Fig. 1. The roughness parameter required for the radar retrieval model can be obtained either from 1) the rms height map as shown in Fig. 1, derived from interpolation of point sampled rms height for each 1-km pixel according to field measurements and a land use map; or from 2) the relationship with the surface roughness parameter h used in the passive retrieval, being approximately 2.6 times h [15]. Both options have been tested, with the former showing poorer results in terms of the accuracy of radar retrieval, probably due to the uncertainties involved in the estimation of 1-km resolution rms height from the limited point sampled data. Therefore, s was estimated as 2.6 times h

in this paper, for the purpose of radar retrieval and backscatter prediction.

III. Methodology

The Bayesian merging method is briefly stated here with details available in [11]. The optimal estimates of soil moisture $\theta(F)$ at fine resolution "F" (1 km, 3 km or 9 km resolution in this paper) can be derived from an initial estimate of the background soil moisture θ_b, updated according to the difference between the observations Z and predicted observation $h([\theta_b])$ through the Kalman filter state update equation [16]

$$[\theta(F)] = [\theta_b] + [K] \times \{[Z] - h([\theta_b]) \tag{1}$$

which is effectively an implementation of Bayes' Theorem. When applied to the SMAPEx area, $[\theta\ (F)]$ is the vector of final retrieved soil moisture at each 1-km pixel across the entire 36 km $\times$ 36 km area, and $[\theta_b]$ is the vector of background soil moisture for each 1-km pixel across the entire SMAP footprint. In this application, the background is taken as the soil moisture retrieved from either Tb_h at 36-km resolution using the single-channel passive microwave retrieval method [17] as a spatially uniform field, or from the 1-km resolution PLIS backscatter using the single-channel active microwave retrieval method, based on Oh's model [18]. Both alternative background soil moisture sources are tested in later Sections IV-A and IV-B. The vector $[Z]$ contains the observations of Tb_h and Tb_v at 36-km resolution, and σ_{hh}, σ_{vv}, and σ_{hv} at 1-km resolution. The observation function $h([\theta_b])$ provides the predictions of Tb and backscatter from the radiometer and radar forward models for a vegetation-covered soil using the background soil moisture θ_b on the 1-km resolution grid. The matrix $[K]$ is the Kalman gain based on the uncertainties of the background states and observations through

$$[K] = [P][H^T]/([H][P][H^T] + [R]) \tag{2}$$

where $[P]$ represents the error covariance matrix of the background soil moisture field. In this paper, it is estimated by comparing the reference soil moisture [13] to the background soil moisture $[\theta_b]$, or as the difference between the two alternative background fields, from radar and radiometer, as shown in later Sections IV-A and IV-B. The results from both approaches are compared with the purpose to identify a practical way of estimating $[P]$ operationally. $[R]$ is the observation error covariance matrix based on the instrument characteristics and data processing accuracy, especially the accuracy of calibration and incidence angle normalization, as seen in [13]. $[H]$ is the linearized observation operator, which is the first derivative (Jacobian) of $h([\theta_b])$ obtained from

$$[H] = \delta h([\theta_b])/\delta[\theta]. \tag{3}$$

The observation vector $[Z]$ contains two 36-km brightness temperatures (at h- and v-pol) and three backscatter observations (at hh-, vv-, and hv-pol) for each 1 km $\times$ 1 km pixels; a total of 3890 observations across the entire area. Each vector/matrix can be written as

$$[Z] = [\mathrm{Tb}_h \quad \mathrm{Tb}_v \quad \sigma_{\mathrm{hh},1} \quad \sigma_{\mathrm{vv},1} \quad \sigma_{\mathrm{hv},1} \quad \ldots \quad \sigma_{\mathrm{hh},1296} \quad \sigma_{\mathrm{vv},1296} \quad \sigma_{\mathrm{hv},1296}]^T_{3890\times 1} \tag{4}$$

$$h([\theta]) = [\mathrm{Tb}_h(\theta_b) \quad \mathrm{Tb}_v(\theta_b) \quad \sigma_{\mathrm{hh},1}(\theta_b) \quad \sigma_{\mathrm{vv},1}(\theta_b) \quad \sigma_{\mathrm{hv},1}(\theta_b) \quad \ldots \quad \sigma_{\mathrm{hh},1296}(\theta_b) \quad \sigma_{\mathrm{vv},1296}(\theta_b) \quad \sigma_{\mathrm{hv},1296}(\theta_b)]^T_{3890\times 1} \tag{5}$$

$$[H] = \begin{bmatrix} \delta\mathrm{Tb}_h/\delta\theta_{f,1} & \cdots & \delta\mathrm{Tb}_h/\delta\theta_{f,1296} \\ \vdots & \ddots & \vdots \\ \delta\sigma_{\mathrm{hv},1296}/\delta\theta_{f,1} & \cdots & \delta\sigma_{\mathrm{hv},1296}/\delta\theta_{f,1296} \end{bmatrix}^T_{3890\times 1296}. \tag{6}$$

In (4)–(6), 1296 is the number of 1 km $\times$ 1 km pixels across the site and 3890 is the total number of observations: one Tb observation at each of h- and v-polarizations and 1296 backscatter observations at each of hh-, vv-, and hv-polarization. The background soil moisture estimated from 36-km radiometer is then compared with the soil moisture inversed from 1-km radar backscatter to evaluate its error covariance. Therefore, the 1296 diagonal elements of matrix $[P]$ were assigned the error covariance of the background soil moisture with the off-diagonal elements set to be zero, assuming that each 1-km pixel has uncorrelated soil moisture errors. This assumption is appropriated as the noise levels contained in radar backscatter and ancillary data can be treated as uncorrelated at the 1-km resolution. The 3890 diagonal elements of matrix $[R]$ were assigned based on the accuracy of the radiometer and radar observations with the off-diagonal elements again set to be zero, assuming that observation errors were uncorrelated both spatially and between correlations. It is likely that the different polarization Tb and radar observation errors will be correlated. Moreover, the error between radar pixel observations within a radiometer footprint will also be correlated. However, such correlations were not included in the observation error covariance matrix of this demonstration because of the lack of knowledge on the degree of these correlations.

The final downscaled soil moisture field $[\theta\ (F)]$ was evaluated against the 1-km soil moisture reference map derived from the 1-km PLMR [14]. Results of the Bayesian algorithm were also compared to the "best" linear algorithm in [10], and with the soil moisture inversions from 36-km Tb at h-pol (applied to the higher resolution grid as a uniform field) and from 1-km resolution backscatter at hh-pol. Details of those results are shown in Section IV-C.

IV. Results and Discussion

A. Passive-Only and Active-Only Soil Moisture Retrieval

The background soil moisture field can be estimated from direct inversion of either the 36-km radiometer Tb or from the 1-km radar backscatter. Based on the observations and available ancillary parameters stated previously, the 36-km resolution soil moisture was obtained from the 36-km radiometer Tbat h-pol using the single channel $\tau-\omega$ model [17]. The time series of radiometer observations and retrieved soil moisture across the nine days of SMAPEx-3 are found in Table I. Similarly, the background soil moisture field was obtained from the 1-km resolution radar backscatter at hh-pol through the active soil moisture retrieval model as in [11].

An example of radar retrieved soil moisture at 1-km resolution on days D3, D5, and D8 is shown in Fig. 2, where

TABLE I

TIME SERIES OF OBSERVED Tb IN (k) AT h-POL AND v-POL AT 36-km RESOLUTION ACROSS THE NINE DAYS OF SMAPEx-3, AND THE SOIL MOISTURE (cm^3/cm^3) ESTIMATED FROM THE Tb_h VALUES USING THE SINGLE-CHANNEL PASSIVE MICROWAVE RETRIEVAL METHOD. ALSO SHOWN ARE FORWARD MODEL ESTIMATED BRIGHTNESS TEMPERATURES AT 36-km RESOLUTION (FROM RADIOMETER INVERSED BACKGROUND SOIL MOISTURE) AND THEIR FIRST DERIVATIVES (JACOBIAN), AT h-POL AND v-POL AT 36-km RESOLUTION ACROSS NINE DAYS OF SMAPEx-3

	D1	**D2**	**D3**	**D4**	**D5**	**D6**	**D7**	**D8**	**D9**
Observed Tb_h (K)	235	234	230	232	237	240	241	244	244
Observed Tb_v (K)	259	258	252	256	260	261	260	264	264
Estimated Tb_h (K)	230	218	229	231	235	237	238	242	242
Estimated Tb_v (K)	265	256	262	264	267	269	269	272	272
Jacobian of Tb_h (K/(cm^3/cm^3))	-305	-269	-290	-286	-298	-295	-305	-316	-313
Jacobian of Tb_v (K/(cm^3/cm^3))	-188	-190	-188	-181	-181	-177	-181	-180	-178
Background soil moisture (cm^3/cm^3)	0.099	0.094	0.120	0.122	0.095	0.095	0.088	0.074	0.078

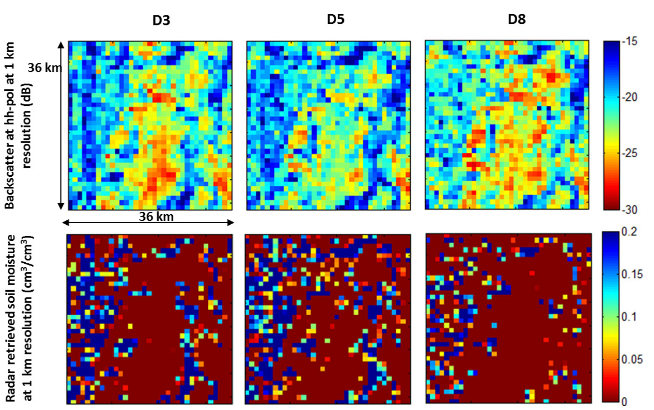

Fig. 2. Radar observations at hh-pol at 1-km resolution on D3, D5, and D8 of SMAPEx-3, together with the soil moisture (cm^3/cm^3) maps retrieved from those radar observations.

a contrast in soil moisture values can be seen between the grassland in the middle area and the cropping land on west and east sides. It should be noted that the accuracy of soil moisture retrieval from radar is highly affected by the surface roughness and vegetation structural parameters. In addition, default parameters relating vegetation and roughness were used during soil moisture retrieval and forward modeling, which may influence the accuracy of retrieval from radar and consequently also affect the accuracy of the downscaled soil moisture. Apart from being taken as the background soil moisture field, these radar and radiometer inversed soil moisture products have also been compared with the downscaled soil moisture obtained from the Bayesian merging algorithm, as shown in later Section IV-C.

B. Selection of the Background Soil Moisture

In order to decide whether the radar or radiometer retrieved soil moisture is more suitable as background soil moisture, a preliminary selection was conducted. During this selection, the radiometer and the radar-derived soil moisture were chosen as the respective background soil moisture fields, and the error covariance $[P]$ of the background soil moisture is obtained from comparison between the background soil moisture and the reference soil moisture, as discussed in the Section IV-A.

The forward model estimate of Tb and σ and their first derivatives (Jacobian) were obtained using the background soil moisture from the radiometer or radar inversion, respectively. The time series of estimated Tb and the associated Jacobians, assuming the radiometer-only 36-km soil moisture product as the background, are shown in Table I across the nine days with an example of estimated σ and the Jacobian on D5 shown in Fig. 3. In this case, the RMSE of the estimated and observed Tb across nine days was found to be 6 K at h-pol and 7 K at v-pol, while the RMSE of the estimated and observed backscatter was around 2.1 dB at hh-pol, 1.6 dB at vv-pol, and 10.1 dB at hv-pol. The time series of estimated Tb and their Jacobians, assuming the radar-only 1-km soil moisture as the background, are shown in Table II across the nine days, with an example of estimated σ and the Jacobian on D5 shown in Fig. 4. Consequently, the RMSE of the estimated and observed Tb across the nine days was around 11 K at h-pol and 13 K at v-pol, being much higher than when using the radiometer retrieved soil moisture as the background. The RMSE of the estimated and observed backscatter was around 3.1 dB at hh-pol, 2.4 dB at vv-pol, and 11.3 dB at hv-pol.

This evaluation was performed on each of the nine flight days of SMAPEx-3, with similar results obtained for each day; day D5 is taken as an example here and shown in Fig. 5. Using

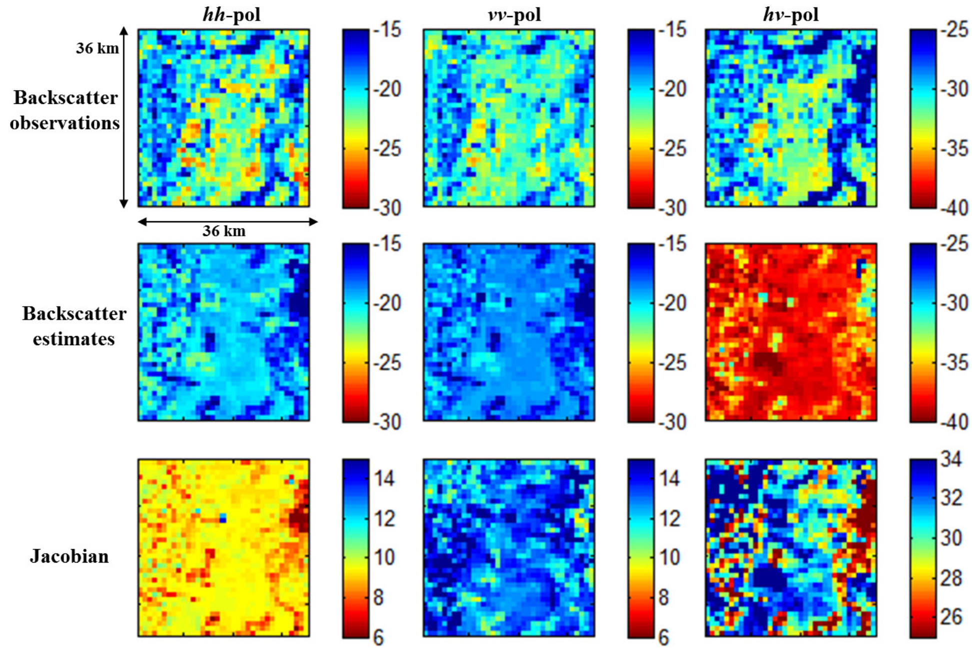

Fig. 3. Example of radar backscatter observations, estimates, and first derivatives (Jacobian) at hh-pol, vv-pol, and hv-pol on D5 (September 15, 2011), using the 36-km resolution background soil moisture derived from the radiometer on D5. Different color-bar scales are used for hh-pol, vv-pol, and hv-pol.

TABLE II

TIME SERIES OF OBSERVED Tb IN (K) AT h-POL AND v-POL AT 36-km RESOLUTION ACROSS NINE DAYS OF SMAPEx-3, AND AVERAGE SOIL MOISTURE (cm^3/cm^3) ESTIMATED FROM RADAR BACKSCATTER (σ_{hh}) USING THE ACTIVE MICROWAVE RETRIEVAL METHOD. ALSO SHOWN ARE FORWARD MODEL ESTIMATED BRIGHTNESS TEMPERATURES (USING SPATIALLY AGGREGATED 1-km RESOLUTION RADAR INVERSED BACKGROUND SOIL MOISTURE) AND THEIR FIRST DERIVATIVES (JACOBIAN), AT h-POL AND v-POL AT 36-km RESOLUTION ACROSS NINE DAYS OF SMAPEx-3

	D1	**D2**	**D3**	**D4**	**D5**	**D6**	**D7**	**D8**	**D9**
Observed Tb_h (K)	235	234	230	232	237	240	241	244	244
Observed Tb_v (K)	259	258	252	256	260	261	260	264	264
Estimated Tb_h (K)	224	225	241	243	240	253	253	257	256
Estimated Tb_v (K)	262	261	269	272	270	278	278	279	279
Jacobian of Tb_h (K/(cm^3/cm^3))	-287	-292	-329	-325	-313	-339	-348	-356	-349
Jacobian of Tb_v (K/(cm^3/cm^3))	-189	-192	-182	-173	-178	-158	-167	-162	-159
Background soil moisture (cm^3/cm^3)	0.124	0.119	0.070	0.068	0.081	0.047	0.046	0.035	0.04

the radiometer retrieved soil moisture as the background; the RMSE against the reference was 0.025 cm^3/cm^3 at 1-km resolution. In terms of the correlation between downscaled and reference soil moisture, the R^2 approximated to 0.85. In contrast, when using radar retrieved soil moisture as the background, the resulting RMSE against the reference was 0.145 cm^3/cm^3 and the R^2 in this case was around 0.06. Results on other days were similar to those on D5, indicating that the use of soil moisture obtained from radiometer observations as the background had much better results on the accuracy of downscaled soil moisture than the use of soil moisture products retrieved from radar as the background. The main reason for the poor results using radar-only soil moisture as the background could be attributed to the poor background soil moisture field from the use of default ancillary parameters during retrieval and forward estimation. Therefore, based on this comparison of using radar and radiometer retrieved soil moisture individually as the background, the use of radiometer

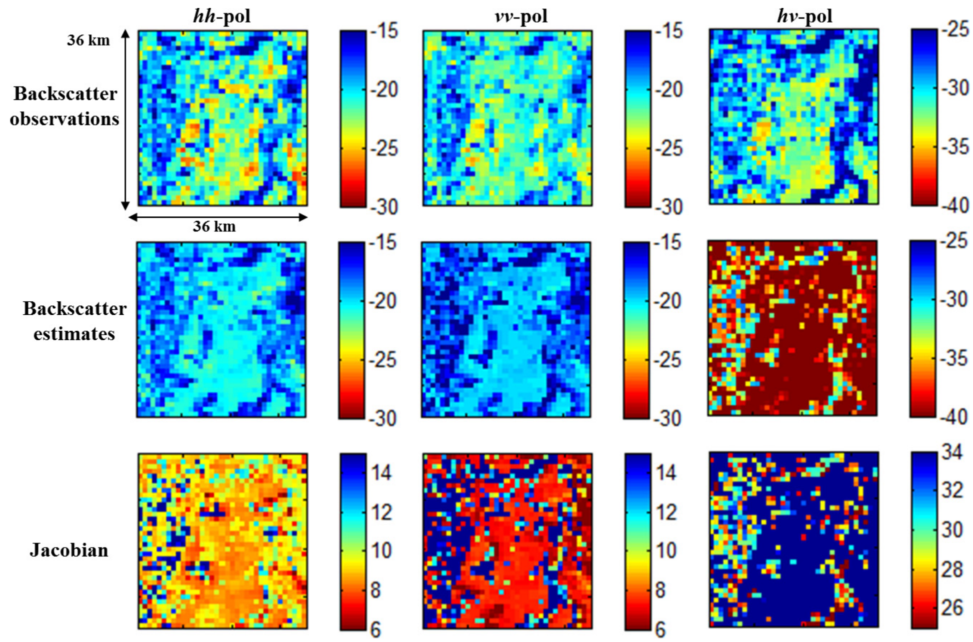

Fig. 4. Example of radar observations, backscatter estimates, and the first derivatives (Jacobian) at hh-pol, vv-pol, and hv-pol on day D5 (September15, 2011), using 1-km resolution background soil moisture from radar on D5. Different color-bar scales are used for hh-pol, vv-pol, and hv-pol.

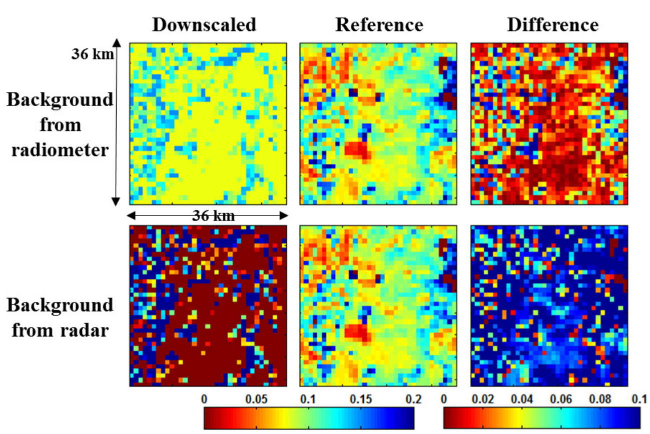

Fig. 5. Comparison of downscaled soil moisture on D5 (September 15, 2011) from different backgrounds, i.e., either the 36-km resolution soil moisture inversed from PLMR Tb, or 1-km resolution soil moisture inversed from PLIS backscatter. Downscaled results are evaluated against the reference soil moisture retrieved from 1-km resolution PLMR Tb single-channel retrieval.

inversion was selected for further evaluation of the Bayesian method.

C. Downscaled Results of the Bayesian Merging Method

The radiometer retrieved soil moisture was selected as the background soil moisture field, upon which the predictions of the Tband backscatter values were obtained. As for the error covariance $[P]$ of the background soil moisture, it was obtained from comparing the radiometer and radar-only retrieved soil moisture, as the true soil moisture is not available in terms of application to SMAP. The $[P]$ estimated in this way was then compared to the "true" $[P]$, estimated from the difference between background and reference soil moisture maps. Across nine days of SMAPEx-3, the average RMSE of the estimated and "true" diagonal elements of $[P]$ differed by 0.04 $(\text{cm}^3/\text{cm}^3)^2$. While the following downscaling results are based on the estimated $[P]$, as the true soil moisture at fine resolution is not available in an operational SMAP application, results are compared with those based on the "true" diagonal elements of $[P]$ so as to evaluate the impact on the downscaling accuracy.

The downscaled soil moisture at 1-km resolution was obtained for each of nine days through the Bayesian merging method. Results at other resolutions (i.e., 3 and 9 km) were also obtained using two methods: 1) by linearly aggregating the downscaled 1-km soil moisture to 3 and 9 km, respectively; or 2) by directly using the 3- or 9-km resolution radar observations rather than the 1-km resolution radar observation as the input. Both methods have been conducted with a minor difference in the accuracy of downscaled soil moisture, being less than 0.002 cm^3/cm^3 at 9-km resolution. Consequently, all of the figures and statistics shown here are from linear aggregation.

Three days, including D3, D5, and D8, were chosen from the full nine days experiment period as an example of the downscaling results. Day D3 represented the "wet" condition as a raining event happened during the first couple of days, D8 represented the "dry" condition after a drying-down period, and D5 was selected to represent the status in between. Results on those three days are shown in Figs. 6–8; water-bodies were removed prior to conduct the downscaling procedure.

By comparing the downscaled soil moisture to the reference soil moisture map, it is noted that the error of downscaling was greater in the eastern and western areas than in the middle of the SMAPEx site, probably due to the effect from different land cover types. The eastern and western areas were dominated by cropping which had various conditions in terms

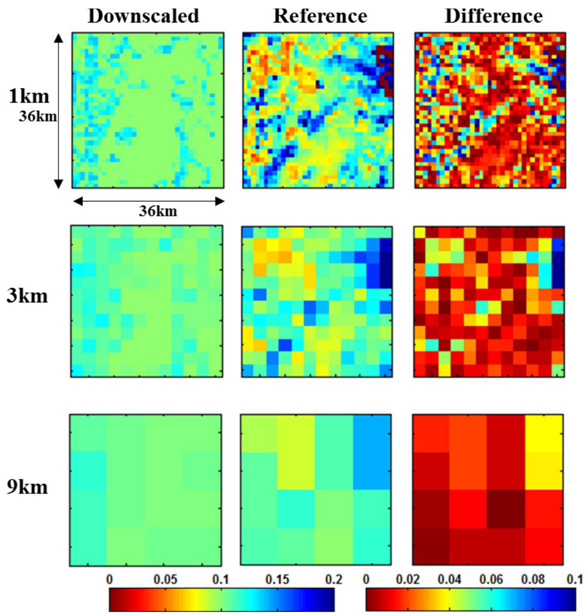

Fig. 6. Comparison of downscaled soil moisture maps (cm^3/cm^3) from the Bayesian merging algorithm and the reference at different resolutions (1, 3, and 9 km). Data were collected on D3 (September 10, 2011) of SMAPEx-3. Pixels in black at1-km resolution in the northeast of the reference map are the water-bodies which have been removed prior to conducting the downscaling algorithm. Also shown is the absolute difference for each pixel by comparing the downscaled soil moisture and the reference soil moisture.

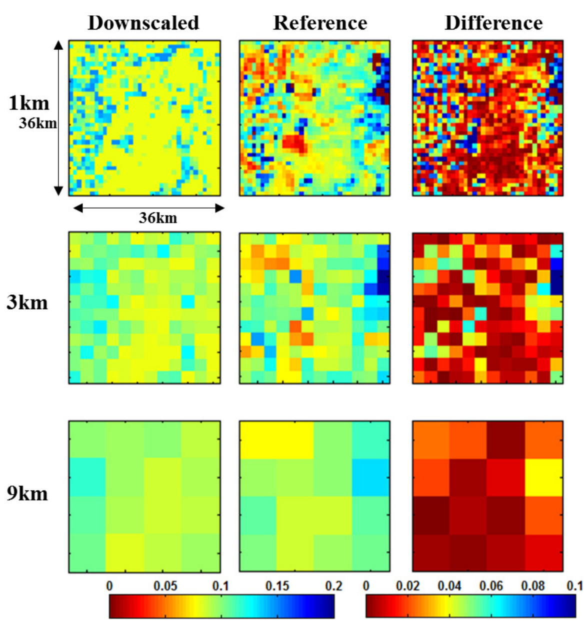

Fig. 7. Comparison of downscaled soil moisture maps (cm^3/cm^3) from the Bayesian merging algorithm and the reference at different resolutions (1, 3, and 9 km). Data were collected on D5 (September 15, 2011) of SMAPEx-3. Pixels in black at1-km resolution in the northeast of the reference map are the water-bodies which have been removed prior to conducting the downscaling algorithm. Also shown is the absolute difference for each pixel by comparing the downscaled soil moisture and the reference soil moisture.

of vegetation types, heights, VWC, biomass, and roughness, while the middle area was mainly occupied by relatively homogeneous grassland with more uniform surface conditions. As radar retrievals and the prediction of observations were

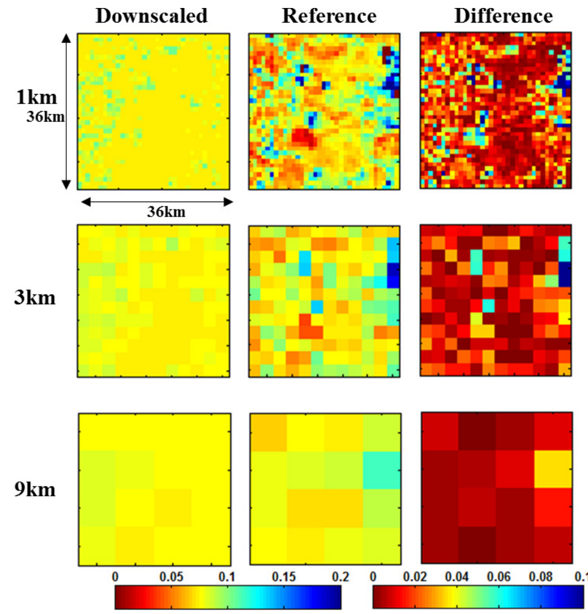

Fig. 8. Comparison of downscaled soil moisture maps (cm^3/cm^3) from the Bayesian merging algorithm and the reference at different resolutions (1, 3, and 9 km). Data were collected on D8 (September 21, 2011) of SMAPEx-3. Pixels in black at1-km resolution in the northeast of the reference map are the water-bodies which have been removed prior to conducting the downscaling algorithm. Also shown is the absolute difference for each pixel by comparing the downscaled soil moisture and the reference soil moisture.

affected more by the cropping than grassland area, the accuracy of the distribution of soil moisture retrieved from radar across the entire site was hampered by the heterogeneity in vegetation. However, the influence from the surface conditions was lowered when aggregated to larger scale, as the variations in the vegetation and surface roughness were smoothed out by averaging the pixels at 1- to 3- and to 9-km resolution. Consequently, the error of downscaling reduced from 1 to 9 km. By comparing the pattern in the downscaled soil moisture map to the pattern in the reference map it was found that results on D3 was poorest in terms of pattern matching among those three days. The reference map at 1-km resolution in Fig. 6 had higher soil moisture content, not only in the cropping areas but also shown in a strip spreading from the Left-bottom corner to the center of the SMAPEx site, because of rain in that area. However, the downscaled result in Fig. 6 could not capture this soil moisture pattern. In contrast, results on D5 and D8 showed better pattern match than D3, mainly because heterogeneity in soil moisture across the entire site is reduced.

By comparing the results for D5 in Figs. 5 and 7 based on different $[P]$, the RMSE of downscaled soil moisture at 1-km resolution was around 0.020 cm^3/cm^3 in Fig. 5 when using the "true" $[P]$ and 0.043 cm^3/cm^3 in Fig. 7 when using the approximate $[P]$. The latter had a higher error due to the poorer estimation of $[P]$. Consequently, it is expected that more accurate estimation of $[P]$, including correct consideration of the correlations would contribute to better downscaled results. Results on other days can be found in Table III, from which it is noted that the RMSEs based on the "true" $[P]$

TABLE III

RMSE (cm^3/cm^3) OF DOWNSCALED SOIL MOISTURE FROM THE DIFFERENT DOWNSCALING METHODS ACROSS THE NINE DAYS (D1 TO D9) OF SMAPEX-3 AT 1-, 3-, AND 9-km RESOLUTION. * BAYESIAN DOWNSCALING RESULTS BASED ON THE "TRUE" ERROR COVARIANCE [P]

Algorithm	Resolution	D1	D2	D3	D4	D5	D6	D7	D8	D9	Average
Bayesian	1km	0.048	0.059	0.059	0.062	0.043	0.045	0.046	0.048	0.041	0.050
	3 km	0.038	0.046	0.039	0.039	0.029	0.031	0.026	0.029	0.026	0.034
	9 km	0.026	0.030	0.024	0.027	0.017	0.020	0.009	0.017	0.013	0.020
Bayesian*	1km	0.018	0.022	0.022	0.022	0.020	0.016	0.015	0.018	0.018	0.019
	3 km	0.016	0.021	0.017	0.016	0.017	0.015	0.015	0.016	0.016	0.017
	9 km	0.013	0.020	0.011	0.012	0.012	0.013	0.012	0.012	0.012	0.013
Optional	1km	0.048	0.053	0.047	0.040	0.037	0.040	0.041	0.038	0.032	0.042
	3 km	0.037	0.042	0.035	0.030	0.028	0.025	0.025	0.028	0.022	0.030
	9 km	0.025	0.029	0.025	0.021	0.018	0.020	0.015	0.019	0.015	0.021
Radiometer retrieval	1km	0.064	0.095	0.059	0.056	0.061	0.056	0.051	0.050	0.052	0.061
	3 km	0.044	0.068	0.04	0.038	0.042	0.037	0.029	0.032	0.033	0.040
	9 km	0.032	0.059	0.025	0.025	0.024	0.022	0.017	0.019	0.020	0.027
Radar retrieval	1km	0.154	0.161	0.146	0.143	0.144	0.129	0.121	0.113	0.115	0.136
	3 km	0.099	0.096	0.091	0.092	0.084	0.083	0.070	0.071	0.069	0.084
	9 km	0.070	0.057	0.064	0.071	0.052	0.065	0.050	0.056	0.053	0.060

are generally lower than those based on the [P] approximated from radiometer and radar retrieved soil moisture, and from all other methods across all nine days. The average RMSE using the "true" [P] was around 0.019 cm^3/cm^3 at 1 km, 0.017 cm^3/cm^3 at 3 km, and 0.013 cm^3/cm^3 at 9 km, respectively, which would be the "best" performance of the Bayesian merging method given that the estimation [P] is improved to be very close to the "true" [P].

According to Table III, the error of downscaling reduced when aggregating from 1 to 9 km, with an improvement in accuracy of around 0.030 cm^3/cm^3. It is also noticed that the error of downscaling reduced, following the drying down from D1 to D9 due to the corresponding decreased heterogeneity of the surface conditions. This is consistent with results found from the other methods, as also shown in Table III. The poorest results were from the radar-only retrieval method, due to the strong influence from vegetation and surface roughness conditions and the poor predictive skill of this model using default parameters. This was followed by the radiometer-only retrieval, which used a uniform soil moisture posting across the entire site. Unsurprisingly, the best downscaling results were found from the more sophisticated downscaling methods that rely upon merging data from the active and passive approaches, with an improvement of approximately 0.01 cm^3/cm^3 over the radiometer-only method and 0.04 cm^3/cm^3 over the radar-only method at 9-km resolution. The optional method and the Bayesian method (when using the approximate [P]) showed minor difference in terms of RMSE, with both being around 0.02 cm^3/cm^3 at 9-km resolution.

Apart from the evaluation on individual days, comparison of these four methods was also conducted by combining all nine days of results, as shown in the scatterplots in Fig. 9. The RMSE indicated in Fig. 9 was calculated by comparing all nine days' time series of downscaled soil moisture with time series of reference soil moisture. The correlation between downscaled soil moisture and reference across nine days, denoted by correlation coefficient R^2, was also studied. Again, the radar-only retrieval method showed the poorest correlation between downscaled and reference soil moisture, confirming that radar alone has little potential to provide a medium-resolution soil moisture product with high accuracy without first making significant improvements to the algorithm and/or its parameterisation. Although the radiometer-only retrieval method had an RMSE close to that of the optional and Bayesian methods, it showed very poor spatial correlation between the downscaled and reference soil moisture, attributed to the fact that the same soil moisture was used at each

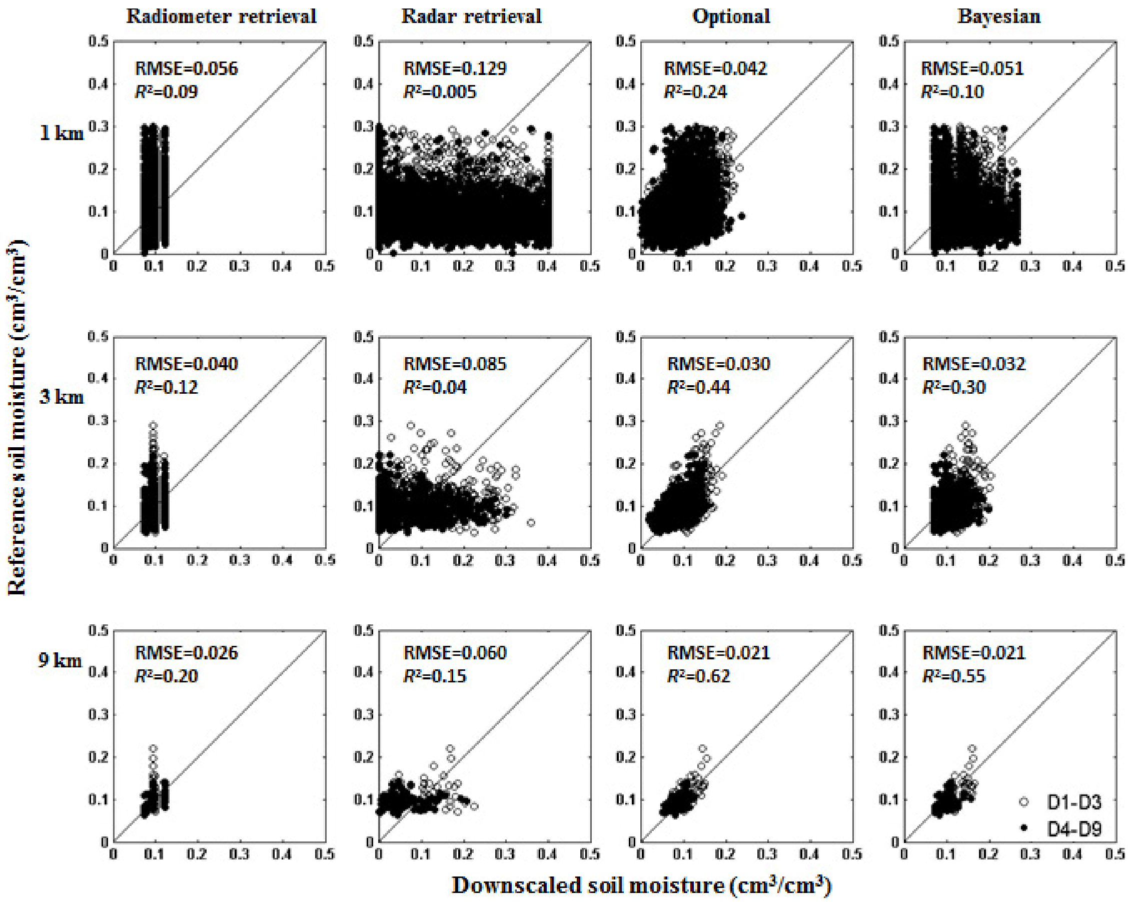

Fig. 9. Scatterplot of the reference and downscaled soil moisture from the radiometer-only retrieval method, radar-only retrieval method, the optional downscaling algorithm for SMAP, and the Bayesian merging method, applied at 1-, 3-, and 9-km resolution. Performance of each method was evaluated in terms of RMSE (cm^3/cm^3) and correlation (R^2) between downscaled and reference soil moisture. Data are from all nine days of SMAPEx-3, with data from Day 1 to Day 3 denoted by open circles, while data from Day 4 to Day 9 are denoted by solid circles.

1 km × 1 km pixel. Therefore, the variation of soil moisture across the entire site was not well captured by the radiometer-only method, with the more sophisticated methods adding considerable spatial skill. In terms of the Bayesian merging method, its downscaled soil moisture at 1-km resolution was found to be poorly related to the reference soil moisture, with this situation improving considerably at 9-km resolution, being similar to the scenario for the optional method. Consequently, the optional and Bayesian merging methods were found to have similar correlation between downscaled and reference soil moisture at 9-km resolution, but the optional method showed a superiority in downscaling soil moisture when applied at higher resolutions. Results from the nine days were divided into two groups (D1–D3 and D4–D9) in order to differentiate the behavior of downscaling algorithm with and without influence from the rain period. As shown in Fig. 9, downscaled soil moisture on D1–D3 were less correlated with the reference than those on D4–D9, due to the more heterogeneous surface conditions on the first couple of days following the rain event.

The RMSE and R^2 for each pixel have also been calculated by using the time series of downscaled soil moisture value and reference soil moisture across the nine days at that pixel. The spatial distribution of RMSE and R^2 for the different methods can be shown in Figs. 10 and 11. In comparison to the other methods, the radar-only retrieval method showed the greatest error and poorest correlation in retrieving medium-resolution soil moisture. The large errors for the radar-only retrieval were expected due to the difficulty associated with the radar inversion modeling.

In terms of the impact from land cover type, the cropping areas had higher RMSE and lower R^2 when compared to the grassland areas, as shown in the downscaled map from the optional method and Bayesian method, due to the strong influence from vegetation and surface roughness on radar observations. But when averaging to larger scale, the difference in RMSE and R^2 across the entire site decreases. Especially at 9 km, the Bayesian downscaling algorithm showed very promising results in terms of RMSE and R^2.

V. Conclusion

The Bayesian merging method was tested for its ability to provide a medium-resolution soil moisture map by using coarse resolution radiometer observations and fine resolution radar observations. The main objective of this paper was to assess this downscaling approach for its application to the SMAP mission, by using realistic experimental data rather than the synthetic data used in its development. The data set used here was from the SMAPEx-3 field campaign in Australia. With the accuracy of the Bayesian merging method

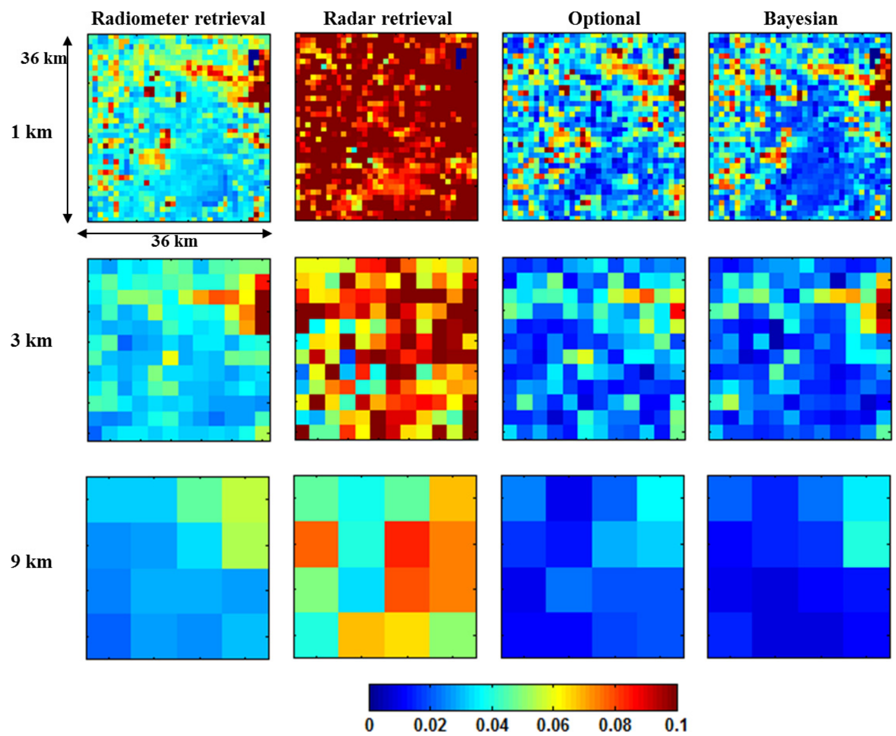

Fig. 10. Spatial distribution of RMSE (cm^3/cm^3) for radiometer-only retrieval method, radar-only retrieval method, the optional downscaling algorithm for SMAP, and the Bayesian merging method across the entire SMAPEx site at 1-, 3-, and 9-km resolution, respectively. RMSE for each pixel was calculated from the downscaled soil moisture and the reference soil moisture at this pixel across nine days of SMAPEx-3.

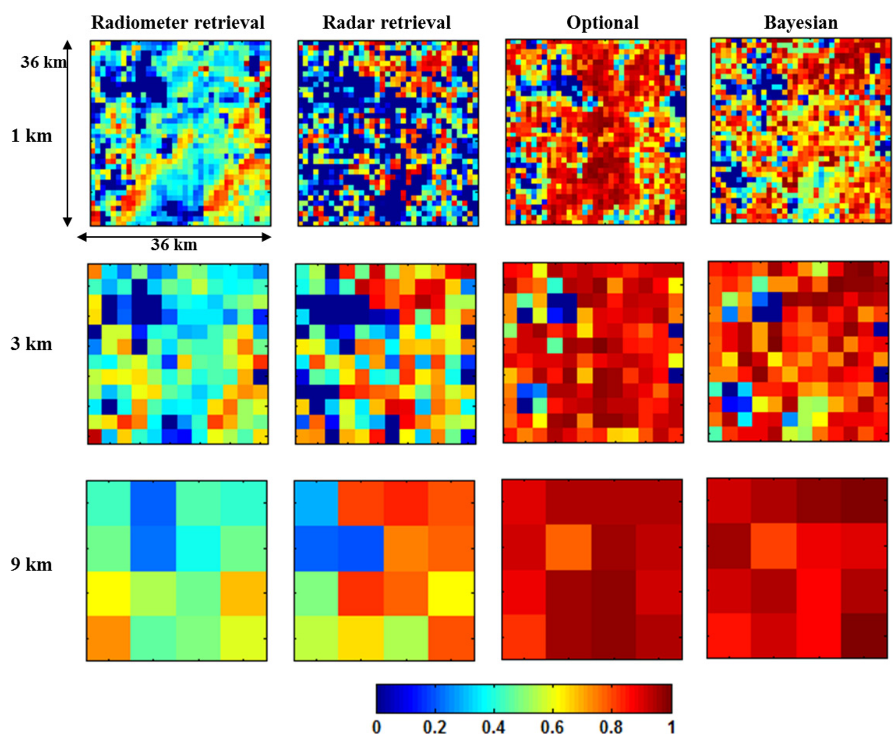

Fig. 11. Spatial distribution of correlation coefficient (R^2) for radiometer-only retrieval method, radar-only retrieval method, the optional downscaling algorithm for SMAP, and the Bayesian merging method across the entire SMAPEx site at 1-, 3-, and 9-km resolution, respectively. R^2 for each pixel was calculated from the downscaled soil moisture and the reference soil moisture at this pixel across nine days of SMAPEx-3.

affected by the accuracy of soil moisture retrieval from fine resolution radar observations, it is expected that a better radar retrieval algorithm would likely improve the Bayesian method performance.

In comparison with other medium-resolution soil moisture retrieval methods, this nonlinear Bayesian merging method had similar results in terms of RMSE and correlation R^2 at 9-km resolution as the "best" linear downscaling algorithms tested in [10], and had much better results than radar-only or radiometer-only retrieval methods. The main limitation of the Bayesian method was the use of default parameters involved in the radar retrieval model. Accordingly, it is expected that by using an improved radar model the Bayesian merging method will have great potential to retrieve more accurate soil moisture at medium resolution then the alternative methods proposed at present.

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