



## Abstract

Combining information derived from satellite-based passive and active microwave sensors has the potential to offer improved retrievals of surface soil moisture variations at global scales. Here we propose a technique to take advantage of retrieval characteristics of passive (AMSR-E) and active (ASCAT) microwave satellite estimates over sparse-to-moderately vegetated areas to obtain an improved soil moisture product. To do this, absolute soil moisture values from AMSR-E and relative soil moisture derived from ASCAT are rescaled against a reference land surface model data set using a cumulative distribution function (CDF) matching approach. While this technique imposes the bias of the reference to the rescaled satellite products, it adjusts both satellite products to the same range and almost preserves the correlation between satellite products and in situ measurements. Comparisons with in situ data demonstrated that over the regions where the correlation coefficient between rescaled AMSR-E and ASCAT is above 0.65 (hereafter referred to as transitional regions), merging the different satellite products together increases the number of observations while minimally changing the accuracy of soil moisture retrievals. These transitional regions also delineate the boundary between sparsely and moderately vegetated regions where rescaled AMSR-E and ASCAT are respectively used in the merged product. Thus the merged product carries the advantages of better spatial coverage overall and increased number of observations particularly for the transitional regions. The combination approach developed in this study has the potential to be applied to existing microwave satellites as well as to new microwave missions. Accordingly, a long-term global soil moisture dataset can be developed and extended, enhancing basic understanding of the role of soil moisture in the water, energy and carbon cycles.

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## 1 Introduction

Passive and active microwave satellites have been shown to provide a useful retrievals of near-surface soil moisture variations at regional and global scales (e.g., Wagner et al., 2003; Wen et al., 2003; Njoku et al., 2003; McCabe et al., 2005; Gao et al., 2006; Owe et al., 2008), as they can penetrate cloud cover conditions and are sensitive to water on the earth surface. A series of operational satellite-based passive microwave sensors have been available since 1978, including the Scanning Multichannel Microwave Radiometer (SMMR) (1978–1987), the Special Sensor Microwave Imager (SSM/I) of the Defense Meteorological Satellite Program (since 1987), the microwave imager from the Tropical Rainfall Measuring Mission (TRMM) (since 1997), and more recently the Advanced Microwave Scanning Radiometer–Earth Observing System (AMSR-E) onboard the Aqua satellite (since 2002). The first global active microwave satellite observed soil moisture product was acquired by the European Remote Sensing (ERS-1) scatterometer from 1992. ERS-2 started collecting data from March 1996, while the Advanced Scatterometer (ASCAT) onboard the Meteorological Operational satellite programme (MetOp) was launched in October 2006. The Soil Moisture and Ocean Salinity (SMOS) satellite launched in November 2009 carries the low frequency L-band sensor. While currently at the calibration stage, it is expected to continue the developing record of globally retrieved soil moisture data. In the coming years, numerous new satellite missions with microwave instruments are scheduled for launch (e.g., Soil Moisture Active Passive (SMAP), Aquarius, Deformation, Ecosystem Structure and Dynamics of Ice (DESDynI), and Argentine Microwaves Observation Satellite (SAOCOM)), and are expected to bring soil moisture retrievals with higher accuracy.

Both passive and active microwave techniques have inherent advantages and disadvantages. Higher accuracy of passive microwave soil moisture is expected over regions with low vegetation density, as the effects of vegetation attenuation are less (Jackson and Schmugge, 1995; Njoku and Entekhabi, 1996). Dorigo et al. (2010) utilized the triple collocation approach to estimate the error in passive and active microwave soil

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moisture retrievals from AMSR-E and ASCAT C-band data, and found that generally AMSR-E performs better over sparsely vegetated regions and ASCAT better over moderately vegetated regions. Over regions where the vegetation density lies between low and moderate, the individual satellite products display similar performance, which is also supported by De Jeu et al. (2008). From physical principles, it is expected that the higher the microwave frequency, the lower the accuracy of soil moisture retrievals (Parinussa et al., 2010). However, passive microwave soil moisture retrievals from the higher frequency TRMM-TMI X-band (10.7 GHz) were shown to be more accurate than active microwave retrievals from the lower frequency ERS-2 C-band (5.3 GHz) over some sparsely vegetated regions (Scipal et al., 2008), which might be related the low signal to noise ratio of ERS-2 over these sparsely vegetated regions. Clearly, there is value in identifying an approach to combine the features of both active and passive microwave sensors over these varying vegetation types to develop an improved soil moisture product.

One approach to take advantage of features from both microwave techniques is to combine passive and active microwave observations at the retrieval level: that is, “blending” soil moisture products derived from different passive and active microwave satellite instruments. This approach should be applicable to both past and current microwave satellites, as well as new missions that are expected to bring higher accuracy of soil moisture retrievals. Together these data allow a long-term global soil moisture to be provided and extended.

However, there are several challenges in accomplishing this objective. First, within the domain of passive or active microwave satellites, no single satellite covers the entire period. Differences in sensor specifications (e.g., different microwave frequencies and resolutions) prevent merging soil moisture estimates from different instruments directly. Second, the currently available global passive and active microwave products provide absolute and relative soil moisture respectively. Third, the accuracy of soil moisture retrievals over varying vegetation cover differs from passive or active microwave sensors, making global estimation with a single sensor a difficult task.

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As a step towards developing a continuous time series of soil moisture, this study addresses the latter two challenges by developing a method that can combine passive and active microwave soil moisture retrievals from sensors with similar frequency to obtain an improved blended product.

## 2 Data sources

### 2.1 AMSR-E (VUA-NASA product)

The AMSR-E sensor onboard National Aeronautics and Space Administration (NASA) Aqua satellite has provided passive microwave measurements at 6.9 GHz (C-band) and five higher frequencies (including 36.5 GHz Ka-band) since May 2002, with daily ascending (13:30 equatorial local crossing time) and descending (01:30 equatorial local crossing time) overpasses, over a swath width of 1445 km.

There are a number of algorithms available to retrieve soil moisture using AMSR-E observed brightness temperatures (Owe et al., 2008; Njoku et al., 2003; Jackson, 1993). A number of comparison studies have demonstrated that soil moisture retrievals by the algorithm developed by Vrije Universiteit Amsterdam in collaboration with NASA (hereafter VUA-NASA) show good agreement with in situ data over sparsely to moderately vegetated regions (Draper et al., 2009; Wagner et al., 2007; Gruhier et al., 2010), thus the VUA-NASA AMSR-E C-band product was used in this study. The C-band soil moisture represents the top few centimetres of soil, depending on the wetness. We only use the soil moisture retrievals ( $\text{m}^3 \text{m}^{-3}$ ) acquired by AMSR-E descending passes, as the much smaller temperature gradients between the vegetation and the surface at midnight are more favourable for accurate retrieval (De Jeu, 2003).

### 2.2 ASCAT (TUV product)

The ASCAT onboard the MetOp is a real aperture radar operating at 5.255 GHz (C-band) since October 2006. Three antennas on each side of the satellite ground track

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measure the backscatter from the earth surface in two 550 km wide swaths. The three antennas on each side are oriented to broadside and  $\pm 45^\circ$  of broadside, and so make sequential observations of the backscattering coefficient of each point of interest from three directions.

The backscatter at different incidence angles makes it possible to determine the annual cycle of the backscatter incidence angle relationship which is a prerequisite for correcting seasonal vegetation effects (Bartalis et al., 2007). After removing the effects of vegetation growth and senescence, the remaining signal can be interpreted as soil moisture variations. Soil moisture variations are adjusted between the historically lowest (0%) and highest (100%) values, producing a time series of relative soil moisture for the topmost centimetres of the soil. This change detection algorithm, originally developed for soil moisture retrievals from ERS-1 and 2 by Technische Universität Wien (TUW) (Wagner et al., 1999) was applied to ASCAT with minor adaptations (Naeimi et al., 2009).

The descending and ascending equatorial crossing time of ASCAT are respectively 09:30 and 21:30. To make the comparison with AMSR-E descending (01:30) product possible, the morning swaths and the evening swaths of the day before were averaged. Both AMSR-E and ASCAT products were resampled into  $0.25^\circ$  (about 25 km) resolution for the period from 1 January through 31 December 2007.

A snow mask was developed based on ERA-Interim reanalysis data. ERA-Interim is the latest global atmospheric reanalysis produced by the European Centre for Medium-Range Weather Forecasts (ECMWF), covering the data-rich period since 1989 (Simmons et al., 2007a, b; Uppala et al., 2008; Dee and Uppala, 2009). ERA-Interim products are publicly available on the ECMWF Data Server, at a  $1.5^\circ$  resolution ([http://data-portal.ecmwf.int/data/d/interim\\_daily/](http://data-portal.ecmwf.int/data/d/interim_daily/)). ASCAT soil moisture retrievals were masked out if the reanalysis indicated surface temperature below zero degree Celsius or snow depth greater than zero millimetre.

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## 2.3 Land surface model (Noah) product

Noah is a land surface model that forms a component of the Global Land Data Assimilation System (GLDAS). The Noah model product with 3-hour time interval and 0.25° resolution is available for 2000 onwards (<ftp://agdisc.gsfc.nasa.gov/data/s4pa/>).

The model was forced by combination of NOAA/GDAS atmospheric analysis fields, spatially and temporally disaggregated NOAA Climate Prediction Center Merged Analysis of Precipitation (CMAP) fields, and observation based downward shortwave and longwave radiation fields derived using the method of the Air Force Weather Agency's Agricultural Meteorological system (Rodell et al., 2004).

In Noah, the vertical profiles of sand and clay are taken into account by using a four-layered soil description with a 10 cm thick top layer. Soil moisture dynamics of the top layer are governed by infiltration, surface and sub-surface runoff, gradient diffusion, gravity and evapotranspiration. The unit of Noah soil moisture is  $\text{kg m}^{-2}$ . Given that the soil layer depth is 10 cm, Noah soil moisture ( $\text{kg m}^{-2}$ ) was converted to volumetric soil moisture ( $\text{m}^3 \text{m}^{-3}$ ) for this study.

## 2.4 In situ measurements

In situ soil moisture measurements are used in this study for comparison with the estimates from AMSR-E, ASCAT and Noah, including:

- OZNET network from south-east Australia (Young et al., 2008; Rüdiger et al., 2007);
- REMEDHUS network from central Spain (Martínez-Fernández and Ceballos, 2005);
- SMOSMANIA network from southern France (Albergel et al., 2008; Calvet et al., 2007); and
- CNR-IRPI network from Italy (Brocca et al., 2008; Brocca et al., 2009).

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Data were downloaded from the International Soil Moisture Network (<http://www.ipf.tuwien.ac.at/insitu/index.php/in-situ-networks.html>). The shallowest measurements represent approximately the top 5–8 cm, comparable with estimates derived from microwave observations and Noah simulations. The land use around the measurement stations is mainly grasslands, crops and grazing, which may be considered representative for low to moderate vegetation density.

### 3 Methods

The combination technique consists of two steps: rescaling and then merging the data, both of which are described in more detail below.

#### 3.1 Rescaling

As noted previously, AMSR-E and ASCAT products provide absolute and relative soil moisture respectively. To combine these data, one product needs adjustment against the other, or both require adjustment against an independent reference data set. From previous analysis, AMSR-E VUA-NASA C-band product has been observed to perform better over sparsely vegetated areas whereas ASCAT TUV product outperforms AMSR-E in moderately vegetated regions (Dorigo et al., 2010). Given this, the possibility of adjusting one product against the other is removed.

As a result, an independent reference is needed against which both products can be adjusted. The reference is expected to have the following characteristics: global coverage with a spatial resolution and temporal interval that are comparable with AMSR-E and ASCAT products (e.g., roughly 25 km resolution and daily interval); long time record for the sake of yielding long term satellite observed soil moisture product; and providing reasonable surface soil moisture estimates for all land cover types (i.e., representative soil layer is not deeper than 10 cm).

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The Noah model was identified as satisfying the requirements above and therefore selected as the reference data set against which both satellite-based observations are rescaled. In addition, the Noah model and the VUA-NASA algorithm use a common soil property dataset (<http://ldas.gsfc.nasa.gov/gldas/GLDASsoils.php>) based on the Food and Agriculture Organization (FAO) Soil Map of the World, which is linked to a global database of over 1300 soil samples. In this study, the 3-hourly simulated soil moisture of the top layer was aggregated to daily averages.

The approach used to adjust microwave satellite observed against the Noah simulated soil moisture is the cumulative distribution function (CDF) matching technique. This matching technique has been used successfully in a number of previous studies. Reichle and Koster (2004) merged satellite soil moisture observations with model data by CDF matching, and both Anagnostou et al. (1999) and Atlas et al. (1990) established reflectivity-rainfall relationships for calibration of radar or satellite observations of precipitation using CDF matching. Recently, Liu et al. (2009) produced a 29-year satellite soil and vegetation moisture data set over Australia by merging several passive microwave products using the CDF matching technique.

The CDF matching approach was applied for each grid point individually. An example taken from the grid cell at 34.625° S, 146.125° E is shown in Fig. 1. First, soil moisture values from days when both Noah (Fig. 1a, black dotted line, left y-axis) and ASCAT (blue start, right y-axis) data are available are used to generate their own CDF curves. Then the 0th, 5th, 10th, 25th, 50th, 75th, 90th, 95th and 100th percentiles of Noah and ASCAT CDF curves were used to divide the cumulative distribution into eight segments (Fig. 1b). In Fig. 1c, the nine percentile values from the ASCAT CDF curve are plotted against those of Noah. Based on these, eight linear equations were obtained to adjust ASCAT data falling into different segments against Noah data. Rescaled ASCAT soil moisture is shown in Fig. 1a (red start, y-axis on the left). Figure 1d shows the original AMSR-E (blue start, right y-axis), rescaled AMSR-E (red star, left y-axis) and Noah soil moisture for the same grid cell.

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## 3.2 Merging

The process of rescaling ensures that both of the satellite-based soil moisture products are within the same range before undertaking merging. As mentioned previously, AMSR-E VUA-NASA and ASCAT TUW soil moisture perform well over sparsely and moderately vegetated regions respectively (Dorigo et al., 2010). In the blended product, the rescaled AMSR-E and ASCAT data are respectively used over regions with low and moderate vegetation density. Over regions where the vegetation density lies between low and moderate, the individual satellite products display similar performance and both can be used.

Comparisons with in situ soil moisture measurements (McCabe et al., 2005) may assist in determining when the rescaled satellite soil moisture shows equivalent performance. In addition, comparisons with in situ data can identify whether the CDF matching approach changes the performance of the original satellite soil moisture retrievals. To examine this further, an analysis against in situ data was undertaken based on the following methodology:

1. Calculate the correlation coefficient ( $R$ ) and root mean squared error (RMSE) between soil moisture estimates (AMSR-E and Noah) and in situ measurements. Only the correlation coefficient between ASCAT and in situ measurements was determined as these values represent the percentage of surface wetness.
2. Identify occasions when AMSR-E, ASCAT and Noah have coincident overpasses and use the corresponding soil moisture estimates at these times to develop CDF curves for each product.
3. Rescale AMSR-E and ASCAT against Noah using the CDF curves built in Step 2, producing rescaled AMSR-E and ASCAT products.
4. Calculate the correlation coefficient and RMSE between the rescaled satellite products and in situ soil moisture measurements, and also the correlation coefficient between rescaled AMSR-E and rescaled ASCAT individually.

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5. Merge all rescaled AMSR-E and rescaled ASCAT by calculating an averaged remote sensing based product. Where two coincident values are not available, the single satellite based estimate is used instead. The correlation coefficient and RMSE between the newly merged product and in situ measurements are then calculated.

A comparison of these statistics is undertaken against in situ measurements at the different stages of processing undertaken above (i.e., original, rescaled and merged).

## 4 Results and discussions

### 4.1 Comparison with in situ measurements

10 The relationships between soil moisture estimates from AMSR-E, ASCAT and Noah and in situ measurements presented in Table 1 represent three different situations: (1) ASCAT performs better; (2) AMSR-E performs better and (3) both satellite-based products have similar performance.

Several common characteristics can be observed under different situations. (1) The CDF rescaling method only slightly changes the correlation coefficient ( $R$ ) between the satellite-based and in situ soil moisture. (2) The rescaling approach tends to impose the RMSE of Noah on the rescaled products. (3) Merging two rescaled satellite products can increase the number of observations. (4) The statistics (i.e.,  $R$  and RMSE) of the merged product lie somewhere in between the two rescaled satellite products.

20 The most obvious divergence among different situations is that: (1) when only one satellite product agrees well with in situ soil moisture, the correlation between two satellite products is generally low and the agreement between the merged product and in situ measurements becomes much worse (see Case 1 and 2); and (2) when both satellite-based products are highly correlated with in situ measurements, their correlation with each other is high and the correlation coefficient between the merged  
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product and in situ measurements is comparable to those of the individual rescaled satellite products (see Case 3).

It therefore appears beneficial to take the average of two rescaled satellite-based products when both are highly correlated with in situ measurements, which can increase the number of observations while minimally changing the statistics ( $R$  and RMSE).

To investigate whether there is a connection between (1) the correlation coefficient between two rescaled satellite products and (2) their individual correlation with in situ measurements, we plotted both in Fig. 2. It can be observed that at least one satellite product reasonably agrees with in situ measurements for the sites studied here. In addition, when both satellite products are highly correlated (i.e.,  $R$  is higher than 0.65 on x-axis), their correlations with in situ data are similarly high (i.e.,  $R$  is higher than 0.6 and their difference is smaller than 0.1). It should be noted that although a high correlation coefficient between two satellite-based products does not directly prove that both are highly correlated with in situ data, it demonstrates that two fully independent datasets capture the same temporal variations, which should provide some confidence in their signals.

## 4.2 Spatial and temporal coverage

The correlation analysis between AMSR-E VUA-NASA and ASCAT TUW soil moisture products was carried out globally to delineate the regions having a correlation coefficient above 0.65 (Fig. 3). The regions shown in Fig. 3 generally have low to moderate vegetation density, hereafter referred to as the “transitional regions”. In the merged product, AMSR-E VUA-NASA soil moisture is used to cover the regions with lower vegetation density than the transitional regions; otherwise ASCAT TUW soil moisture is used.

As has been discussed previously, the lower the vegetation density, the lower the error of passive microwave soil moisture can be expected, as the effects of vegetation attenuation become less (Jackson and Schmugge, 1995; Njoku and Entekhabi,

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1996). Thus we can use the error of passive microwave soil moisture retrievals as an indicator for the vegetation density. Parinussa et al. (2010) utilized an analytical solution to estimate the error structure of AMSR-E C-band soil moisture retrieved using the VUA-NASA algorithm (Fig. 4). The average error over these “transitional regions” is  $0.064 \text{ m}^3 \text{ m}^{-3}$ , which is comparable with the estimated absolute accuracy of AMSR-E C-band as derived from in situ observations (i.e.,  $0.06 \text{ m}^3 \text{ m}^{-3}$ , De Jeu et al., 2008) and thus represent a reasonable threshold to delineate the regions covered by passive or active microwave soil moisture (see Fig. 5). The spatial coverage shown in Fig. 5 agrees well with the results of Dorigo et al. (2010), in which the triple collocation technique was utilized on AMSR-E VUA-NASA, ASCAT TUW C-band, and Noah soil moisture to determine the areas over which either AMSR-E or ASCAT has a smaller error value. This agreement between two independent methods strengthens the spatial coverage identified in this paper (Fig. 5).

Then we focus on the temporal coverage of the merged product, that is, the ratio between the number of days with observations and the total number of days within the observation period. On average, the ratio for the descending overpasses of AMSR-E is around 0.5. In other words, it takes the descending overpasses of AMSR-E roughly two days to achieve the global coverage. It takes the ascending and descending overpasses of ASCAT together approximately two days to do so. Over the transitional regions where AMSR-E and ASCAT products are combined, this ratio value can generally increase to 0.8 (see Fig. 6).

## 5 Conclusions

In this study, we developed a two-step method of rescaling and merging to combine AMSR-E VUA-NASA and ASCAT TUW C-band soil moisture retrievals. First, the AMSR-E ( $\text{m}^3 \text{ m}^{-3}$ ) and ASCAT (%) products are rescaled against Noah simulated soil moisture using a CDF matching method to bring them in the same dynamic range. This adjustment method only slightly changes the temporal patterns of the original products.

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Second, by comparison with in situ measurements, we demonstrate that when both rescaled satellite-based products are highly correlated (i.e.,  $R > 0.65$ ), merging them is able to strengthen the temporal patterns captured by the individual instrument and increases the number of observations. The rescaled AMSR-E and ASCAT products are used for sparsely and moderately vegetated regions respectively. For the transitional regions where both products are highly correlated, the averages of both rescaled products are taken. Thus the merged product carries the advantages of better spatial coverage overall and increased number of observations particularly for the transitional regions.

Although good results are achieved in this data merging approach, there are a number of opportunities for refinement of the technique. The merged product has some uncertainties due to the inherent characteristics of the reference Noah simulated soil moisture and the CDF matching approach used in this study. The rescaled approach tends to impose the bias of the reference on the rescaled satellite products. The bias of rescaled product might be larger than the original product attributed to the large bias of the reference (see Case 2 in Table 1). In addition, the range of Noah simulated soil moisture seems to be relatively constrained (see Fig. 1d). At a global scale, a maximum range of  $0.35 \text{ m}^3 \text{ m}^{-3}$  can be observed over regions with a strong winter precipitation (e.g., Iran and Turkey) and a minimum range of about  $0.1 \text{ m}^3 \text{ m}^{-3}$  over deserts, glaciers, and tropical rain forests. Improvements on the land surface model simulations would lead to a better merged satellite-based soil moisture.

Another potential issue is radio frequency interference (RFI) affects on the AMSR-E C-band, which is observed in United States, Japan, the Middle East and elsewhere (see Njoku et al., 2005). RFI can be expected to reduce the accuracy of soil moisture estimates from AMSR-E C-band and consequently the merged product. A possible solution to this issue would be the use of AMSR-E X-band soil moisture retrievals instead of C-band over these regions, although these data express a reduced penetration depth. When the soil moisture retrievals from the new missions (e.g., SMOS and SMAP) are available, blending them with existing products is expected to provide

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a better merged product as L-band radiometer and scatterometer would bring more accurate estimates of surface soil moisture (Kerr et al., 2000; SMAP Mission, 2007).

Despite the expected long term global soil moisture product with increased number of observations and higher accuracy, gaps still exist in the satellite observed products due to the inherent characteristics of satellite orbits and swath widths. This may affect the application of satellite-based soil moisture, particularly for analyses on short time basis (e.g., daily and weekly). Filling the gaps in satellite-based soil moisture products in a reasonable manner will be one of the emphases in the future analysis.

The approach developed in this study enables the generation of a long-term global passive/active microwave satellite-based soil moisture data set, which will allow us to conduct a number of experiments. The “transitional regions” identified in this study are in line with the “hot spots” where strong coupling between soil moisture and precipitation are expected (Koster et al., 2004). The enriched information of satellite-based soil moisture by combining passive and active microwave products may enhance the understanding of land surface-atmosphere interactions and improve weather and climate prediction skills over these regions. In addition, the analysis of long-term trend and water cycle acceleration/deceleration can be carried out. The enhanced basic understanding of the role of soil moisture in water, energy and carbon cycles can be expected with the available of this long-term global microwave satellite-based soil moisture data set.

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**Table 1.** Relationships between in situ measurements and satellite/model-based soil moisture estimates at different stages (i.e., original, rescaled and merged) under three different situations. The last row represents the correlation coefficient ( $R$ ) between rescaled AMSR-E and rescaled ASCAT.

	Case 1 (43.875° N, 0.125° W, France)			Case 2 (35.125° S, 150.125° E, Australia)			Case 3 (41.375° N, 5.375° W, Spain)		
Relationships between in situ measurements and									
ORIGINAL	AMSR-E	ASCAT	NOAH	AMSR-E	ASCAT	NOAH	AMSR-E	ASCAT	NOAH
$N$	217	205	336	230	246	365	270	213	365
$R$	0.50	0.74	0.80	0.77	0.64	0.79	0.79	0.76	0.66
RMSE	0.449	–	0.103	0.087	–	0.158	0.125	–	0.041
RESCALED	AMSR-E	ASCAT	–	AMSR-E	ASCAT	–	AMSR-E	ASCAT	–
$N$	217	205	–	230	246	–	270	213	–
$R$	0.50	0.73	–	0.76	0.61	–	0.78	0.76	–
RMSE	0.111	0.105	–	0.168	0.170	–	0.033	0.035	–
MERGED	AMSR-E/ASCAT		–	AMSR-E/ASCAT		–	AMSR-E/ASCAT		–
$N$	281		–	328		–	327		–
$R$	0.65		–	0.70		–	0.77		–
RMSE	0.106		–	0.166		–	0.032		–
$R$ between rescaled AMSR-E and ASCAT	0.31			0.59			0.76		

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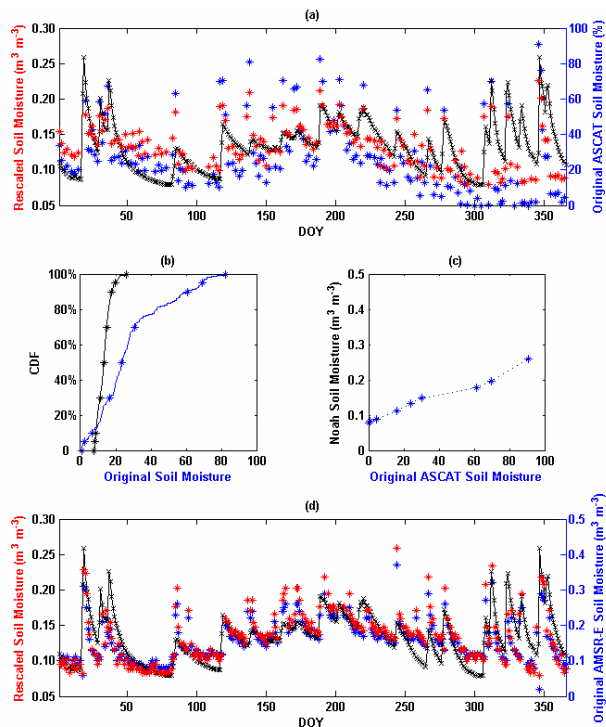
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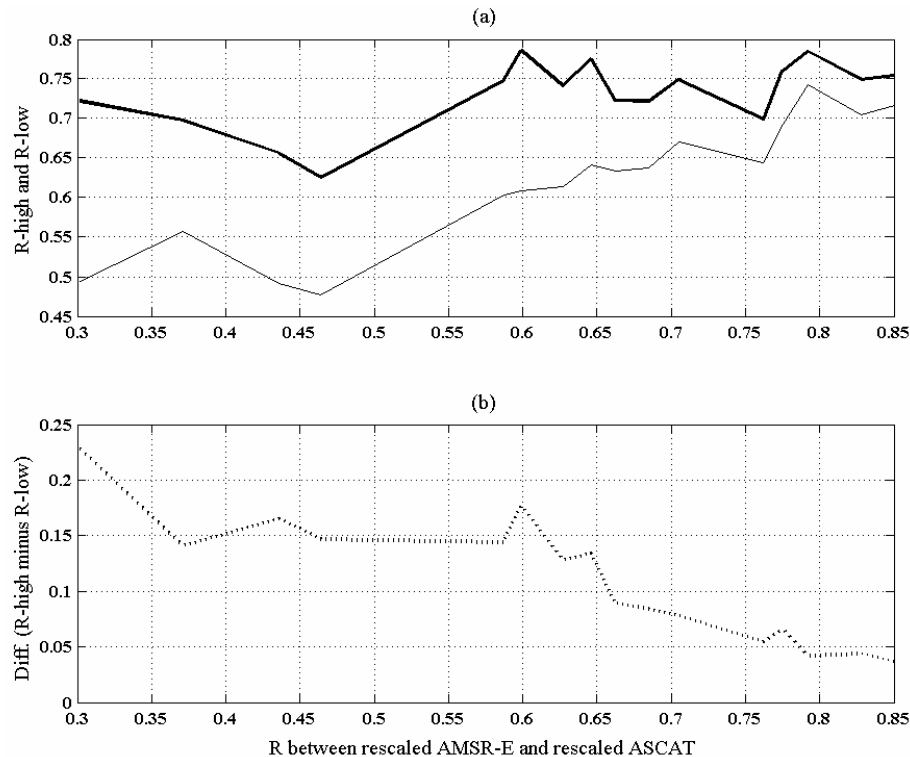
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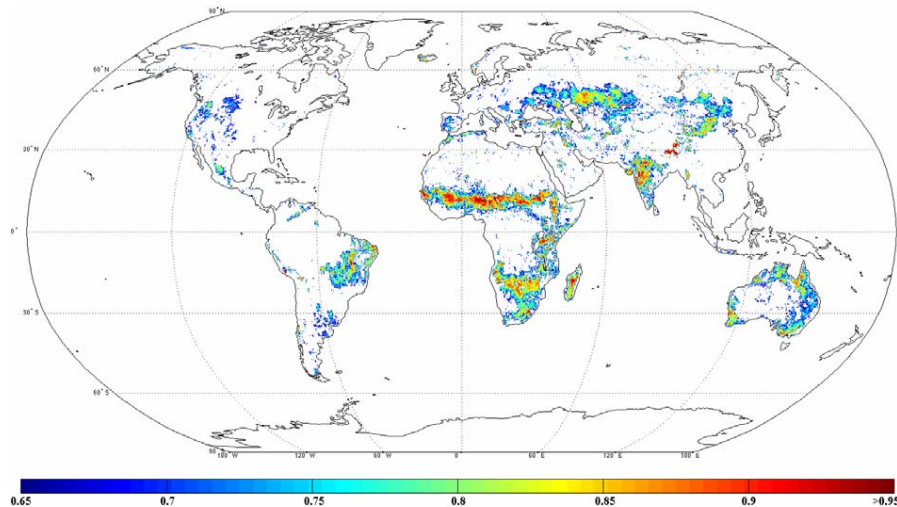
**Fig. 1.** Example illustrating how cumulative distribution function (CDF) matching adjustment is used in this study. **(a)** Original ASCAT (blue), rescaled ASCAT (red), and Noah (black) soil moisture for the grid cell at  $34.625^\circ \text{S}$ ,  $146.125^\circ \text{E}$ . **(b)** ASCAT retrievals were adjusted against Noah simulations. The 0th, 5th, 10th, 25th, 50th, 75th, 90th, 95th and 100th percentiles of ASCAT (blue) and Noah (black) CDF curves are marked, dividing the distribution into eight segments. **(c)** Resulting linear equations of ASCAT against Noah. Original ASCAT data falling in different segments have different adjusting equations. **(d)** Original AMSR-E (blue), rescaled AMSR-E (red), and Noah (black) soil moisture for the same grid cell.

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**Fig. 2.** Correlation coefficients between both rescaled satellite products (x-axis) against **(a)** their individual correlation coefficient with in situ measurements and **(b)** the difference in their individual correlation coefficient. The bold line represents the higher correlation coefficient value between rescaled satellite products and in situ measurements. The solid line represents the lower correlation coefficient value. The dotted line is the difference between the higher and lower correlation coefficient, that is, bold line minus solid line.



**Fig. 3.** Regions with high correlation coefficient ( $R > 0.65$ ) between rescaled AMSR-E and rescaled ASCAT for the year of 2007.

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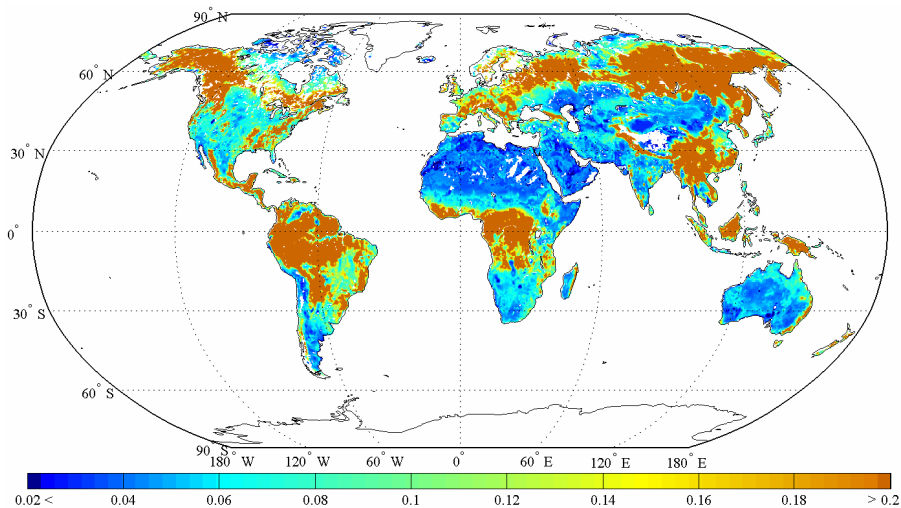
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**Fig. 4.** Global map of the quantitative uncertainty estimate for VUA-NASA Land Parameter Retrieval Model retrieved soil moisture from AMSR-E C-band observations (unit:  $\text{m}^3 \text{m}^{-3}$ ) (from Parinussa et al., 2010).

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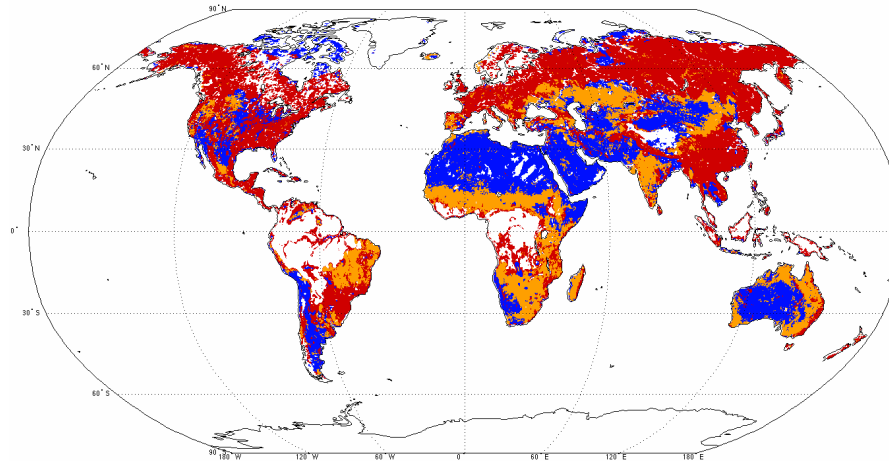
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**Fig. 5.** Spatial coverage by AMSR-E (blue), ASCAT (red) or the averages of both (orange) in the merged product. Tropical rain forests are masked out due to their high vegetation density.

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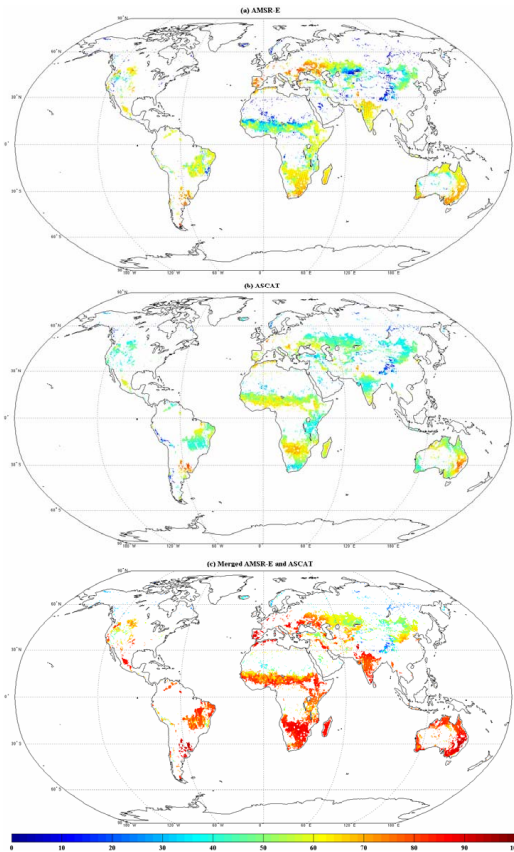
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**Fig. 6.** Temporal coverage percentage (i.e., the number of days with observations divided by the total number of total days) of AMSR-E, ASCAT and merged product over the transitional regions for the year of 2007.

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