Disaggregation as a top-down approach for evaluating 40 km resolution SMOS data using point-scale measurements: Application to AACES-1

Olivier Merlin*[a], Christoph Rüdiger[b], Philippe Richaume[a], Ahmad Al Bitar[a], Arnaud Mialon[a], Jeffrey P. Walker[b], Yann Kerr[a]

[a]Centre d'Etudes Spatiales de la Biosphère (CESBIO), 18 Ave. Edouard Belin, 31401 Toulouse, France;

[b]Department of Civil Engineering, Monash University, Clayton, Victoria 3800, Australia

ABSTRACT

The SMOS (Soil Moisture and Ocean Salinity) satellite provides soil moisture data at about 40 km resolution globally. Validation of SMOS data using in situ measurements is complicated due to the large integrated scale of remote sensing observations. Nevertheless, different approaches can be used to circumvent the direct comparison. One is to upscale ground measurements using aggregation rules. Another is to downscale (or disaggregate) remote sensing data at the representativeness scale of ground measurements. This study combines both approaches to make ground and remote sensing data match at an intermediate spatial scale. On one hand, the local-scale in situ soil moisture data collected during the first AACES (Australian Airborne Calibration/validation Experiments for SMOS) are aggregated to 4 km resolution. On the other hand, a disaggregation methodology of SMOS data based on 1 km resolution MODIS (MODerate resolution Imaging Spectroradiometer) data is implemented at 4 km resolution over the Murrumbidgee catchment, the site of the AACES campaign. Results indicate a correlation coefficient between disaggregated and ground observations of 0.92. The y-intercept of the linear regression between disaggregated and ground observations is very close to 0. However, the slope of that line is 0.44 only. This seems to highlight an issue with either the dielectric constant model or the roughness parameter value currently used in the SMOS retrieval algorithm.

Keywords: SMOS, AACES, soil moisture, calibration/validation, disaggregation, downscaling, field experiment

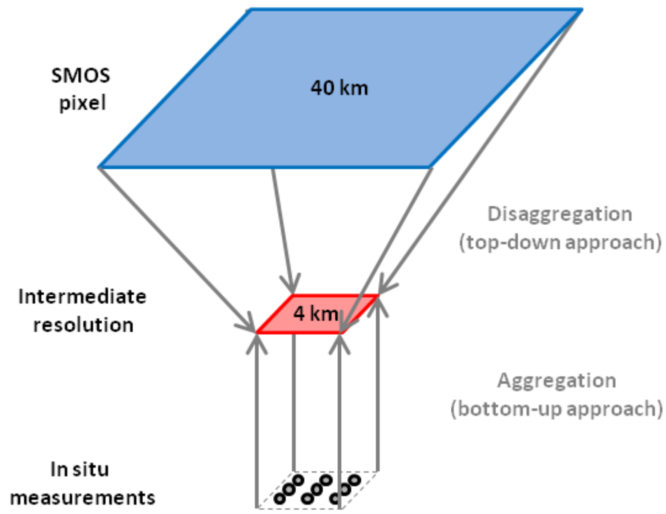

Figure 1. Proposed approach for calibrating/validating SMOS data using ground measurements.

*olivier.merlin@cesbio.cnes.fr; phone 33 5 61 55 66 38

1. INTRODUCTION

Passive microwave remote sensing has the capability to provide key elements of the global environment. Nevertheless, the link between remote sensing observations (electromagnetic waves) and biophysical variables (such as soil and vegetation characteristics) is relatively indirect. Therefore, radiative transfer models must be calibrated and validated beforehand. One difficulty in calibrating/validating retrieval algorithms in the passive microwave domain is the coarse resolution of current spaceborne observations, which typically ranges from 40 to 100 km. Comparison of such data with local in situ measurements still represents a challenge, especially over heterogeneous manned and natural land surfaces.

The SMOS (Soil Moisture and Ocean Salinity, Kerr et al., 2010 [4]) satellite was launched on November 2, 2009. Over land, the SMOS mission aims at providing surface soil moisture data at a spatial resolution better than 50 km and a repeat cycle of less than 3 days. The payload is a 2-D interferometer equipped with 69 elementary L-band antennas regularly spaced along Y-shaped arms. This entirely new concept allows observing any pixel in the 1000 km wide field of view from a range of incidence angles. It also allows reconstructing brightness temperatures on a fixed sampling grid.

Since the SMOS launch, various field experiments have been undertaken to calibrate the SMOS algorithms and evaluate reconstructed brightness temperatures and retrieved soil moisture. The AACES (Australian Airborne Calibration/validation Experiment for SMOS, Peischl et al., 2009 [12]) is the most comprehensive campaign series world-wide dedicated to SMOS calibration/validation. Two one-month long experiments are planned in the Austral summer and winter 2010, the former having been conducted in January/February 2010. The data collected in each AACES campaign include 1 km resolution airborne brightness temperature mapped over a 100 km by 500 km area, and thirteen days of extensive ground measurements.

This study develops a methodology to facilitate the calibration/validation of SMOS data using local-scale ground measurements such as those collected during AACES. As illustrated in Figure 1, the methodology combines top-down and bottom-up approaches to make remote sensing and in situ data match at an intermediate spatial scale of 4 km. The key step in the procedure is a disaggregation method of 40 km resolution SMOS soil moisture at 4 km resolution using 1 km resolution MODIS (MODerate resolution Imaging Spectroradiometer) data (Merlin et al., 2008 [6]).

2. DATA COLLECTION AND PRE-PROCESSING

The AACES experiments have been planned to provide ground and airborne soil moisture data during one month over an area of approximately 100 km by 500 km in the Murrumbidgee River catchment, in southeastern Australia. The first AACES campaign was undertaken in summer 2010 from January 18 to February 21 (Peischl et al., 2009 [12]). The same protocol including ground sampling and flight lines will be repeated in the following Austral winter to collect soil moisture data during the two main seasons. Figure 2a presents the 240 km by 600 km study area including the twenty ground sampling locations (5 km by 2 km extent, oriented along the flight track). The background image is the MODIS 250 m resolution 16-day NDVI product of February 2. The climate of the Murrumbidgee catchment area ranges from semi-arid in the west to alpine in the east, with a strong rainfall and potential evapotranspiration gradient in the west-east direction. Figure 2b gives an overview of a 40 km resolution grid similar to the SMOS observation grid overlaid with an intermediate (4 km) resolution grid and the ground sampling areas.

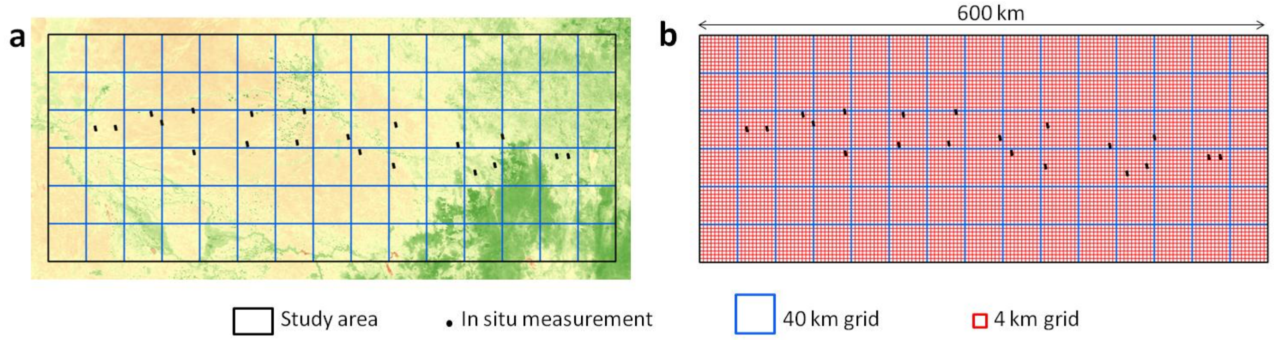

Figure 2. Overview of the AACES-1 ground sampling locations overlaid with 40 km (SMOS) and 4 km (disaggregation) resolution grids.

2.1 HDAS

During AACES-1, a spatially enabled platform (Hydraprobe Data Acquisition System, HDAS) was used to collect extensive measurements of near-surface soil moisture. HDAS is a handheld system integrating the soil dielectric sensor and a pocket PC with GPS receiver allowing for direct storage of location and measurement with GIS software. HDAS measurements were calibrated using the approach presented in Merlin et al., 2007 [5] with an error estimated to about 0.03 vol./vol..

Table 1 lists the thirteen dates of ground sampling. On each date, two different areas were sampled along transects every 50 m. A total of six adjacent 5 km long transects separated by 330 m were walked to cover each area of 10 km^2. Three separate HDAS measurements were made at each node of the sampling grid in order to limit observational errors.

In this study, HDAS soil moisture data are aggregated at 4 km resolution by averaging all measurements made within each pixel of the intermediate resolution grid.

Table 1. Overpass time of SMOS and MODIS on each of the thirteen sampling days when data are usable (successful retrievals for SMOS, and cloud free conditions for MODIS). It is also indicated whether the areas covered by ground sampling and both instruments are overlapping.

Ground sampling date	**Day of Year 2010**	**SMOS data collected at**	**Cloud free MODIS data collected at**	**HDAS, SMOS level 2 and cloud free MODIS data are overlapping**
January 20	20	6 pm	10 am and 1 pm	Yes
January 22	22	6 am	10 am	No
January 25	25	6 pm	10 am and 1 pm	Yes
January 28	28	6 am and 6 pm	10 am	Yes
January 30	30	6 am	10 am	Yes
February 2	33	-	-	-
February 5	36	-	-	-
February 7	38	6 am	10 am	No
February 10	41	-	-	-
February 12	43	-	-	-
February 15	46	6 am	1 pm	Yes
February 18	49	6 am	1 pm	Yes
February 21	51	6 am and 6 pm	10 am	No

2.2 SMOS

SMOS has a 6 am (ascending) and 6 pm (descending) equator crossing time. Table 1 lists the overpass time of SMOS on the thirteen ground sampling dates. No time is indicated when no SMOS level 2 soil moisture product is available.

The sampling grid of the SMOS level 2 soil moisture product is called DGG as Discrete Global Grid (Kerr et al., 2008 [3]). It has a node separation of about 15 km. This is lower than the mean observation resolution (about 43 km) because SMOS sensor oversamples the observation scene by a factor of about 7. In this study, the disaggregation procedure takes advantage of the oversampling of SMOS data to potentially reduce (and provide an estimate of) random errors in disaggregated SMOS data. Instead of using a single snapshot SMOS image, the algorithm uses five independent snapshots, which are generated by (i) sliding a 40 km resolution grid and (ii) extracting the DGG nodes approximately centered on each 40 km pixel. The extraction of SMOS DGG nodes is presented in the schematic diagram of Figure 3.

The 40 km resolution grid that fits the study area corresponds to Resampling 1. An additional 20 km resolution grid centered on the 40 km resolution grid is overlaid to select the DGG node(s) that fall(s) near the center of the 40 km resolution pixels with a +/- 10 km tolerance. Similarly, Resampling 2, 3, 4 and 5 are performed by sliding the 40 km resolution grid of (-10 km;+10 km), (+10 km; +10 km), (-10 km;-10 km) and (+10 km; -10 km), respectively. The five independent data sets can then be used as input to the disaggregation algorithm.

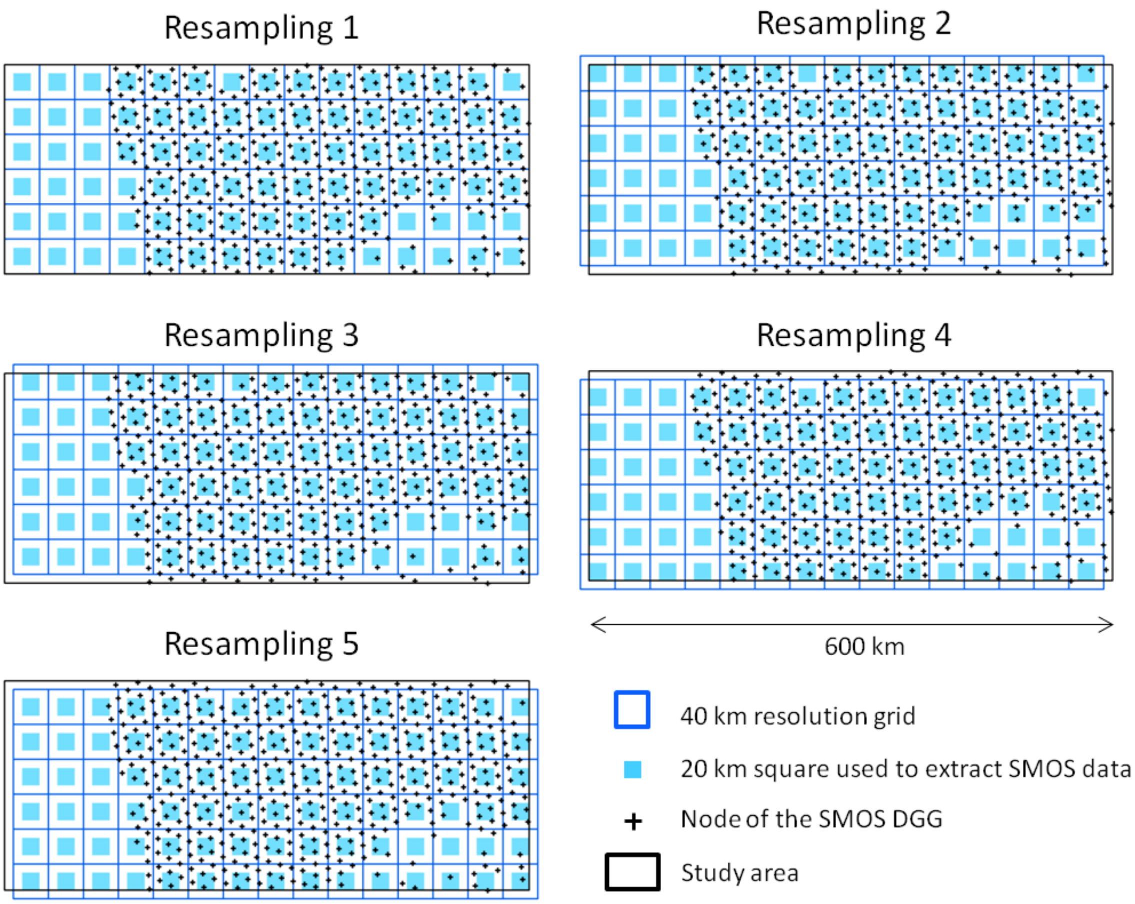

Figure 3. Five independent SMOS snapshot images are generated by extracting the DGG nodes corresponding to five different 40 km resolution grids. Images correspond to ascending data collected on February 18.

2.3 MODIS

The MODIS data used in this paper are the Version 5 MODIS/Terra (10 am) and MODIS/Aqua (1 pm) 1 km resolution daily surface temperature, and MODIS/Terra 1 km resolution 16-day NDVI. The 16-day NDVI product is cloud free. Table 1 lists the overpass time of MODIS on the dates with ground sampling and cloud free conditions within the study area. There are six days with overlapping HDAS, SMOS and cloud free MODIS data. Note that the random uncertainties in MODIS data are accounted for in the disaggregation algorithm. They are reduced by a factor of 4 by aggregating the 1 km resolution MODIS-derived soil moisture proxy at 4 km resolution.

3. DISAGGREGATION ALGORITHM

3.1 Downscaling relationship

The disaggregation approach was developed in Merlin et al., 2008 [6] and improved in Merlin et al., 2010 [9]. The downscaling relationship can be written as

$$\theta_{4\,km} = \theta_{SMOS,\,40\,km} + \left(\frac{\partial \theta_{mod}}{\partial \beta}\right)_{40\,km} \times \left(\beta_{MODIS,\,4\,km} - \left\langle \beta_{MODIS,\,4\,km} \right\rangle_{40\,km}\right) \tag{1}$$

with θ_{SMOS} being the SMOS level 2 soil moisture, β_{MODIS} the MODIS derived soil evaporative efficiency (ratio of actual to potential evaporation), $\langle \beta_{MODIS} \rangle_{40\,km}$ its average within a SMOS pixel and $(\partial\theta / \partial\beta)$ the partial derivative evaluated at SMOS scale of soil moisture with respect to soil evaporative efficiency. MODIS derived soil evaporative efficiency is expressed as

$$\beta_{MODIS,\,4\,km} = \left\langle \frac{T_{smax} - T_{s,1km}}{T_{smax} - T_{smin}} \right\rangle_{4\,km} \tag{2}$$

with T_s being the MODIS derived soil skin temperature, T_{smax} the soil skin temperature at $\beta = 0$ and T_{smin} the soil skin temperature at $\beta = 1$. In this study, T_{smin} is estimated as the minimum MODIS land surface temperature within the SMOS pixel. MODIS derived soil skin temperature is estimated as

$$T_{s,1km} = \frac{T_{MODIS} - f_{1km} \cdot T_{v,1km}}{1 - f_{1km}} \tag{3}$$

with T_{MODIS} being the 1 km resolution MODIS land surface temperature, f the MODIS derived fractional vegetation cover and T_v the vegetation temperature. In this study vegetation temperature is assumed to be uniform and equal to the minimum MODIS temperature observed within the SMOS pixel. Therefore $T_v = T_{smin}$. In Equation (2), T_{smax} is estimated as the maximum soil skin temperature computed in Equation (3) within the SMOS pixel. In Equation (3), fractional vegetation cover is estimated as

$$f_{1km} = \frac{NDVI_{MODIS} - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \tag{4}$$

with $NDVI_{MODIS}$ being the 1 km resolution MODIS NDVI, $NDVI_{min}$ the NDVI corresponding to bare soil and $NDVI_{max}$ the NDVI corresponding to full-cover vegetation. Minimum and maximum NDVI are set to 0 and 1 respectively. Note that the formulation in Equation (4) provides an estimate of the fraction of green (photosynthetically active) vegetation cover and not the total vegetation cover (Merlin et al., 2010 [8]). Consequently, Equation (3) implicitly assumes that the temperature of senescent (photosynthetically inactive) vegetation is equal to T_{smax} and that the evaporative efficiency of the soil underneath full-cover senescent vegetation is zero.

The partial derivative in Equation (1) is estimated using the soil evaporative efficiency model β_{mod} in Noilhan and Planton, 1989 [11]

$$\beta_{mod} = \frac{1}{2}\left[1 - \cos\left(\frac{\theta}{\theta_{fc}}\pi\right)\right] \tag{5}$$

with θ_{fc} being the soil moisture at field capacity. By inverting Equation (5), one obtains

$$\theta_{mod} = \frac{\theta_{fc}}{\pi}\cos^{-1}(1 - 2\beta) \tag{5}$$

In this study, parameter θ_{fc} is calibrated at 40 km resolution from the time series of SMOS soil moisture and aggregated MODIS derived soil evaporative efficiency.

3.2 Algorithm

The disaggregation algorithm consists in (i) calibrating the parameter θ_{fc}, (ii) applying the downscaling relationship of Equation (1) to an ensemble of input data sets (iii) running the disaggregation procedure using each input data set and (iv) averaging the disaggregated soil moisture for all data sets.

The soil moisture at field capacity is estimated by minimizing the difference between the MODIS derived soil evaporative efficiency aggregated at SMOS resolution and the soil evaporative efficiency modeled by Equation (5) using SMOS soil moisture as input. A value of θ_{fc} is obtained on each date when the coverage of SMOS L2 soil moisture product overlaps the coverage of MODIS land surface temperature product. In practice, the calibrated value for each SMOS pixel is set to the temporal average of adjusted daily parameters.

In optimal conditions, an ensemble of 20 independent data sets could be used as input to the disaggregation by considering the five independent extracted SMOS data sets, the two overpass times of SMOS (if available) and the two overpass times of MODIS (if available). However, this case did not occur during AACES-1 with concurrent ground sampling. In addition, separating the different potential error sources (such as overpass times) is an asset for calibration/validation activities. Therefore, on each date with overlapping HDAS, SMOS and cloud free MODIS data, we considered the ensemble composed of the 5 resampled SMOS data sets only.

Finally, the downscaling relationship in Equation (1) is applied to the ensemble of input data sets and the soil moisture disaggregated from the 5 input data sets is averaged on each 4 km resolution pixel within the study area.

4. APPLICATION

As indicated in Table 1, there are six days with overlapping HDAS, SMOS level 2 soil moisture and cloud free MODIS land surface temperature data: February 20, 25, 28 and 30 and February 15 and 18. The disaggregation algorithm is applied on each of these six dates. An example of disaggregated soil moisture image is presented in Figure 4 for data on February 18.

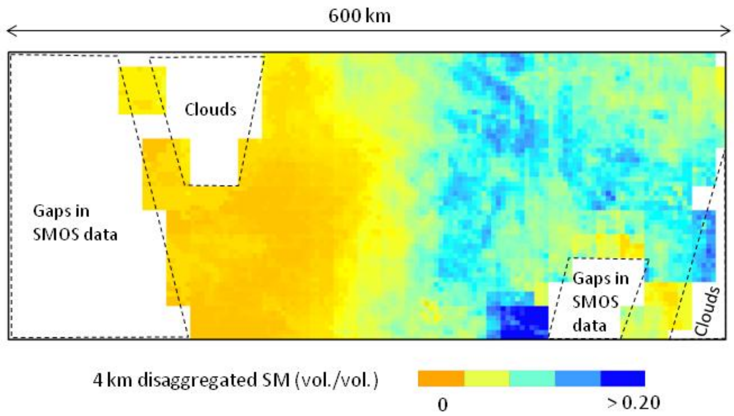

Figure 4. Image of the soil moisture disaggregated at 4 km resolution over the Murrumbidgee catchment for SMOS and MODIS data collected on February 18, 2010.

Although the variability of disaggregated soil moisture is generally smooth at 4 km resolution, a "boxy" artifact is still apparent at 40 km resolution, especially near the edges of SMOS and MODIS overlapping areas. This artifact is probably due to the irregular sampling of SMOS data in these areas. The gaps in the image are attributed to either gaps in SMOS level 2 soil moisture or the presence of clouds. The MODIS image collected on February 18 was mostly cloud free except in the two areas indicated on the map in Figure 4. Gaps in SMOS soil moisture may be due to different reasons: (i) no soil moisture value was retrieved by the SMOS processor or (ii) a non physical value was retrieved and rejected by the processor. In our case, surface conditions were relatively dry and the Dobson model (Dobson et al., 1985 [1]) currently used in the SMOS processor is known to be unstable in dry conditions, especially when applied to sandy soils as those encountered in a large part of southeastern Australia. Although further analysis is required to firmly assess the cause of these gaps, it is anticipated that the replacement of the current dielectric model with the Mironov model (Mironov et al., 2004 [10]) would significantly improve the number of successful retrievals in this area.

Figure 5 plots the disaggregated soil moisture as a function of in situ measurements at the intermediate scale of 4 km. It is apparent that disaggregated soil moisture systematically underestimates HDAS observations. However the correlation between disaggregated and ground soil moisture is 0.92 and the y-intercept of the linear regression is close to zero. Therefore, the mismatch between disaggregated and ground observations is probably due to a slope or sensitivity problem. A number of studies have indicated that soil roughness parameter mainly controls the slope between disaggregated and in situ soil moisture (e.g. Merlin et al., 2009 [7]) and it can compensate the mismatch of sensing depth between an L-band radiometer (about 2 cm) and most ground monitoring devices (about 5 cm) (Escorihuela et al., 2010 [2]). In the current version of the SMOS level 2 processor, the soil roughness parameter noted HR is set to 0.1, which corresponds to a smooth soil. It is anticipated that an increase of HR to about 0.3 would artificially make the slope between disaggregated and in situ soil moisture increase to a value closer to 1. Note that HR is largely empirical and poorly known at 40 km scale. Consequently, it requires to be fitted from data at SMOS resolution. These preliminary results and hypotheses will be investigated again after the release of the next version of the SMOS level 2 processor including Mironov's dielectric constant model.

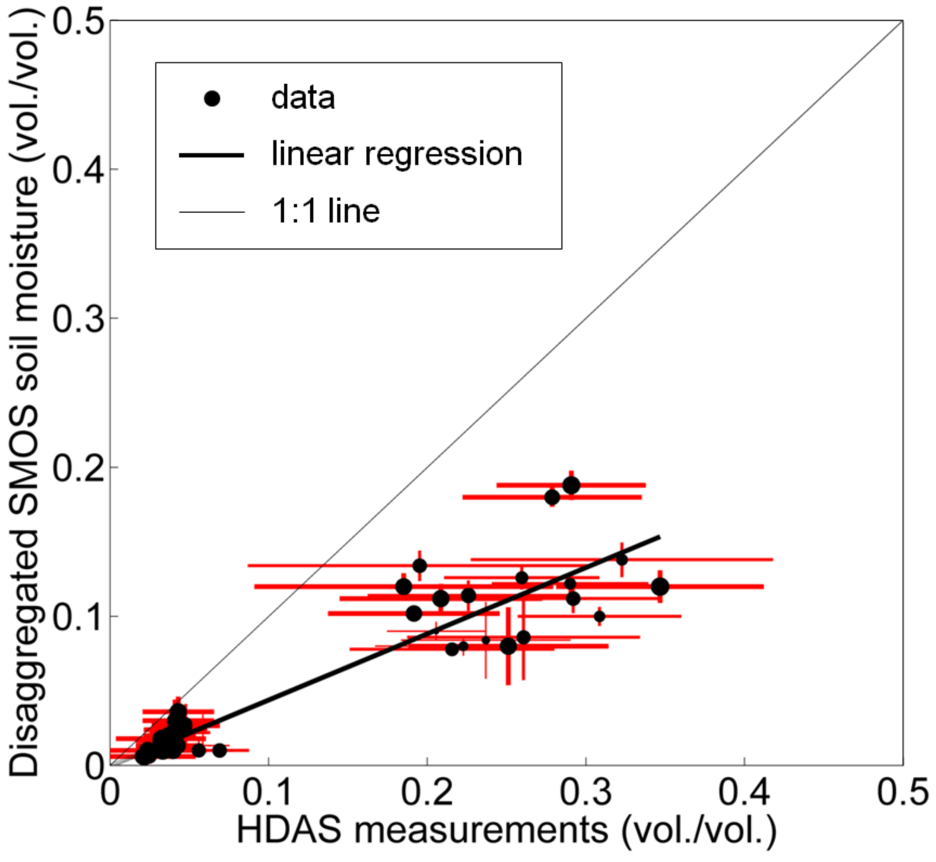

Figure 5. Disaggregated soil moisture is plotted against 4 km resolution aggregated HDAS measurements for data on all dates. Horizontal errorbars represent the standard deviation of ground measurements. Vertical errorbars represent the standard deviation of disaggregated soil moisture within the 5 independent input data sets. The size of makers and errorbars is linked to the number of available HDAS measurements within 4 km pixels.

5. CONCLUSION

A disaggregation methodology is applied to 40 km resolution SMOS data to try and evaluate the level 2 soil moisture product at 4 km resolution using local scale in situ measurements. Very extensive ground measurements were recently made during the first AACES campaign in a 100 km by 500 km area in southeastern Australia. Those measurements were aggregated at the downscaling resolution (4 km) and compared to the disaggregated SMOS soil moisture. Results indicate that the disaggregated soil moisture systematically underestimates ground measurements. However, the correlation coefficient between disaggregated and ground observations is found to be 0.92 with a y-intercept of the linear regression close to zero. It is anticipated that the replacement of the dielectric constant model in the next released version of the SMOS level 2 processor would directly fix this slope problem. Alternatively, an increase of the soil roughness parameter to about 0.3 would artificially make the slope increase to about 1. These results illustrate the usefulness of top-down approaches for evaluating coarse-resolution remote sensing data using ground-based observations.

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