Triple Collocation Analysis of Soil Moisture From Metop-A ASCAT and SMOS Against JRA-55 and ERA-Interim

Kengo Miyaoka, Alexander Gruber, Francesca Ticconi, *Member, IEEE*, Sebastian Hahn, Wolfgang Wagner, *Senior Member, IEEE*, Julia Figa-Saldaña, and Craig Anderson

***Abstract*—This study investigates the quality of Advanced Scatterometer (ASCAT) surface soil moisture (SSM) retrievals with respect to other SSM products derived from the passive Soil Moisture and Ocean Salinity (SMOS) mission and two reanalysis datasets, i.e., the JRA-55 and the ERA-Interim. In particular, the purposes of this study are to 1) characterize the global error structure of the satellite products, 2) understand the spatiotemporal variability of SSM at global scale, and 3) investigate in which areas the assimilation of satellite data may add value to reanalysis. For these purposes, we applied standard statistical methods as well as triple collocation analysis (TCA) for estimating signal-to-noise ratios (SNR). In line with previous studies, we find large and spatially variable biases between all four datasets, but overall spatiotemporal dynamics as reflected in Hovmöller diagrams agree well. With the exception of arid and semiarid environments, ASCAT performs better than SMOS in terms of both its correlation with the models and the SNR. As a result of TCA, we recognize the potential areas for assimilation of ASCAT data, characterized by a high SNR of the satellite data compared to the models, to be the savanna regions in Africa and Central Asia, southwestern North America, and eastern Australia.**

***Index Terms*—Advanced Scatterometer (ASCAT), data assimilation, soil moisture, Soil Moisture and Ocean Salinity (SMOS), triple collocation.**

I. Introduction

SOIL moisture is one of the key components of the water cycle. Despite its total mass is small compared to other water storages, it has a large effect in numerical weather prediction, especially on surface temperature and humidity [1]. Because of the high spatiotemporal variability of soil moisture at small scales [2], soil moisture is difficult to monitor on regional to global scales using *in situ* observations. This is because the setup and maintenance of dense *in situ* networks capable of reflecting large-scale soil moisture patterns well is challenging and costly. Nonetheless, some regions in the United States, Europe, and Australia start to be well covered by *in situ* networks [3], which are key to validating and further improving regional to global-scale soil moisture datasets, which may be derived by remote sensing, land surface modeling, and/or reanalysis.

From satellites, the most direct way of measuring soil moisture is via the use of active and passive microwave remote sensing instruments operating in the 1–10-GHz range [4]. Two satellite missions specifically designed for measuring soil moisture are the Soil Moisture and Ocean Salinity (SMOS) mission of the European Space Agency (ESA) launched in 2009 [5] and the Soil Moisture Active Passive (SMAP) mission launched by the National Aeronautics and Space Administration in 2016 [6]. Both SMOS and SMAP operate at L-band (1–2 GHz), whereas after the early failure of the active measurement mode of SMAP, both missions deliver now only passive microwave measurements at a resolution of about 40 km. Adding to the capabilities of these two experimental missions, there are several operational active and passive microwave sensors, which provide soil moisture measurements at C-band (4–8 GHz) and X-band (8–12 GHz). One of these instruments is the Advanced Scatterometer (ASCAT), which is an active microwave sensor operated at 5.255 GHz flown on board of the series of three METOP satellites. Like for its predecessor instrument, the scatterometer on board of the European Remote Sensing Satellites (ERS), its primary mission objective is to monitor winds over the oceans. Yet, given the long-term nature and quality of the ASCAT soil moisture products, the number of ASCAT soil moisture applications has been growing steadily since the launch of the near real-time (NRT) ASCAT soil moisture services in 2008 [7]. Wagner *et al.* [8] formulated the soil moisture retrieval algorithm for the ERS-1/2 scatterometer, and the authors of [9] and [10] adapted it for use with the ASCAT.

One of the most important applications of the NRT ASCAT soil moisture data services is numerical weather prediction (NWP). Motivated by a number of successful NWP assimilation experiments, several meteorological forecast centers have already started to use the ASCAT soil moisture data for ver-

Manuscript received June 30, 2016; revised October 24, 2016; accepted November 9, 2016. Date of publication February 5, 2017; date of current version May 24, 2017. This work was supported in part by the EUMETSAT Visiting Scientists Program and by the Japanese Government Short-term Overseas Fellowship Program of the Japan National Personnel Authority, and in part by the eartH2Observe project (European Union's Seventh Framework Program, Grant 603608). *(Corresponding author: Kengo Miyaoka.)*

K. Miyaoka is with the Japan Meteorological Agency, Tokyo 100-8122, Japan (e-mail: kengo_miyaoka@met.kishou.go.jp).

A. Gruber, S. Hahn, and W. Wagner are with the Department of Geodesy and Geoinformation, Vienna University of Technology, 1040 Vienna, Austria (e-mail: alexander.gruber@geo.tuwien.ac.at; sebastian.hahn@geo.tuwien.ac.at; wolfgang.wagner@geo.tuwien.ac.at).

F. Ticconi, J. Figa-Saldaña, and C. Anderson are with EUMETSAT, 64295 Darmstadt, Germany (e-mail: francesca.ticconi@eumetsat.int; jula.figa@eumetsat.int; craig.anderson@eumetsat.int).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/JSTARS.2016.2632306

TABLE I
MAIN CHARACTERISTICS OF THE SOIL MOISTURE PRODUCTS

Soil Moisture Products	Spatial Resolution	Observation Time	Sampling depth and units	Reference
ASCAT	25 km/12.5 km sam-pling	09:30 (Descending) and 21:30 (Ascend-ing) overpass (Local Solar Time)	~0–1 cm Degree of saturation (%)	Bartalis *et al.* (2007)
SMOS level 3 (SMOSL3)	0.25°	06:00 (Ascending) and 18:00 (Descend-ing) overpass (Local Solar Time)	~0–3 cm Volumetric SSM contents (m^3/m^3)	Kerr *et al.* (2012) (2012)
JRA-55	~0.562° (640 × 320 Reduced Gaussian)	6 hourly (Product data time interval)	0–2 cm Volumetric SSM con-tents (m^3/m^3)	Kobayashi *et al.* (2015)
ERA-Interim	~0.703 ° (512 × 256 Reduced Gaussian)	6 hourly (Product data time interval)	0–7 cm Volumetric SSM con-tents (m^3/m^3)	Dee *et al.* (2011)

ification and assimilation. The U.K. Met office, for instance, started to operate a nudging scheme-based assimilation system in 2010 [11], which led to improved screen-level parameters over the Tropics, in Australia and in North America. Also the European Center for Medium-range Weather Forecasts (ECMWF) implemented an assimilation system in 2010, which is based on a simplified extended Kalman filter, and also showed improvements of the screen-level parameters and the soil moisture forecasts [12].

The validation of remotely sensed soil moisture datasets is often based on relative intercomparison with *in situ* data that are considered as ground "truth" [13], [14]. However, the large-scale mismatch of these measurement systems (point measurements versus spatially integrating satellite footprints) gives rise to representativeness errors, which often exceed the actual retrieval errors of the dataset under validation [15], [16]. Also, *in situ* networks cover only a small fraction of the land surface and are, therefore, not sufficient for comprehensively validating satellite datasets under all possible climate and land cover conditions [3]. A common alternative is to compare satellite retrievals with the output from land surface models [17], which might be similar in their spatial resolution and globally available, but contain significant modeling errors themselves and their quality is often not well characterized [18].

Triple collocation analysis (TCA) [19], [20] is a method that can mitigate these issues. It estimates the individual random error variances or signal-to-noise ratios (SNR) of three spatiotemporally collocated datasets of the same geophysical variable without requiring any of them to be selected as supposedly error-free reference. Furthermore, it can provide unbiased error or SNR estimates even in the presence of representativeness errors [20].

In this study, soil moisture retrievals from ASCAT and SMOS as well as modeled soil moisture from ERA-Interim and JRA-55 are validated by means of TCA and the most common relative performance intercomparison metrics, i.e., the correlation coefficient (R), the bias, and the unbiased root-mean-square difference (ubRMSD) [21]. TCA assumptions are tested by investigating the consistency between satellite error estimates when exchanging the third dataset (i.e., the land surface model) in the triplet. Moreover, Hovmöller diagrams are calculated to investigate the spatiotemporal consistency of the datasets. Finally, we investigate the potential of ASCAT and SMOS observation for improving reanalysis data. This is, to our best knowledge, the first study that 1) investigates global error properties of remotely sensed and modeled soil moisture datasets by means of the SNR following the suggestion of [20] and [22] and 2) applies TCA on soil moisture estimates from the JRA-55 model.

Datasets are described in Section II and their main characteristics are summarized in Table I. Preprocessing steps and methods are described Sections III and IV, respectively. Results are shown in Section V.

II. DATASETS

A. Metop ASCAT Soil Moisture

The ASCAT is an active microwave radar (C-band, 5.255 GHz), and it is part of the payload on-board the series of Meteorological Operational Platforms (Metop satellites) operated by European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT). The first satellite (Metop-A) was launched in October 2006 and the second one (Metop-B) in September 2012. The third and last satellite (Metop-C) is currently scheduled for 2018. ASCAT is measuring the normalized radar cross section from the Earth surface under various azimuth and incidence angle combinations with a revisit time of one to two days. The original purpose of the ASCAT instrument is to monitor wind speed and direction over the ocean, but research has shown that the data can also be used for land applications, such as monitoring of soil moisture [9].

In this study, we use the Metop-A ASCAT DR2015 soil moisture 12.5-km sampling data record provided by the EUMETSAT Satellite Application Facility (SAF) on support to operational hydrology and water management (H-SAF, http://hsaf.meteoam.it). The spatial resolution of the dataset is 25–34 km × 25–34 km sampled on an Earth-fixed discrete global grid with a regular spacing of 12.5 km × 12.5 km. The unit of the relative surface soil moisture estimates is degree of saturation, with 0% corresponding to dry and 100% to saturated soil water conditions. If volumetric units are required, porosity information can be used to translate degree of saturation (%) to absolute units (m^3/m^3). Global soil porosity information of the top layer (0–0.40 m) derived from the Harmonized World Soil Database (version 1.0) is available on the ESA-CCI website (http://www.esa-soilmoisture-cci.org) and has been used to translate the Metop ASCAT surface soil moisture to absolute units.

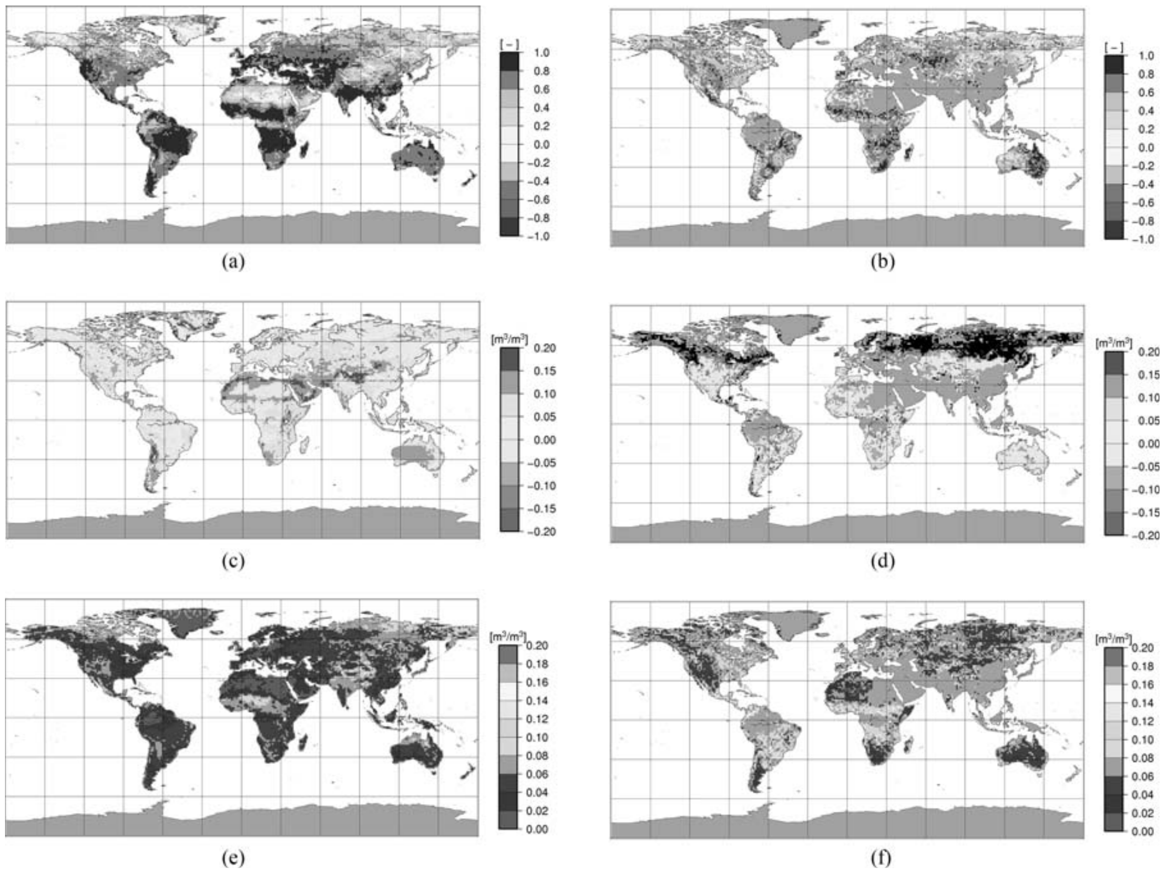

Fig. 1. (a) Correlation ($p \leq 0.05$), (c) bias (ERA-Interin – JRA-55), and (e) ubRMSD between ERA-Interim and JRA-55. (b) Correlation ($p \leq 0.05$), (d) bias (SMOS – ASCAT), and (f) ubRMSD between SMOS and ASCAT.

Only measurements from morning (descending) overpasses have been used in this study following [8], [14], [23] which reported that these seem to be more sensitive to soil moisture changes, which might be explained by a stronger near-surface and root-zone coupling during this time of the day [24].

B. SMOS Soil Moisture

The SMOS mission started as ESA's second Earth Explorer Opportunity Mission and was launched in November 2009. SMOS carries a single payload, an L-band (1.4 GHz) 2-D interferometric radiometer (microwave imaging radiometer using aperture synthesis, MIRAS) measuring the microwave energy emitted from Earth's surface [5]. MIRAS consists of a central structure and three deployable arms (Y-shape) with 69 equally distributed antenna elements. In order to achieve a suitable spatial resolution to monitor SMOS, the antenna aperture has been synthesized by the multitude of small antennas. The multiangular and full-polarization brightness temperature measurements are used to retrieve surface soil moisture over landmasses with a spatial resolution of 35–50 km and a revisit time of one to three days.

The SMOS surface soil moisture product is provided in volumetric units (m^3/m^3) and available either in swath geometry (Level 2) from ESA's Data Processing Ground Segment (DPGS) or in global mode (Level 3) from the Centre Aval de Traitement des Données SMOS (CATDS) [25]. The latter makes use of a multiorbital retrieval technique and is projected on the EASE grid. In our analysis, we make use of the SMOS Level 3 (SMOSL3) surface soil moisture product, which has been recently reprocessed using CATDS processor's version 300 (DPGS version v620).

C. JRA-55 Reanalysis

The Japanese 55-year Reanalysis (JRA-55) is the second global atmospheric reanalysis [26] produced by the Japan Meteorological Agency (JMA). It covers the period from 1958 to present and is based on a four-dimensional variational analysis (4D-VAR) for all periods. The land surface analysis in the JRA-55 is an offline version of the JMA Simple Biosphere model [27], [28]. Surface soil moisture is provided as degree of saturation, associated with the 0–2 cm (topmost) soil layer and available 6 hourly on a spectral model grid at TL319 resolution (approx. 55 km). Porosity data are applied using the vegetation types from [29] along with a guideline given in [30].

D. ERA-Interim Reanalysis

ERA-Interim is the latest global atmospheric reanalysis produced by the ECMWF [31]. It covers the period from 1979 until present using a 4D-VAR system with a 12 h analysis window

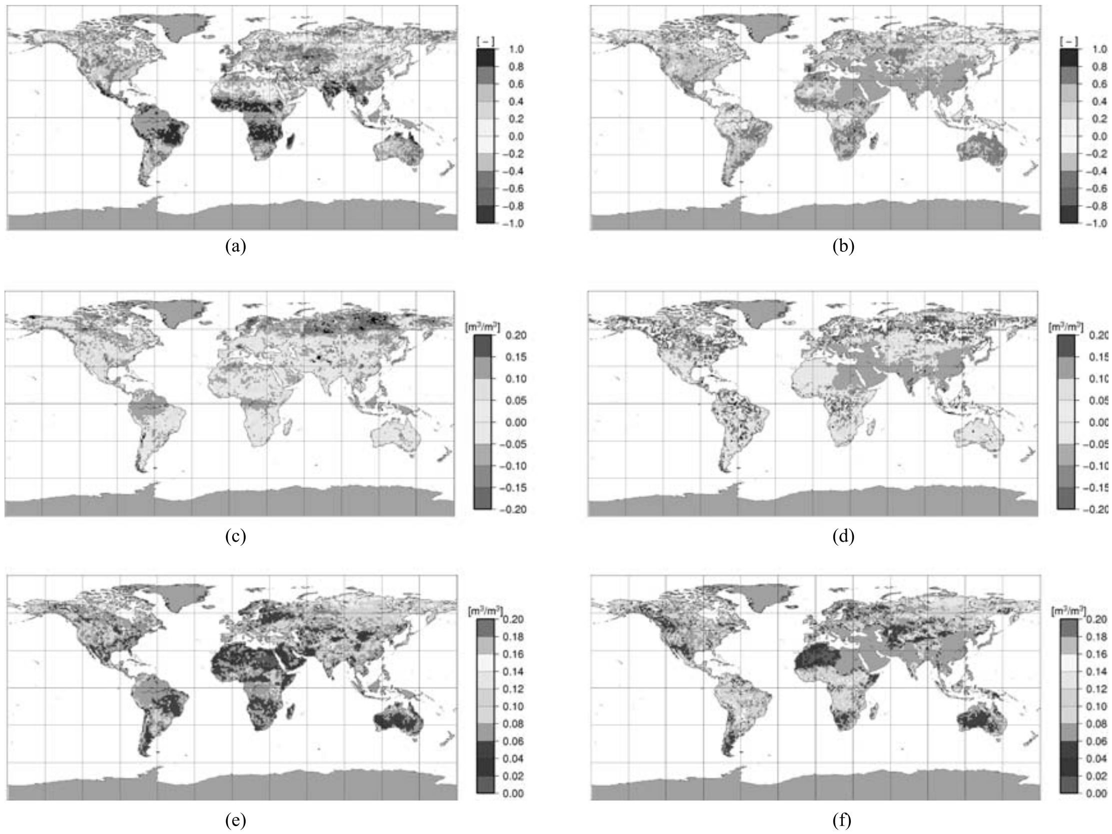

Fig. 2. (a) Correlation ($p \leq 0.05$), (c) bias (JRA-55 – ASCAT), and (e) ubRMSD between JRA-55 and ASCAT. (b) Correlation ($p \leq 0.05$), (d) bias (JRA-55 – SMOS), and (f) ubRMSD between JRA-55 and SMOS.

and the TESSEL land surface scheme [32], [33]. The surface soil moisture data used in this study are associated with the 0–7 cm (topmost) soil layer and is available 6 hourly with a spatial resolution of approximately 80 km (spectral T255).

III. Preprocessing

Each dataset is resampled to a regular $1.25^\circ \times 1.25^\circ$ grid using a nearest-neighbor search. The Generic Mapping Tool [34] has been used for this purpose. Invalid satellite measurements have been masked prior to the analysis. The Metop ASCAT soil moisture values were filtered using the attached processing flag. The SMOS L3 product includes a Data Quality Index (DQX) and the probability of radio frequency interference (RFI). Retrievals were filtered on days where the DQX equals the fill value and/or where the RFI-probability $>10\%$. In addition, measurements of both ASCAT and SMOS have been filtered out on days where the soil temperature was less than 0° Celsius or snow depth was larger than 0 cm (according to ERA-Interim estimates). The temporal period of analysis was January 2010 to December 2013.

IV. Methods

A. Standard Performance Metrics

Relative intercomparison between the datasets was performed using the linear Pearson correlation coefficient (R), the bias, and the ubRMSD, which are defined as follows:

$$\mathrm{R} = \frac{\sigma_{\mathrm{xy}}}{\sqrt{\sigma_x^2 \sigma_y^2}} \tag{1}$$

$$\mathrm{bias} = \bar{x} - \bar{y} \tag{2}$$

$$\mathrm{ubRMSD} = \sqrt{\frac{1}{n}\sum \left((x_i - \bar{x}) - (y_i - \bar{y})\right)^2} \tag{3}$$

where x and y are the spatiotemporally collocated datasets, n is the number of data pairs, σ_{xy} is the covariance between x and y, and σ_x^2 and σ_y^2 are the variances of x and y, respectively. The overbar represents the temporal mean of a variable.

B. Hovmöller Diagram

A Hovmöller diagram represents the temporal evolution of spatially continuous data. The abscissa shows the time and the ordinate the dataset values averaged either over all latitudes or over all longitudes [35]. Here, we use the longitudinal averages for analyzing the consistency between the datasets in capturing mean seasonal global soil moisture dynamics [36].

C. Triple Collocation Analysis

In this study, we apply TCA [19] to estimate the SNRs of the datasets, which provide the most meaningful measure for quality intercomparison [20], [22]. Their estimation is based on

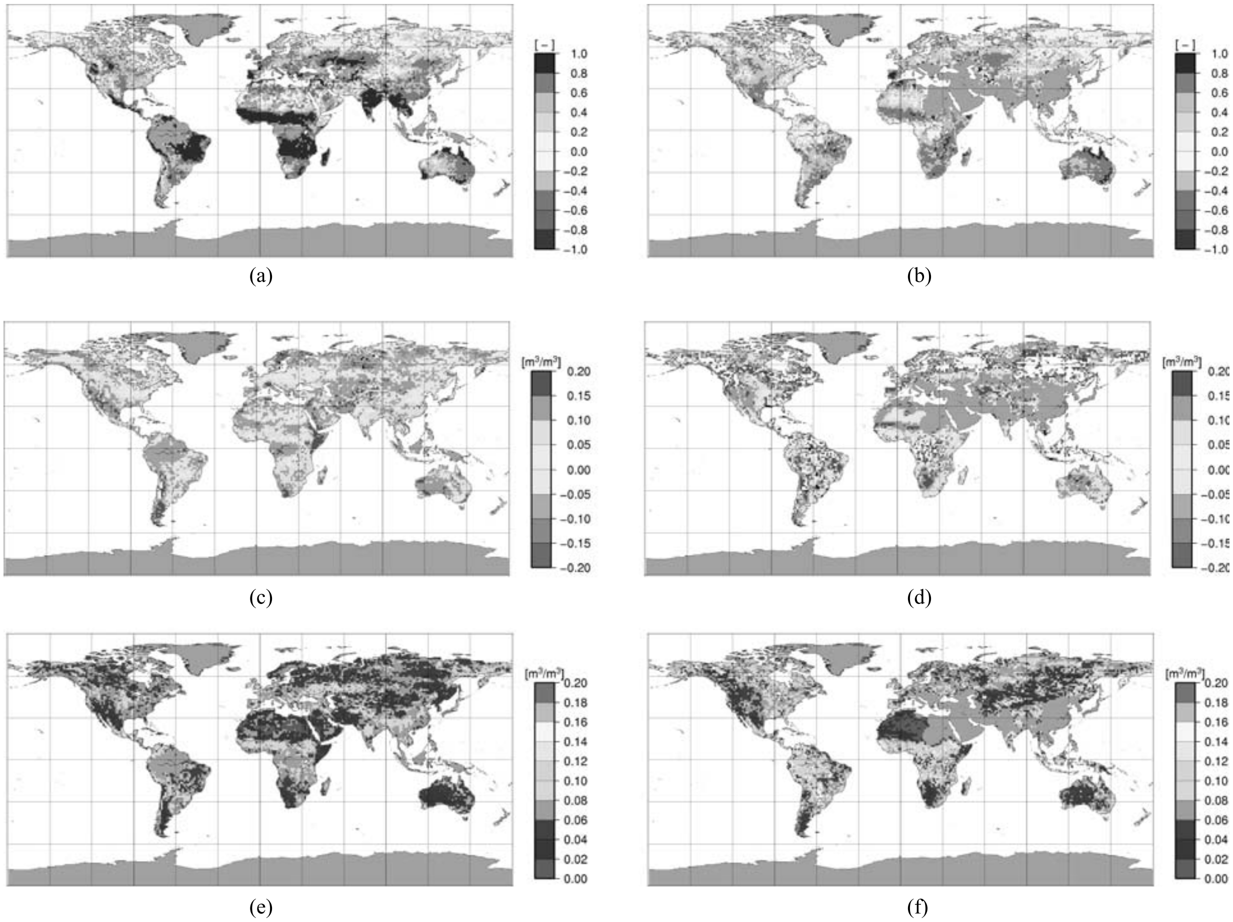

Fig. 3. (a) Correlation ($p \leq 0.05$), (c) bias (ERA-Interim – ASCAT), and (e) ubRMSD between ERA-Interim and ASCAT. (b) Correlation ($p \leq 0.05$), (d) bias (ERA-Interim – SMOS), and (f) ubRMSD between ERA-Interim and SMOS.

a linear error model of the form

$$i = \alpha_i + \beta_i \theta + \epsilon_i \tag{4}$$

where $i \in [X, Y, Z]$ are three spatially and temporally collocated datasets, θ is the unknown true soil moisture value, α_i and β_i are systematic additive and multiplicative biases of dataset i with respect to the true state, and ϵ_i represents additive zero-mean random noise. Notice that the random errors of the datasets are assumed to be mutually uncorrelated and orthogonal (i.e., independent from the true soil moisture state). Different direct and indirect representations of the SNR can be estimated through TCA [20], [22], [37]. Here, we use the logarithmic SNR as proposed by Gruber *et al.* [20], which is estimated as

$$\mathrm{SNR}_i \ [\mathrm{dB}] = 10 \log \left(\frac{\sigma_i^2 \sigma_{\mathrm{jk}}}{\sigma_{\mathrm{ij}} \sigma_{\mathrm{ik}}} - 1 \right) = 10 \log \left(\frac{\beta_i^2 \sigma_\theta^2}{\sigma_{\epsilon_i}^2} \right) \tag{5}$$

where $\beta_i^2 \sigma_\theta^2$ represents the signal variance of dataset i, which can be considered as its sensitivity to soil moisture changes, and $\sigma_{\epsilon_i}^2$ represents the random error variance. For a detailed derivation of (5), we refer the reader to [20].

V. Results and Discussion

A. Comparison Between JRA-55 and ERA-Interim

Fig. 1(a), (c), and (e) shows the correlation, the bias, and the ubRMSD between ERA-Interim and JRA-55, respectively. Almost all areas show strong positive correlation ($\sim$0.6 on average), while the smallest values ($<$0.2) are observed in the Sahara, from northern China to central and eastern Siberia, in Alaska and over Greenland. ERA-Interim soil moisture estimates are slightly wetter ($\sim$0.05 $\mathrm{m^3/m^3}$) in most areas, while it is much wetter (more than 0.10 $\mathrm{m^3/m^3}$) in arid regions such as from the Arabian Peninsula to northeastern China, southwestern parts of South America, Australia and South Africa. JRA-55 soil moisture estimates are wetter mainly in the Mississippi river basin in the U.S., the Amazon region, and in areas east of the Lena river.

Notice that ERA-Interim assimilates "SYNOP" observation data (in particular 2 m temperature and humidity), whereas no assimilation is performed in the JRA-55 model, which might partly explain the observed differences between the two models, in particular the large ubRMSD values. However, further investigation is required for an in-depth understanding of these differences, which is beyond the scope of this paper.

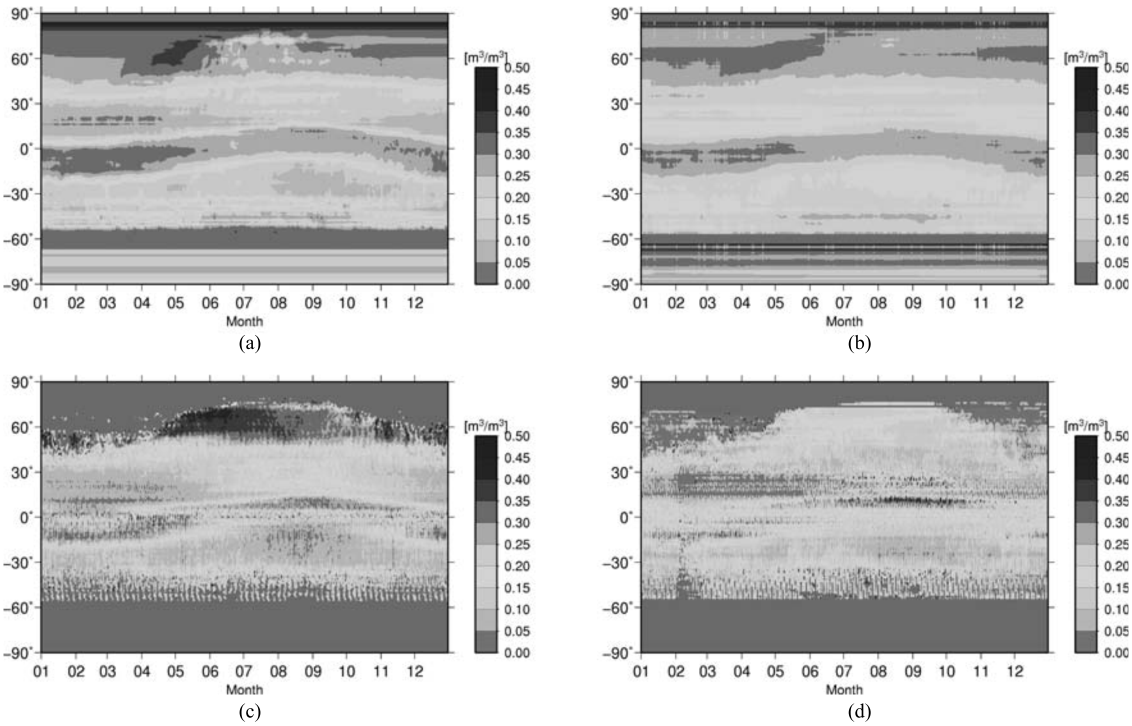

Fig. 4. 2013 Hovmöller diagrams for (a) JRA-55, (b) ERA-Interim, (c) ASCAT, and (d) SMOS.

B. *Comparison Between Metop ASCAT and SMOS*

Fig. 1(b), (d), and (f) shows the correlation, the bias, and the ubRMSD between SMOS and ASCAT, respectively. Notice that no estimates are available in large parts of Eurasia due to RFI contamination in SMOS data. Tropical forests are also masked as it is not possible to retrieve soil moisture in these regions. Almost all regions show positive correlations except for the Sahara Desert and some parts of Canada. SMOS retrievals are consistently dryer in almost all regions with the largest differences (>0.2 m^3/m^3) being observed over high latitudes, which likely results from a systematic soil moisture overestimation of ASCAT in those areas due to issues in the retrieval model parameter estimation [38].

C. *Comparison Between Reanalysis and Satellite Soil Moisture*

Fig. 2 shows the correlation, the bias, and the ubRMSD between JRA-55 and the two satellite products, respectively, and Fig. 3 shows the correlation, the bias, and the ubRMSD between ERA-Interim and the two satellite products, respectively. ASCAT correlates well with both models with the highest values (>0.8) occurring over Africa, India, the Indochina peninsula, and southeastern Brazil and lower to slightly negative correlations occurring over Siberia and arid regions, most prominently the Sahara desert and the Arabian Peninsula. In terms of the bias, ASCAT retrievals are wetter than both JRA-55 (more than 0.10 m^3/m^3) and ERA-Interim (more than 0.05 m^3/m^3) in most high-latitude areas for the above described reason and—compared to JRA-55—in most arid regions (about 0.05 m^3/m^3). Notice that these biases might also partly result from errors in the FAO porosity estimates, which were used to convert ASCAT retrievals to volumetric units. Correlation patterns for SMOS look quite similar but with lower magnitudes (for both positive and negative correlations) and without the strong negative correlation in arid regions. Moreover, SMOS shows a strong dry bias in almost all regions when compared to ERA-Interim, and also in northern latitudes as well as central Africa and South America when compared to JRA-55.

D. *Hovmöller Diagram*

Hovmöller diagrams for all datasets are shown in Fig. 4. One can see that all datasets generally resolve the same mean seasonal global soil moisture dynamics, for example, the distinct seasonal changes around the equator which are related to Monsoon changes and the intertropical convergence zone. While the overall patterns of all datasets agree well, ERA-Interim and SMOS show a lower variability, and ASCAT and SMOS show higher frequency components. The latter indicate a larger sensitivity to short-term events, probably because of their more shallow sensing depth as opposed to the deeper-layer model structure, which basically acts as a low-pass filter on surface soil moisture dynamics. Notice that also the aforementioned wet bias of ASCAT in high latitudes ($> 60°$ N) is well represented in the Hovmöller diagram, most prominently in the spring and early summer season.

E. *Triple Collocation Analysis*

Fig. 5 shows the TCA-based SNR estimates when using JRA-55, ASCAT, and SMOS as triplet (left), and when using ERA-Interim, ASCAT, and SMOS as triplet (right). The two individual

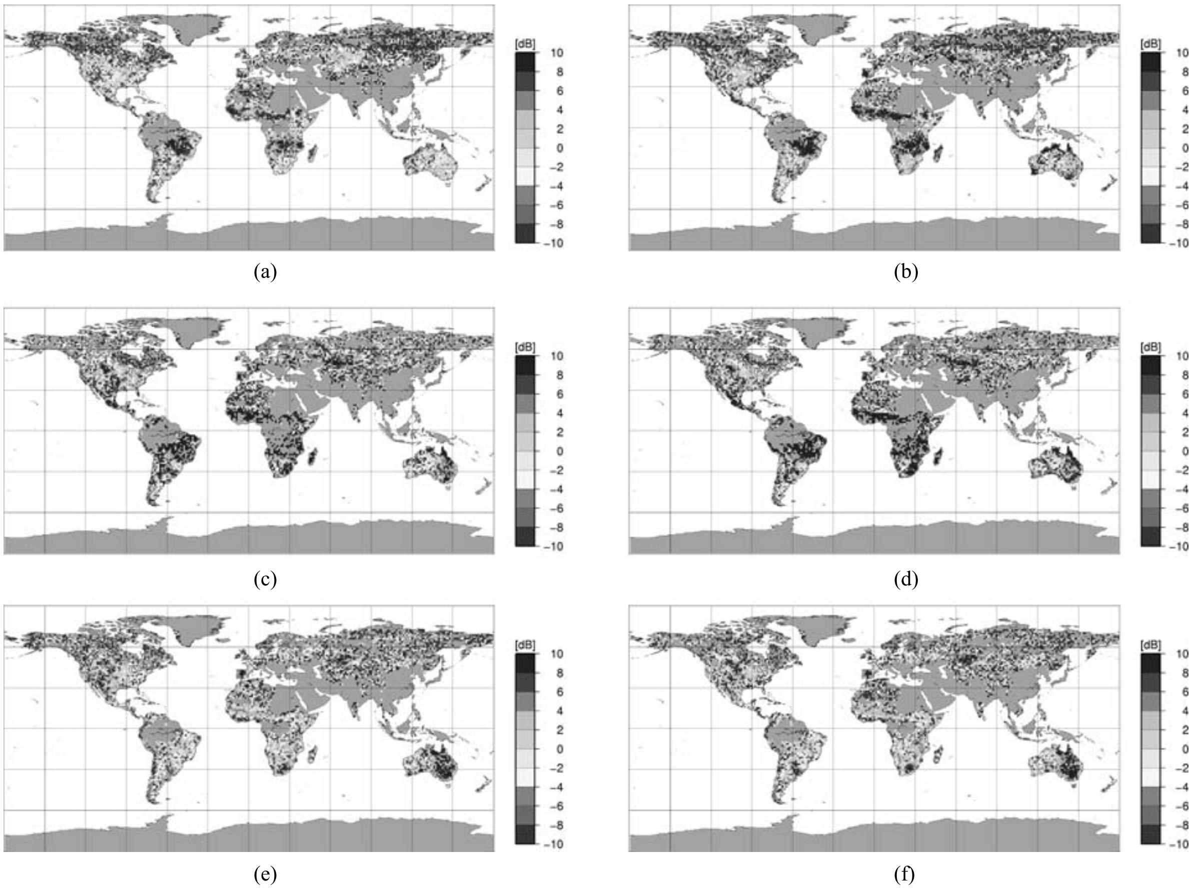

Fig. 5. SNR [dB] estimates for (a) JRA-55, (c) ASCAT, and (e) SMOS (used together as triplet in TCA), and for (b) ERA-Interim, (d) ASCAT, and (f) SMOS (used together as triplet in TCA).

SNR estimates for ASCAT and SMOS (see Fig. 5(c) and (d), and Fig. 5(e) and (f), respectively) are in good agreement when exchanging the model dataset, which can also be seen in Fig. 6. Discrepancies are fairly random and can be attributed to estimation uncertainties due to limited sample size [39], which is confirmed by the increasing spread with increasing latitude where the number of observations decreases due to masking of frozen and freeze/thaw conditions. This good agreement between the individual SNR estimates indicates that TCA assumptions are not violated.

Low SNRs for all datasets are observed in high latitude areas and arid regions (less than -8.0 dB). These are expected since these areas are known to be difficult for spaceborne soil moisture retrieval. Also, they are scarce in ground meteorological observations, which poses a challenge for land surface modeling and reanalysis.

ERA-Interim performs slightly better (more than 2.0 dB) than JRA-55 while showing very similar spatial SNR patterns overall. This may result from the use of very similar forcing data, while ERA-Interim additionally assimilates "SYNOP" observation data (see Section V-A), which typically reduces random errors and should, therefore, be reflected in the SNR.

ASCAT shows higher SNRs (more than 2.0 dB) than SMOS in large parts of southern America, central and southern Africa, and Europe. SMOS performs better mainly over Australia and the western U.S. Overall, ASCAT seems to perform generally better in more densely vegetated areas, whereas SMOS seems to show a better performance in more sparsely vegetated regions. This is particularly striking as the lower frequency L-band SMOS observations are commonly expected to be less sensitive to vegetation coverage than the C-band ASCAT observations [6]. However, results are consistent with other studies, which found that active soil moisture retrievals seem to outperform passive retrievals in more densely vegetated areas regardless of the wavelength [40], [41]. This suggests that while microwave frequency is important, there are also other factors that have a strong impact on soil moisture retrieval accuracy, including but not limited to the radiometric resolution, polarization, measurement geometry, and sensing principles (e.g., active versus passive).

Notice that spatial SNR patterns for ASCAT and SMOS slightly deviate from random error patterns shown in other studies such as [41] as the SNR takes also the soil moisture signal variability into account [20], [42]. Such differences can be found, for instance, in areas north of the Sahel, where low SNRs (less than -6.0 dB) are observed for both ASCAT and SMOS, while retrievals are seemingly accurate when looking into error variances only, or as another example in Brazil where

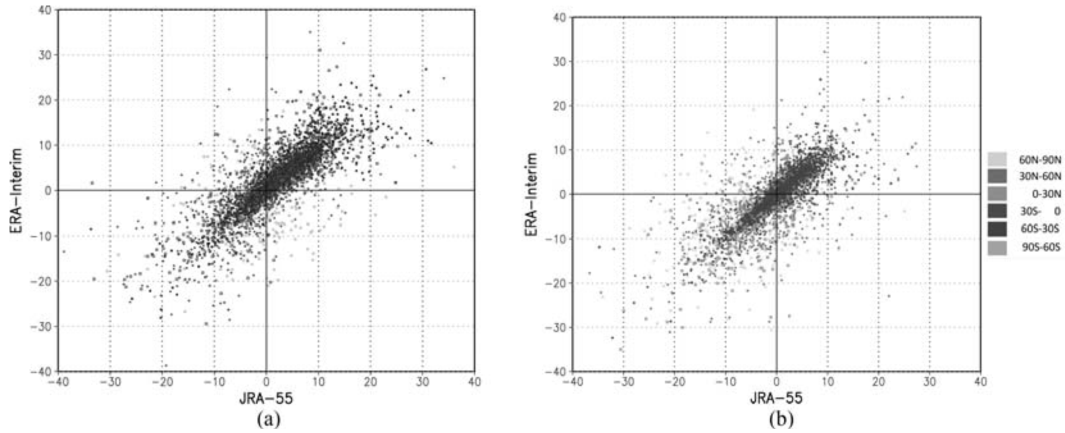

Fig. 6. Comparison of SNR [dB] estimates for ASCAT (a) and SMOS (b) when using JRA-55 to fill the triplet (x-axis) and when using ERA-Interim to fill the triplet (y-axis). Colors represent the latitude.

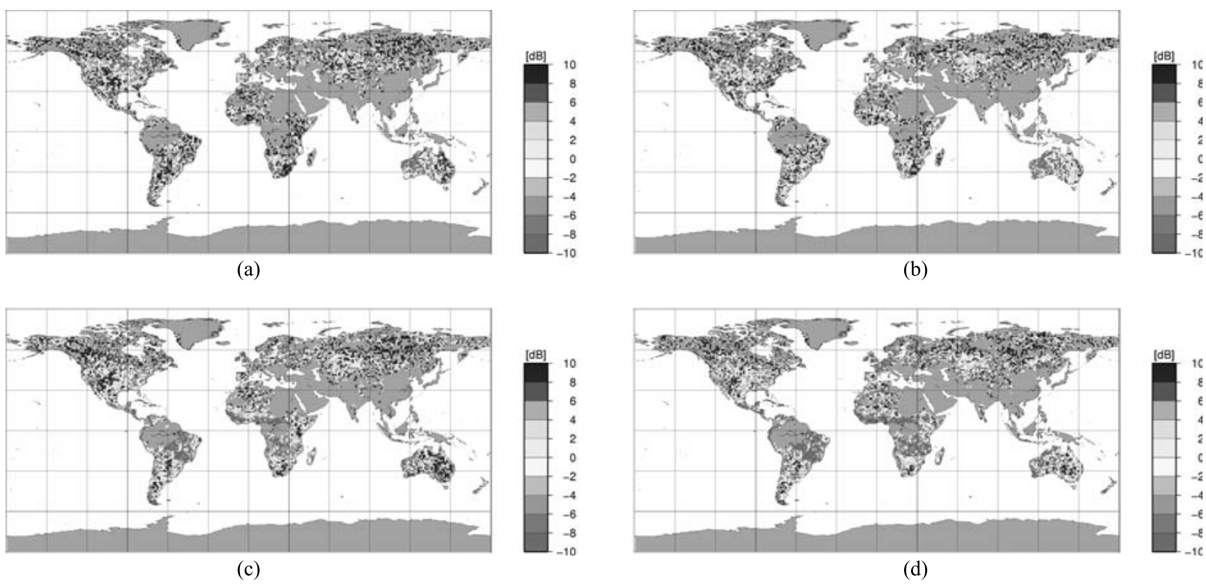

Fig. 7. SNR [dB] differences: (a) ASCAT—JRA-55, (c) SMOS—JRA-55, (b) ASCAT—ERA-Interim, and (d) SMOS—ERA-Interim.

ASCAT shows very good SNR values (more than 8.0 dB), while error variances are quite high.

Fig. 7 further shows the SNR differences between ASCAT and the two land surface models, as well as SMOS and the two land surface models. ASCAT outperforms the modeled datasets in northern regions, eastern Australia, central and southern Africa, large parts of South America, and the central US. SMOS shows higher SNRs (more than 3.0 dB) than the modeled datasets especially in large parts of Australia, some parts in southern Africa and southern America, and the more western parts of the U.S. In most of these regions, the model forcing data has a significantly reduced station density, which may explain the observed superiority of the satellite observations there.

Notice that these SNR differences carry important information about the potential utility of the satellite datasets for data assimilation. The purpose of data assimilation is to improve the quality of model estimates whenever observations are available. The weight that is given to a model estimate and an observation during an update step is directly determined by their respective random error variance, while systematic errors are usually corrected for by rescaling the observations into the model space. Therefore, differences between the SNRs of the model and the observation dataset, as shown in Fig. 7, can provide an indication about the potential skill improvement when assimilating these observations as was already found by Draper *et al.* [42].

Consequently, the largest skill improvements are expected in regions where the SNRs of the observations exceed those of the model (e.g., large parts of Africa and Southern America for ASCAT, or large areas in western Australia for SMOS). Regions with an opposite sign in the SNR differences (i.e., higher SNRs for the model than for the observations) might still benefit from assimilating the observations, yet there may be a physical boundary when the SNR drops below 0 dB, which represents the point where the noise variance starts to exceed the signal variance. Assimilating such observation will probably no longer add information to the model estimates. However, further research is needed to quantitatively assess the relationship between absolute and relative SNR magnitudes and the actual skill gain upon assimilation.

VI. Conclusion

In this study, we investigated the performance of spaceborne soil moisture retrievals from ASCAT and SMOS against two reanalysis datasets (JRA-55 and ERA-Interim) by means of classical intercomparison metrics (i.e., correlation coefficients, biases, and unbiased root-mean-square differences) as well as SNR estimates gleaned from TCA. Results indicate good consistency among the two satellite products and the two model datasets. Largest differences are observed in tropical forests, arid regions, and high latitudes (i.e., areas with long frozen periods). SNR differences between modeled and satellite-based soil moisture estimates were used to locate areas where large improvements in modeling skill can be expected upon assimilation of the satellite observations. In general, ASCAT seems to be more promising for data assimilation than SMOS. Future research will include the quantitative assessment of the relationship between SNR properties and the utility for data assimilation.

Acknowledgment

The authors would like to thank Dr. L. Butenko for providing source code for data processing, S. Kobayashi for advising on the usage of JRA-55, and CATDS for providing the SMOS L3 dataset (http://catds.ifremer.fr). JRA-55 data was provided by the Japanese 55-year Reanalysis (JRA-55) project, carried out by the JMA. ERA-Interim data were provided by the European Center for Medium-Range Weather Forecasts.

References

[1] R. H. Reichle, W. T. Crow, R. D. Koster, H. O. Sharif, and S. P. P. Mahanama, "Contribution of soil moisture retrievals to land data assimilation products," *Geophys. Res. Lett.*, vol. 35, no. 1, Jan. 2008, Art. no. L01404.

[2] L. Brocca, F. Melone, T. Moramarco, and R. Morbidelli, "Spatial-temporal variability of soil moisture and its estimation across scales: Soil moisture spatiotemporal variability," *Water Resour. Res.*, vol. 46, no. 2, Feb. 2010, Art. no. W02516.

[3] W. A. Dorigo *et al.*, "The international soil moisture network: A data hosting facility for global in situ soil moisture measurements," *Hydrol. Earth Syst. Sci.*, vol. 15, no. 5, pp. 1675–1698, May 2011.

[4] W. Wagner *et al.*, "Fusion of active and passive microwave observations to create an essential climate variable data record on soil moisture," in *Proc. XXII Int. Soc. Photogrammetry Remote Sens. Congr.*, Melbourne, Australia, 2012, vol. 25, pp. 315–321.

[5] Y. H. Kerr *et al.*, "The SMOS mission: New tool for monitoring key elements of the global water cycle," *Proc. IEEE*, vol. 98, no. 5, pp. 666–687, May 2010.

[6] D. Entekhabi *et al.*, "The soil moisture active passive (SMAP) mission," *Proc. IEEE*, vol. 98, no. 5, pp. 704–716, May 2010.

[7] W. Wagner *et al.*, "Operations, challenges, and prospects of satellite-based surface soil moisture data services," in *Remote Sensing of Energy Fluxes and Soil Moisture Content*. Boca Raton, FL, USA: CRC Press, Oct. 2013, pp. 463–488.

[8] W. Wagner, G. Lemoine, and H. Rott, "A method for estimating soil moisture from ERS scatterometer and soil data," *Remote Sens. Environ.*, vol. 70, no. 2, pp. 191–207, 1999.

[9] Z. Bartalis *et al.*, "Initial soil moisture retrievals from the METOP-A advanced scatterometer (ASCAT)," *Geophys. Res. lett.*, vol. 34, 2007, Art. no. L20401.

[10] V. Naeimi, K. Scipal, Z. Bartalis, S. Hasenauer, and W. Wagner, "An improved soil moisture retrieval algorithm for ERS and METOP scatterometer observations," *IEEE Trans. Geosci. Remote Sens.*, vol. 47, no. 7, pp. 1999–2013, Jul. 2009.

[11] I. Dharssi, K. J. Bovis, B. Macpherson, and C. P. Jones, "Operational assimilation of ASCAT surface soil wetness at the met office," *Hydrol. Earth Syst. Sci.*, vol. 15, no. 8, pp. 2729–2746, Aug. 2011.

[12] P. de Rosnay, M. Drusch, D. Vasiljevic, G. Balsamo, C. Albergel, and L. Isaksen, "A simplified extended Kalman filter for the global operational soil moisture analysis at ECMWF," *Quart. J. Roy. Meteorol. Soc.*, vol. 139, pp. 1199–1213, 2012.

[13] L. Brocca, F. Melone, T. Moramarco, W. Wagner, and S. Hasenauer, "ASCAT soil wetness index validation through in situ and modeled soil moisture data in central Italy," *Remote Sens. Environ.*, vol. 114, pp. 2745–2755, Nov. 2010.

[14] C. Draper, J.-F. Mahfouf, J.-C. Calvet, E. Martin, and W. Wagner, "Assimilation of ASCAT near-surface soil moisture into the SIM hydrological model over France," *Hydrol. Earth Syst. Sci.*, vol. 15, no. 12, pp. 3829–3841, Dec. 2011.

[15] D. G. Miralles, W. T. Crow, and M. H. Cosh, "Estimating spatial sampling errors in coarse-scale soil moisture estimates derived from point-scale observations," *J. Hydrometeorol.*, vol. 11, no. 6, pp. 1423–1429, Dec. 2010.

[16] A. Gruber, W. Dorigo, S. Zwieback, A. Xaver, and W. Wagner, "Characterizing coarse-scale representativeness of in situ soil moisture measurements from the international soil moisture network," *Vadose Zone J.*, vol. 12, no. 2, 2013, doi: 10.2136/vzj2012.0170.

[17] D. J. Leroux *et al.*, "Comparison between SMOS, VUA, ASCAT, and ECMWF soil moisture products over four watersheds in U.S," *IEEE Trans. Geosci. Remote Sens.*, vol. 52, no. 3, pp. 1562–1571, 2014.

[18] C. Albergel *et al.*, "Evaluation of remotely sensed and modelled soil moisture products using global ground-based in situ observations," *Remote Sens. Environ.*, vol. 118, pp. 215–226, Mar. 2012.

[19] A. Stoffelen, "Toward the true near-surface wind speed: Error modeling and calibration using triple collocation," *J. Geophys. Res.*, vol. 103, no. C4, pp. 7755–7766, 1998.

[20] A. Gruber, C.-H. Su, S. Zwieback, W. Crow, W. Dorigo, and W. Wagner, "Recent advances in (soil moisture) triple collocation analysis," *Int. J. Appl. Earth Observ. Geoinf.*, vol. 45, pp. 200–211, Mar. 2016.

[21] D. Entekhabi, R. H. Reichle, R. D. Koster, and W. T. Crow, "Performance metrics for soil moisture retrievals and application requirements," *J. Hydrometeorol.*, vol. 11, no. 3, pp. 832–840, Jun. 2010.

[22] C. Draper, R. Reichle, R. de Jeu, V. Naeimi, R. Parinussa, and W. Wagner, "Estimating root mean square errors in remotely sensed soil moisture over continental scale domains," *Remote Sens. Enviorn.*, vol. 137, pp. 288–298, Oct. 2013.

[23] C. Albergel *et al.*, "An evaluation of ASCAT surface soil moisture products with in-situ observations in southwestern france," *Hydrol. Earth Syst. Sci*, vol. 13, pp. 115–124, Mar. 2009.

[24] J. M. Mahfouf, C. S. Draper, and J. P. Walker, "Root zone soil moisture from the assimilation of screen-level variables and remotely sensed soil moisture," *J. Geophys. Res.*, vol. 116, 2011, Art. no. D02127.

[25] E. Jacquette *et al.*, "SMOS CATDS level 3 global products over land," *Proc. SPIE*, vol. 7824, Oct. 2010, Art. no. 78240K.

[26] S. Kobayashi *et al.*, "The JRA-55 reanalysis: General specifications and basic characteristics," *J. Meteorol. Soc. Jpn. Ser. II*, vol. 93, no. 1, pp. 5–48, 2015.

[27] P. J. Sellers, Y. Mintz, Y. C. Sud, and A. Dalcher, "A simple biosphere model (SIB) for use within general circulation models," *J. Atmos. Sci.*, vol. 43, no. 6, pp. 505–531, Mar. 1986.

[28] N. Sato *et al.*, "Effects of implementing the simple biosphere model in a general circulation model," *J. Atmos. Sci.*, vol. 46, no. 18, pp. 2757–2782, Sep. 1989.

[29] J. L. Dorman and P. J. Sellers, "A global climatology of Albedo, roughness length and stomatal resistance for atmospheric general circulation models as represented by the simple biosphere model (SiB)," *J. Appl. Meteorol.*, vol. 28, no. 9, pp. 833–855, Sep. 1989.

[30] Japan Meteorological Agency, *JRA-55 Product Users' Handbook: Model Grid Data*, Japan, Tech. Rep., 2014. [Online]. Available: http://jra.kishou.go.jp/JRA-55/index_en.html
[31] D. P. Dee *et al.*, "The ERA-Interim reanalysis: configuration and performance of the data assimilation system," *Quart. J. Roy. Meteorol. Soc.*, vol. 137, no. 656, pp. 553–597, Apr. 2011.
[32] P. Viterbo and A. C. M. Beljaars, "An improved land surface parameterization scheme in the ECMWF model and its validation," *J. Climate*, vol. 8, no. 11, pp. 2716–2748, Nov. 1995.
[33] P. Viterbo, A. Beljaars, J.-F. Mahfouf, and J. Teixeira, "The representation of soil moisture freezing and its impact on the stable boundary layer," *Quart. J. Roy. Meteorol. Soc.*, vol. 125, no. 559, pp. 2401–2426, Oct. 1999. [Online]. Available: http://doi.wiley.com/10.1002/qj.49712555904
[34] P. Wessel, W. H. F. Smith, R. Scharroo, J. Luis, and F. Wobbe, "Generic mapping tools: Improved version released," *Eos, Trans. Amer. Phys. Union*, vol. 94, no. 45, pp. 409–410, Nov. 2013. [Online]. Available: http://doi.wiley.com/10.1002/2013EO450001
[35] E. Hovmöller, "The Trough-and-Ridge diagram," *Tellus*, vol. 1, no. 2, pp. 62–66, May 1949.
[36] J. Blunden and D. S. Arndt, "State of the climate in 2015," *Bull. Amer. Meteorol. Soc.*, vol. 97, no. 8, 2016, Art. no. Si-S275.
[37] K. A. McColl, J. Vogelzang, A. G. Konings, D. Entekhabi, M. Piles, and A. Stoffelen, "Extended triple collocation: Estimating errors and correlation coefficients with respect to an unknown target: Extended triple collocation," *Geophys. Res. Lett.*, vol. 41, pp. 6229–6236, Sep. 2014.
[38] M. Vreugdenhil *et al.*, "Intercomparison of vegetation variables derived from scatterometers," *IEEE JSTARS*, vol. 104, no. 2, pp. 155–170, 2016.
[39] S. Zwieback, K. Scipal, W. Dorigo, and W. Wagner, "Structural and statistical properties of the collocation technique for error characterization," *Nonlinear Processes Geophys.*, vol. 19, no. 1, pp. 69–80, 2012.
[40] W. A. Dorigo *et al.*, "Error characterisation of global active and passive microwave soil moisture datasets," *Hydrol. Earth Syst. Sci.*, vol. 14, no. 12, pp. 2605–2616, 2010.
[41] A. Al-Yaari *et al.*, "Global-scale comparison of passive (SMOS) and active (ASCAT) satellite based microwave soil moisture retrievals with soil moisture simulations (MERRA-Land)," *Remote Sens. Environ.*, vol. 152, pp. 614–626, Sep. 2014.
[42] C. S. Draper, R. H. Reichle, G. J. M. De Lannoy, and Q. Liu, "Assimilation of passive and active microwave soil moisture retrievals," *Geophys. Res. Lett.*, vol. 39, no. 4, Feb. 2012, Art. no. L04401.

Kengo Miyaoka was born in Tokyo, Japan, in 1973. He received the M.Sc. degree in geography from Tokyo Metropolitan University, Tokyo, in 2000.

He has been with the Japan Meteorological Agency (JMA), Tokyo, Japan, since 2000. From 2000 to 2002, he was at the Wakkanai Local Meteorological Office. From 2002 to 2006, he was with the Meteorological Satellite Center of JMA and handled the satellite navigation of GOES9, MTSAT-1R. Since 2006, he has been working in the Climate Prediction Division of the Global Environment and Marine Department. His main tasks are the development and maintenance of the numerical prediction system with a focus on land surface analysis. In the JRA-55 project, he worked on preparation of the satellite-derived snow data. In autumn 2015, he spent six months as a Visiting Scientist at the EUMETSAT, the TU-Wien, and the European Center for Medium-Range Weather Forecasts working with microwave scatterometer (ASCAT) data. He is currently working on upgrading the system for the land surface analysis in both the operational numerical forecast system and the next generation of the Japan Reanalysis Project.

Alexander Gruber was born in Vienna, Austria, in 1988. He received the Dipl.-Ing. (M.Sc.) degree in geodesy and geophysics and the Dr.techn. (Ph.D.) degree in surveying and geoinformation, both with excellence, in 2013 and 2016, respectively, both from Vienna University of Technology, Vienna, Austria.

Since 2011, he has been a Project Assistant with the Research Group Remote Sensing, Department of Geodesy and Geoinformation, Vienna University of Technology, and has been involved in a large number of research projects. His core expertise lies in soil moisture retrieval from synthetic aperture radar and scatterometer instruments, error characterization of earth observation datasets, up- and downscaling techniques, and data assimilation. He has authored and coauthored a large number of peer-reviewed journal papers, conference papers, and book chapters and acts as a reviewer for many SCI journals in the field of remote sensing and earth observation.

Francesca Ticconi (S'06–M'03) received the Laurea degree (*summa cum laude*) in electronic engineering and the Ph.D. degree in electromagnetism from Sapienza University of Rome, Rome, Italy, in 2003 and 2007, respectively.

From July 2003 to October 2005, she was with the Italian Environmental Protection Agency (APAT), analyzing the development of new technologies suitable for minimizing electromagnetic emissions. After the Ph.D. degree, from November 2007 to September 2008, she was at the Centre of Terrestrial Carbon Dynamics, University of Sheffield, where she worked on synthetic aperture radar image processing for forest monitoring. After that period, she was a scientific collaborator at the German Aerospace Centre (DLR) until December 2010, where she studied scattering electromagnetic models for the interpretation of polarimetric and interferometric SAR data. Then, she was at the School of Earth and Environment, University of Leeds, where her activity focused on measuring changes of glaciers and Greenland ice sheets by using radar altimetry. She is currently a Science Support Consultant at the Remote Sensing and Product Division, EUMETSAT, Darmstadt, Germany. She is involved in developing the processing algorithms for the generation of the next scatterometer data from the planned scatterometer instrument, which will be on board the EPS-SG satellites. She is also working on the product specification and the calibration/validation plan. Her research interests include the study of wave scattering and propagation from the Earth's surface, with application to the microwave remote sensing of biogeophysical environmental parameters like soil moisture content, soil roughness parameters, and vegetation parameters. She is also interested in the remote observation of the oceans and the cryosphere.

Dr. Ticconi is a member of the IEEE Geoscience and Remote Sensing Society.

Sebastian Hahn was born in Vienna, Austria, in 1985. He received the B.Sc. degree in geodesy and geomatic engineering and the M.Sc. degree in geodesy and geophysics in 2009 and 2011, respectively, from Vienna University of Technology, Vienna, where he is currently working toward the Ph.D. degree.

Since April 2010, he has been a Project Assistant with the Research Group Remote Sensing, Department of Geodesy and Geoinformation, Vienna University of Technology. He is currently one of the key developers for the software package WARP (Soil Water Retrieval Package), which represents the implementation of the TU Wien soil moisture retrieval algorithm. As a developer, he is focused on software design, multiprocessing, model calibration, and algorithmic improvements, which is in light of his Ph.D. studies. His main research interests include remote sensing over land using active microwave instruments, active soil moisture retrieval algorithms, software development, and validation of soil moisture products.

Wolfgang Wagner (M'98–SM'07) was born in Wels, Austria, in 1969. He received the Dipl.-Ing. (M.Sc.) degree in physics and the Dr.techn. (Ph.D.) degree in remote sensing, both with excellence, from Vienna University of Technology, Vienna, Austria, in 1995 and 1999, respectively.

In support of his master and Ph.D. studies, he received fellowships to carry out research at the University of Bern, Atmospheric Environment Service Canada, NASA Goddard Space Flight Center, European Space Agency, and the Joint Research Centre of the European Commission. From 1999 to 2001, he was with the German Aerospace Agency (DLR). In 2001, he was appointed as a Professor for remote sensing in Vienna University of Technology. Since 2012, he has been the Head of the Department of Geodesy and Geoinformation, Vienna University of Technology, where he is also a Cofounder and Head of Science of the Earth Observation Data Centre for Water Resources Monitoring. He focuses on active remote sensing techniques, in particular scatterometry, synthetic aperture radar, and full-waveform airborne laser scanning. His main research interests include geophysical parameter retrieval techniques for remote sensing data and application development.

Dr. Wagner is a member of the Science Advisory Groups for Sentinel-1 (ESA), METOP ASCAT, and METOP-SG SCA (EUMETSAT and ESA), and a member of the GCOS/GTOS/WCRP Terrestrial Observation Panel for Climate. He was the ISPRS Commission VII President from 2008 to 2012 and an Editor-in-Chief of the open access journal *Remote Sensing* from 2009 to 2011.

Julia Figa-Saldaña received the M.Sci. degree in civil engineering from the Universitat Politecnica de Catalunya, Barcelona, Spain, in 1993.

Since then, she has been involved in radar remote sensing processing and applications. She joined EUMETSAT, Darmstadt, Germany, in 1999 and was involved in the specification and development of the Advanced SCATterometer (ASCAT) mission processing and cal/val activities, later going on to support the EUMETSAT Polar System Operations. Since 2013, she has been leading the science and operational support to activities related to Marine Meteorology applications, particularly for the EUMETSAT scatterometer programs and co-chairing the ESA/EUMETSAT Scatterometer Science Advisory Group. In June 2016, she joined the Jason-CS/Sentinel-6 project at EUMETSAT as a Ground Segment Manager.

Craig Anderson received the B.Sc. (Hons.) degree in applied mathematics and the Ph.D. degree in theoretical solar physics from the University of St Andrews, St Andrews, U.K.

He worked for several years with the Marconi Research Centre, Great Baddow, U.K., developing applications for airborne and spaceborne synthetic aperture radars before joining EUMETSAT, Darmstadt, Germany. For the last ten years, he has been involved in the calibration and validation of the advanced scatterometer (ASCAT) instruments on the Metop-A and Metop-B satellites.