GEOPHYSICAL RESEARCH LETTERS, VOL. 39, L04401, doi:10.1029/2011GL050655, 2012

Assimilation of passive and active microwave soil moisture retrievals

C. S. Draper,[1,2] R. H. Reichle,[1] G. J. M. De Lannoy,[1,2,3] and Q. Liu[1,4]

Received 20 December 2011; revised 18 January 2012; accepted 19 January 2012; published 18 February 2012.

[1] Near-surface soil moisture observations from the active microwave ASCAT and the passive microwave AMSR-E satellite instruments are assimilated, both separately and together, into the NASA Catchment land surface model over 3.5 years using an ensemble Kalman filter. The impact of each assimilation is evaluated using in situ soil moisture observations from 85 sites in the US and Australia, in terms of the anomaly time series correlation-coefficient, R. The skill gained by assimilating either ASCAT or AMSR-E was very similar, even when separated by land cover type. Over all sites, the mean root-zone R was significantly increased from 0.45 for an open-loop, to 0.55, 0.54, and 0.56 by the assimilation of ASCAT, AMSR-E, and both, respectively. Each assimilation also had a positive impact over each land cover type sampled. For maximum accuracy and coverage it is recommended that active and passive microwave observations be assimilated together. **Citation:** Draper, C. S., R. H. Reichle, G. J. M. De Lannoy, and Q. Liu (2012), Assimilation of passive and active microwave soil moisture retrievals, *Geophys. Res. Lett.*, *39*, L04401, doi:10.1029/2011GL050655.

1. Introduction

[2] Root-zone soil moisture is an important control over the partition of land surface energy and moisture, and the assimilation of remotely sensed near-surface soil moisture can improve model profile soil moisture [*Bolten et al.*, 2010; *Liu et al.*, 2011]. To date, efforts to assimilate remotely sensed near-surface soil moisture at large scales have focused on soil moisture derived from the passive microwave Advanced Microwave Scanning Radiometer for the Earth Observing System (AMSR-E) and the active microwave Advanced Scatterometer (ASCAT; together with its predecessors on the European Remote Sensing satellites (ERS)).

[3] The assimilation of passive and active microwave soil moisture data has not yet been directly compared, and so the assimilation of ASCAT and AMSR-E soil moisture, both separately and together, is compared here. The assimilation is performed over 3.5 years with the NASA Catchment land surface model, using an Ensemble Kalman Filter (EnKF). Since the soil moisture retrieval skill from active and passive microwave data is thought to differ according to surface characteristics [*Dorigo et al.*, 2010], the soil moisture skill from each assimilation experiment is assessed according to land cover type, by comparison to in situ soil moisture observations from the US and Australia. The contribution of the model and observation skill to the skill of the assimilation output is also examined.

2. Data and Methods

2.1. Satellite Soil Moisture Data

[4] The ASCAT soil moisture data used here were provided by the Vienna University of Technology. Soil moisture observations are obtained from ASCAT radar backscatter coefficients using the semiempirical change detection approach of *Wagner et al.* [1999, 2010]. This yields an observation of the Surface Degree of Saturation (SDS), which ranges between 0 and 100%, representing the driest and wettest observations at each location, respectively. The ASCAT SDS data relate to soil moisture over a ~1 cm deep surface layer, and have a resolution of approximately 25 km.

[5] For AMSR-E, soil moisture data retrieved by the Free University of Amsterdam from X-band brightness temperatures, using the Land Parameter Retrieval Model (LPRM) [*Owe et al.*, 2001; *de Jeu and Owe*, 2003], were used. The X-band observations have a resolution of 38 km, and relate to a surface layer depth slightly less than 1 cm. An antenna problem has prevented AMSR-E from observing since October 2011, however the LPRM is now being applied to Coriolis WindSat brightness temperatures, yielding similar accuracy as was achieved from AMSR-E [*Parinussa et al.*, 2012].

[6] The ASCAT and AMSR-E soil moisture data were assimilated over the maximum available coincident data record, from January 2007 to May 2010. Using a nearest neighbor approach, the satellite observations were interpolated from their native resolutions to the 25 km land modeling grid used in this experiment (Section 2.3). The quality control applied prior to the assimilation differed for each data set, according to the particularities of passive and active microwave observations, and the ancillary data provided with each. The occurrence of dense vegetation was initially screened using information provided with each data set. For ASCAT the Estimated Soil Moisture Error (ESME) flag includes a signal of dense vegetation, and an upper limit of 14% (in SDS units) for the ESME was applied (V. Naeimi, personal communication, 2011). For AMSR-E a vegetation optical depth upper limit of 0.8 was used [*Owe et al.*, 2001]. Additionally, AMSR-E and ASCAT data were discarded where MODIS land cover data from Boston University [*Friedl et al.*, 2002] indicated forests (> 60% trees or woody vegetation).

[7] Topographic Complexity (TC), defined as the standard deviation of the elevation (at 30 arc-seconds) within a

[1]Global Modeling and Assimilation Office, NASA Goddard Space Flight Center, Greenbelt, Maryland, USA.
[2]GESTAR, Universities Space Research Association, Columbia, Maryland, USA.
[3]Laboratory of Hydrology and Water Management, Ghent University, Ghent, Belgium.
[4]Science Applications International Corporation, Beltsville, Maryland, USA.

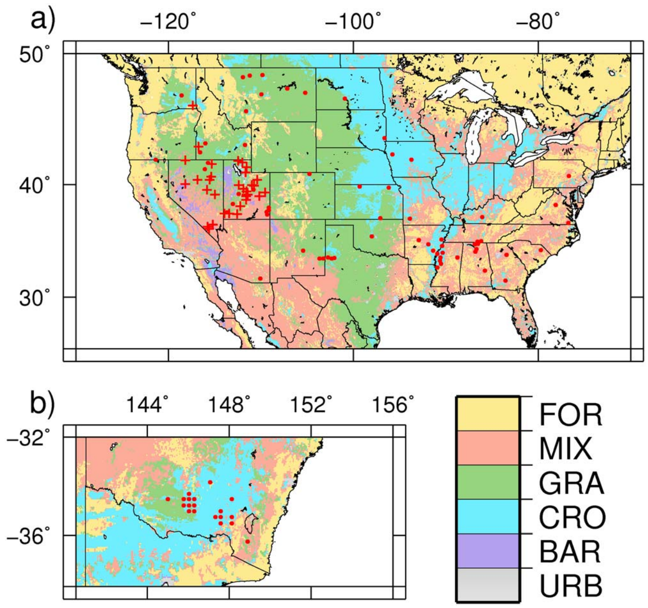

Figure 1. Location of (a) SCAN/SNOTEL and (b) Murrumbidgee monitoring sites used to evaluate satellite and model soil moisture estimates, overlaid with MODIS land cover classes (FORest, MIXed cover, GRAssland, CROpland, BARren, and URBan). Sites with topographic complexity > 10% are shown as crosses.

12.5 km grid cell, normalized between 0 and 100%, is provided with the ASCAT data. ASCAT soil moisture observations in grid cells with TC >10% were discarded, as will be discussed further in Section 3.2. Also, AMSR-E data flagged by the LPRM as having moderate/strong radio frequency interference were discarded. Information on water surfaces is not provided with the LPRM data, and so both ASCAT and AMSR-E were screened to remove grid cells with a wetland fraction (provided with the ASCAT data) above 10%. A final stage of quality control was applied within the assimilation, by discarding all observations where the model indicated a frozen surface, snow cover, or precipitation.

2.2. Evaluation With in Situ Soil Moisture

[8] The impact of assimilating each data set was evaluated using in situ soil moisture data from the United States Department of Agriculture's Soil Climate Analysis Network (SCAN) / Snowpack Telemetry (SNOTEL) [*Schaefer et al.*, 2007] network in the contiguous US, and from the Murrumbidgee Soil Moisture Monitoring Network (available at www.oznet.org.au), operated by the University of Melbourne and Monash University, in southeast Australia. The (modeled and satellite) surface soil moisture was evaluated using in situ observations at 5 cm depth from both networks, while the (modeled) root-zone soil moisture was evaluated using SCAN/SNOTEL observations at 20 cm, and Murrumbidgee observations at 30 cm; these depths were selected to give the best fit to the model root-zone soil moisture temporal dynamics.

[9] For the SCAN/SNOTEL network there were 66 sites with sufficient in situ, ASCAT, and AMSR-E soil moisture data for use in this experiment (Figure 1a, dots), plus an additional 33 sites with in situ and AMSR-E data but no ASCAT data due to high topographic complexity (Figure 1a, crosses). Each of these sites was located in a different cell of the 25 km modeling grid. In the Murrumbidgee basin, there were 19 grid cells (Figure 1b) with in situ, ASCAT, and AMSR-E data, four of which contained two or three in situ stations which were averaged in to a single in situ time series per grid cell. An initial comparison showed that the assimilation results for the SCAN/SNOTEL and Murrumbidgee sites were very similar, and so results from both networks are combined below.

[10] The skill of a given soil moisture estimate was measured using the anomaly time series correlation-coefficient (R) with the in situ soil moisture. The anomalies were defined as the difference of the data from the 31 day moving average, with the moving averages based on data from all years for the 31 day period surrounding each day of year. R was calculated using daily average soil moisture time series, excluding days when the in situ observations indicate frozen conditions. For each R estimate a 95% Confidence Interval (CI) was calculated using a Fisher Z transform. Soil moisture anomaly time series are highly autocorrelated, reducing the number of independent data in the time series and introducing a bias into statistical inference. Hence the CIs were calculated using the effective sample size of *Dawdy and Matalas* [1964]:

$$N_{eff} = N\left(1 - r_x r_y\right) / \left(1 + r_x r_y\right),$$

where N is the number of samples, and r_x and r_y are the lag-1 autocorrelation of the two time series being compared.

[11] Finally, a single skill value, together with its 95% CI, was estimated for each land cover class, by averaging the skill estimates within each land cover class, and dividing the sum of the CIs by the square root of the number of sites. The land cover classes were based on MODIS land cover data from Boston University [*Friedl et al.*, 2002]. MODIS land cover classes with 10–60% trees or woody vegetation were combined into the 'mixed cover' class.

2.3. The Modeling and Data Assimilation Systems

[12] The assimilation experiments were conducted with the Catchment model [*Koster et al.*, 2000], run at 25 km resolution over the in situ monitoring networks and forced with surface meteorological data from the NASA Modern-Era Retrospective analysis for Research and Applications (MERRA) [*Rienecker et al.*, 2011]. A 1-D EnKF with 12 ensemble members and a 3 hour assimilation cycle was used for the assimilation [*Liu et al.*, 2011]. Prior to assimilation, the ASCAT and AMSR-E data were rescaled to the Catchment soil moisture climatology by matching their cumulative distribution functions [*Reichle and Koster*, 2004].

[13] The ensemble was generated using the same perturbations to the meteorological forcing and model states as *Liu et al.* [2011]. The observation error standard deviations (st-dev) were defined in the climatology of the observed data sets, and then scaled (locally) into the Catchment model climatology by the ratio of the model and observation time series st-devs. For AMSR-E a spatially and temporally constant error st-dev of 0.08 m^3m^{-3} (in the AMSR-E climatology) was used following *Liu et al.* [2011], resulting in a mean error st-dev of 0.03 m^3m^{-3} in the model climatology. The error st-dev is smaller in the Catchment space since the temporal variability of the AMSR-E soil moisture is much higher than that of Catchment. Since the two data sets have similar overall skill [*Dorigo et al.*, 2010], a (spatially/temporally constant) error st-dev of 10% (SDS) was used for

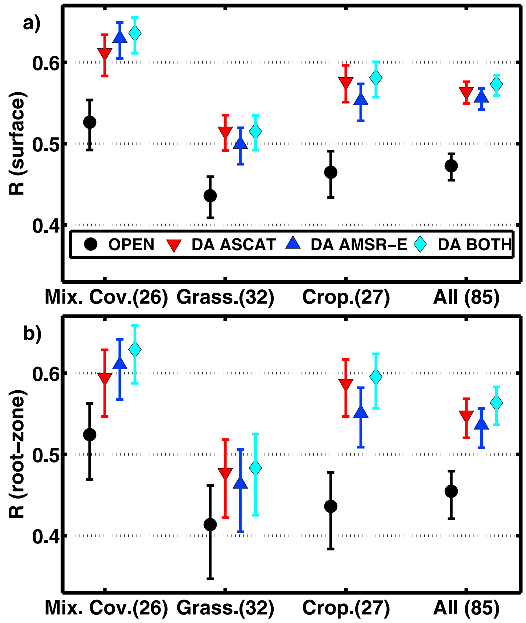

Figure 2. Mean skill for (a) surface and (b) root-zone soil moisture from the OPEN-loop model, and the data assimilation (DA) of ASCAT, AMSR-E, and BOTH, averaged across each land cover class, with 95% confidence intervals. The number of sites in each land cover class is given in the axis labels. Skill is based on all nonfrozen days in the experiment period.

ASCAT, to give the same mean error st-dev in the model climatology as for AMSR-E.

[14] In Section 3.1 the impact of assimilating the ASCAT and AMSR-E observations is compared over the 85 in situ soil moisture sites with high quality observations from both satellites (dots in Figure 1). For these experiments an average of 1197 AMSR-E and 822 ASCAT observations (over 3.5 years) were assimilated at each SCAN/SNOTEL site, and an average of 1624 AMSR-E and 1066 ASCAT observations were assimilated at each Murrumbidgee site (where frozen conditions rarely occur). Even though both sensors are in sun-synchronous orbits, AMSR-E had higher temporal coverage since it had a larger view area (one 1450 km wide swath) than ASCAT (two 550 km wide swaths). In Section 3.2 the skill improvement from assimilating near-surface soil moisture is examined as a function of the skill of the assimilated observations and of the model. To increase the range of observation skills sampled, the experimental domain was expanded in Section 3.2 to include the assimilation of AMSR-E (but not ASCAT) at the 33 sites with high TC (crosses in Figure 1) at which the ASCAT observations have poor skill.

3. Results and Discussion

3.1. Assimilation Skill by Land Cover Class

[15] For the 85 sites with high quality satellite data, Figure 2 shows the estimated R (anomaly-time series correlation-coefficient with in situ data) and its 95% CI for the surface and root-zone soil moisture, averaged across each land cover class, and across all sites. Results for the open-loop (ensemble mean, no assimilation) Catchment model, and for the assimilation of ASCAT, AMSR-E, and both, are plotted separately. Averaged across all 85 sites, the mean surface soil moisture skill was increased from 0.47 for the open-loop model, to 0.56 by the assimilation of ASCAT or AMSR-E, and to 0.57 by the assimilation both. For the root-zone, the mean skill was increased from 0.45 for the open-loop model, to 0.55 for the assimilation of ASCAT, 0.54 for the assimilation of AMSR-E, and 0.56 for the assimilation of both. In each case the mean skill increase from assimilating the satellite soil moisture data was statistically significant (at the 5% level).

[16] For each land cover class, assimilating the satellite soil moisture data improved the mean R, usually significantly. The single-sensor assimilation experiments (of ASCAT or AMSR-E) yielded very similar improvements to the mean R, while the combined assimilation (ASCAT and AMSR-E) generally matched or slightly exceeded the mean R from the single-sensor assimilation experiments. Prior to assimilation, the open-loop model had significantly higher skill for the more vegetated mixed cover class than for the grassland or cropland classes in Figure 2. The relatively low open-loop skill for croplands is not surprising, since Catchment does not account for cropping practices. In contrast, croplands are well suited to soil moisture remote sensing and the satellite observations performed well at these sites, so that each assimilation significantly improved the mean R (by >0.1 in most cases in Figure 2). Consequently, after assimilation the cropland R was much closer to that of the mixed cover, especially in the root-zone. While the assimilation did improve the mean R for the grasslands (and significantly in the surface layer), even after assimilation the mean grassland R for both soil layers was below the other land cover classes (significantly in many cases). The mean R for the mixed cover sites improved significantly in all cases except for the root-zone soil moisture after assimilating ASCAT. Consequently, the mixed cover class had the highest mean assimilation skill.

3.2. Contribution of Observation Skill to Assimilation Skill

[17] Figure 3 compares the skill of the ASCAT and AMSR-E observations. To compare the satellite skill

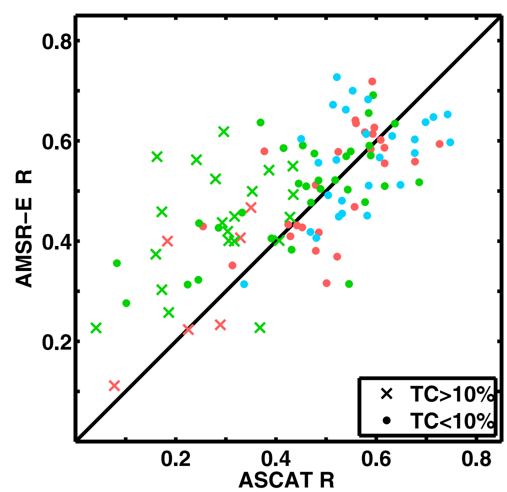

Figure 3. AMSR-E vs. ASCAT skill based only on days with data available from both data sets. Dots (crosses) indicate sites with topographic complexity (TC) below (above) 10%. Colors indicate land cover class according to Figure 1 legend. Six TC>10% data points with negative ASCAT skill are not shown.

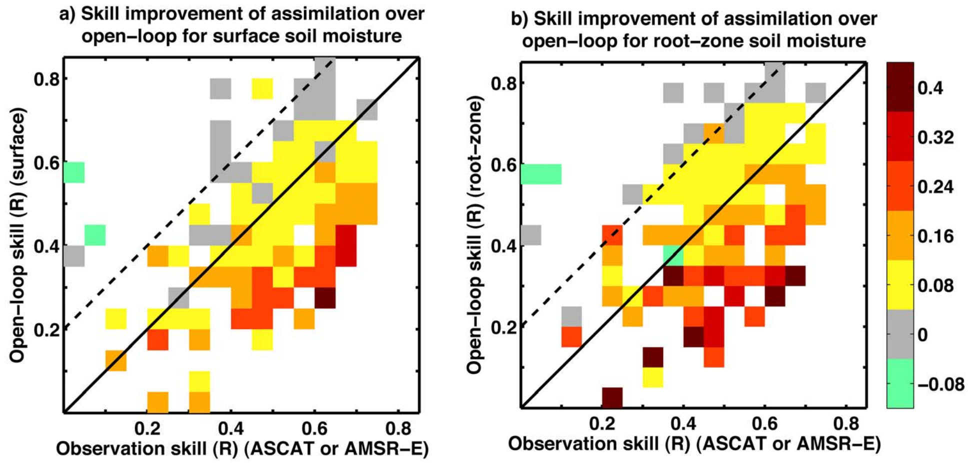

Figure 4. Skill improvement (ΔR) from assimilating either ASCAT or AMSR-E for (a) surface and (b) root-zone soil moisture, as a function of the open-loop and observation skill. Skill improvement is defined as the skill of the assimilation product minus the open-loop skill, with skill based only on days with data available from both satellites.

estimates the R values in Figure 3 (and Figure 4) are based only on days with both ASCAT and AMSR-E data. The 33 sites with topographic complexity >10% are plotted as crosses, demonstrating the reduced ASCAT skill at these sites. Averaged over the 24 grassland sites with TC >10% the mean R for ASCAT was 0.23, significantly less than the mean R of 0.43 for the 33 grassland sites with TC ≤10%. By contrast, the mean AMSR-E R for the grassland sites with TC >10% was 0.44, comparable to 0.48 for the grassland sites with TC ≤10%. ASCAT soil moisture data have lower skill in arid locations [*Dorigo et al.*, 2010], which may have contributed to their reduced R in mountainous regions, however comparing the ASCAT R to various aridity indexes did not reveal a relationship. For AMSR-E the lower skill over mountainous sites is likely due to increased heterogeneity, and small amounts of snow, rocks, and lakes, rather than a direct effect of complex topography. Averaged over the nonmountainous sites (TC ≤10%), ASCAT and AMSR-E had similar skill, with a mean R of 0.50 for ASCAT and 0.51 for AMSR-E. Also, in Figure 3 variations around the one-to-one line are at best weakly related to land cover class (consistent with the similar skill for each assimilation in Figure 2), contrary to the evidence of *Dorigo et al.* [2010].

[18] Finally, Figure 4 shows the skill increase (ΔR) relative to the open-loop model from the single-sensor assimilation of ASCAT or AMSR-E, as a function of the R of the open-loop model and of the assimilated (ASCAT or AMSR-E) observations. Since the R and ΔR for the single-sensor assimilation of ASCAT or AMSR-E were generally similar, the results from the two experiments are combined in Figure 4. Also the observation and open-loop R values are binned into units of 0.05, giving an average of 2.2 in situ sites per filled square in Figure 4.

[19] Figure 4 is analogous to Figures 2c and 2d of *Reichle et al.* [2008] and uses satellite data to confirm their main findings (which were based on synthetic experiments). In general, for a given combination of open-loop and observation skill, the skill gained through assimilation was slightly higher for the root-zone (Figure 4b) than for the surface soil moisture (Figure 4a). For both soil layers, assimilating observations with R no more than 0.2 below the open-loop R (below the dashed line in Figure 4) generally increased the soil moisture skill (i.e., $\Delta R > 0$), with the improvements increasing up to $\Delta R \approx 0.4$ as the observation R increased relative to the open-loop R.

[20] Unlike in the work by *Reichle et al.* [2008], Figure 4b did not benefit from adaptive tuning of the model and observation error covariances, or from averaging over a large domain. Future work will test whether refining the assimilation error covariances to account for spatial variation in the relative observation and open-loop skill can improve upon our results. However, the consistently positive impact of our assimilation experiments, as well as the similarity between Figure 4 and *Reichle et al.* [2008] indicate that our current error specifications are reasonable, and sufficient to test the benefit of assimilating the ASCAT and AMSR-E data sets. Finally, the similarity between our results and the synthetic experiments of *Reichle et al.* [2008] suggests that our R value metric (based on in situ observations) is providing an accurate measure of soil moisture skill.

4. Summary and Conclusions

[21] Near-surface soil moisture observations derived from the active microwave ASCAT scatterometer and the passive microwave AMSR-E radiometer were assimilated into NASA's Catchment land surface model, both separately and together. The impact of assimilating each data set on the modeled soil moisture skill was evaluated using in situ soil moisture observations from 85 sites in the SCAN/SNOTEL network in the US and the Murrumbidgee Soil Moisture Monitoring Network in southeast Australia. With careful quality control of the satellite data, assimilating either ASCAT or AMSR-E data improved the modeled soil moisture skill (anomaly correlation with in situ data) at nearly every site, and the surface and root-zone soil moisture skill averaged across all 85 sites was significantly improved by assimilating either (or both) data sets.

[22] Where the satellite soil moisture skill was no more than 0.2 less than the open-loop skill, the assimilation improved the soil moisture skill, with the improvements increasing (up to 0.4) as the observation skill increased relative to that of the open-loop model. The model and

observation skill differed between land cover classes, highlighting that land cover information should be provided when evaluating soil moisture estimates. Assimilating either ASCAT or AMSR-E improved the mean skill for each land cover class considered here, with significant improvements for root-zone soil moisture over croplands and mixed cover (10–60% trees or wooded vegetation), and for surface soil moisture over croplands, grasslands, and mixed cover. At the frequencies observed by AMSR-E and ASCAT, dense vegetation limits the accuracy of soil moisture observations, and so the improvements obtained over the moderately vegetated mixed cover sites are very encouraging.

[23] The improvement in skill from assimilating either ASCAT or AMSR-E was very similar, even when considered by land cover class. Following the recent malfunction of the AMSR-E instrument, applications currently assimilating AMSR-E should thus be able to switch to ASCAT data without loss of accuracy. In our experiments, assimilating both data sets consistently matched or exceeded the best results from the single-sensor assimilation experiments. Also, the ASCAT soil moisture retrieval skill was significantly lower over complex terrain, while assimilating the AMSR-E data generated small improvements at these locations. Consequently, for maximum accuracy and spatial coverage it is recommended that passive (AMSR-E or WindSat) and active (ASCAT) near-surface soil moisture be assimilated together if possible.

[24] **Acknowledgments.** We are grateful to all who contributed to the data sets used in this study. In particular we acknowledge Richard de Jeu and colleagues (VUA), Wolfgang Wagner and colleagues (TU-Wien), and staff at ESA, Monash University, NASA, USDA, and the University of Melbourne. G. De Lannoy is funded by the Research Foundation Flanders.

[25] The Editor thanks two anonymous reviewers for their assistance in evaluating this paper.

References

Bolten, J. D., W. T. Crow, X. Zhan, T. J. Jackson, and C. A. Reynolds (2010), Evaluating the utility of remotely sensed soil moisture retrievals for operational agricultural drought monitoring, *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.*, *3*, 57–66, doi:10.1109/JSTARS.2009.2037163.

Dawdy, D., and N. Matalas (1964), Statistical and probability analysis of hydrologic data, part III: analysis of variance, covariance and time series, in *Handbook of Applied Hydrology: A Compendium of Water-Resources Technology*, pp. 8.68–8.91, McGraw-Hill, New York.

de Jeu, R. A. M., and M. Owe (2003), Further validation of a new methodology for surface moisture and vegetation optical depth retrieval, *Int. J. Remote Sens.*, *24*, 4559–4578, doi:10.1080/0143116031000095934.

Dorigo, W. A., K. Scipal, R. M. Parinussa, Y. Y. Liu, W. Wagner, R. A. M. de Jeu, and V. Naeimi (2010), Error characterisation of global active and passive microwave soil moisture datasets, *Hydrol. Earth Syst. Sci.*, *14*, 2605–2616, doi:10.5194/hess-14-2605-2010.

Friedl, M. A., et al. (2002), Global land cover mapping from MODIS: Algorithms and early results, *Remote Sens. Environ.*, *83*, 287–302, doi:10.1016/S0034-4257(02)00078-0.

Koster, R. D., M. J. Suarez, A. Ducharne, M. Stieglitz, and P. Kumar (2000), A catchment-based approach to modeling land surface processes in a general circulation model 1. Model structure, *J. Geophys. Res.*, *105*(D20), 24,809–24,822,doi:10.1029/2000JD900327.

Liu, Q., R. H. Reichle, R. Bindlish, M. H. Cosh, W. T. Crow, R. A. M. de Jeu, G. J. M. De Lannoy, G. J. Huffman, and T. J. Jackson (2011), The contributions of precipitation and soil moisture observations to the skill of soil moisture estimates in a land data assimilation system, *J. Hydrometeorol.*, *12*, 750–765, doi:10.1175/JHM-D-10-05000.1.

Owe, M., R. A. M. de Jeu, and J. P. Walker (2001), A methodology for surface soil moisture and vegetation optical depth retrieval using the microwave polarization difference index, *IEEE Trans. Geosci. Remote Sens.*, *39*, 1643–1654, doi:10.1109/36.942542.

Parinussa, R. M., T. R. H. Holmes, and R. A. M. de Jeu (2012), Soil moisture retrievals from the WindSat spaceborne polarimetric microwave radiometer, *IEEE Trans. Geosci. Remote*, doi:10.1109/TGRS.2011.2174643, in press.

Reichle, R. H., and R. D. Koster (2004), Bias reduction in short records of satellite soil moisture, *Geophys. Res. Lett.*, *31*, L19501, doi:10.1029/2004GL020938.

Reichle, R. H., W. T. Crow, R. D. Koster, H. O. Sharif, and S. P. P. Mahanama (2008), Contribution of soil moisture retrievals to land data assimilation products, *Geophys. Res. Lett.*, *35*, L01404, doi:10.1029/2007GL031986.

Rienecker, M. M., et al. (2011), MERRA: NASA's Modern-Era Retrospective Analysis for Research and Applications, *J. Clim.*, *24*, 3624–3648, doi:0.1175/JCLI-D-11-00015.1.

Schaefer, G. L., M. H. Cosh, and T. J. Jackson (2007), The USDA Natural Resources Conservation Service Soil Climate Analysis Network (SCAN), *J. Atmos. Oceanic Technol.*, *24*, 2073–2077, doi:10.1175/2007JTECHA930.1.

Wagner, W., G. Lemoine, and H. Rott (1999), A method for estimating soil moisture from ERS scatterometer and soil data, *Remote Sens. Environ.*, *70*, 191–207, doi:10.1016/S0034-4257(99)00036-X.

Wagner, W., Z. Bartalis, V. Naeimi, S.-E. Park, J. Figa-Saldaña, and H. Bonekamp (2010), Status of the MetOp ASCAT soil moisture product, in *2010 IGARRS Proceedings*, pp. 276–279, Inst. Electr. and Electron. Eng., New York, doi:10.1109/IGARSS.2010.5653358.

G. J. M. De Lannoy, C. S. Draper, Q. Liu, and R. H. Reichle, Global Modeling and Assimilation Office, NASA Goddard Space Flight Center, Code 610.1, Greenbelt, MD 20771, USA. (clara.draper@nasa.gov)