Combining satellite observations to develop a global soil moisture product for near real-time applications

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Abstract

The soil moiture 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 ten 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 degrees. 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 product 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 two 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 product is nearly as accurate as the existing ESA CCI SM product and, therefore, of significant value for operational applications such as drought and flood forecasting, agricultural index insurance or weather forecasting.

Keywords: Soil Moisture, Remote Sensing, Global Analysis

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). It is a decisive or even limiting factor in many processes related to agriculture, climate change, energy fluxes, hydrology and hydro-climatic extreme events (Brocca et al., 2010; Greve et al., 2014; Jung et al., 2010; Legates et al., 2010; Qiu et al., 2014; Seneviratne et al., 2010; Sheffield and Wood, 2008; Taylor et al., 2012, p.201; Trenberth et al., 2014). Along with temperature and precipitation, soil moisture is ranked a top priority variable in all societal benefit areas listed by the Group on Earth Observations (agriculture, biodiversity, climate, disasters, ecosystems, energy, health, water and weather) (Group on Earth Observations, 2012). Also aid organizations, whose potential regions of interest may encompass whole sub-continents, are gradually discovering the importance of soil moisture for assessments of drought-related food insecurity. The complexity of processes that involve soil moisture becomes obvious when atmospheric feedback loops are analysed. Koster et al. (2004), for instance, found that the response of the atmosphere to changes in soil moisture is neither linear, nor unidirectional. Additionally, the distribution of soil moisture is by nature very heterogeneous (Western et al., 2004) and changes can appear rapidly.

Traditional measurements of soil moisture relied on direct in-situ methods, such as gravimetric samples or time domain reflectometry (Dorigo et al., 2011; Wagner et al., 2007). In-situ observations are to date the most accurate localized measurement of soil moisture, but only models or satellites are able to provide spatially-consistent information on a global scale. However, datasets derived from space-borne microwave sensors are not yet able to capture variability at the scale of metres at sub-daily intervals. Hence, the concept of temporal stability (Brocca et al., 2009; Vachaud et al., 1985), which describes a quasi-linear relationship between soil moisture variations over time on different spatial scales, allows using coarse information acquired via satellites to understand local to regional phenomena.

Satellite instruments capable of retrieving information about soil moisture have been available since the late 1970s. However, despite the existence of several individual space-borne soil moisture products, a harmonized long-term dataset was missing until the Water Cycle Multi-mission Observation Strategy (WACMOS) project and the Climate Change Initiative (CCI) of the European Space Agency (ESA) released the first 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 (Dorigo et al. 2015). The latest official release of the ESA CCI SM product (CCI SM v02.2) covers a period from 1978 to 2014. Product updates that extend the temporal coverage are performed 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 wide variety of studies (Dorigo and De Jeu 2016). 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, 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 per cent 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. Nicolai-Shaw et al. (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. 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 (Hirschi et al., 2014).

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. In case of weather prediction, for instance, 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, 2007; Drusch et al., 2009; Scipal et al., 2008). In case of drought monitoring, it can be used to fill the gap between satellite-based estimates of rainfall and vegetation vigor (Enenkel et al., 2014). However, the current ESA CCI SM product does not fulfil this requirement with regard to updates at appropriate time steps. To bridge this gap, this study concentrates on the quality assessment of a soil moisture dataset that is based 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 two space-based sensors. One of these sensors is a radar, the Advanced Scatterometer (ASCAT) on-board the MetOp-A and MetOp-B satellites, the other one a radiometer, the Avanced Microwave Scanning Radiometer (AMSR2) on-board GCOM-W1 (Global Change Observation Mission - Water). NRT means that both the observations from ASCAT and AMSR2 are available within two to three hours after the satellite overpass. 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 and implement these adaptations. A main challenge for this task is the qualitative difference in offline and NRT observations (section 2) and their manifestation in the CCI NRT processing chain. Second, we investigate how well the CCI NRT dataset compares to ESA CCI SM on a global scale. 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 radiometers (Al-Yaari et al., 2014; Dorigo et al., 2010; 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) due to volume scattering of the microwave beam. The following section describes the general characteristics of the reprocessed ESA CCI SM product, as well as the operational products from ASCAT and AMSR2 that are used to generate the extension of the ESA CCI SM 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 ten satellites (Fig. **1**). It is available at daily time steps and on a 0.25° x 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 observation frequency that was used for the retrieval of soil moisture, the moment of the measurement, ascending or descending orbit and snow/frozen soil probability. According to Liu et al. (2011b; 2012), soil porosity values derived from 1300 global samples 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 also applied in GLDAS, which is used as a reference dataset to rescale soil moisture estimates from all active and passive sensors in Fig. **1** via cumulative distribution function matching (Liu et al., 2009; Reichle and Koster, 2004).

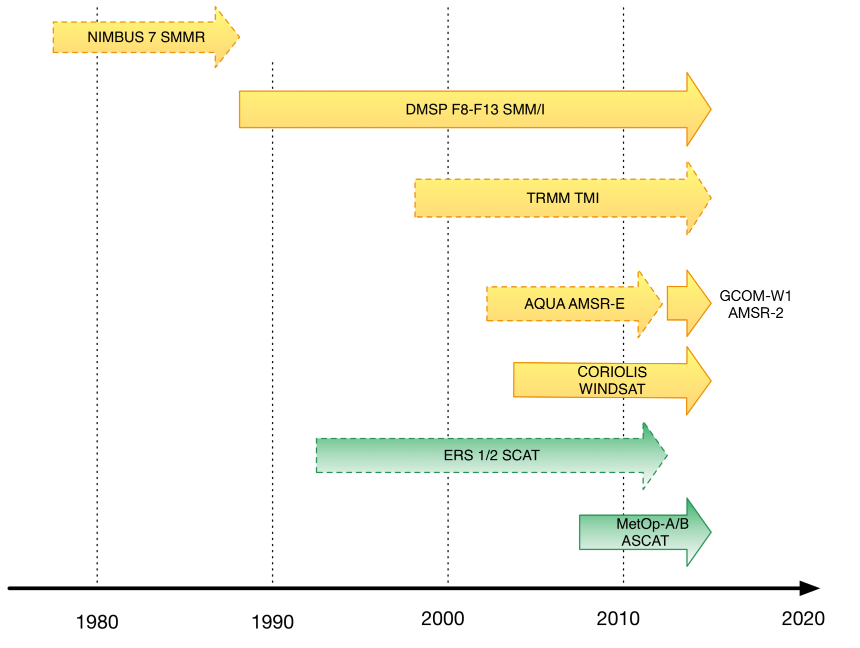

Fig. 1 Satellites and sensors used for generating the offline ESA CCI SM dataset and the daily continuation via ASCAT and AMSR2; Dotted lines indicate inactive missions; Yellow arrows represent passive measurements, green arrows represent active measurements; The ESA CCI SM dataset only includes SSM/I data until 2007.

2.2 Active Microwave Measurements from the ASCAT scatterometer

The ASCAT sensors 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. This principle is exploited by the TU Wien Water Retrieval Package (WARP), a change detection algorithm that results in relative surface soil moisture observations. These observations are 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).

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 offline WARP processing chain and its operational version WARP NRT. While the offline WARP processor generates soil moisture on a discrete global grid, the WARP NRT product is distributed from EUMETSAT (European Organisation for the Exploitation of Meteorological Satellites) in orbit geometry. It is available 135 minutes 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, updates related to algorithmic improvements and updates in the calibration of the backscatter measurement usually take a lot of time (Wagner et al., 2013). As a result, the quality of NRT soil moisture data lags behind the quality of reprocessed datasets.

Validations of the NRT soil moisture product disseminated via EUMETCAST (Albergel et al., 2012) yielded an average root mean squared difference (RMSD) of 0.08 m^3/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.

2.3 Passive Microwave Measurements from the AMSR2 radiometer

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, AMSR2 on-board the GCOM-W1 satellite measures brightness temperature at different bands (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 observation angle at 55 degrees, resulting in a “conically-shaped” footprint and a swath width of 1445 km. Both radiometer observations in 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. Several studies compared the performance of soil moisture products from the AMSR sensors and ASCAT (Brocca et al., 2011; Dorigo et al., 2010; Gruber et al., 2016), leading to overall comparable performance. An

intercomparison over 17 European sites (Brocca et al., 2011), for instance, 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 AMSR2 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

The AMSR2 soil moisture product 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 comparable (Parinussa et al., 2014). However, just like its predecessor AMSR-E, AMSR2 needs to cope with radio frequency interference (RFI) that is capable of jeopardizing whole satellite missions (Oliva et al., 2012). Currently, the RFI masking is based on a decision-tree that selects the passive microwave observations in the lowest available frequency that is free of RFI for each individual grid point (Fig. A**7**). In most cases the 6.9 GHz channel can be used.

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 either the active, passive and merged component of the CCI NRT dataset (explained in section 3), are used.

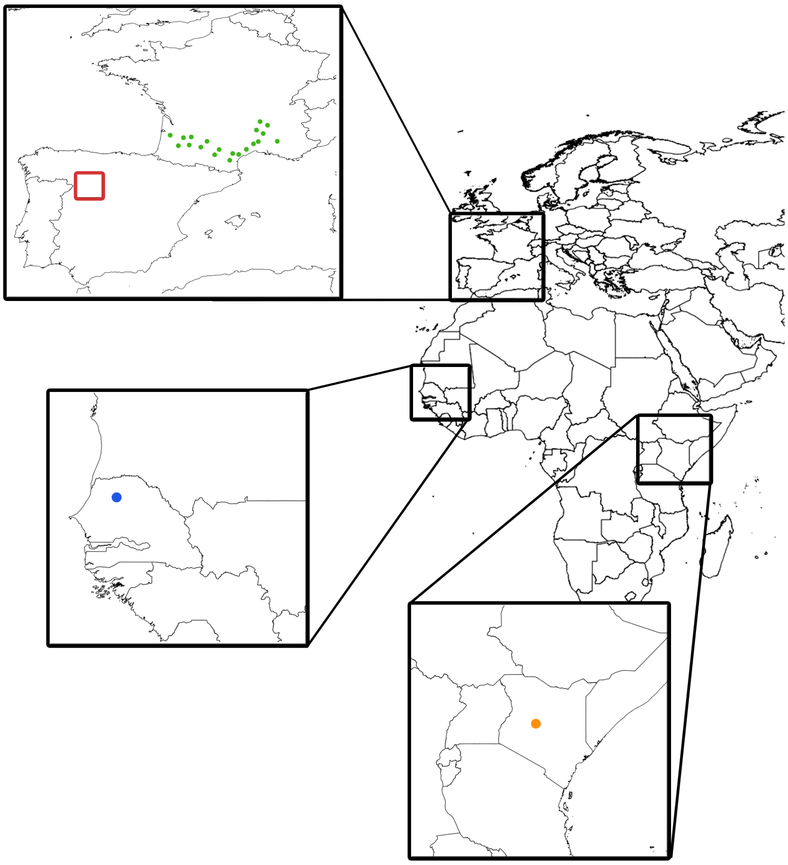

Fig. 2 Location of the networks used for validation in this study (Smosmania, France, green dots; Remedhus, Spain, red rectangle; Dahra, Senegal, blue dot; Cosmos, Kenya, orange dot)

Accordingly, we extracted 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 centimetres (respectively 10 centimetres 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 parts. 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.

3.1 Integrating NRT ASCAT and AMRS2 into the ESA CCI SM dataset

The integration of NRT ASCAT and AMSR2 observations into the ESA CCI SM builds on the procedures used to generate the standard ESA CCI SM products (Liu et al., 2011a, 2012; Wagner et al., 2012). Fig. **3** illustrates the main processing steps for the integration of NRT soil moisture observation in a flow chart. The most recent ESA CCI SM product covers the years 1978 to 2014. The CCI NRT dataset extends this temporal coverage to the present with an overlap for 2013/2014.

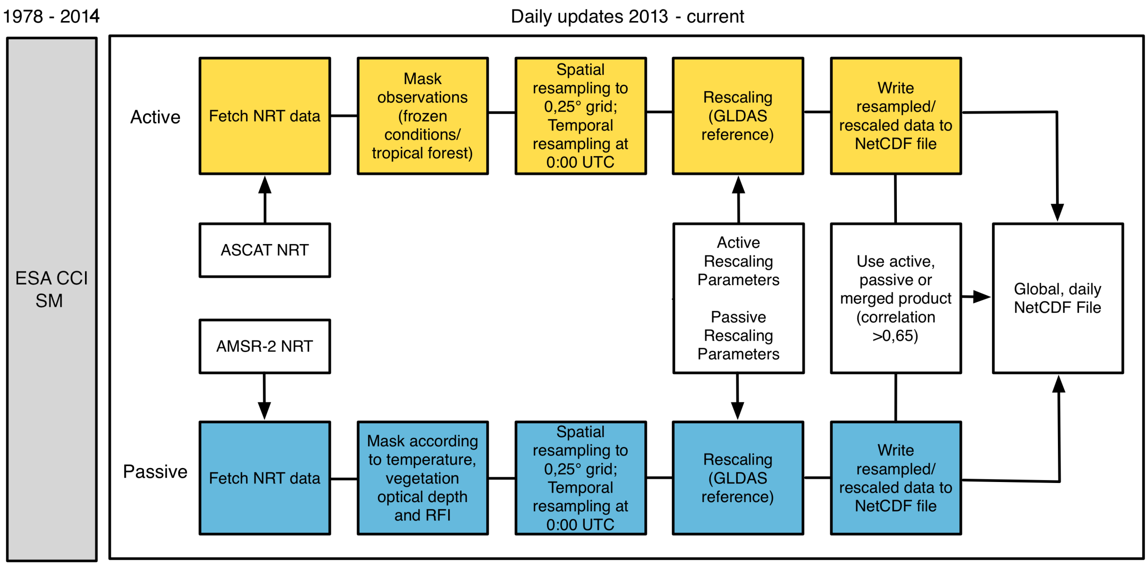

Fig. 3 Schematic flowchart illustrating the methodology for extending the ESA CCI SM dataset via NRT observations from ASCAT and AMSR2. The GLDAS1-Noah dataset is used as a scaling reference.

As for the ESA CCI SM processing chain all ASCAT level 2 data (surface soil moisture in orbit geometry) are first masked according to snow-covered/frozen conditions based on the ECMWF ERA Interim Re-Analysis product and vegetation density based on vegetation optical depth (VOD). VOD is 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.

The AMSR2 data are masked for soil skin temperature below 0°C, RFI and VOD. After the spatial resampling via a regular hamming window to a 0.25° grid we apply the temporal resampling to 00:00

UTC reference time via nearest neighbour search. In contrast to ASCAT, from which both ascending and descending orbits are used, we only use the descending (night-time) observations from AMSR2 (Lei et al., 2015). Both datasets are rescaled to the reference soil moisture dataset (GLDAS 1-NOAH) via piecewise linear CDF matching (Liu et al., 2011a). 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.

Fig. **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 low vegetation density (VOD < 0.24), whereas the TU-Wien ASCAT product is applied in regions with moderate to high vegetation density (VOD 0.60). So-called transition zones between dry and humid climates 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**).

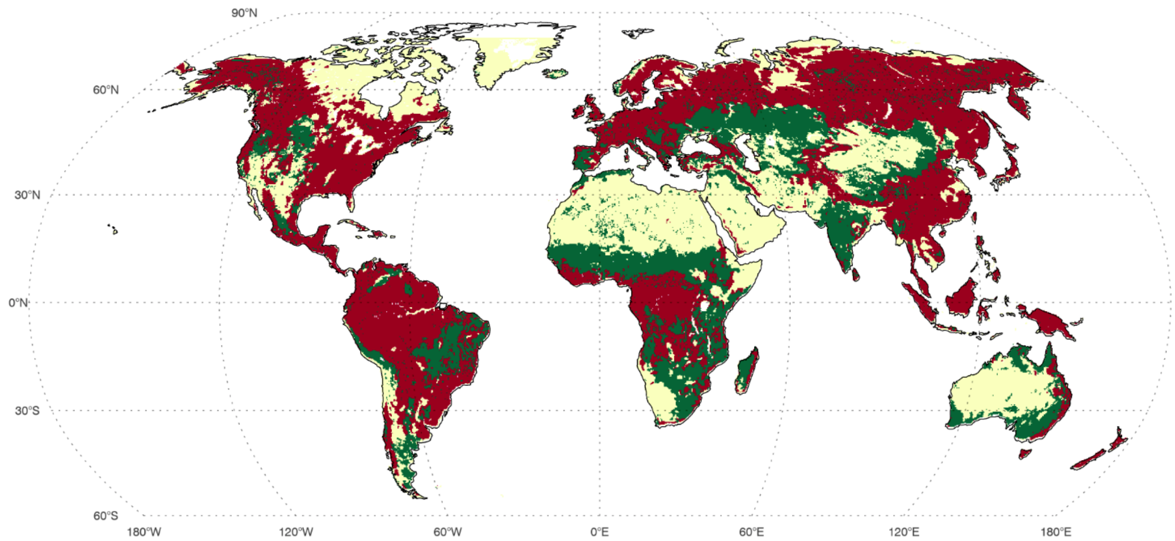

Fig. 4 Global blending map illustrating where active sensors (red), passive sensors (yellow) and the average of both (green) is used to generate the ESA CCI SM product (modified from Liu et al. 2012)

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) between ESA CCI SM and CCI NRT for an overlapping year (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 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 m^3/m^3
- Unbiased root mean squared difference (ubRMSD) in m^3/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 CCI NRT and ESA CCI SM/in-situ observations, respectively.

$$\bar{E} = \bar{f} - \bar{r} \tag{1}$$

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.

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

4 Results

The Pearson correlation coefficient (R) yields an average correlation of 0.80 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 Sahara, the US West coast and several large mountain ranges (e. g. 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.

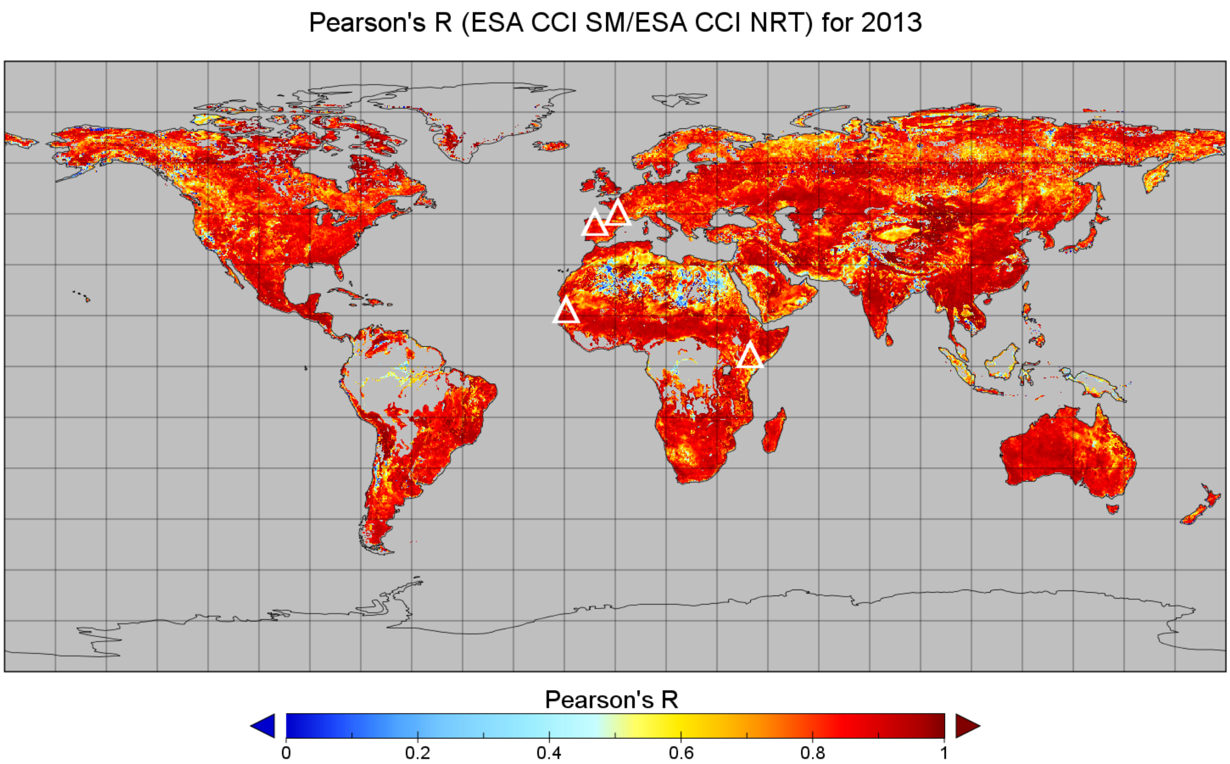

Fig. 5 Global correlation (Pearson's R) for ESA CCI SM and CCI NRT for 2013 (no negative correlations were observed); The white triangles illustrate the location of the in-situ stations/networks

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 average Pearson correlation coefficient for all in-situ stations is 0.58 (ESA CCI SM), and 0.49 (CCI NRT), respectively. The statistical scores for the Smosmania and the Remedhus network are comparable to the findings of Albergel et al. (2012) or Dorigo et al. (2015). The bias and the unbiased RMSD are slightly higher for CCI NRT.

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 Albergel et al. (2013). Table 2 lists the Pearson correlation coefficient, which is on average lower for the anomalies than for their normal time series and also lower for CCI NRT than for ESA CCI SM. Again, both the bias and the unbiased RMSD are higher for CCI NRT.

The Pearson and Spearman correlation coefficients between ESA CCI SM and CCI NRT over the location of the in-situ stations confirm the global picture with an average R of 0.80 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. The corresponding Fig. **6** shows an R of 0.93 and a Spearman’s correlation coefficient (S) of 0.96. However, in the same network we also observe the worst agreement (R = 0.62, S = 65) at a station named “Savenes” (not shown).

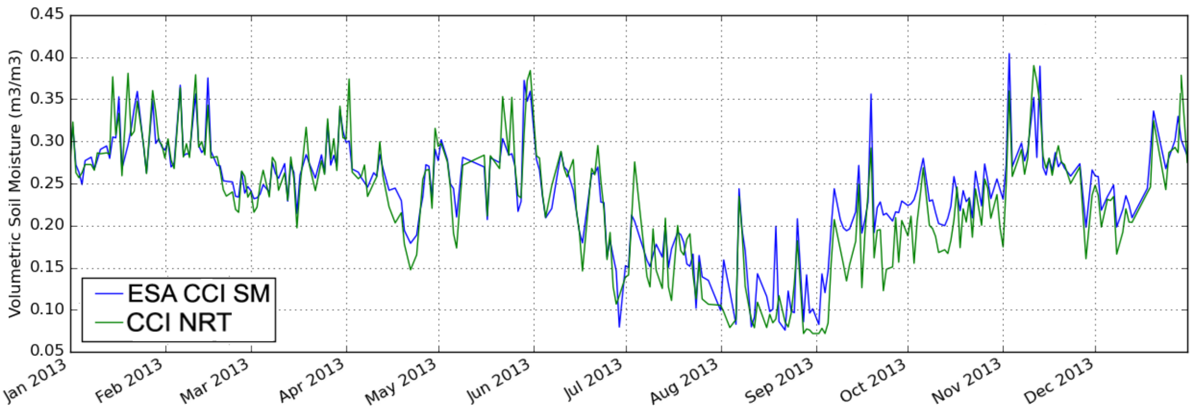

Fig. 6 Illustration of ESA CCI SM and CCI NRT over the “Urgons” station of the Smosmania network (R = 0.93; S = 0.96)

Global maps of the absolute differences between both datasets for 2013 (Fig. B**8**) and the four seasons (Fig. B**9** to Fig. B**12** Appendix) show a systematic positive bias in CCI NRT of up to 0.30 m^3/m^3 in regions like East Africa or Pakistan. compared to ESA CCI SM in regions such as East Africa, parts of the Sahel and Pakistan. This effect is stronger in spring and summer than in autumn and winter. In the central United States, large parts of Australia and Southern Africa the bias overestimation is smaller. Since the overestimation mainly appears in regions where the AMSR2 dataset is used (Fig. 4) and to understand the bias of soil moisture over Europe during winter 2013 we also analyse the absolute difference between the offline and the NRT ASCAT and AMSR2 datasets (Fig. C**13** and Fig. C**14**). Compared to the offline product, AMSR2 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 NRT 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.

5 Discussion and Conclusions

The global daily update of the ESA CCI SM surface soil moisture dataset is motivated by uncertainties in the performance of operational retrieval algorithms for radars/radiometers (in our case ASCAT and AMSR2) and by an increasing interest in multi-sensor soil moisture across a wide range of applications. The need for improved and more timely soil moisture representations in agricultural drought monitoring is one of the strongest motivations (Anderson et al., 2012; Bolten and Crow, 2012; Enenkel et al., 2014; Hirschi et al., 2014). The CCI NRT dataset was generated by adapting the ESA CCI SM processing chain for operational NRT soil moisture retrievals. Just like in the offline product the merging scheme considers each sensor's individual strengths and limitations. ASCAT, for instance, performs better than AMSR2 at higher vegetation densities, while one strength of AMSR2 is the retrieval over semi-arid and arid regions (Liu et al., 2011a). A first validation is carried out, looking at the correlation of ESA CCI SM and the new CCI NRT dataset on a global scale and their agreement over in-situ stations that had been selected based on their reliability, temporal coverage and ability to reflect the individual components (active/passive/combined) of the CCI NRT dataset. In addition, we analyse the agreement of the ESA CCI SM/CCI NRT/in-situ anomalies and we calculate the absolute differences between both datasets on a global scale.

Our main findings are:

- There is a high agreement between the CCI NRT dataset and the ESA CCI SM dataset on a global scale for the entire year of 2013 (average R = 0.8). This finding also indicates a good performance of soil moisture observations from ASCAT and AMSR2 and therefore the operational readiness of the CCI NRT algorithm. Low correlations are for instance observed in areas that permanently show low levels of soil moisture, such as the arid zones of Northern Africa, which show a high sensitivity for rainfall events. Since most of these regions are covered by AMSR2, the most likely error sources are the GLDAS-based rescaling parameters.
- The validation with in-situ observations in Spain, France, Senegal and Kenya yields less accurate results for the CCI NRT dataset than for ESA CCI SM. 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 m^3m^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.

  Also with regard to absolute difference the general agreement between CCI NRT and ESA CCI SM is satisfying. A comparison of both datasets for 2013 reveals a bias of CCI NRT over

Europe during Winter 2013 (Fig. C**13**; Appendix) and an bias over several dry areas, e. g. over parts of Africa and Australia (Fig. C**14**; Appendix), which is likely related to intercalibration issues between AMSR2 and its predecessor AMSR-E (Okuyama and Imaoka, 2015).

We expect that, apart from solving the AMSR2 intercalibration issues and a dynamic snow map for ASCAT, which should improve the performance during winter, 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 used in this study differ in their absolute calibration level affecting the soil moisture values. 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, which are currently based on parameters that had been developed for the offline ASCAT product. Second, the currently static RFI map for AMSR2 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 for the specific implementation in the CCI NRT product. This is the first method that takes the additional 7.3 GHz channel into account, which was specifically added to the AMSR-E sensor constellation and proved to mitigate issues related to RFI.

Despite these issues, the development of an operational processing chain that allows daily soil moisture updates is particularly promising with regard to applications that aim at the confirmation of satellite-based rainfall estimates (Brocca et al., 2013) or at closing the gap between rainfall estimates and the response of vegetation (Enenkel et al., 2014). In this regard, the integration of the latest generation of soil moisture sensors, such as Sentinel-1 of the ESA and the European Commission (EC) or NASA's SMAP (Soil Moisture Active/Passive), whose L-band radiometer is still active after the failure of the radar, could lead to further improvements. These new sensors are able to retrieve soil moisture at a far higher resolution than ASCAT or AMSR2 – in case of Sentinel 1 around one kilometre for operational products and below 100 metres 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 per cent 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.

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. 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. A pre-operational dataset will soon be available via the Remote Sensing Research Group of the Vienna University of Technology (http://rs.geo.tuwien.ac.at/)

Author contribution

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

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Appendix A

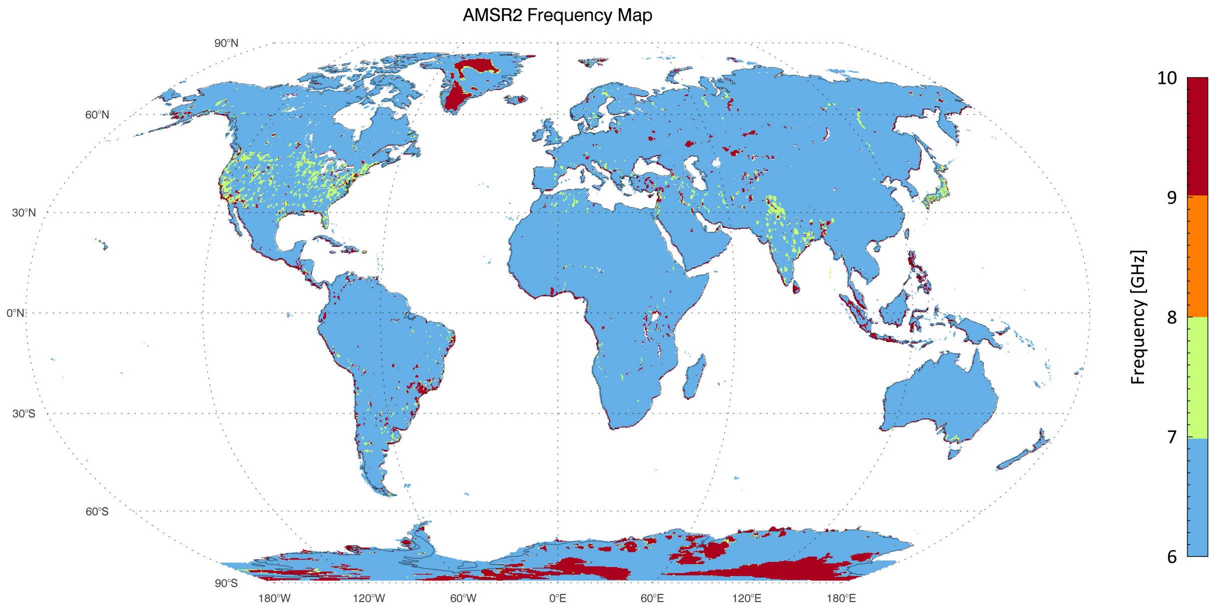

Fig. A7 Global map illustrating which frequency used by AMSR2 is the least affected by RFI

Appendix B

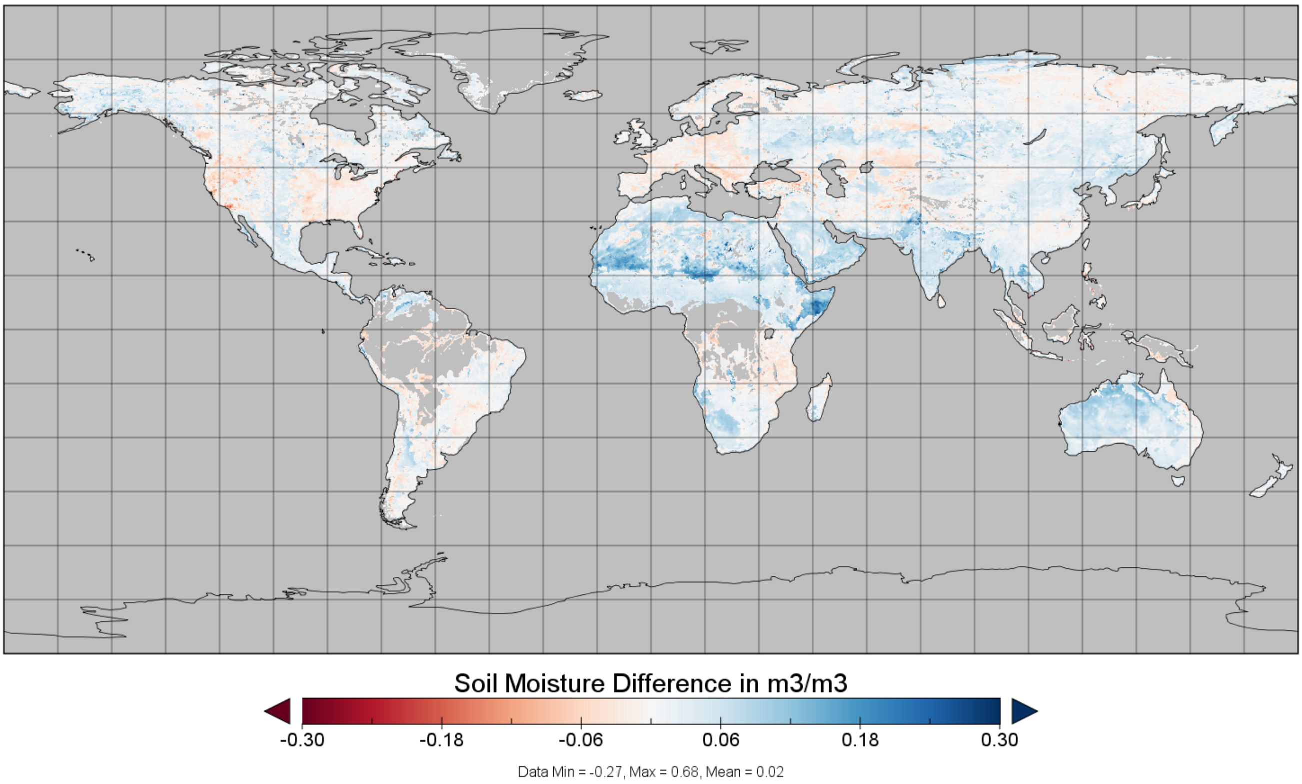

Fig. B8 Absolute differences in soil moisture (ESA CCI SM minus CCI NRT) for the entire year of 2013

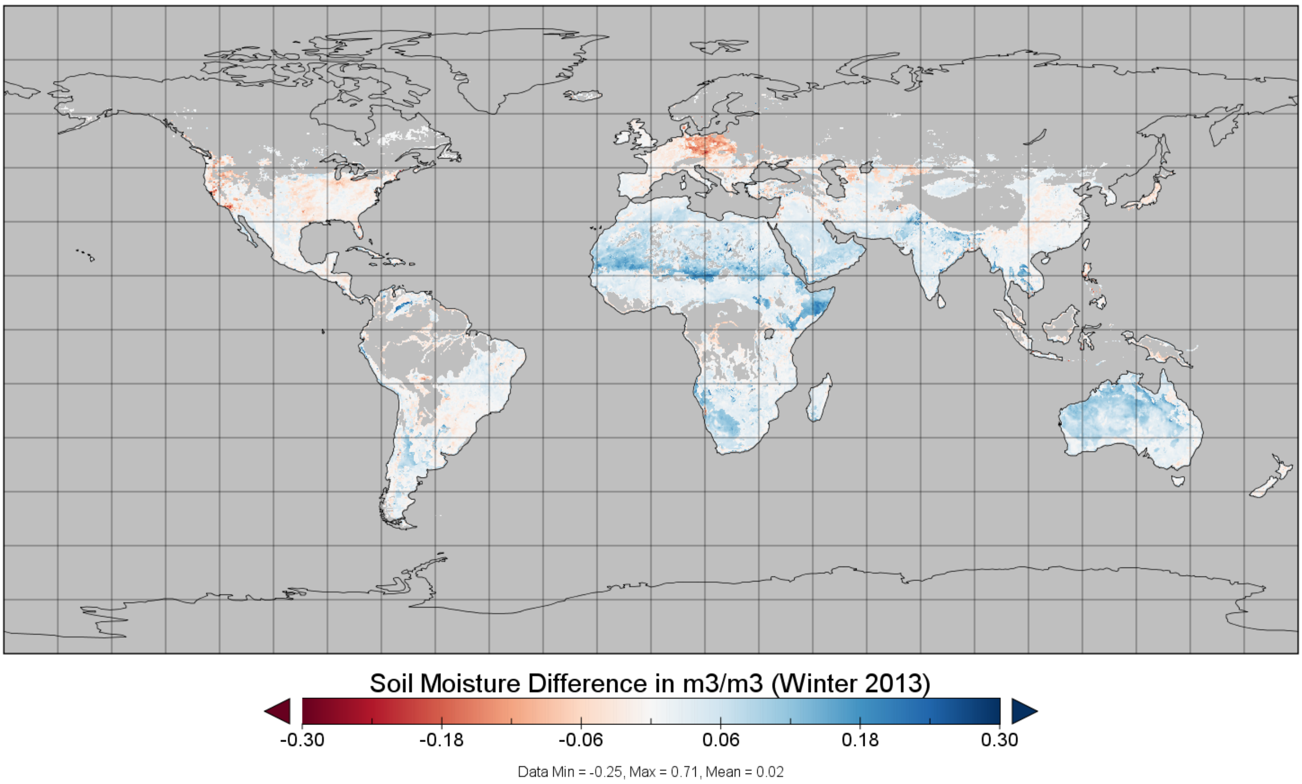

Fig. B9 Absolute differences in soil moisture (ESA CCI SM minus CCI NRT) for Winter 2013

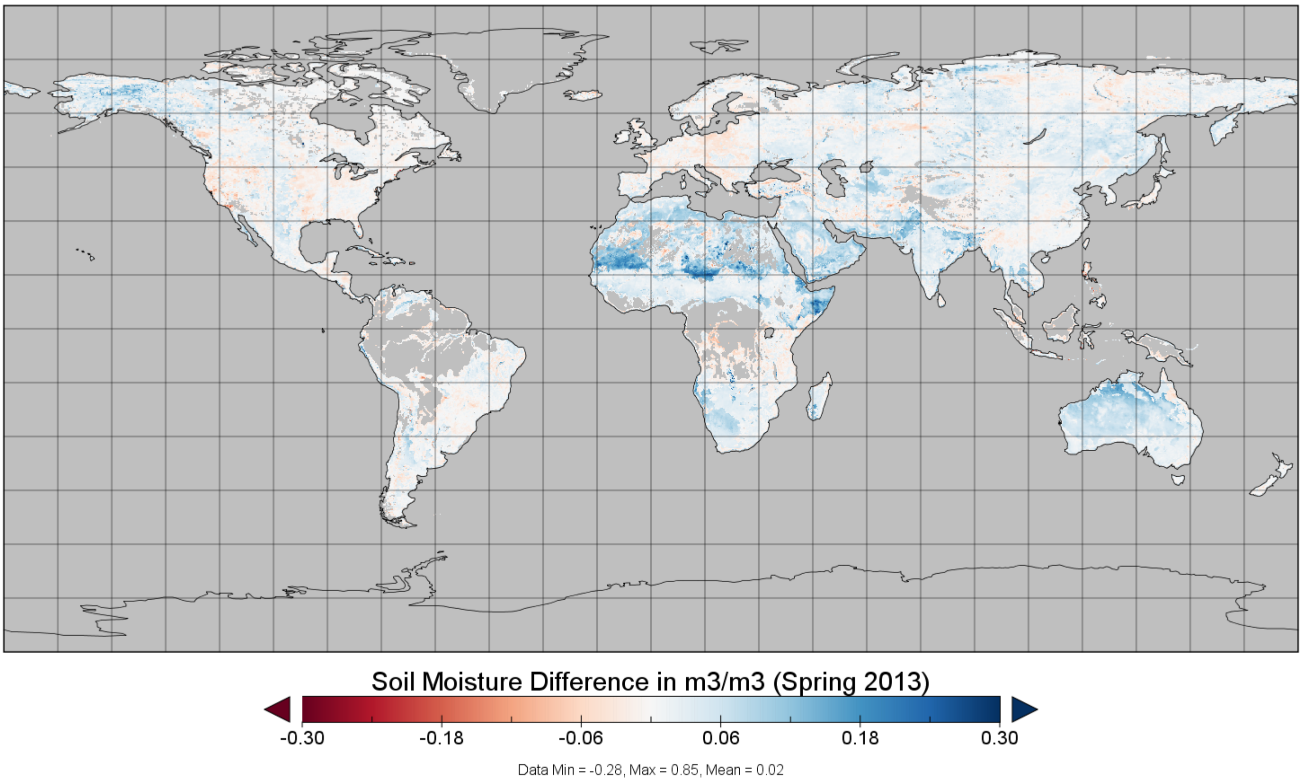

Fig. B10 Absolute differences in soil moisture (ESA CCI SM minus CCI NRT) for Spring 2013

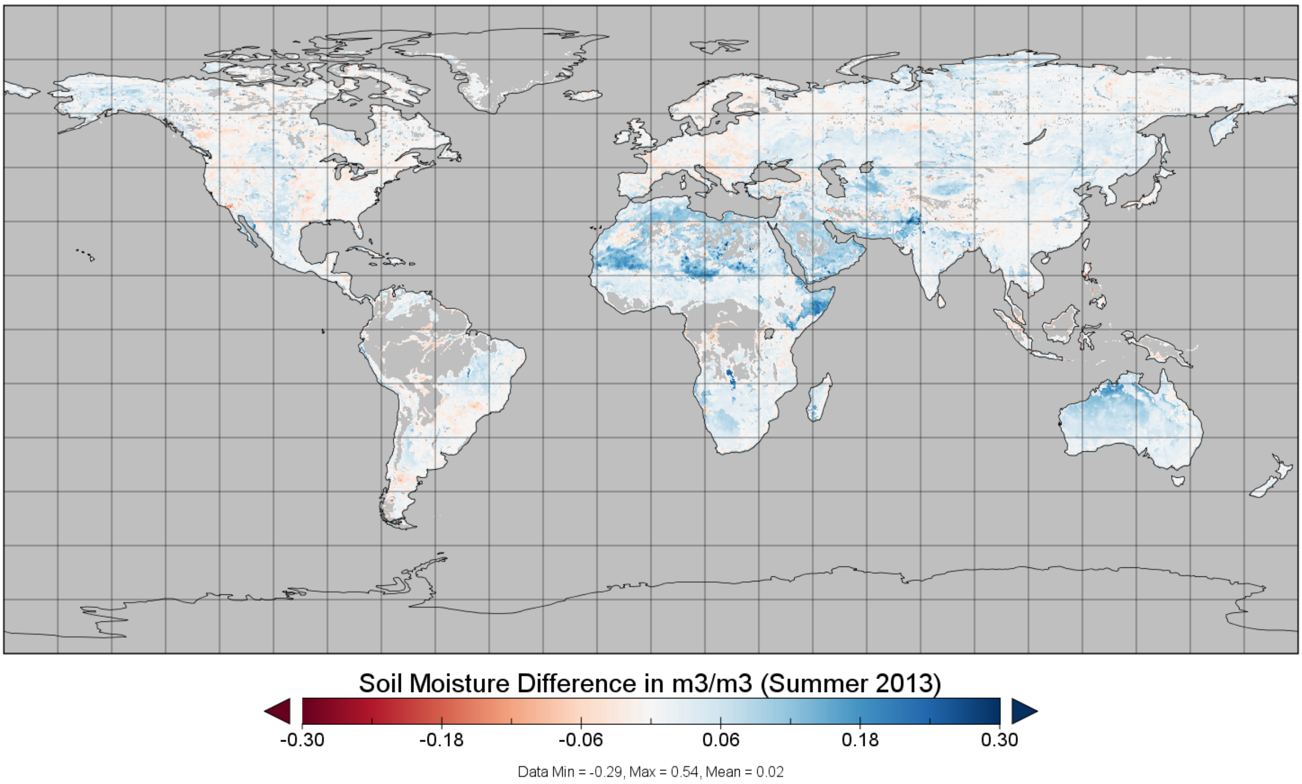

Fig. B11 Absolute differences in soil moisture (ESA CCI SM minus CCI NRT) for Summer 2013

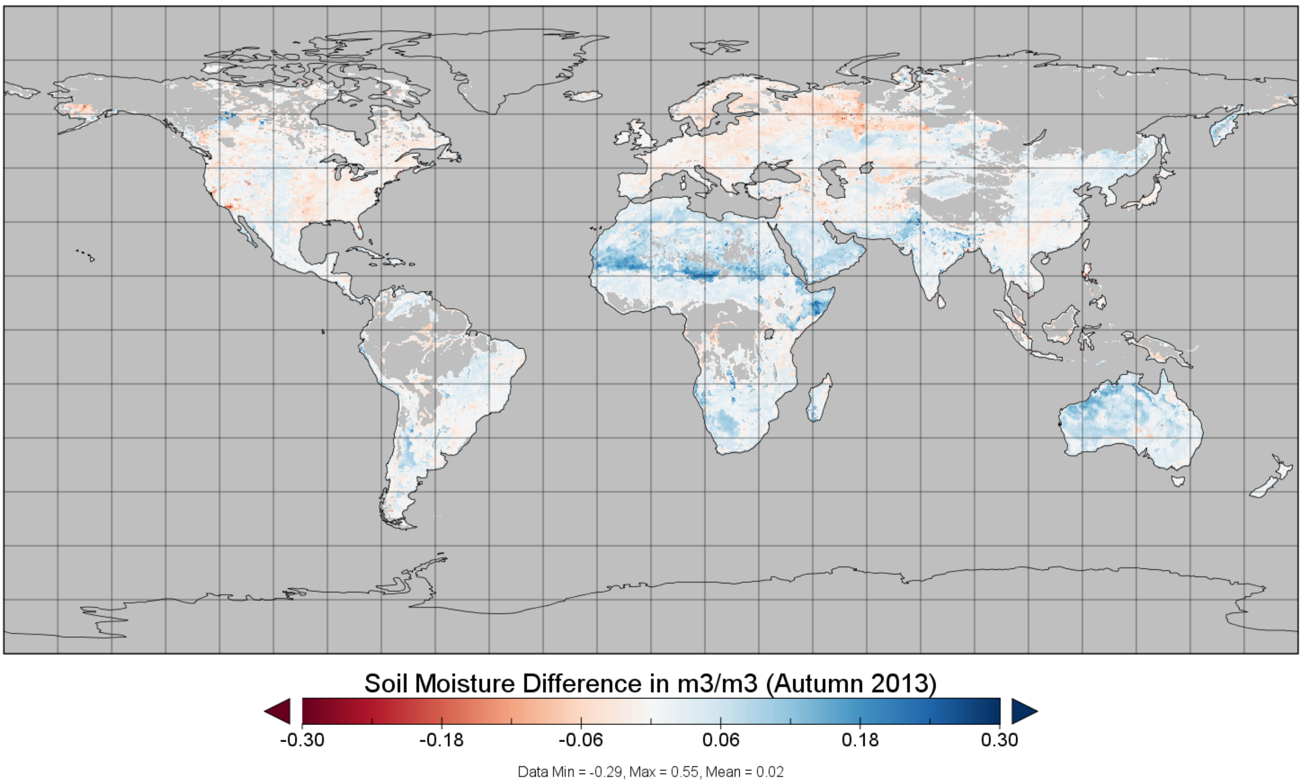

Fig. B12 Absolute differences in soil moisture (ESA CCI SM minus CCI NRT) for Autumn 2013

Appendix C

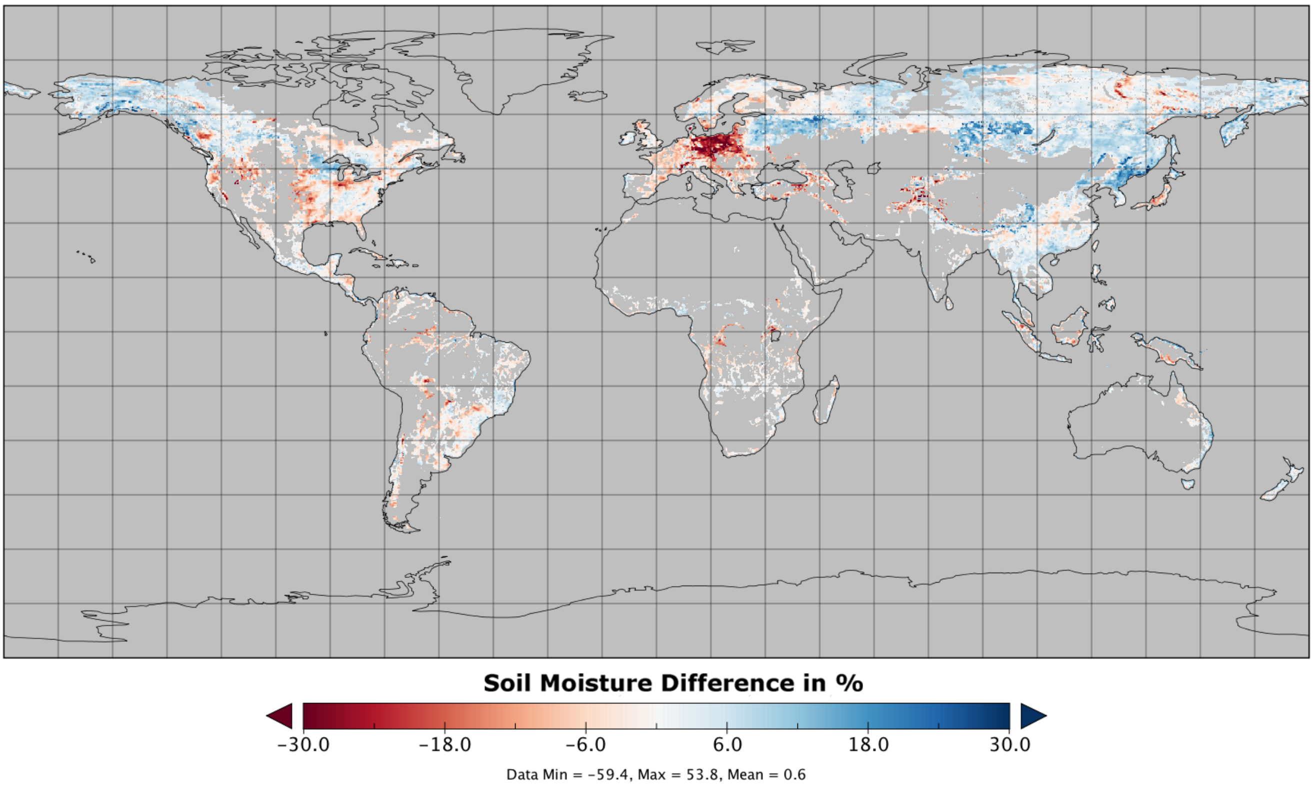

Fig. C13 Absolute differences in soil moisture for ASCAT (ASCAT NRT minus ASCAT offline) for the entire year of 2013 (masked according to the blending map in Fig. 4)

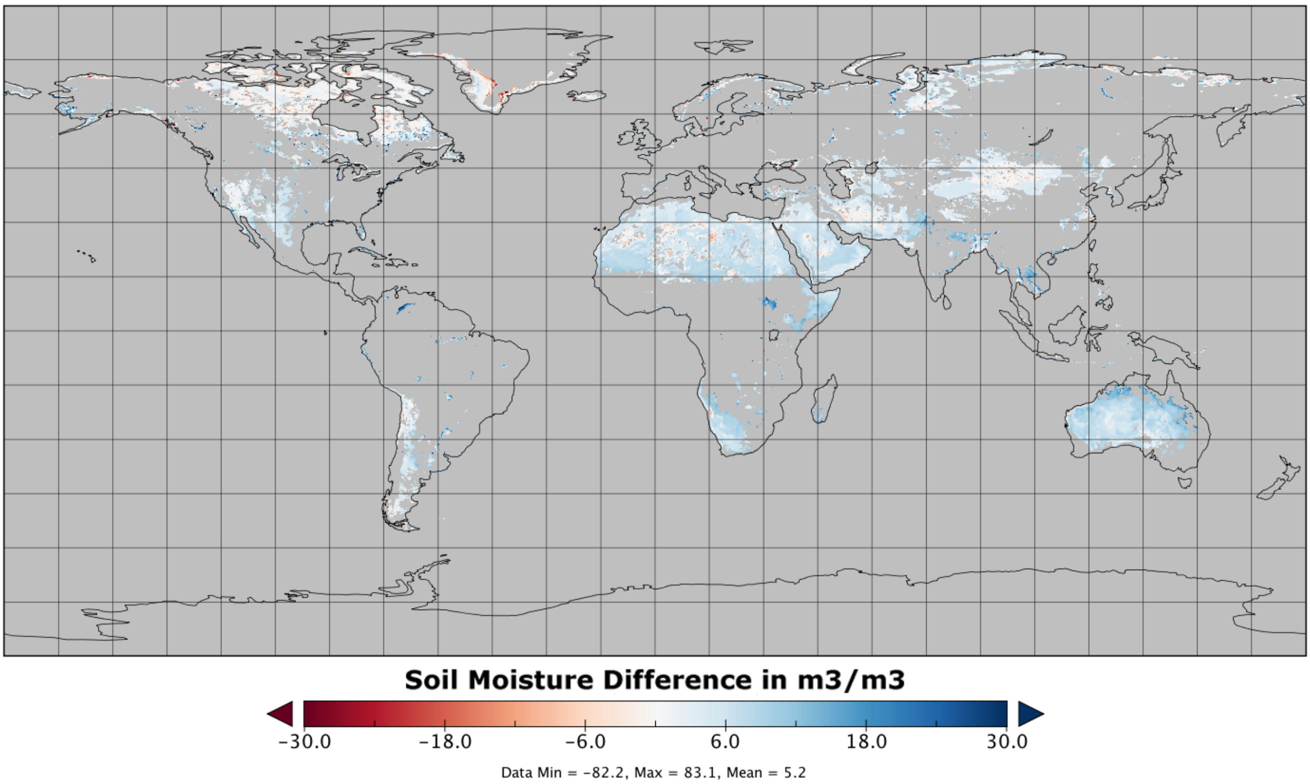

Fig. C14 Absolute differences in soil moisture for AMSR2 (AMSR2 NRT minus AMSR2 offline) for the entire year of 2013 (masked according to the blending map in Fig. 4)

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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	R for ESA CCI	R 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	N.A.	N.A.	0.004	0.008

Table 1 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	R for ESA CCI	R 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	N.A.	N.A.	0.002	0.002