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► To cite this version:

Nemesio Rodriguez-fernandez, Yann H. Kerr, Jean-Pierre Wigneron, Amen Al Yaari, Richard de Jeu, et al.. Eleven-years of an homogeneous soil moisture dataset from AMSR-E and SMOS observations. 2015 International Geoscience and Remote Sensing Symposium IGARSS, Jul 2015, Milan, Italy. hal-01594697

HAL Id: hal-01594697

<https://hal.science/hal-01594697v1>

Submitted on 5 Jun 2020

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ELEVEN-YEARS OF AN HOMOGENEOUS SOIL MOISTURE DATASET FROM AMSR-E AND SMOS OBSERVATIONS

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1. INTRODUCTION

Soil moisture (SM) represents less than 1/10000 of the total water of our planet but it plays an important role as it affects the water and energy exchanges at the land surface/atmosphere interface and it is the reservoir of water for agriculture and vegetation in general. SM has been endorsed by the Global Climate Observing System (GCOS) as an Essential Climate Variable. In order to use SM information for climate modeling, SM datasets spanning long time periods are needed. In the context of the European Space Agency (ESA) Climate Change Initiative (CCI) several strategies have been evaluated to merge SM datasets from different microwave sensors [1]. These strategies consist typically in merging *a posteriori* several SM datasets computed with different algorithms applied to data from different sensors. In addition, they do not include data from the Soil Moisture and Ocean Salinity (SMOS) satellite [2], which is the first mission specifically designed to retrieve SM from space. In the context of an ESA funded project, we have studied several approaches to add SMOS data to long term SM datasets. In a first phase, three different approaches are tested to merge ESA SMOS and NASA/JAXA Advanced Scanning Microwave Radiometer (AMSR-E): (i) applying the LPRM algorithm to SMOS data (ii) using SMOS SM as reference to determine simple regression equations linking AMSR-E brightness temperatures to SMOS SM and recomputing a SM dataset from AMSR-E observations (iii) using neural networks (NNs) trained with ECMWF numerical weather prediction models reanalysis to recompute new SM datasets coherent by construction using as input data from SMOS or AMSR-E. This paper is mainly devoted to the third approach.

2. DATA SETS AND METHODS

The datasets used in this study are: (i) MODIS NDVI. (ii) Brightness temperatures (T_b 's) measured at L-Band (1.4 GHz), incidence angles from 0 to 65° and vertical (V) and horizontal (H) polarizations in the period from June 1st, 2010 to December 31st, 2013. (iii) AMSR-E T_b 's measured at 6.9, 10.7, 18.7, 23.8, 36.5 and 89 GHz for H and V polarizations at an incidence angle of $\sim 55^\circ$ from 2002 to October 2011. (iv) ECOCLIMAP soil texture maps [3].

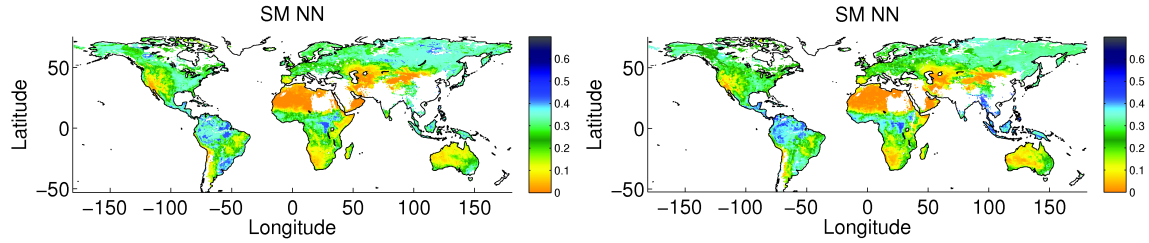


Fig. 1. SM monthly average for July 2010 obtained by neural networks using SMOS brightness temperatures for incidence angles from 25 to 60°, MODIS NDVI (left) and AMSR-E brightness temperatures from 6.9 to 36.5 GHz (right). In addition, both neural networks also use ECOCLIMAP soil texture as input.

The SMOS operational SM retrieval algorithm is based on a physical model [4]. In addition, it has been shown recently the good performances of an inverse model based in neural networks [5] using the approach of [6], which consists in training the neural networks with ECMWF numerical weather prediction models [7]. This study uses the same approach but two neural networks algorithms have been defined and optimized using AMSR-E or SMOS as input data in the periods 2003-Oct 2011 and 2010-2014, respectively. The two missions overlapping period has been used to demonstrate the consistency of the SM dataset produced with both algorithms by comparing monthly averages of SM and by comparing with time series of in situ measurements at selected locations. Other SM products such as the SMOS operational SM [4] and ECMWF model SM are also compared at those sites.

3. RESULTS

The first part of this study consists in defining a NN methodology adapted to AMSR-E. Different input configurations using AMSR-E have been studied. Table 1 shows a summary of the results. The correlation and RMS of the NN output and ECMWF SM are computed for different combinations of input data. The performance of the NN improves when adding more frequency channels from 6.9 up to 89 GHz, even if the contribution of the 89 GHz channel is very small. The NN performances are higher when using T_b 's as input instead of the polarization index ($PI = (T_b^V - T_b^H)/(T_b^V + T_b^H)$) used by the LPRM algorithm [8] or other neural network algorithms [9]. As shown in [5] for the SMOS case, the performance of the NN using AMSR-E as input data and trained with ECMWF SM simulations improves when using soil texture maps as input (clay and sand fractions). For instance when using the lowest frequency channel, R increases from 0.79 to 0.83 (NN “2Tb” and “2Tb,tex”, respectively). In contrast, when more T_b 's measured at higher frequencies are added as input, the contribution of NDVI decreases. When using all the frequency bands, including the 89 GHz channel, the NDVI contribution is negligible and the correlation of NN SM and ECMWF SM is as high as 0.9 (only using AMSR-E plus soil texture information as input). For comparison, the global score obtained using SMOS T_b 's from 7 angle bins from 25° to 65°, soil texture and NDVI is $R = 0.88$ (NN SM with respect to ECMWF SM). In conclusion, both NNs using AMSR-E or SMOS data as input exhibit similar performances to capture the SM variability in the ECMWF models.

Table 1. Performance of the NN on test AMSR-E data not used for the training. The NN SM predictions are compared to the ECMWF SM in the 0-7 cm depth layer. The input labels in the first column are the following: "2Tb" are H and V T_b 's for the lowest frequency, "6Tb" are H and V for the two lowest frequencies... "tex" stands for soil texture (sand and clay fractions) and NDVI is MODIS NDVI. Finally "6PI" means polarization index at 6 frequency bands.

Input	R	RMSE
2Tb	0.79	0.092
2Tb,tex	0.83	0.085
6Tb,tex	0.88	0.072
6Tb,tex,NDVI	0.89	0.069
10Tb	0.87	0.075
10Tb,tex	0.89	0.068
10Tb,tex,VI	0.90	0.065
6PI	0.79	0.092
12Tb,tex	0.90	0.067
12Tb,tex,NDVI	0.90	0.064

4. DISCUSSION

In order to check the consistency of the two NN SM datasets, the trained NNs have been applied to AMSR-E and SMOS T_b 's in the period from June to September 2010, which has not been used for the training of the NNs. Figure 1 shows the monthly average for July 2010 computed from the daily SM inversions by NN using SMOS or AMSR-E data as input. The two maps are very similar, proving that the produced SM is consistent using SMOS or AMSR-E as input. In addition, the performances of those two NNs have been evaluated against *in situ* measurements of the USDA-SCAN network. Figure 2 shows a comparison over one site of NN SM, SMOS L3 SM, ECMWF SM and the *in situ* measurements. The two NN time series compare well with each other.

Finally, the best NN algorithm developed to invert AMSR-E data in the AMSR-E and SMOS overlapping period has been used to invert all AMSR-E observations from 2003. The long time series of SM obtained with neural networks (2003-2013) will be compared to in-situ measurements and ECMWF ERA-Interim SM at selected locations. This long-term soil moisture dataset can be used for hydrological and climate application and it is the first step towards a longer dataset which will include additional sensors.

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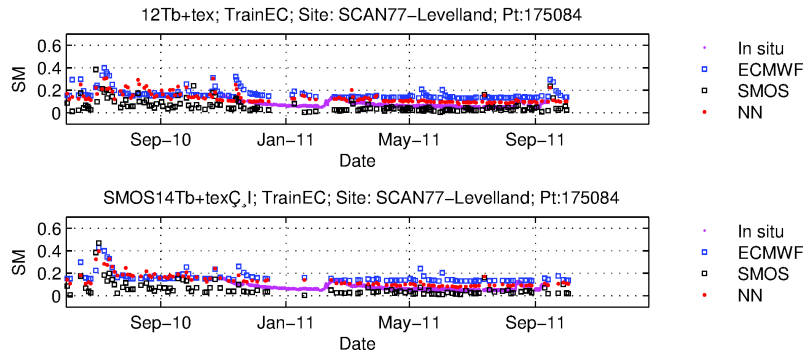


Fig. 2. Example of two time series over the SMOS and AMSR-E overlapping period for the SCAN Levelland site (the magenta line represents the in situ measurements). Upper panel: SM computed with the neural network using AMSR-E data as input (red points). Lower panel: using SMOS data as input (red points). In addition, ECMWF SM and SMOS L3 SM are also represented in both panels.

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