



# RADIO SCIENCE FOR HUMANITY

## Towards a new climate record of soil moisture *Vers un nouveau jeux de données d'humidité des sols d'intérêt climatique*

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### Abstract:

Three methods to retrieve soil moisture (SM) from AMSR-E observations using SMOS SM as a reference are discussed and evaluated. The goal is to obtain longer time series of SM with no significant bias and with a similar dynamical range to that of the SMOS SM dataset. The new datasets were evaluated together with the ESA Climate Change Initiative SM dataset against the MERRA-Land and ERA-Land models for the 2003-2011 period. All datasets show a significant bias with respect to models for boreal regions and high correlations over regions other than the tropical and boreal forest. All the global SM datasets were also evaluated against a large number of *in situ* measurements over four continents. Over Australia all datasets show a strong level of agreement with *in situ* measurements. Models perform better over Europe and mountainous regions in North America. Remote sensing datasets perform as well as models for other North American sites and perform better than models over the Sahel region.

### Résumé:

Trois méthodes pour mesurer l'humidité du sol à partir d'observations AMSR-E, en utilisant SMOS comme référence, sont présentées. L'objectif est d'obtenir des séries temporelles plus longues mais sans biais significatif par rapport à SMOS et avec la même climatologie. Ces nouveaux jeux de données ont été comparés à celui du Climate Change Initiative de l'ESA et à ceux des modèles numériques MERRA-Land et ERA-Land dans la période 2003-2011. Tous les données montrent des biais significatifs par rapport aux modèles dans les régions boréales et des corrélations élevées partout excepte dans les régions de forêt tropicale et boréale. Les données ont été également évaluées par rapport à des mesures de terrain dans un grand nombre de sites. En Australie tous les jeux de données sont en bon accord avec les mesures de terrain. Les modèles obtiennent en général des meilleurs résultats en Europe et dans les régions montagneuses en Amérique du Nord. Finalement, les données de télédétection obtiennent des résultats aussi bons que les modèles dans d'autres sites en Amérique du Nord et meilleures dans la région du Sahel.

## 1 Introduction

Understanding the Earth's climate and how it is changing is one of the major challenges of the twenty-first century. Climatic patterns can only be reliably detected in time series that are sufficiently long (at least a few decades) because otherwise, natural short-scale variations can hide the longer term trends. Therefore, to understand the climate evolution, a combination of long-term models and observations is needed. Sustained observations from satellites can contribute significantly to this goal, and this is the objective of observational programs, such as the European Space Agency (ESA) Climate Change Initiative (CCI): to provide information on variables that were identified as "essential climate variables" (ECVs) by the Global Climate Observing System (GCOS) in the context of the United Nations Framework Convention on Climate Change (UNFCCC).

Soil moisture (SM) has been endorsed by the GCOS as an ECV, as it affects the water and energy fluxes at the land surface/atmosphere interface [1]. Therefore, one of the ESA CCI projects, launched in 2010, focuses on SM. As already mentioned, in order to use SM information for climate modeling, SM datasets spanning long time periods are needed. The ESA SM CCI has developed a strategy [2] that consists of merging a posteriori

different SM datasets obtained with different algorithms applied to data from different microwave active and passive sensors. The scaling of the different datasets is done using as a reference a land surface model (such as GLDAS Noah) [2].

The Soil Moisture and Ocean Salinity (SMOS) satellite was launched in November 2009, and it is the first mission specifically designed to retrieve SM from space. Many studies have evaluated the SMOS SM dataset in comparison to other remote sensing datasets, models and in situ measurements [3, 4, 5]. SMOS shows very good global performance although other remote sensing and model products can show better performances at some sites. In any case, datasets from the only two instruments specifically conceived of to measure SM, SMOS and Soil Moisture Active Passive (SMAP), compare very well with each other [6].

Since the ESA SM CCI started shortly after the SMOS launch, SMOS is not included in the CCI. However, it is important to investigate ways of including SMOS data in the long-term SM datasets and of evaluating the new datasets. One of the advantages of SMOS is that it can observe at a lower frequency (1.4 GHz) than previous instruments, and this frequency is less affected by the vegetation cover. A pertinent first step towards that goal is to study how to obtain a coherent dataset from SMOS and the NASA/JAXA Advanced Scanning Microwave Radiometer (AMSR-E), which operated from 2003–2011. This paper discusses and compares three approaches have been discussed in the literature: (i) adapting the Land Parameter Retrieval Model (LPRM) algorithm to SMOS data [7]; (ii) using SMOS SM as a reference to compute local linear regression equations linking AMSR-E  $T_b$ 's to SMOS SM and recomputing a SM dataset from AMSR-E observations [8]. (iii) using SMOS SM as reference to find a global non-linear regression relationship linking AMSR-E  $T_b$ 's to SMOS SM and recomputing an SM dataset from the AMSR-E observations [9].

## 2 Data

SMOS [10] was launched on 2 November 2009 to measure the thermal emission from the Earth in the 1.4-GHz protected frequency range in full-polarization and for incidence angles from  $0^\circ$ – $60^\circ$ . The footprint (full width at half maximum of the synthesized beam) is  $\sim 43$  km on average [10]. The Equator overpass time is 6:00 a.m./p.m. for ascending/descending orbits. The SMOS SM retrieval algorithm is based on the iterative minimization of the difference of a forward model and the brightness temperatures ( $T_b$ 's) measured by SMOS [11]. The Centre Aval de Traitement de Données SMOS (CATDS) Level 3 daily product (SMOS L3 SM, [12]) Version 3.00 in EASE grid version 2 was used in this study.

The Advanced Microwave Scanning Radiometer for the Earth Observation System (AMSR-E) is a six-frequency dual-polarized total-power passive microwave radiometer dedicated to observing water-related geophysical parameters [13]. AMSR-E was launched in May 2002, on-board the Aqua satellite, which follows a near-polar Sun-synchronous orbit of 98.8-min periods, crossing the Equator at 1:30 p.m. local time for ascending orbits and at 1:30 a.m. for descending orbits. AMSR-E observed the Earth until October 2011, in six frequency bands: 6.9 GHz (C-band), 10.7 GHz (X-band), 18.7 GHz, 23.8 GHz, 36.5 GHz and 89.0 GHz, at a constant incidence angle of  $55^\circ$ . The footprint size depends on the frequency; for instance, it is (cross-track  $\times$  along-track)  $43 \times 75$  km<sup>2</sup> and  $29 \times 51$  km<sup>2</sup> at 6.9 and 10.7 GHz, respectively.

The AMSR-E SM datasets compared in this study are:

1. The Land Parameter Retrieval Model (LPRM) SM dataset used in this study was obtained with an optimized single scattering albedo, a new roughness model and using both AMSR-E and SMOS observations [7].
2. The “AMSR-E Reg” SM dataset [8] has been obtained by computing local linear regressions linking the surface reflectivity for vertical and horizontal polarization and SMOS L3 SM using a set of three free parameters for each grid point.
3. The AMSR-E NN (Neural Network) SM dataset has been obtained using a neural network to find a global non-linear relationship from AMSR-E brightness temperatures to SMOS L3 SM during the concurrent operations of both instruments (June 2010–October 2011). The trained NN has been used to retrieve SM from AMSR-E from 2003 to 2011.

The data used to evaluate the SMOS-based AMSR-E datasets are :

1. The ESA Climate Change Initiative Soil Moisture, which has been derived from different active and passive instruments that are scaled into a common climatology by matching their cumulative distribution functions (CDF) to those of AMSR-E for the passive datasets or ASCAT for the active datasets [2].
2. The Modern-Era Retrospective analysis for Research and Applications-Land (MERRA-Land) [14] is an atmospheric re-analysis that makes use of the Goddard Earth Observing System model Version 5 and the data assimilation system Version 5.2.0 with an updated precipitation forcing and catchment land surface model compared to the normal MERRA dataset. It was developed by NASA and is available from the beginning of 1980 to the present day. In the current study, the top 2-cm SM is used.

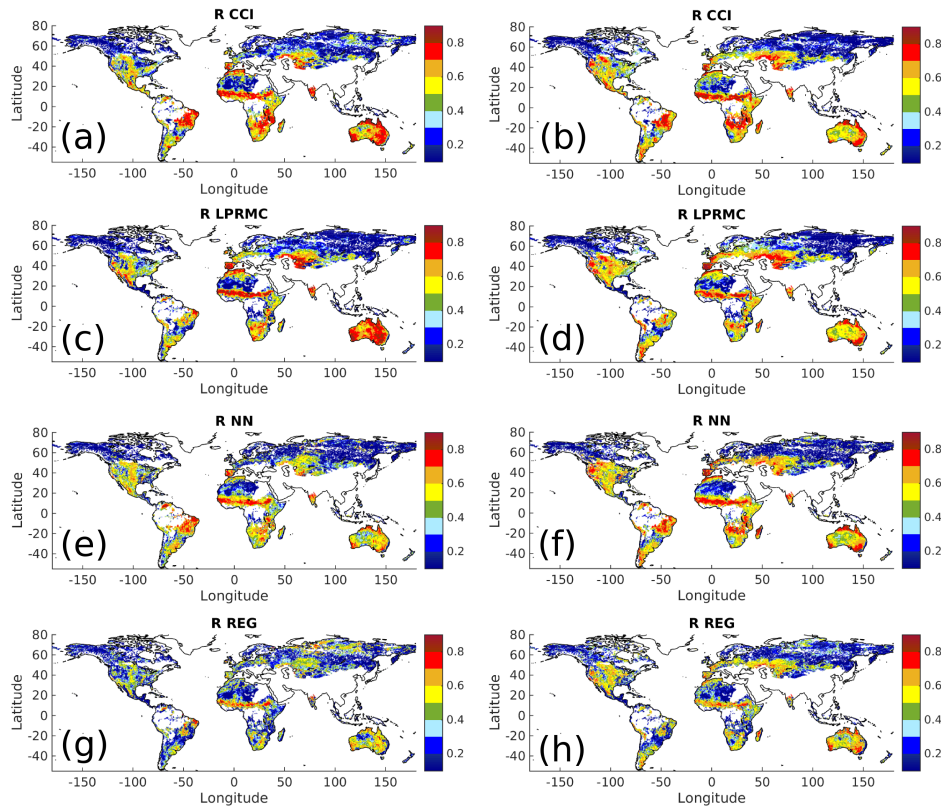


Figure 1 – Pearson correlation of remote sensing products with respect to Modern-Era Retrospective analysis for Research and Applications-Land (MERRA-Land) (left panels) and ERA-Land (right panels). The remote sensing products evaluated are, from top to bottom: ESA CCI (a,b); AMSR-E LPRM C-Band (c,d); AMSR-E NN (e,f); and AMSR-E Reg(g,h).

3. The data used in this study were extracted from a global Tiled ECMWF Scheme for Surface Exchanges over Land (TESSEL) with improved hydrology simulation of surface parameters from 1979–2014. The land surface model has been forced with the atmosphere from the ERA-Interim re-analysis [15]. This dataset will subsequently be referred to as ERA-Land and differs from the ERA-Interim/Land [16] only in the precipitation forcing, which was not rescaled to match Global Precipitation Climatology Project (GPCP) monthly means since GPCP Version 2.1 was not available after 2010.

The CCI, MERRA-Land and ERA-Land datasets were spatially interpolated to the EASEv2 grid by the area-overlap weighted average. The data have also been interpolated to the time of AMSR-E acquisitions by linear interpolation. Snow and frozen soil filters have been applied to the data.

Finally, the AMSR-E NN SM datasets discussed in this paper, were evaluated against in situ measurements at a depth of 5 cm for a large number of sites. RFI, snow and frozen soil filters have been applied to the data. The in situ measurements have been compared to the closest point of the EASEv2 grid. To select a given in situ measurement, a time window of  $\pm 30$  min around the time of AMSR-E acquisitions has been applied. Data from a given time are used to compute statistics metrics only if an SM value is available for all of the datasets, ensuring that all time series contain exactly the same number of points. A minimum lower limit of 200 points in a time series has been fixed to use the time series to compute the metrics.

### 3 Methods and results

The AMSR-E SM datasets have been compared to other datasets using classical statistical metrics, such as the mean, the Pearson correlation (R), the bias and the standard deviation of the difference (STDD). The root mean square of the differences (RMSD) is not discussed, as it is a function of the bias and the STDD ( $\text{RMSD}^2 = \text{STDD}^2 + \text{Bias}^2$ ). In some studies, the STDD is calculated indirectly from the bias and the RMSD and called unbiased-RMSD.

Firstly, the temporal signatures have been compared by computing the Pearson correlation of both AMSR-E datasets with respect to the two model datasets (Figure 1). The temporal variations of SM in the four remote sensing datasets (AMSR-E NN, AMSR-E Reg, AMSR-E LPRM and CCI) are in good agreement, as they show similar spatial patterns. AMSR-E Reg SM shows higher correlation with model data at high latitudes, in

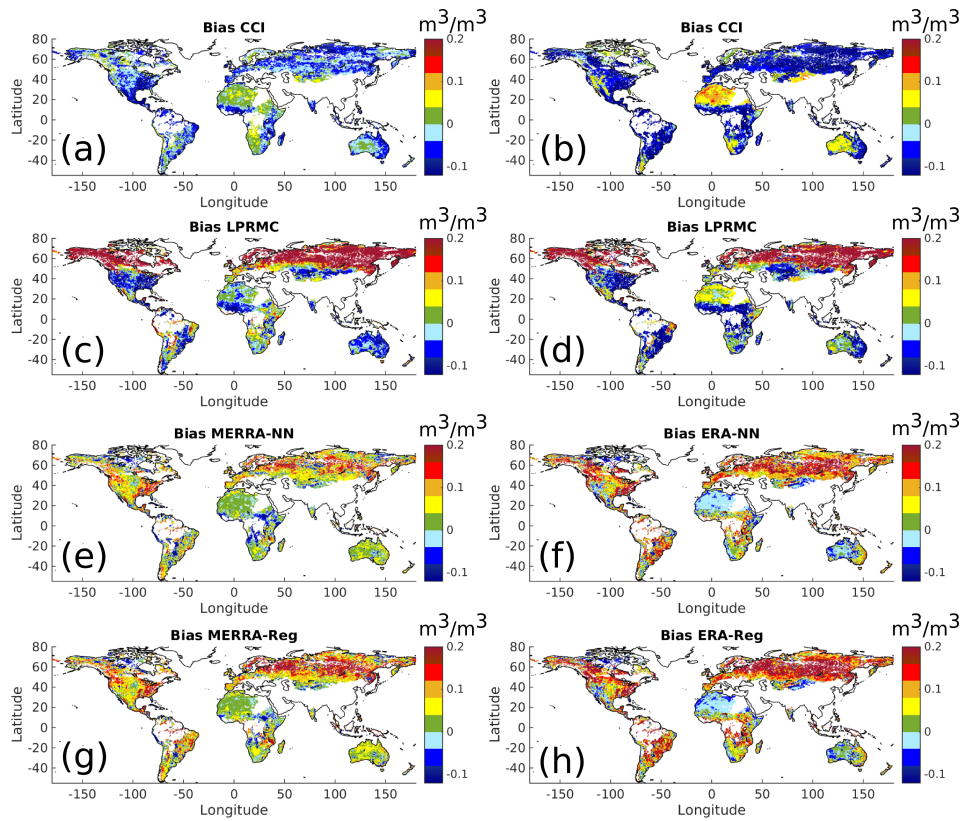


Figure 2 – Bias of remote sensing products with respect to MERRA-Land (left panels) and ERA-Land (right panels). The remote sensing products evaluated are, from top to bottom, ESA CCI (a,b), AMSR-E LPRM C-Band (c,d), AMSR-E NN (e,f) and AMSR-E Reg (g,h). The bias has been computed as the mean of the remote sensing data minus the mean of model data except for AMSR-E Reg and NN, for which the bias shown is the mean of the model data minus the mean of the remote sensing data.

particular with respect to MERRA-Land (Figure 1g); otherwise, the correlation with model data is in general lower than that of other remote sensing datasets. LPRM shows a widespread high correlation with MERRA-Land over Australia (Figure 1c); in contrast, all remote sensing datasets show a more inhomogeneous correlation with respect to ERA-Land in this region (Figure 1b,d,f,h). On the other hand, the correlation is significantly higher with ERA-Land over North America. It is also noteworthy that the correlation maps of AMSR-E LPRM SM and SMOS L3 SM with respect to the ECMWF-DAS2 product (H-TESEL model with ASCAT SM data assimilation) discussed in [17] show similar spatial patterns.

In addition to the temporal signatures, in order to compare the absolute values, the STDD and the bias were also computed (Fig. 2). Both ERA and MERRA models are, in general, in between AMSR-E NN and AMSR-E LPRM. The same behavior has previously been found for SMOS L3 and AMSR-E LPRM with respect to ECMWF-DAS2 [17]. The CCI dataset shows a low bias with respect to MERRA, but one should bear in mind that the SM datasets used to compute this product have been re-scaled using a model as a reference.

The STDD shows a significant spatial patterns and values close to  $0.1 \text{ m}^3/\text{m}^3$  for LPRM with respect to both MERRA and ERA (Fig. 3), in particular for latitudes above  $\sim 45^\circ$ . The STDD computed for the other three products is significantly lower, in particular with respect to MERRA-Land for AMSR-E Reg and NN, with STDD lower than  $0.05 \text{ m}^3/\text{m}^3$  for most of the globe. The lower bias with respect to MERRA in comparison to ERA could be related to a shallower top soil layer in MERRA (0–2 cm) compared to ERA (0–7 cm).

### 3.1 Local Evaluation against In Situ Measurements

The AMSR-E SM datasets, together with the model datasets, were evaluated against in situ measurements. For each site, the STDD, R and bias with respect to the in situ measurement have been computed. The results are summarized in Table 4. Firstly, it is interesting to remark that the results for the AMSR-E LPRM and Reg SM and for the CCI SM compare well to other studies carried out using the same data, even if the time period of the evaluation protocol is not exactly the same [18, 8, 19, 20].

With respect to sites in Europe (REMEDIHUS, SMOSMANIA, UDC-SMOS, SWEX-Poland, HOBE, MOL-RAO), the best scores in terms of correlation are obtained by the ERA-Land model. MERRA-Land also shows

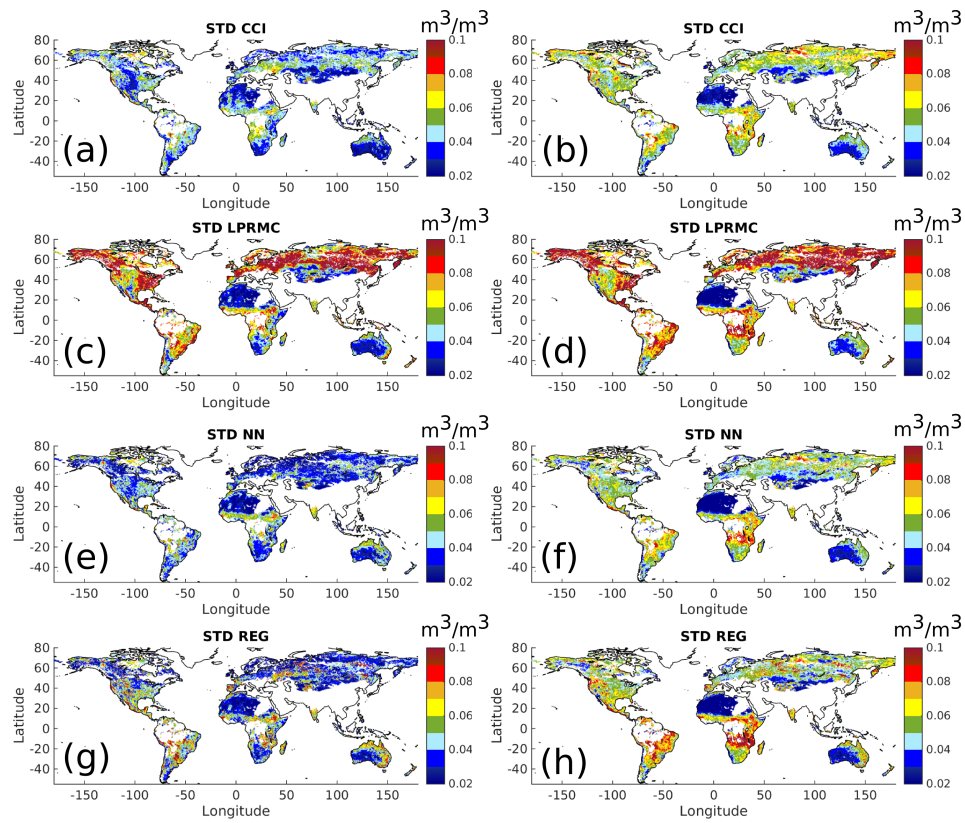


Figure 3 – Standard deviation of the difference of remote sensing products with respect to MERRA-Land (left panels) and ERA-Land (right panels). The remote sensing products evaluated are, from top to bottom, ESA CCI (a,b), AMSR-E LPRM C-Band (c,d), AMSR-E NN (e,f) and AMSR-E Reg (g,h).

better correlation than remote sensing products for some networks, but lower values for other networks. The fact that the ERA-Land model performs best in this region can be due to the fact that in Europe, models are well constrained by a dense network of in situ observations and, on the other hand, to the fact that there are RFI sources that could degrade the quality of the remote sensing products. With respect to the remote sensing products, the best correlations are found for LPRM and NN. In terms of STDD and bias, AMSR-E NN gives the best agreement with the in situ measurements.

The situation is different in the Sahel (AMMA, DAHRA, CARBOAFRICA), where the correlation is significantly better for remote sensing products than for model products. This can be partially attributed to the precipitation that drives the models. For example ERA-Interim is known to have significant problems representing the West Africa Monsoon [21]. The best remote sensing product in this region is LPRM, which gives high correlation values for the four networks, while the performances of other products are more variable. In terms of bias, the best datasets are the two SMOS-based ones, AMSR-E Reg and NN. AMSR-E Reg also gives the lowest STDD for two of the four networks. In these regions, the surface-atmosphere coupling is strong [1], but there are few in situ observations. The positive results of the remote sensing products show the interest of assimilating these data into numerical weather prediction models.

All of the products perform very well for the OzNet networks in Australia, correctly reproducing the temporal evolution of the in situ time series (Pearson correlations 0.7–0.8), in particular when comparing with sensors sampling the 0–5-cm depth. Correlations remain high when comparing with the 0–8-cm sensors, except for AMSR-E NN and Reg.

In North America, the dataset showing the best correlations is ERA-Land. Both models show higher correlations than remote sensing data for mountainous networks (SNOTEL and Reynolds Creek) and SCAN. In Little Washita, AMSR-E NN and CCI show a correlation close to ERA-Land (0.70–0.72 versus 0.76), while in Little River LPRM, AMSR-E Reg, NN and ERA-Land show very similar correlation. AMSR-E NN shows the lowest mean STDD for most networks.

## 4 Conclusions

Three new AMSR-E SM datasets compatible with SMOS-SM have been compared to the ESA CCI SM dataset, the MERRA-Land and ERA-Land models. The NN SM dataset show similar features with respect to models as the other remote sensing datasets. All of the AMSR-E SM datasets show a significant bias for boreal forest regions, in particular the LPRM one. LPRM shows the best agreement with MERRA in terms of correlation over Australia. The three AMSR-E datasets show a better agreement in terms of correlation with ERA-Land over North America. The two SMOS-based AMSR-E datasets (NN and Reg) show a lower STDD and bias than LPRM in many regions.

The AMSR-E SM NN dataset has also been evaluated against in situ measurements of soil moisture in a large number of sites (over 400). The same evaluation has been performed for the CCI SM, MERRA-Land, ERA-Land, AMSR-E LPRM and AMSR-E Reg. Models compare better to in situ measurements over Europe, in particular ERA-Land. This could be due to the large number of measurements constraining the numerical weather prediction models in this region and to the fact that the remote sensing observations could be polluted by artificial emission. In contrast, in the Sahel area, remote sensing datasets show better statistics than models, in particular AMSR-E LPRM, in terms of correlation and AMSR-E NN in terms of bias and STDD. These results suggest the potential added value of assimilating remote sensing data into models (numerical weather predictions models, reanalysis, hydrological models) in this region due to the lack of in situ observations and the convective nature of precipitation. Moreover, this region has been also linked with a strong land-atmosphere coupling, which provides a further motivation to better constrain soil moisture evolution using remote sensing data. Over Australia, all SM products show a similar very good agreement with in situ measurements. In North America, MERRA and ERA models show higher correlations with in situ measurements over mountainous regions, but remote sensing datasets, in particular AMSR-E LPRM and NN, show similar statistics for the other networks. In summary, the new approaches studied in this paper are promising methods to re-compute an SM dataset from a passive radiometer using as reference data an SM dataset produced with a different radiometer to obtain longer, consistent by construction, datasets.

## 5 Acknowledgements

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Table 4 – Standard deviation of the difference (STDD), Pearson correlation and bias computed for the AMSRE SM NN, LPRM (X and C band), AMSR-E Reg, CCI SM, ERA-Land, MERRA-Land with respect to in situ measurements. The bias is defined as the mean of a given SM product minus the mean of in situ SM.

| SM    | STDD<br>m <sup>3</sup> /m <sup>3</sup> | R         | Bias<br>m <sup>3</sup> /m <sup>3</sup> | STDD<br>m <sup>3</sup> /m <sup>3</sup> | R         | Bias<br>m <sup>3</sup> /m <sup>3</sup> | STDD<br>m <sup>3</sup> /m <sup>3</sup> | R         | Bias<br>m <sup>3</sup> /m <sup>3</sup> | STDD<br>m <sup>3</sup> /m <sup>3</sup> | R         | Bias<br>m <sup>3</sup> /m <sup>3</sup> |
|-------|----------------------------------------|-----------|----------------------------------------|----------------------------------------|-----------|----------------------------------------|----------------------------------------|-----------|----------------------------------------|----------------------------------------|-----------|----------------------------------------|
|       | AMMA                                   | Benin     | 0.05 0.05                              | AMMA                                   | Niger     | 0.05 0.05                              | Little River                           | 0.00 0.05 |                                        | HOBE                                   | 0.00 0.05 |                                        |
| MERRA | 0.058                                  | 0.62      | 0.190                                  | 0.052                                  | 0.26      | 0.115                                  | 0.047                                  | 0.63      | 0.198                                  | 0.028                                  | 0.57      | 0.013                                  |
| ERA   | 0.049                                  | 0.82      | 0.305                                  | 0.038                                  | 0.43      | 0.035                                  | 0.046                                  | 0.72      | 0.302                                  | 0.042                                  | 0.83      | 0.054                                  |
| NN    | 0.052                                  | 0.79      | 0.103                                  | 0.040                                  | 0.74      | 0.024                                  | 0.032                                  | 0.72      | 0.105                                  | 0.030                                  | 0.59      | 0.002                                  |
| LPRMX | 0.065                                  | 0.74      | 0.059                                  | 0.030                                  | 0.76      | 0.049                                  | 0.082                                  | 0.65      | 0.213                                  | 0.063                                  | 0.53      | 0.226                                  |
| LPRMC | 0.063                                  | 0.78      | 0.066                                  | 0.031                                  | 0.77      | 0.036                                  | 0.070                                  | 0.69      | 0.140                                  | 0.065                                  | 0.36      | 0.210                                  |
| CCI   | 0.041                                  | 0.85      | 0.094                                  | 0.044                                  | 0.72      | 0.109                                  | 0.048                                  | 0.42      | 0.138                                  | 0.038                                  | 0.44      | 0.042                                  |
| Reg   | 0.050                                  | 0.75      | 0.092                                  | 0.069                                  | 0.66      | 0.019                                  | 0.035                                  | 0.70      | 0.097                                  | 0.038                                  | 0.53      | -0.004                                 |
|       | CARBOAFRICA                            | 0.05      |                                        | OZNET                                  | 0.00 0.05 |                                        | Little Washita                         | 0.00 0.05 |                                        | SWEX                                   | 0.05 0.05 |                                        |
| MERRA | 0.032                                  | 0.52      | 0.057                                  | 0.062                                  | 0.72      | 0.066                                  | 0.042                                  | 0.64      | 0.081                                  | 0.053                                  | 0.63      | -0.048                                 |
| ERA   | 0.048                                  | 0.63      | 0.116                                  | 0.058                                  | 0.75      | 0.097                                  | 0.053                                  | 0.76      | 0.116                                  | 0.050                                  | 0.68      | -0.003                                 |
| NN    | 0.021                                  | 0.64      | 0.003                                  | 0.063                                  | 0.72      | 0.022                                  | 0.039                                  | 0.72      | 0.002                                  | 0.059                                  | 0.47      | -0.010                                 |
| LPRMX | 0.026                                  | 0.68      | 0.019                                  | 0.067                                  | 0.75      | 0.065                                  | 0.083                                  | 0.56      | 0.132                                  | 0.129                                  | 0.47      | 0.180                                  |
| LPRMC | 0.024                                  | 0.71      | 0.016                                  | 0.062                                  | 0.76      | 0.045                                  | 0.070                                  | 0.66      | 0.025                                  | 0.087                                  | 0.50      | 0.132                                  |
| CCI   | 0.055                                  | 0.72      | 0.084                                  | 0.058                                  | 0.76      | 0.020                                  | 0.041                                  | 0.70      | 0.046                                  | 0.069                                  | 0.41      | -0.024                                 |
| Reg   | 0.018                                  | 0.60      | 0.011                                  | 0.072                                  | 0.68      | 0.062                                  | 0.052                                  | 0.58      | 0.016                                  | 0.063                                  | 0.48      | -0.027                                 |
|       | DAHRA                                  | 0.05 0.05 |                                        | OZNET                                  | 0.00 0.08 |                                        | ARM                                    | 0.05 0.05 |                                        | SMOSMANIA                              | 0.05      |                                        |
| MERRA | 0.057                                  | 0.55      | 0.099                                  | 0.040                                  | 0.78      | 0.067                                  | 0.039                                  | 0.51      | -0.062                                 | 0.060                                  | 0.75      | 0.001                                  |
| ERA   | 0.056                                  | 0.65      | 0.059                                  | 0.049                                  | 0.76      | 0.108                                  | 0.068                                  | 0.57      | -0.055                                 | 0.057                                  | 0.79      | 0.036                                  |
| NN    | 0.044                                  | 0.77      | 0.029                                  | 0.057                                  | 0.62      | 0.025                                  | 0.050                                  | 0.54      | -0.136                                 | 0.074                                  | 0.51      | -0.084                                 |
| LPRMX | 0.052                                  | 0.73      | 0.055                                  | 0.078                                  | 0.74      | 0.063                                  | 0.099                                  | 0.52      | -0.008                                 | 0.113                                  | 0.70      | 0.118                                  |
| LPRMC | 0.046                                  | 0.77      | 0.046                                  | 0.075                                  | 0.72      | 0.032                                  | 0.081                                  | 0.54      | -0.100                                 | 0.101                                  | 0.68      | 0.113                                  |
| CCI   | 0.064                                  | 0.71      | 0.147                                  | 0.043                                  | 0.74      | 0.023                                  | 0.042                                  | 0.51      | -0.105                                 | 0.073                                  | 0.55      | -0.016                                 |
| Reg   | 0.025                                  | 0.65      | -0.023                                 | 0.098                                  | 0.53      | 0.077                                  | 0.070                                  | 0.49      | -0.129                                 | 0.074                                  | 0.62      | -0.106                                 |
|       | SNOTEL                                 | 0.05 0.05 |                                        | Reynolds Creek                         | 0.00 0.05 |                                        | SCAN                                   | 0.05 0.05 |                                        |                                        |           |                                        |
| MERRA | 0.073                                  | 0.66      | 0.022                                  | 0.056                                  | 0.77      | 0.056                                  | 0.061                                  | 0.59      | 0.046                                  |                                        |           |                                        |
| ERA   | 0.084                                  | 0.51      | -0.025                                 | 0.059                                  | 0.79      | -0.015                                 | 0.067                                  | 0.60      | 0.043                                  |                                        |           |                                        |
| NN    | 0.087                                  | 0.35      | -0.091                                 | 0.066                                  | 0.58      | -0.042                                 | 0.067                                  | 0.50      | -0.039                                 |                                        |           |                                        |
| LPRMX | 0.105                                  | 0.35      | 0.078                                  | 0.075                                  | 0.65      | 0.109                                  | 0.106                                  | 0.52      | 0.123                                  |                                        |           |                                        |
| LPRMC | 0.105                                  | 0.34      | 0.002                                  | 0.085                                  | 0.63      | 0.011                                  | 0.092                                  | 0.53      | 0.027                                  |                                        |           |                                        |
| CCI   | 0.092                                  | 0.32      | -0.008                                 | 0.061                                  | 0.66      | 0.060                                  | 0.068                                  | 0.47      | 0.002                                  |                                        |           |                                        |
| Reg   | 0.093                                  | 0.31      | -0.097                                 | 0.082                                  | 0.50      | -0.023                                 | 0.076                                  | 0.47      | -0.061                                 |                                        |           |                                        |
|       | REMEDIHUS                              | 0.00 0.05 |                                        | MOL-RAO                                | 0.08 0.08 |                                        | UDC-SMOS                               | 0.05 0.05 |                                        |                                        |           |                                        |
| MERRA | 0.058                                  | 0.60      | 0.108                                  | 0.044                                  | 0.69      | 0.085                                  | 0.086                                  | 0.17      | 0.007                                  |                                        |           |                                        |
| ERA   | 0.074                                  | 0.65      | 0.150                                  | 0.037                                  | 0.81      | 0.143                                  | 0.074                                  | 0.55      | 0.016                                  |                                        |           |                                        |
| NN    | 0.065                                  | 0.56      | -0.024                                 | 0.045                                  | 0.66      | -0.030                                 | 0.080                                  | 0.46      | -0.157                                 |                                        |           |                                        |
| LPRMX | 0.108                                  | 0.59      | 0.109                                  | 0.082                                  | 0.65      | 0.249                                  | 0.124                                  | 0.43      | 0.072                                  |                                        |           |                                        |
| LPRMC | 0.088                                  | 0.64      | 0.117                                  | 0.057                                  | 0.65      | 0.193                                  | 0.099                                  | 0.45      | 0.031                                  |                                        |           |                                        |
| CCI   | 0.065                                  | 0.58      | 0.075                                  | 0.056                                  | 0.45      | 0.089                                  | 0.079                                  | 0.42      | -0.083                                 |                                        |           |                                        |
| Reg   | 0.112                                  | 0.56      | -0.027                                 | 0.053                                  | 0.47      | -0.031                                 | 0.085                                  | 0.17      | -0.140                                 |                                        |           |                                        |

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