

This discussion paper is/has been under review for the journal Hydrology and Earth System Sciences (HESS). Please refer to the corresponding final paper in HESS if available.

Combining satellite observations to develop a daily global soil moisture product for a wide range of applications

M. Enenkel¹, C. Reimer¹, W. Dorigo¹, W. Wagner¹, I. Pfeil¹, R. Parinussa², and R. De Jeu³

¹Vienna University of Technology, Department of Geodesy and Geoinformation, Vienna, Austria

²School of Civil and Environmental Engineering, The University of New South Wales, Sydney, Australia

³Transmissivity B. V., Noordwijk, the Netherlands

Received: 14 October 2015 – Accepted: 15 October 2015 – Published: 3 November 2015

Correspondence to: M. Enenkel (markus.enenkel@geo.tuwien.ac.at)

Published by Copernicus Publications on behalf of the European Geosciences Union.

HESSD

12, 11549–11589, 2015

Combining satellite
observations to
develop a daily global
soil moisture product

M. Enenkel et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



Abstract

The soil moisture dataset that is generated via the Climate Change Initiative (CCI) of the European Space Agency (ESA) (ESA CCI SM) is a popular research product. It is composed of observations from nine different satellites and aims to exploit the individual strengths of active (radar) and passive (radiometer) sensors, thereby providing surface soil moisture estimates at a spatial resolution of 0.25° . However, the annual updating cycle limits the use of the ESA CCI SM dataset for operational applications. Therefore, this study proposes an adaptation of the ESA CCI processing chain for daily global updates via satellite-derived near real-time (NRT) soil moisture observations. In order to extend the ESA CCI SM dataset from 1978 to present we use NRT observations from the Advanced SCATterometer on-board the MetOp satellites and the Advanced Microwave Scanning Radiometer 2 on-board GCOM-W. Since these NRT observations do not incorporate the latest algorithmic updates, parameter databases, and intercalibration efforts, by nature they offer a lower quality than reprocessed offline datasets. Our findings indicate that, despite issues in arid regions, the new “CCI NRT” dataset shows a good correlation with ESA CCI SM. The average global correlation coefficient between CCI NRT and ESA CCI SM (Pearson’s R) is 0.8. An initial validation with 40 in-situ observations in France, Kenya, Senegal and Kenya yields an average R of 0.58 and 0.49 for ESA CCI SM and CCI NRT respectively. In summary, the CCI NRT dataset is getting ready for operational use, supporting applications such as drought and flood monitoring, weather forecasting or agricultural applications.

1 Introduction

Soil moisture, the water in the soils’ pore space, is one of very few environmental variables that directly link atmospheric processes to land surface conditions (Legates et al., 2010; Taylor et al., 2012). Despite the tiny share of soil moisture in the global water budget of only a few per mille (Gleick and White, 1993), it is a decisive or even limiting factor

HESSD

12, 11549–11589, 2015

Combining satellite observations to develop a daily global soil moisture product

M. Enenkel et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



multi-sensor soil moisture product (Liu et al., 2011a, 2012; Wagner et al., 2012). The ESA CCI soil moisture dataset (ESA CCI SM) relies on the merging of different active (radar) and passive (radiometer) microwave instrument observations into a single consistent product. The latest official release of the ESA CCI SM product (CCI SM v02.1) covers a period from 1978 to 2013. Product updates that extend the temporal coverage are performed regularly every year by incorporating new observations from radars and radiometers. Since its release in 2012, the ESA CCI SM dataset has been used in a variety of studies.

Yuan et al. (2015), for instance, analysed the performance of ESA CCI SM to detect short-term (monthly to seasonal) droughts in China with respect to in-situ observations and two soil moisture reanalysis datasets that are derived from land surface models, namely the Global Land Data Assimilation System (GLDAS) (Rodell et al., 2004) and ERA Interim (Dee et al., 2011). ESA CCI SM captured less than 60% of drought months at the scale of in-situ stations. However, comparable to the reanalysis products, it performed well with regard to the detection of inter-annual variations of short-term drought on river basin scale, particularly in sparsely vegetated areas. The studies of Nicolai-Shaw (2015) confirm these findings over North America by comparing ESA CCI SM with reanalysis products of the European Centre for Medium Range Weather Forecasting (ECMWF) and in-situ observations. Regarding the spatial representativeness, ESA CCI SM showed a higher agreement with the in-situ observations than the reanalysis data. With respect to the absolute values, however, the agreement between ESA CCI SM and the reanalysis data was higher. Another study of McNally et al. (2015) showed the superiority of the Water Requirement Satisfaction Index in Senegal and Niger when fed with ESA CCI SM instead of a water-balance model output. Finally, ESA CCI SM was also used to identify global trends in soil moisture with regard to vegetation (Barichivich et al., 2014; Dorigo et al., 2012; Muñoz et al., 2014) and to improve the understanding of the land–atmosphere coupling (Bauer-Marschallinger et al., 2013; Hirschi et al., 2014).

HESSD

12, 11549–11589, 2015

Combining satellite observations to develop a daily global soil moisture product

M. Enenkel et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



However, decision-makers in various applications and domains (e.g. weather prediction, drought and flood monitoring, index-based agricultural insurance) need more timely soil moisture product updates at daily or sometimes even sub-daily intervals. The current ESA CCI SM product does not fulfil this requirement. As a consequence, this study concentrates on the adaptation of the ESA CCI soil moisture processing chain to perform daily product updates by seamlessly integrating near real-time (NRT) soil moisture observations from the Advanced Scatterometer (ASCAT) on-board MetOp-A/MetOp-B and the AMSR-2 radiometer on-board GCOM-W1. NRT means that both the observations from ASCAT and AMSR-2 are available within two to three hours. The resulting dataset is called “CCI NRT”. It is intended to extend the 35 years of soil moisture observations available via the ESA CCI SM dataset on a daily basis. This study has two objectives. First, we analyse which adaptations of the current processing chain are required to generate a CCI NRT soil moisture product. Second, we investigate how well the CCI NRT dataset compares to ESA CCI SM on a global scale. This task is particularly challenging due to the difference in quality between reprocessed and NRT soil moisture observations. An initial validation of the CCI NRT and the ESA CCI SM dataset is carried out with respect to 40 in-situ stations in France, Senegal, Spain and Kenya.

2 Datasets used

Depending on the sensor, space-based soil moisture retrievals show large variations in performance on a global scale. C-band radars (e.g. ASCAT), for instance, are better suited to retrieve soil moisture over moderate vegetation cover than the AMSR-2 radiometer (Al-Yaari et al., 2014; Gruhier et al., 2010; Rüdiger et al., 2009). Simultaneously, radars are facing challenges in super-arid regions that are often characterized by sandy soils (Wagner et al., 2003, 2007). This latter phenomenon is not such a big issue for radiometers, but radars emit a microwave beam that can be affected by volume scattering in very dry soils. However, this phenomenon is not fully understood yet. The

HESSD

12, 11549–11589, 2015

Combining satellite observations to develop a daily global soil moisture product

M. Enenkel et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



following section describes the general characteristics of the reprocessed ESA CCI SM product, as well as the operational products from ASCAT and AMSR-2 that are used to generate the extension of the dataset via daily updates.

2.1 ESA CCI surface soil moisture

The ESA CCI soil moisture product was generated in accordance with the World Meteorological Organization’s (2008) report on “Future Climate Change Research and Observation”. The report highlights the importance of collecting, harmonizing and validating soil moisture observations from different sources to extend the temporal and spatial coverage, to improve data quality (also for further data assimilation), to support the understanding of feedback mechanisms and the prediction of extreme events.

The ESA CCI SM dataset incorporates the measurements of nine satellites (Fig. 1). It is available at daily time steps and on a 0.25° × 0.25° latitude/longitude global array of grid points. The quality flags, which are distributed in combination with the dataset, provide information about the sensor and the used frequency, the moment of the measurement, ascending or descending orbit and snow/frozen soil probability. In order to generate soil moisture in volumetric units (m³ m⁻³) soil porosity values are derived from 1300 global samples collected by the Food and Agriculture Organization (FAO). According to Liu et al. (2011b, 2012), these porosity values are used in the algorithm developed by the VU University Amsterdam and the National Aeronautics and Space Administration (NASA) to generate soil moisture data from passive sensors via the Land Parameter Retrieval Model (LPRM) (Holmes et al., 2009; Owe et al., 2008). The same porosity values are applied in GLDAS, which is used as a reference dataset to rescale soil moisture estimates from all sensors via CDF (Cumulative Distribution Function) matching (Liu et al., 2009; Reichle and Koster, 2004).

Combining satellite observations to develop a daily global soil moisture product

M. Enenkel et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures



Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



2.2 Active measurements (radar) based on ASCAT

The advanced scatterometers (ASCAT) on-board MetOp A/B are real aperture radar sensors. Their soil moisture retrieval is based on the backscatter of microwaves that are sensitive to the dielectric properties of the water molecule, resulting in a quasi-linear increase relationship between increasing water content and microwave backscatter. ASCAT operates in C-band (5.255 GHz), scanning two 550 km swaths with three antennas on each side. Consequently, every location is scanned from three different angles, enabling corrections for vegetation cover by analysing measurement differences at different angles. The TU-Wien change detection algorithm results in a relative surface soil moisture measurement that is scaled between the historically lowest and highest values, corresponding to a completely dry surface and soil saturation (Bartalis et al., 2005; Wagner et al., 1999, 2013). Validations of the NRT soil moisture product disseminated via EUMETCAST (Albergel et al., 2012) yielded an average RMSD of $0.08\text{ m}^3\text{ m}^{-3}$ for more than 200 in-situ stations around the globe. While the global average of all correlations was $r = 0.5$, the best correlation ($r = 0.8$) was achieved for an in-situ network in Australia (OZNET). In general, the correlations were higher during winter months.

The TU-Wien Water Retrieval Package (WARP) is optimized to estimate model parameters from multi-year backscatter time series on a discrete global grid (DGG). These parameters help to understand the characteristics of scattering effects on a global scale, which are affected by land cover, surface roughness, etc. However, there are large differences between soil moisture derived from ASCAT via the WARP processing chain and its operational version WARP NRT, which is used to generate soil moisture observations in orbit geometry (swath format). The NRT product is distributed from EUMETSAT (European Organisation for the Exploitation of Meteorological Satellites) in orbit geometry. It is available 135 min after the overpass of the two ASCAT sensors on board the MetOp A and MetOp B satellites. An advantage of WARP NRT is the high robustness and speed of the processing chain (less than a minute for one ASCAT orbit). However, according to Wagner et al. (2013) its main drawback is that updates

HESSD

12, 11549–11589, 2015

Combining satellite observations to develop a daily global soil moisture product

M. Enenkel et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures



Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



related to algorithmic improvements and updates in the calibration of the backscatter measurement usually take a lot of time. As a result, the quality of NRT soil moisture data lags behind the quality of reprocessed datasets.

2.3 Passive measurements (radiometer) based on AMSR-2

Passive retrievals are based on the dielectric contrast between dry and wet soil that leads to changes in emissivity from 0.96 for dry soils and below 0.6 for wet soils (Njoku and Li, 1999; Schmugge and Jackson, 1994). Being very similar to its predecessor AMSR-E, AMSR-2 on-board the GCOM-W1 satellite measures brightness temperature at different frequencies (C-, X- and Ku-band) with vertical and horizontal polarizations at each frequency. In addition, the Ka-band (36.5/37 GHz) is used to estimate brightness temperature (Holmes et al., 2009). In contrast to ASCAT, the AMSR sensors have a fixed incidence angle at 55°, resulting in a “conically-shaped” footprint and a swath width of 1445 km. Both the ESA CCI SM dataset and its NRT equivalent only use night time measurements (Liu et al., 2011), because a smaller temperature gradient between the soil and vegetation facilitates more precise observations (de Jeu et al., 2014). The LPRM transforms information about the dielectric constant into volumetric soil moisture by applying an empirical model (Wang and Schmugge, 1980). Similar to ASCAT, measurements over frozen or snow-covered soils are not possible due to the immovability of the water molecules. An intercomparison of soil moisture products from AMSR-E and ASCAT over 17 European sites (Brocca et al., 2011) resulted in comparable correlation values with observed (modelled) data of 0.71 (0.74) for ASCAT and 0.62 (0.72) for AMSR-E. The AMSR-2 NRT dataset is distributed from NASA and the Japan Aerospace Exploration Agency (JAXA). It is available at NASA’s Global Change Master Directory: [http://gcmd.gsfc.nasa.gov/r/d/\[GCMD\]GES_DISC_LPRM_AMSR2_SOILM2_V001](http://gcmd.gsfc.nasa.gov/r/d/[GCMD]GES_DISC_LPRM_AMSR2_SOILM2_V001).

The operational AMSR-2 soil moisture products that was used to create the ESA CCI SM dataset is a different version than the current operational product that we use to develop the CCI NRT product, but both products are very similar. However, just like its

Combining satellite observations to develop a daily global soil moisture product

M. Enenkel et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



predecessor AMSR-E, AMSR-2 needs to cope with radio frequency interference (RFI) that is capable of jeopardizing whole satellite missions (Oliva et al., 2012). Figure A1 shows the RFI masking for all available frequencies on a global scale.

2.4 In-situ networks

All in-situ measurements used for this study were obtained via the International Soil Moisture Network (Dorigo et al., 2011, 2013). The single probes/networks (Fig. 2) were selected to cover regions in which each of the three elements of the CCI NRT dataset, namely its active, passive and merged component, are used.

Accordingly, we extract measurements from the Smosmania network (Albergel et al., 2008) in the South of France to validate the active component of the daily ESA CCI surface soil moisture updates, from the Remedhus network (Sanchez et al., 2012) in the West of Spain to validate the merged active/passive component, from the Dahra network in Senegal and the Cosmos network in Kenya to validate the passive component. The Smosmania (Albergel et al., 2008) and Dahra networks are equipped with the same type of probes (ThetaProbe ML2X), while the Remedhus network that covers the Duero basin relies on Stevens HydraProbes. The Cosmos station in Kenya relies on a cosmic-ray probe. All in-situ observations were filtered for stations that measure the soil moisture content up to a depth of 5 cm (respectively 10 cm for the Cosmos station) to ensure the comparability with the satellite-derived surface soil moisture datasets.

3 Methods

The following section is divided into two sections. Section 3.1 concentrates on the extension of the ESA CCI SM processing chain for daily updates. Section 3.2 explains the corresponding validation of the new dataset on a global scale.

Combining satellite observations to develop a daily global soil moisture product

M. Enenkel et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures



Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



3.1 Adaptation of the CCI soil moisture processing chain for daily updates

The extension of the ESA CCI SM processing chain is based on the method developed by Liu et al. (2011a, 2012). Figure 3 illustrates the main processing steps for the integration of operational soil moisture observation in a flow chart. The entire processing chain was built in the free and open-source software Python.

Just like within the ESA CCI SM processing chain all ASCAT level 2 data are first masked according to frozen conditions and vegetation density. The AMSR-2 data are masked for soil skin temperature below 0 °C, RFI and vegetation optical depth (VOD). After the spatial resampling via a regular hamming window to a 0.25° grid we apply the temporal resampling at 00:00 UTC via nearest neighbour search. In contrast to AMSR-2 both ascending and descending orbits are used in case of ASCAT. Both datasets are rescaled to the reference soil moisture dataset (GLDAS NOAH Version 1.0) via linear CDF matching. Due to the unavailability of the GLDAS dataset in NRT, we apply the scaling functions that were used to generate the original ESA CCI SM dataset. This way it is possible to preserve the datasets' original, relative dynamics, while adjusting them to the same range and distribution.

Figure 4 illustrates the coverage of active, passive and merged data on a global scale. The passive LPRM soil moisture product is used in regions with lower vegetation density, whereas the TU-Wien ASCAT product is applied in regions with higher vegetation density. Vegetation density is represented by vegetation optical depth, a dimensionless variable linked to the vegetation water content and above ground biomass (Liu et al., 2015). VOD has previously been used as an additional indicator for long-term vegetation dynamics (Liu et al., 2011b). It is retrieved simultaneously to soil moisture through the LPRM. So-called transition zones, areas between desert and tropical climate, are characterized by VOD values between 0.24 and 0.60. In these regions the active and the passive product agree well ($R > 0.65$). Therefore, both products can be merged (green areas in Fig. 4).

HESSD

12, 11549–11589, 2015

Combining satellite observations to develop a daily global soil moisture product

M. Enenkel et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures



Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



3.2 Performance metrics and validation

According to Wagner et al. (2013) the validation of satellite data via in-situ observations can be critical due to different issues, such as the high spatio-temporal variability of soil moisture (Western et al., 2002) or a lack of adequate reference datasets (Crow et al., 2012). There are no reference data that represent exactly the same physical quantity as the satellite observation. Acknowledging these limitations, this study concentrates on the following comparative assessments:

- calculating the Pearson's correlation coefficient (R) for ESA CCI SM and CCI NRT for 2013 on a global scale;
- calculating the absolute differences in volumetric soil moisture between both datasets for the entire year of 2013 (including individual calculations for all seasons) on a global scale;
- individual validation for ESA CCI SM and CCI NRT for 2013 over forty in-situ soil moisture observations (two networks, two single stations) in France, Kenya, Senegal and Spain.

For each in-situ observation a nearest neighbour search selects the closest grid point in the satellite-derived datasets. The performance metrics include:

- Pearson correlation (R), indicating a linear relationship between two variables;
- Spearman correlation (S), a non-parametric test that does not rely on any assumption about the distribution of the data;
- the absolute bias in $\text{m}^3 \text{m}^{-3}$;
- unbiased root mean squared difference (RMSD) in $\text{m}^3 \text{m}^{-3}$.

Equation (1) shows that the bias $\bar{E}$ is expressed as the difference between the time series' $\bar{f}$ and reference $\bar{r}$, corresponding to the mean values of ESA CCI SM and CCI NRT.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures



Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



$$\bar{E} = \bar{f} - \bar{r} \quad (1)$$

As the name suggests, the unbiased RMSD considers the overall bias related to the quadratic difference in observations (Taylor, 2001). Consequently, the unbiased RMSD E' in Eq. (2) relates the individual bias for each time series to the corresponding observation values, whereas f_n and r_n again correspond to observations of ESA CCI SM and CCI NRT.

$$E' = \left\{ \frac{1}{N} \sum_{n=1}^N \left[(f_n - \bar{f}) - (r_n - \bar{r}) \right]^2 \right\}^{1/2} \quad (2)$$

4 Results

The Pearson correlation coefficient (R) yields an average correlation of 0.8 for ESA CCI SM and CCI NRT on a global scale (Fig. 5). Regions in which the NRT dataset does not correspond well with the offline datasets include parts of North Africa and the Sahel, the US West coast and the Andes in South America. Tropical forests are masked, because they are impenetrable to radars at the applied frequencies and block the soil moisture emission for radiometers.

Since the good agreement of the ESA CCI SM and the CCI NRT dataset is only meaningful if it represents actual surface soil moisture conditions on the ground we calculate the performance metrics for both datasets related to daily in-situ observations (Table 1). The Pearson correlation coefficient for all in-situ stations is 0.58 (ESA CCI SM), respectively 0.49 (CCI NRT). The statistical scores for the Smosmania and the Remedhus network are comparable to the findings of Albergel et al. (2012), whose calculations resulted in an R of 0.52 and 0.57 for ASCAT. In line with our expectations, the bias and the unbiased RMSD are slightly higher for CCI NRT.

HESSD

12, 11549–11589, 2015

Combining satellite observations to develop a daily global soil moisture product

M. Enenkel et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



The validation results for the corresponding anomalies, which were calculated based on a moving average with a window size of 35 days, are in line with the findings (Brocca et al., 2011). Table 2 lists the Pearson correlation coefficient, which is on average lower for the anomalies than for their time series and, as expected, lower for CCI NRT than for ESA CCI SM. Again, both the bias and the unbiased RMSD are higher for CCI NRT.

In order to understand the temporal behaviour of both datasets over the location of the validation networks we also calculate the Pearson's/Spearman's correlations coefficient over the location of the in-situ stations. These calculations confirm the global picture with an average R of 0.8 and an S of 0.82. The best correlation is observed over the location of the "Urgons" station in the Smosmania network, which is located in a cultivated area in the South of France (Fig. 6).

Finally, we also generate global maps that show the absolute differences of both datasets for 2013 (Fig. B1) and the four seasons (Figs. B2–B5). All maps expose a systematic overestimation in CCI NRT of up to $0.3\text{m}^3\text{m}^{-3}$ compared to ESA CCI SM in regions such as East Africa, parts of the Sahel and Pakistan, whereas the effect is stronger in spring and summer than in autumn and winter. In the central United States, large parts of Australia and Southern Africa this overestimation is less distinct. Since the overestimation mainly appears in regions where the AMSR-2 dataset is used (Fig. 4) and to understand the underestimation of soil moisture over Europe during winter 2013 we also analyse the absolute difference between the offline and the NRT ASCAT and AMSR-2 datasets (Figs. B6 and B7). Compared to the offline product, AMSR-2 NRT tends to overestimate on a global scale, mainly in parts of the Horn of Africa, the Arabic peninsula, parts of Australia, South America and Southern Africa. The strong overestimation in the Horn of Africa is also clearly visible in the CCI NRT dataset. On the contrary, ASCAT tends to underestimate, mainly over Europe with the strongest signal over Winter, parts of the Western United States as well as areas North and East of the Black Sea. In summary, our validation results indicate that, with some exceptions, the new CCI NRT dataset performs well on a global scale in comparison to its offline counterpart.

HESSD

12, 11549–11589, 2015

Combining satellite observations to develop a daily global soil moisture product

M. Enenkel et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



Discussion Paper	Discussion Paper	Discussion Paper	Discussion Paper
------------------	------------------	------------------	------------------

5
10

15

- 20
- 25

Combining satellite observations to develop a daily global soil moisture product

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures



[Back](#)

Close

Full Screen / Esc

[Printer-friendly Version](#)

Interactive Discussion



Combining satellite observations to develop a daily global soil moisture product

M. Enenkel et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



- The validation with in-situ observations in Spain, France, Senegal and Kenya yields lower results for the CCI NRT dataset. The average Pearson correlation coefficient (R) for all in-situ stations is 0.49 (0.58 for ESA CCI SM). The unbiased RMSD for CCI NRT is 0.008 (0.004 for ESA CCI SM). We observe hardly any difference in the overall bias ($0.05 \text{ m}^3 \text{ m}^{-3}$ for both datasets).
- The performance metrics for the corresponding anomalies result in an average correlation coefficient (Pearson) of 0.44 for ESA CCI SM and 0.38 for CCI NRT, respectively.
- A comparison of ESA CCI SM and CCI NRT for 2013 reveals an underestimation of CCI NRT over Europe (particularly during Winter 2013) and an overestimation over several dry areas (particularly in Africa and Australia). In order to understand these biases better we calculated the absolute differences between the corresponding offline and online products of ASCAT and AMSR-2. These calculations confirm the underestimation of the ASCAT NRT product over Europe or the United States (Fig. B6). Although ASCAT NRT tends to over- and underestimate the overall agreement between the offline and online product is satisfying. In case of AMSR-2 (Fig. B7), the systematic overestimation on a global scale, for instance in the Horn of Africa, could be caused by intercalibration issues. In addition to known intercalibration issues between AMSR-2 and its predecessor AMSR-E (Okuyama and Imaoka, 2015) there might be additional issues related to the different operational versions of the AMSR-2 dataset. Nevertheless, also here the general agreement between the passive components in ESA CCI SM and CCI NRT is good.

We expect that, apart from solving the AMSR-2 intercalibration issues and a dynamic snow map for ASCAT, two improvements in the processing chain could lead to considerable improvements in data quality. First, there are differences in the temporal coverage of the MetOp-A ASCAT data used to derive soil moisture model parameters for the offline ASCAT (2007–2014) and ASCAT NRT (2007–2012) products. The offline

and the NRT ASCAT product differ in their absolute calibration level affecting the soil moisture values. An update of the model parameters for the ASCAT NRT product at EUMETSAT is planned for 2015. In this study we apply the rescaling parameters that had been developed for the offline ASCAT product to ASCAT NRT. Despite the good correlation between both products it is likely that their consistency can be improved by reprocessing the rescaling parameters in the CCI NRT processing chain. Second, the currently static RFI map for AMSR-2 could be replaced by a dynamic map that is based on the average RFI values for the previous six months via a moving average. In a recent study (de Nijs et al., 2015), an improved algorithm to detect RFI at the global scale for 6.9 and 7.3 GHz AMSR2 observations was proposed, but remains to be tested. This is the first method that takes the additional 7.3 GHz channel into account, which was specifically added to the AMSR-E sensor concept to improve retrieval issues related to RFI.

Despite these issues, a processing chain that allows daily soil moisture updates is promising in the face of a new generation of soil moisture missions such as Sentinel-1 of the ESA and the European Commission (EC) or NASA's SMAP (Soil Moisture Active/Passive). These new sensors are able to retrieve soil moisture at a far higher resolution than ASCAT or AMSR-2 – around one kilometre for operational products and below 100 m for research products. Of course the higher spatial resolution has a drawback, which is a decrease in temporal resolution. While ASCAT on MetOp-A alone covers more than 80 % of the globe every day, the two Sentinel-1 satellites will take 6–12 days to scan the total global land mass in the default interferometric wide swath (IWS) mode (World Meteorological Organization, 2013). Despite the differences in spatial resolution it is possible to increase the temporal resolution of the CCI NRT dataset to fit various applications. One example is numerical weather prediction, in which satellite-derived soil moisture is usually assimilated via a nudging scheme or an ensemble Kalman filter approach at sub-daily (e.g. six-hourly) increments (Drusch et al., 2009; Scipal et al., 2008).

HESSD

12, 11549–11589, 2015

Combining satellite observations to develop a daily global soil moisture product

M. Enenkel et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



In the face of the upcoming generation of space-based soil moisture sensors it seems to be the most promising approach to exploit each sensor's individual strength to generate the most accurate and complete soil moisture dataset. This way, it will be possible to support decision-makers in various domains with global soil moisture observations. However, developing a user-friendly dataset means more than data access. As a consequence, software packages, such as Python Open Earth Observation Tools (Mistelbauer et al., 2014) are necessary to enable automated updates, the visualization of images/time series/anomalies and the analysis of critical soil moisture thresholds.

Author contributions. Enenkel, M.: Lead author, algorithmic adaptation/implementation of the processing chain, validation. Reimer, C.: algorithmic adaptation of the processing chain. Dorigo, W.: algorithmic adaptation of the processing chain, link to ESA CCI SM. Wagner, W.: overall manuscript structure, state-of-the-art. Pfeil, W.: algorithmic implementation of the processing chain, merging. Parinussa, R.: issues related to radiometric observations, RFI. De Jeu, R.: issues related to radiometric observations.

Acknowledgements. This research was supported and funded within the framework of SATIDA (Satellite Technologies for Improved Drought-Risk Assessment). SATIDA is a project within the Austrian Space Applications Programme (ASAP10) of the Austrian Research Promotion Agency (project number 4277353).

HESSD

12, 11549–11589, 2015

Combining satellite observations to develop a daily global soil moisture product

M. Enenkel et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

⏪

⏩

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



References

- Albergel, C., Rüdiger, C., Pellarin, T., Calvet, J.-C., Fritz, N., Froissard, F., Suquia, D., Petitpa, A., Pignat, B., and Martin, E.: From near-surface to root-zone soil moisture using an exponential filter: an assessment of the method based on in-situ observations and model simulations, *Hydrol. Earth Syst. Sci.*, 12, 1323–1337, doi:10.5194/hess-12-1323-2008, 2008.
- Albergel, C., de Rosnay, P., Gruhier, C., Muñoz-Sabater, J., Hasenauer, S., Isaksen, L., Kerr, Y., and Wagner, W.: Evaluation of remotely sensed and modelled soil moisture products using global ground-based in situ observations, *Remote Sens. Environ.*, 118, 215–226, doi:10.1016/j.rse.2011.11.017, 2012.
- Al-Yaari, A., Wigneron, J.-P., Ducharne, A., Kerr, Y. H., Wagner, W., De Lannoy, G., Reichle, R., Al Bitar, A., Dorigo, W., Richaume, P., and Mialon, A.: Global-scale comparison of passive (SMOS) and active (ASCAT) satellite based microwave soil moisture retrievals with soil moisture simulations (MERRA-Land), *Remote Sens. Environ.*, 152, 614–626, doi:10.1016/j.rse.2014.07.013, 2014.
- Anderson, W. B., Zaitchik, B. F., Hain, C. R., Anderson, M. C., Yilmaz, M. T., Mecikalski, J., and Schultz, L.: Towards an integrated soil moisture drought monitor for East Africa, *Hydrol. Earth Syst. Sci.*, 16, 2893–2913, doi:10.5194/hess-16-2893-2012, 2012.
- Barichivich, J., Briffa, K. R., Myneni, R., Schrier, G. van der, Dorigo, W., Tucker, C. J., Osborn, T. J., and Melvin, T. M.: Temperature and snow-mediated moisture controls of summer photosynthetic activity in northern terrestrial ecosystems between 1982 and 2011, *Remote Sensing*, 6, 1390–1431, doi:10.3390/rs6021390, 2014.
- Bartalis, Z., Scipal, K., and Wagner, W.: Soil moisture products from C-band scatterometers: from Ers-1/2 to Metop, in: *Proceedings of the 2004 ENVISAT & ERS Symposium*, 6–10 September 2004, Salzburg, Austria, ESA SP-572, European Space Agency, Noordwijk, the Netherlands, 2005.
- Bauer-Marschallinger, B., Dorigo, W. A., Wagner, W., and van Dijk, A. I. J. M.: How oceanic oscillation drives soil moisture variations over Mainland Australia: an analysis of 32 years of satellite observations, *J. Climate*, 26, 10159–10173, doi:10.1175/JCLI-D-13-00149.1, 2013.
- Bolten, J. D. and Crow, W. T.: Improved prediction of quasi-global vegetation conditions using remotely-sensed surface soil moisture, *Geophys. Res. Lett.*, 39, L19406, doi:10.1029/2012GL053470, 2012.

HESSD

12, 11549–11589, 2015

Combining satellite observations to develop a daily global soil moisture product

M. Enenkel et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



Combining satellite observations to develop a daily global soil moisture product

M. Enenkel et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



Brocca, L., Melone, F., Moramarco, T., and Morbidelli, R.: Soil moisture temporal stability over experimental areas in Central Italy, *Geoderma*, 148, 364–374, doi:10.1016/j.geoderma.2008.11.004, 2009.

Brocca, L., Melone, F., Moramarco, T., Wagner, W., Naeimi, V., Bartalis, Z., and Hasenauer, S.: Improving runoff prediction through the assimilation of the ASCAT soil moisture product, *Hydrol. Earth Syst. Sci.*, 14, 1881–1893, doi:10.5194/hess-14-1881-2010, 2010.

Brocca, L., Hasenauer, S., Lacava, T., Melone, F., Moramarco, T., Wagner, W., Dorigo, W., Matgen, P., Martínez-Fernández, J., Llorens, P., Latron, J., Martin, C., and Bitelli, M.: Soil moisture estimation through ASCAT and AMSR-E sensors: an intercomparison and validation study across Europe, *Remote Sens. Environ.*, 115, 3390–3408, doi:10.1016/j.rse.2011.08.003, 2011.

Crow, W. T., Berg, A. A., Cosh, M. H., Loew, A., Mohanty, B. P., Panciera, R., de Rosnay, P., Ryu, D., and Walker, J. P.: Upscaling sparse ground-based soil moisture observations for the validation of coarse-resolution satellite soil moisture products, *Rev. Geophys.*, 50, RG2002, doi:10.1029/2011RG000372, 2012.

Dee, D. P., Uppala, S. M., Simmons, A. J., Berrisford, P., Poli, P., Kobayashi, S., Andrae, U., Balmaseda, M. A., Balsamo, G., Bauer, P., Bechtold, P., Beljaars, A. C. M., van de Berg, L., Bidlot, J., Bormann, N., Delsol, C., Dragani, R., Fuentes, M., Geer, A. J., Haimberger, L., Healy, S. B., Hersbach, H., Hólm, E. V., Isaksen, I., Kållberg, P., Köhler, M., Matricardi, M., McNally, A. P., Monge-Sanz, B. M., Morcrette, J.-J., Park, B.-K., Peubey, C., de Rosnay, P., Tavolato, C., Thépaut, J.-N., and Vitart, F.: The ERA-Interim reanalysis: configuration and performance of the data assimilation system, *Q. J. Roy. Meteorol. Soc.*, 137, 553–597, doi:10.1002/qj.828, 2011.

de Jeu, R. A. M., Holmes, T. R. H., Parinussa, R. M., and Owe, M.: A spatially coherent global soil moisture product with improved temporal resolution, *J. Hydrol.*, 516, 284–296, doi:10.1016/j.jhydrol.2014.02.015, 2014.

de Nijs, A. H. A., Parinussa, R. M., de Jeu, R. A. M., Schellekens, J., and Holmes, T. R. H.: A methodology to determine radio-frequency interference in AMSR2 observations, *IEEE T. Geosci. Remote*, 53, 5148–5159, doi:10.1109/TGRS.2015.2417653, 2015.

Dorigo, W. A., Wagner, W., Hohensinn, R., Hahn, S., Paulik, C., Drusch, M., Mecklenburg, S., van Oevelen, P., Robock, A., and Jackson, T.: The International Soil Moisture Network: a data hosting facility for global in situ soil moisture measurements, *Hydrol. Earth Syst. Sci. Discuss.*, 8, 1609–1663, doi:10.5194/hessd-8-1609-2011, 2011.

- Jung, M., Reichstein, M., Ciais, P., Seneviratne, S. I., Sheffield, J., Goulden, M. L., Bonan, G., Cescatti, A., Chen, J., de Jeu, R., Dolman, A. J., Eugster, W., Gerten, D., Gianelle, D., Gobron, N., Heinke, J., Kimball, J., Law, B. E., Montagnani, L., Mu, Q., Mueller, B., Oleson, K., Papale, D., Richardson, A. D., Rouspard, O., Running, S., Tomelleri, E., Viovy, N., Weber, U., Williams, C., Wood, E., Zaehle, S., and Zhang, K.: Recent decline in the global land evapotranspiration trend due to limited moisture supply, *Nature*, 467, 951–954, doi:10.1038/nature09396, 2010.
- Koster, R. D., Guo, Z., Bonan, G., Chan, E., Cox, P., Gordon, C. T., Kanae, S., Kowalczyk, E., Lawrence, D., Liu, P., Lu, C.-H., Malyshev, S., McAvaney, B., Mitchell, K., Mocko, D., Oki, T., Oleson, K., Pitman, A., Sud, Y. C., Taylor, C. M., Versegny, D., Vasic, R., Xue, Y., and Yamada, T.: Regions of Strong Coupling Between Soil Moisture and Precipitation, *Science*, 305, 1138–1140, doi:10.1126/science.1100217, 2004.
- Legates, D. R., Mahmood, R., Levina, D. F., DeLiberty, T. L., Quiring, S. M., Houser, C., and Nelson, F. E.: Soil moisture: a central and unifying theme in physical geography, *Prog. Phys. Geogr.*, 35, 65–86, doi:10.1177/0309133310386514, 2010.
- Liu, Y. Y., van Dijk, A. I. J. M., de Jeu, R. A. M., and Holmes, T. R. H.: An analysis of spatiotemporal variations of soil and vegetation moisture from a 29-year satellite-derived data set over mainland Australia, *Water Resour. Res.*, 45, W07405, doi:10.1029/2008WR007187, 2009.
- Liu, Y. Y., Parinussa, R. M., Dorigo, W. A., De Jeu, R. A. M., Wagner, W., van Dijk, A. I. J. M., McCabe, M. F., and Evans, J. P.: Developing an improved soil moisture dataset by blending passive and active microwave satellite-based retrievals, *Hydrol. Earth Syst. Sci.*, 15, 425–436, doi:10.5194/hess-15-425-2011, 2011a.
- Liu, Y. Y., de Jeu, R. A. M., McCabe, M. F., Evans, J. P., and van Dijk, A. I. J. M.: Global long-term passive microwave satellite-based retrievals of vegetation optical depth, *Geophys. Res. Lett.*, 38, L18402, doi:10.1029/2011GL048684, 2011b.
- Liu, Y. Y., Dorigo, W. A., Parinussa, R. M., de Jeu, R. A. M., Wagner, W., McCabe, M. F., Evans, J. P., and van Dijk, A. I. J. M.: Trend-preserving blending of passive and active microwave soil moisture retrievals, *Remote Sens. Environ.*, 123, 280–297, doi:10.1016/j.rse.2012.03.014, 2012.
- Liu, Y. Y., van Dijk, A. I. J. M., de Jeu, R. A. M., Canadell, J. G., McCabe, M. F., Evans, J. P., and Wang, G.: Recent reversal in loss of global terrestrial biomass, *Nat. Clim. Change*, 5, 470–474, doi:10.1038/nclimate2581, 2015.

HESSD

12, 11549–11589, 2015

Combining satellite observations to develop a daily global soil moisture product

M. Enenkel et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



Combining satellite observations to develop a daily global soil moisture product

M. Enenkel et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



McNally, A., Husak, G. J., Brown, M., Carroll, M., Funk, C., Yatheendradas, S., Arsenault, K., Peters-Lidard, C., and Verdin, J. P.: Calculating crop water requirement satisfaction in the West Africa Sahel with remotely sensed soil moisture, *J. Hydrometeorol.*, 16, 295–305, doi:10.1175/JHM-D-14-0049.1, 2015.

Mistelbauer, T., Enenkel, M., and Wagner, W.: POETS – Python Earth Observation Tools, Poster: GIScience 2014, Vienna, 2014-09-23, in: “Extended Abstract Proceedings of the GIScience 2014”, GeoInfo Series 40, 2014.

Muñoz, A. A., Barichivich, J., Christie, D. A., Dorigo, W., Sauchyn, D., González-Reyes, Á., Villalba, R., Lara, A., Riquelme, N., and González, M. E.: Patterns and drivers of Araucaria araucana forest growth along a biophysical gradient in the northern Patagonian Andes: linking tree rings with satellite observations of soil moisture, *Austral. Ecol.*, 39, 158–169, doi:10.1111/aec.12054, 2014.

Nicolai-Shaw, N., Hirschi, M., Mittelbach, H., and Seneviratne, S. I.: Spatial representativeness of soil moisture using in situ, remote sensing, and land reanalysis data, *J. Geophys. Res.-Atmos.*, doi:10.1002/2015JD023305, in press, 2015.

Njoku, E. G. and Li, L.: Retrieval of land surface parameters using passive microwave measurements at 6–18 GHz, *IEEE T. Geosci. Remote*, 37, 79–93, doi:10.1109/36.739125, 1999.

Okuyama, A. and Imaoka, K.: Intercalibration of Advanced Microwave Scanning Radiometer-2 (AMSR2) brightness temperature, *IEEE T. Geosci. Remote*, 53, 4568–4577, doi:10.1109/TGRS.2015.2402204, 2015.

Oliva, R., Daganzo, E., Kerr, Y. H., Mecklenburg, S., Nieto, S., Richaume, P., and Gruhier, C.: SMOS radio frequency interference scenario: status and actions taken to improve the RFI environment in the 1400–1427-MHz passive band, *IEEE T. Geosci. Remote*, 50, 1427–1439, doi:10.1109/TGRS.2012.2182775, 2012.

Owe, M., de Jeu, R., and Holmes, T.: Multisensor historical climatology of satellite-derived global land surface moisture, *J. Geophys. Res.-Earth*, 113, F01002, doi:10.1029/2007JF000769, 2008.

Qiu, J., Crow, W. T., Nearing, G. S., Mo, X., and Liu, S.: The impact of vertical measurement depth on the information content of soil moisture times series data, *Geophys. Res. Lett.*, 41, 4997–5004, doi:10.1002/2014GL060017, 2014.

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

- Rodell, M., Houser, P. R., Jambor, U., Gottschalck, J., Mitchell, K., Meng, C.-J., Arsenault, K., Cosgrove, B., Radakovich, J., Bosilovich, M., Entin, J. K., Walker, J. P., Lohmann, D., and Toll, D.: The Global Land Data Assimilation System, *B. Am. Meteorol. Soc.*, 85, 381–394, doi:10.1175/BAMS-85-3-381, 2004.
- 5 Rüdiger, C., Calvet, J.-C., Gruhier, C., Holmes, T. R. H., de Jeu, R. A. M., and Wagner, W.: An intercomparison of ERS-Scat and AMSR-E soil moisture observations with model simulations over France, *J. Hydrometeorol.*, 10, 431–447, doi:10.1175/2008JHM997.1, 2009.
- Sanchez, N., Martinez-Fernandez, J., Scaini, A., and Perez-Gutierrez, C.: Validation of the SMOS L2 soil moisture data in the REMEDHUS Network (Spain), *IEEE T. Geosci. Remote*, 10, 1602–1611, doi:10.1109/TGRS.2012.2186971, 2012.
- 10 Schmugge, T. and Jackson, T. J.: Mapping surface soil moisture with microwave radiometers, *Meteorol. Atmos. Phys.*, 54, 213–223, doi:10.1007/BF01030061, 1994.
- Scipal, K., Drusch, M., and Wagner, W.: Assimilation of a ERS scatterometer derived soil moisture index in the ECMWF numerical weather prediction system, *Adv. Water Resour.*, 31, 1101–1112, doi:10.1016/j.advwatres.2008.04.013, 2008.
- 15 Seneviratne, S. I., Corti, T., Davin, E. L., Hirschi, M., Jaeger, E. B., Lehner, I., Orlowsky, B., and Teuling, A. J.: Investigating soil moisture–climate interactions in a changing climate: a review, *Earth-Sci. Rev.*, 99, 125–161, doi:10.1016/j.earscirev.2010.02.004, 2010.
- Sheffield, J. and Wood, E. F.: Global trends and variability in soil moisture and drought characteristics, 1950–2000, from observation-driven simulations of the terrestrial hydrologic cycle, *J. Climate*, 21, 432–458, doi:10.1175/2007JCLI1822.1, 2008.
- 20 Taylor, C. M., de Jeu, R. A. M., Guichard, F., Harris, P. P., and Dorigo, W. A.: Afternoon rain more likely over drier soils, *Nature*, 489, 423–426, doi:10.1038/nature11377, 2012.
- Taylor, K. E.: Summarizing multiple aspects of model performance in a single diagram, *J. Geophys. Res.-Atmos.*, 106, 7183–7192, doi:10.1029/2000JD900719, 2001.
- 25 Trenberth, K. E., Dai, A., van der Schrier, G., Jones, P. D., Barichivich, J., Briffa, K. R., and Sheffield, J.: Global warming and changes in drought, *Nat. Clim. Change*, 4, 17–22, doi:10.1038/nclimate2067, 2014.
- Vachaud, G., Passerat De Silans, A., Balabanis, P., and Vauclin, M.: Temporal stability of spatially measured soil water probability density function, *Soil Sci. Soc. Am. J.*, 49, 822–828, doi:10.2136/sssaj1985.03615995004900040006x, 1985.
- 30

Combining satellite observations to develop a daily global soil moisture product

M. Enenkel et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



Combining satellite observations to develop a daily global soil moisture product

M. Enenkel et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



Wagner, W., Lemoine, G., and Rott, H.: 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, 1999.

Wagner, W., Scipal, K., Pathe, C., Gerten, D., Lucht, W., and Rudolf, B.: Evaluation of the agreement between the first global remotely sensed soil moisture data with model and precipitation data, *J. Geophys. Res.-Atmos.*, 108, 4611, doi:10.1029/2003JD003663, 2003.

Wagner, W., Blöschl, G., Pampaloni, P., Calvet, J. C., Bizzarri, B., Wigneron, J. P., and Kerr, Y.: Operational readiness of microwave remote sensing of soil moisture for hydrologic applications, *Nord. Hydrol.*, 38, 1–20, 2007.

Wagner, W., Dorigo, W., de Jeu, R., Fernandez, D., Benveniste, J., Haas, E., and Ertl, M.: Fusion of active and passive microwave observations to create an essential climate variable data record on soil moisture, *ISPRS Ann. Photogramm. Remote Sens. Spat. Inf. Sci.*, 1-7, 315–321, doi:10.5194/isprsannals-1-7-315-2012, 2012.

Wagner, W., Hahn, S., Kidd, R., Melzer, T., Bartalis, Z., Hasenauer, S., Figa-Saldaña, J., de Rosnay, P., Jann, A., Schneider, S., Komma, J., Kubu, G., Brugger, K., Aubrecht, C., Züger, J., Gangkofner, U., Kienberger, S., Brocca, L., Wang, Y., Blöschl, G., Eitzinger, J., Steinnocher, K., Zeil, P., and Rubel, F.: The ASCAT soil moisture product: a review of its specifications, validation results, and emerging applications, *Meteorol. Z.*, 22, 5–33, doi:10.1127/0941-2948/2013/0399, 2013.

Wang, J. R. and Schmugge, T. J.: An empirical model for the complex dielectric permittivity of soils as a function of water content, *IEEE T. Geosci. Remote, GE-18*, 288–295, doi:10.1109/TGRS.1980.350304, 1980.

Western, A. W., Grayson, R. B., and Blöschl, G.: Scaling of soil moisture: a hydrologic perspective, *Annu. Rev. Earth Pl. Sc.*, 30, 149–180, doi:10.1146/annurev.earth.30.091201.140434, 2002.

Western, A. W., Zhou, S.-L., Grayson, R. B., McMahon, T. A., Blöschl, G., and Wilson, D. J.: Spatial correlation of soil moisture in small catchments and its relationship to dominant spatial hydrological processes, *J. Hydrol.*, 286, 113–134, doi:10.1016/j.jhydrol.2003.09.014, 2004.

World Meteorological Organization: Future Climate Change Research and Observations: GCOS, WCRP and IGBP Learning from the IPCC Fourth Assessment Report, WMO/TD 1418, GCOS-117, WCRP-127, and IGBP Report 58, World Meteorological Organization, Geneva, 2008.

World Meteorological Organization: Sentinel High Level Operations Plan (HLOP), available at: https://www.wmo.int/pages/prog/sat/meetings/documents/PSTG-3_Doc_08-04-02_Sentinel-HLOP.pdf (last access: 17 July 2015), 2013.

Yuan, X., Ma, Z., Pan, M., and Shi, C.: Microwave remote sensing of short-term droughts during crop growing seasons, *Geophys. Res. Lett.*, 42, 4394–4401, doi:10.1002/2015GL064125, 2015.

HESSD

12, 11549–11589, 2015

Combining satellite observations to develop a daily global soil moisture product

M. Enenkel et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures



Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



Combining satellite observations to develop a daily global soil moisture product

M. Enenkel et al.

Table 1. Statistical scores for ESA CCI SM/CCI NRT and in-situ stations/networks (maximum depth 0.1 m) in Spain, France, Kenya and Senegal for 2013 (for the Remedhus and Smosmania networks the table includes the bias range from minimum to maximum).

In-Situ Network	Number of Stations	<i>R</i> for ESA CCI	<i>R</i> for CCI NRT	Bias for ESA CCI	BIAS for CCI NRT	Unbiased RMSD for ESA CCI	Unbiased RMSD for CCI NRT
Remedhus	19	0.60	0.52	−0.079/0.214	−0.075/0.207	0.002	0.003
Smosmania	19	0.54	0.46	−0.129/0.170	−0.135/0.147	0.006	0.012
Cosmos	1	0.66	0.59	0.040	0.028	0.002	0.003
Dahra	1	0.65	0.61	0.128	0.155	0.003	0.003
Average of all Observations		0.58	0.49	NA	NA	0.004	0.008

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures



Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



HESSD

12, 11549–11589, 2015

Combining satellite observations to develop a daily global soil moisture product

M. Enenkel et al.

Table 2. Statistical scores for ESA CCI SM/CCI NRT anomalies and in-situ stations/networks (maximum depth 0.1 m) in Spain, France, Kenya and Senegal for 2013 (for the Remedhus and Smosmania networks the table includes the bias range from minimum to maximum).

In-Situ Network	Number of Stations	<i>R</i> for ESA CCI	<i>R</i> for CCI NRT	Bias for ESA CCI	BIAS for CCI NRT	Unbiased RMSD for ESA CCI	Unbiased RMSD for CCI NRT
Remedhus	19	0.42	0.39	0.000/0.003	0.000/0.005	0.001	0.002
Smosmania	19	0.46	0.39	−0.002/0.005	−0.001/0.008	0.002	0.003
Cosmos	1	0.46	0.32	−0.004	−0.003	0.001	0.002
Dahra	1	0.54	0.29	0.000	0.004	0.001	0.001
Average of all Observations		0.44	0.38	NA	NA	0.002	0.002

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



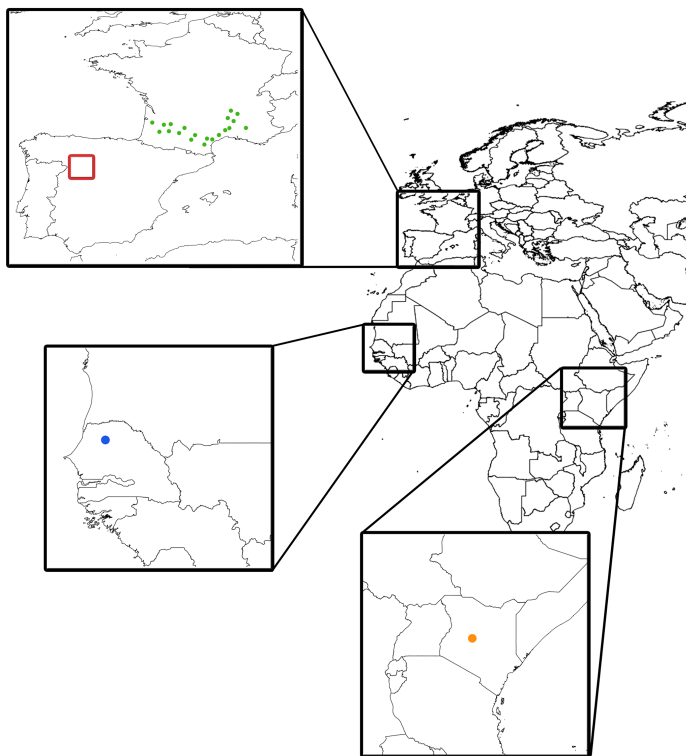


Figure 2. Location of the networks used for validation in this study (Smosmania, France, green dots; Remedhus, Spain, red rectangle; Dahra, Senegal, blue dot; Cosmos, Kenya, orange dot).

Combining satellite observations to develop a daily global soil moisture product

M. Enenkel et al.

1978 - 2013

Daily updates 2014 - current

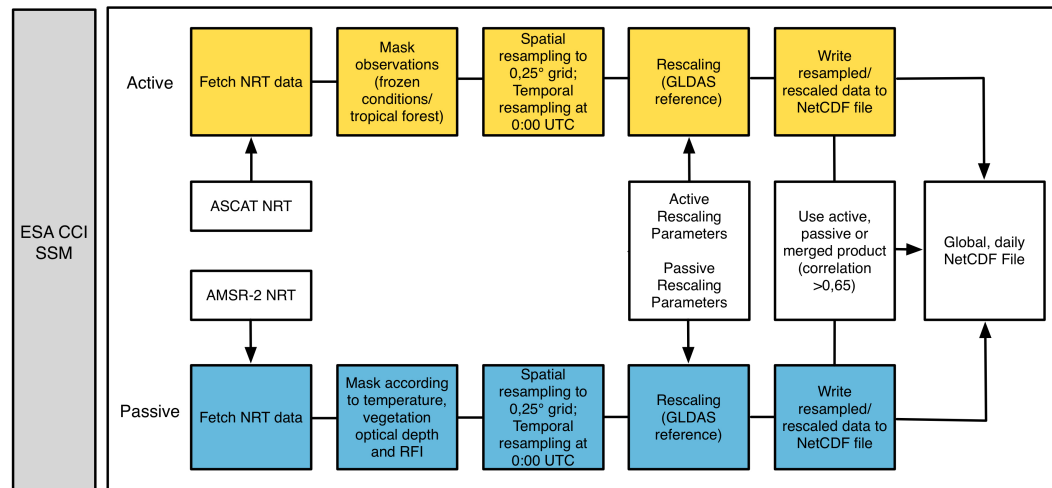


Figure 3. Schematic flowchart illustrating the extension of the processing chain for daily updates with the GLDAS dataset (running on the NOAH land surface model) as a reference.

[Title Page](#)[Abstract](#)[Introduction](#)[Conclusions](#)[References](#)[Tables](#)[Figures](#)[◀](#)[▶](#)[◀](#)[▶](#)[Back](#)[Close](#)[Full Screen / Esc](#)[Printer-friendly Version](#)[Interactive Discussion](#)

HESSD

12, 11549–11589, 2015

Combining satellite observations to develop a daily global soil moisture product

M. Enenkel et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

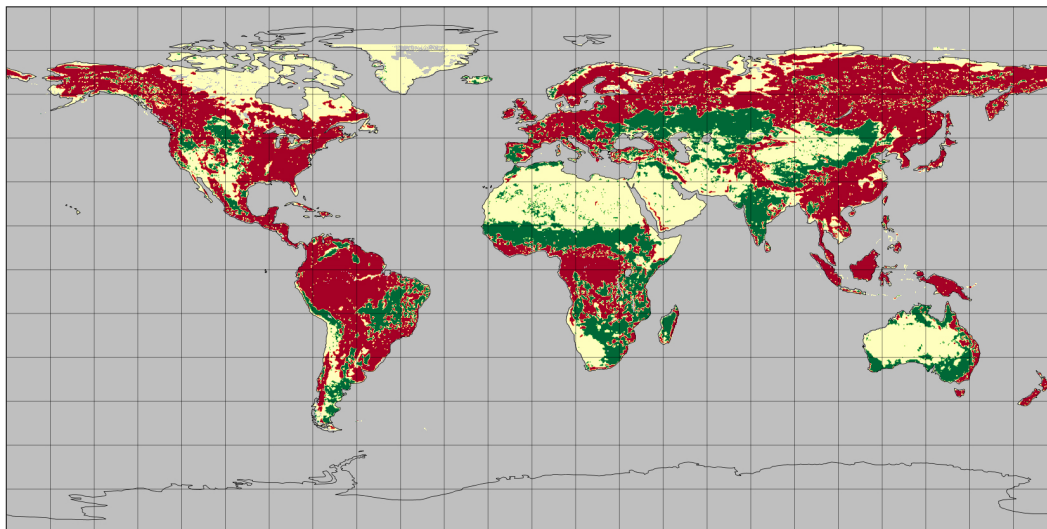


Figure 4. Global blending map illustrating where active sensors (red), passive sensors (yellow) and the average of both (green) is used to generate the ESA CCI SM product.

HESSD

12, 11549–11589, 2015

Combining satellite observations to develop a daily global soil moisture product

M. Enenkel et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



Pearson's R (ESA CCI SM/CCI NRT) for 2013

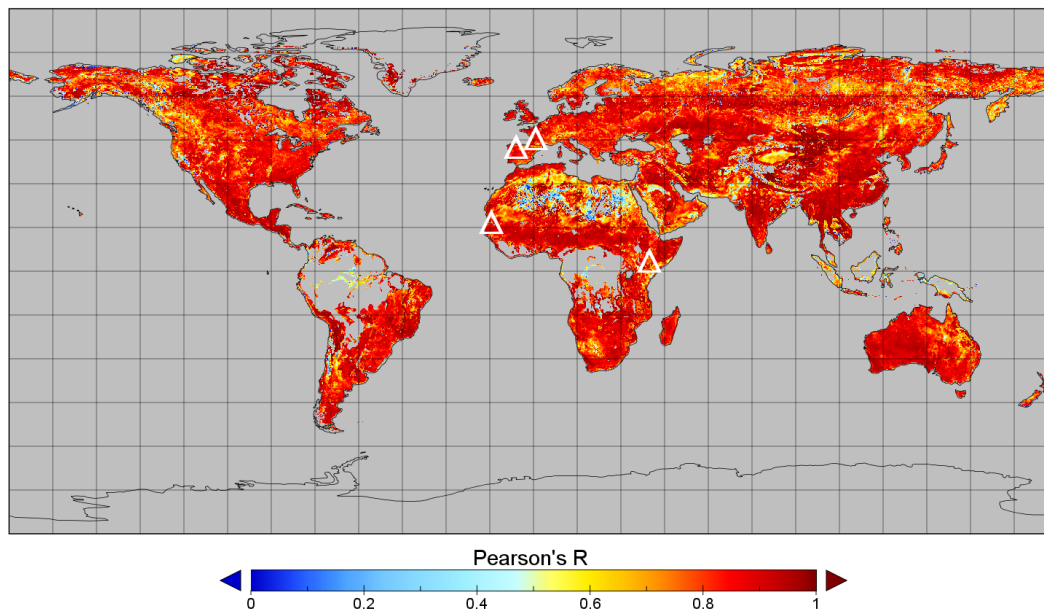


Figure 5. Global correlation (Pearson's R) for ESA CCI SM and CCI NRT for 2013 (no negative correlations were observed); the white triangles illustrate the location of the in-situ stations/networks.

HESSD

12, 11549–11589, 2015

Combining satellite observations to develop a daily global soil moisture product

M. Enenkel et al.

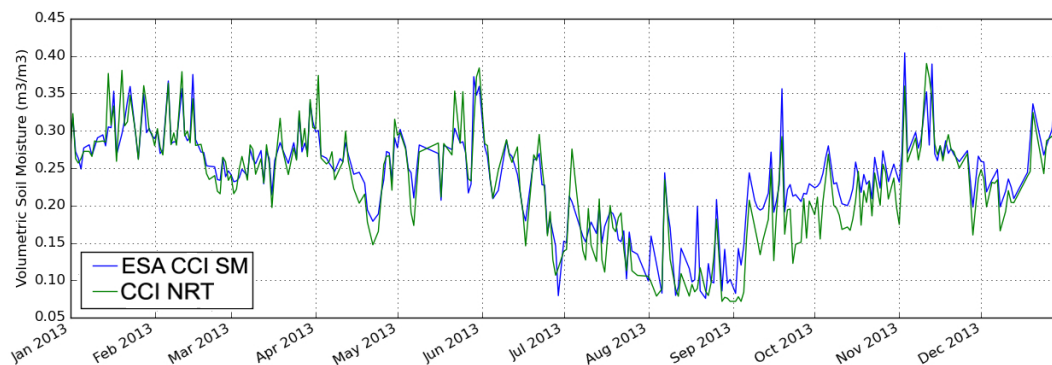


Figure 6. Illustration of ESA CCI SM and CCI NRT over the “Urgons” station of the Smosmania network ($R = 0.93$; $S = 0.96$).

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures



Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



HESSD

12, 11549–11589, 2015

Combining satellite observations to develop a daily global soil moisture product

M. Enenkel et al.

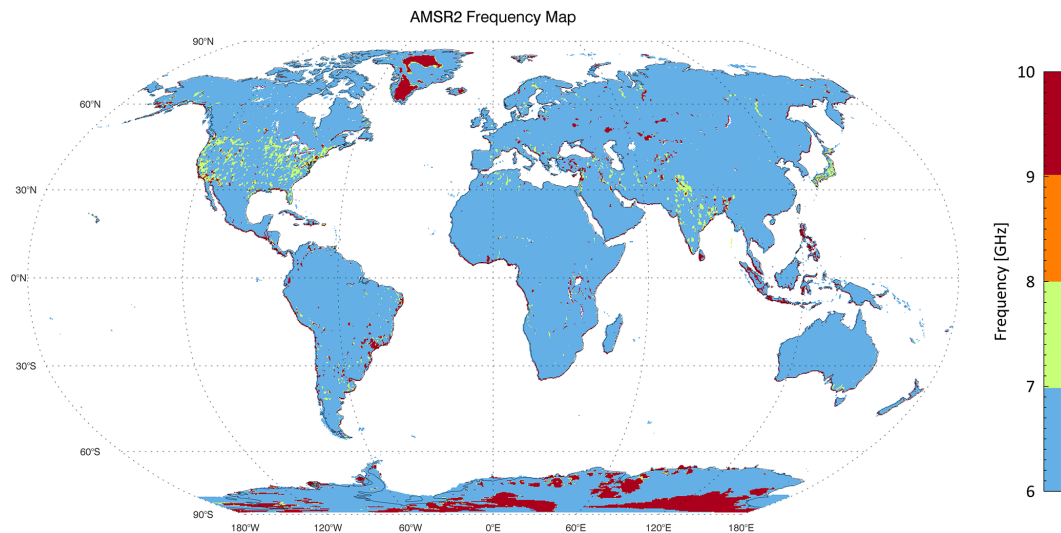


Figure A1. Global map illustrating which frequency used by AMSR-2 is the least affected by RFI.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures



Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



HESSD

12, 11549–11589, 2015

Combining satellite observations to develop a daily global soil moisture product

M. Enenkel et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

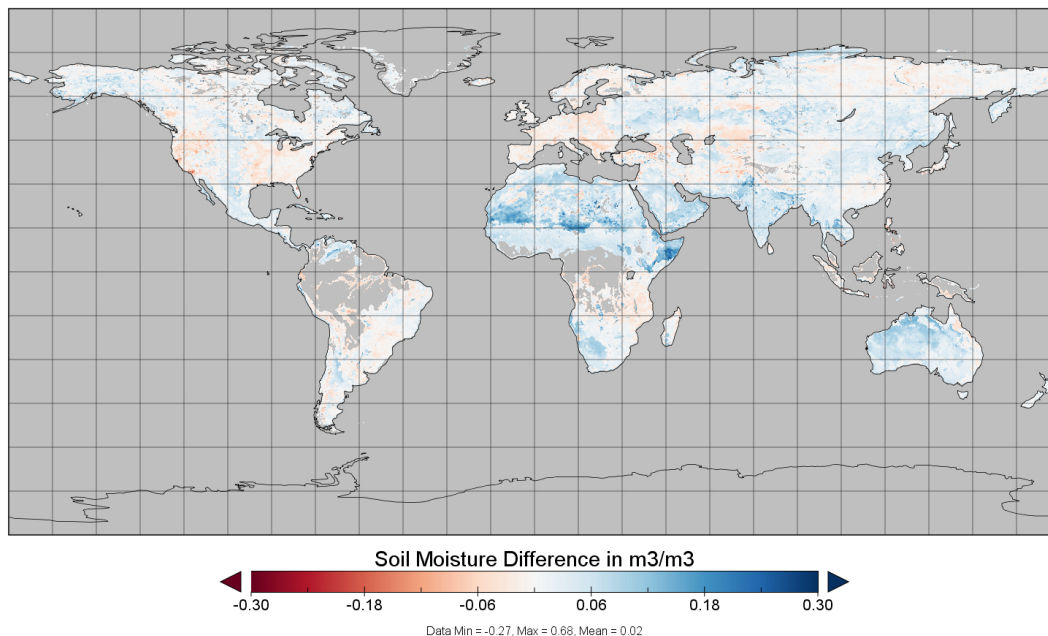


Figure B1. Absolute differences in soil moisture (ESA CCI SM minus CCI NRT) for the entire year of 2013.

HESSD

12, 11549–11589, 2015

Combining satellite observations to develop a daily global soil moisture product

M. Enenkel et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures



Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

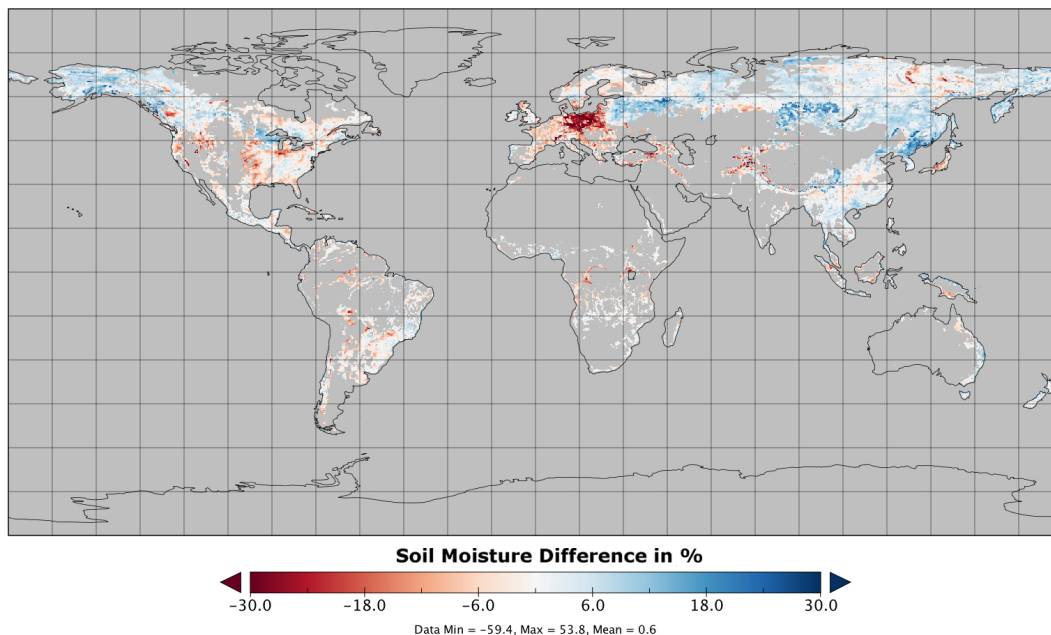


Figure B6. Absolute differences in soil moisture for ASCAT (ASCAT NRT minus ASCAT offline) for the entire year of 2013 (masked according to the blending map in Fig. 4).

HESSD

12, 11549–11589, 2015

Combining satellite observations to develop a daily global soil moisture product

M. Enenkel et al.

[Title Page](#)

Abstract

Introduction

Conclusions

References

Tables

Figures



▶

[Back](#)

Close

Full Screen / Esc

[Printer-friendly Version](#)

Interactive Discussion

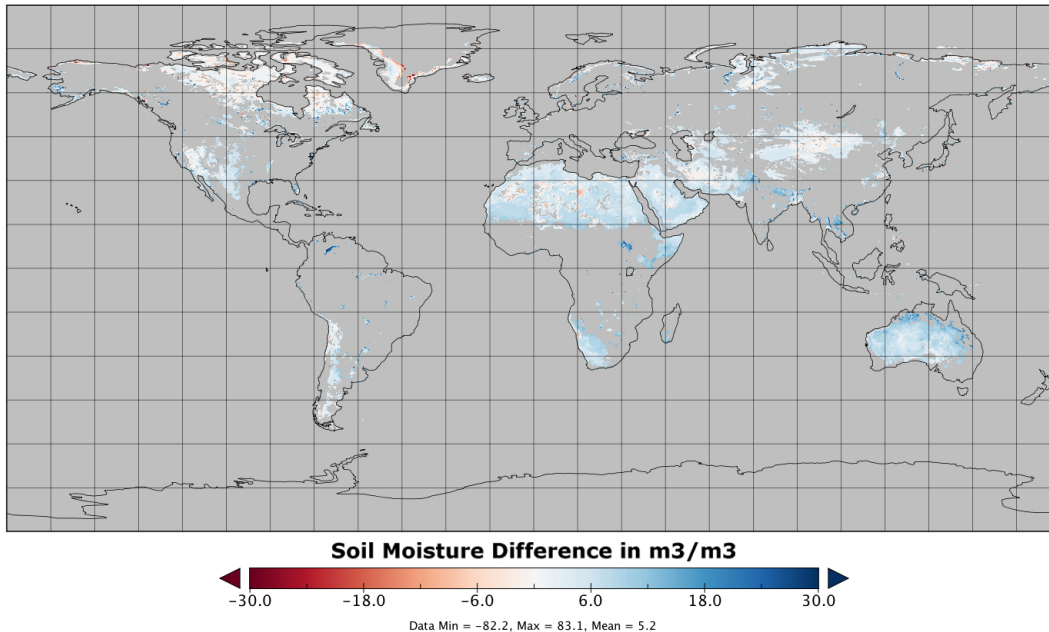


Figure B7. Absolute differences in soil moisture for AMSR-2 (AMSR-2 NRT minus AMSR-2 offline) for the entire year of 2013 (masked according to the blending map in Fig. 4).