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Monitoring multi-decadal satellite earth observation of soil moisture products through land surface reanalyses

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Abstract

Soil moisture from ERA-Land, a revised version of the land surface components of the European Centre for Medium-Range Weather Forecasts Interim reanalysis (ERA-Interim), is used to monitor at a global scale the consistency of a new microwave based multi-satellite surface soil moisture date set (SM-MW) over multi-decadal time period (1980-2010). ERA-Land results from Land Surface Model simulations forced by high quality atmospheric forcing data. It adequately captures the temporal dynamic of soil moisture. ERA-Land's large scale nature, frozen configuration, global availability and ability to accurately represent soil moisture variability make it suitable to complement typical validation approaches of soil moisture from remote sensing based on ground measurements. Considering locations that have significant correlations for each 3-year sub periods within 1980-2010, averaged soil moisture correlations of SM-MW with ERA-Land (at 95% Confidence Interval) are increasing steadily from 1986 to 2010 (from 0.52 ± 0.10, to 0.66 ± 0.04). The lower correlations mirror the periods where only passive microwave from the Special Sensor Microwave/Image (SSM/I, Ku band at 19.3GHZ) sensor were used, highlighting the importance of multi-sensor capabilities. Overall SM-MW is relatively stable over time with respect to ERA-Land. Good agreement is obtained in semi-arid areas, while the tropics and high latitudes (and altitudes) present lower correlations values.

1 Introduction

It has been widely recognized that soil moisture is one of the main drivers of the water, energy and carbon cycles (Legates et al. 2011). It is a crucial variable for numerical weather prediction (NWP) and climate projections because it plays a key role in hydro-meteorological processes. A good representation of soil moisture conditions can help improving the forecasting of precipitation, temperature, droughts and floods (Koster et al., 2004, Taylor et al., 2012, Chen et al., 2011, Brocca et al., 2012, Miralles et al., 2012). For many applications global or continental scale soil moisture maps are needed. As a consequence, a significant amount of studies have been conducted to obtain such information. For that purpose, land surface modelling (Dirmeyer et al., 1999; Georgakakos and Carpenter, 2006 among others), remote sensing techniques (Wagner et al., 1999, 2007; Kerr et al., 2007, 2012; Njoku et al., 2003, Dorigo et al., 2012a) or a combination of both through Land Data Assimilation Systems (LDAS, Dharssi et al., 2011, de Rosnay et al., 2012a, b, Albergel et al, 2012a, Sabater et al., 2007) are used.

Assessing the quality of these products is required and for instance, the release of a new harmonized soil moisture product from remote sensing (SM-MW) within the framework of the European Space Agency's Water Cycle Multi-mission Observation Strategy (WACMOS) and Climate Change Initiative (CCI) projects in 2012 triggered several evaluation studies. A first global trend analysis of SM-MW was conducted by Dorigo et al. (2012a) who found a general decrease of soil moisture over a 23-yr period (1988-2010). Also, they concluded that most significant trends found in SM-MW were visible in other independent datasets, including NDVI from AVHRR-based Global Inventory Monitoring and Modelling Studies (GIMMS) and surface soil moisture from GLDAS-Noah model. Albergel et al. (2013) confronted then SM-MW trends with soil moisture from two revised re-analyses; ERA-Land (Balsamo et al. 2012), an update of the land surface component of the ERA-Interim reanalysis (Dee et al., 2011) from the European Centre for Medium-Range Weather Forecasts (ECMWF) and MERRA-Land (Reichle et al. 2011, Reichle 2012), an enhanced land surface data product based on MERRA reanalysis (Rienecker et al. 2011) by the National Aeronautics and Space Administration (NASA). Most of the major trends found in ERA-Land were also present in SM-MW.

The typical validation approach for model and satellite based data products is to compare them to in situ observations. Albergel et al. (2013) also evaluated ERA-Land, MERRA-Land and SM-MW using ground measurements of soil moisture over 2007-2010. In situ measurements from almost 200 stations from five networks in different countries (USA, Spain, France, China and Australia) were considered for the evaluation. In general, the three products were shown to capture the temporal dynamic of observed surface soil moisture well with averaged correlations (95% confidence interval) of 0.66(±0.038), 0.69(±0.038) and 0.60(±0.061) for ERA-Land, MERRA-Land and SM-MW, respectively. This study revealed that SM-MW agrees well with ground-based observations, but that its performance stays in most cases behind that of the latest generation of global Land Surface Models. Dorigo et al. (2013) provided a more in-depth validation of SM-MW using ground-based observations of 932 sites from 29 different historical and active monitoring networks worldwide from the International Soil Moisture Network (ISMN, http://www.ipf.tuwien.ac.at/insitu/, Dorigo et al. 2011, 2012b). While SM-MW performance appeared to be relatively stable over time, with average Pearson and Spearman correlations around 0.5 and unbiased root mean square differences around 0.05m^3m^{-3}, large differences between networks were observed.

The verification of the soil moisture products using ground measurements is not trivial. Even if in the recent years huge efforts were made to make such observations available in contrasting biomes and climate conditions, long term and large scale ground measurements networks are still sparse. Additionally, different networks will present different characteristics (e.g. measurement methods, installation depths and modes, calibration techniques, measurement interval, and temporal and spatial coverage). Using in situ measurements, the quality of retrieved soil moisture can be accurately assessed for the locations of the stations. By their nature such assessment does not provide spatially complete error fields that are important for understanding the variable product quality across different environment. That is why it is of interest to conceive new validation methods, complementing the existing soil moisture networks (Wagner et al., 2007). Land Surface Models (LSM) can be used to upscale the in situ surface soil moisture observations and complete the evaluation of satellite derived products, assuming that land surface models, forced with high quality atmospheric forcing data, adequately capture the soil moisture temporal dynamic (Albergel et al., 2010). The quality of ECMWF soil moisture products has been highlighted by many studies (Balsamo et al., 2009; Albergel et al., 2010, 2012a, b, c, d) and makes them suitable to complete the evaluation of remotely sensed surface soil moisture. In this study soil moisture from the revised land surface component of the ERA-Interim reanalysis; ERA-Land, is used as a reference to monitor the consistency of the multi-decadal SM-MW product over 1980-2010. Unlike the operational soil moisture product from ECMWF which is based on a continuous effort to improve the analysis and modelling systems, resulting in frequent updates, ERA-Land has a fixed configuration that guarantees a high level of consistency (e.g. in skill) over time.

The ability of ERA-Land to reproduce soil moisture annual variability is first briefly assessed using in situ measurements from 620 stations from 11 networks (in France, Spain, Italy, western Africa, China, Australia, Denmark and the USA) for 2010. Its consistency is also investigated using years 2007, 2008, 2009 for networks that have data over 2007-2010 (in France, Spain, western Africa, Australia and the USA). As Dorigo et al. (2013) used these stations (amongst others) to evaluate SM-MW, it was not repeated here. This study proposes to evaluate the consistency of SM-MW variability over 1980-2010 using ERA-Land as a reference. The different soil moisture products; ERA-Land and SM-

MW, are described in section 2 along with the strategy used for the evaluation. Results are described, discussed in sections 3 and 4, respectively. Section 5 provides a summary and conclusions.

2 Material and Methods

2.1 Soil moisture products

Figure 1 illustrates the mean soil moisture for ERA-Land (Figure 1.a, upper layer; 0-7cm) and SM-MW (Figure 1.b) over 1980-2010. Similar patterns are observed for both products, but ERA-Land soil moisture range is higher than that of SM-MW. Much lower mean values are found with ERA-Land in arid areas (e.g. over the Sahara desert, Middle East, Australia and the Tibetan plateau) and higher values are found in South Asia, Northern Siberia an South-eastern of the USA.

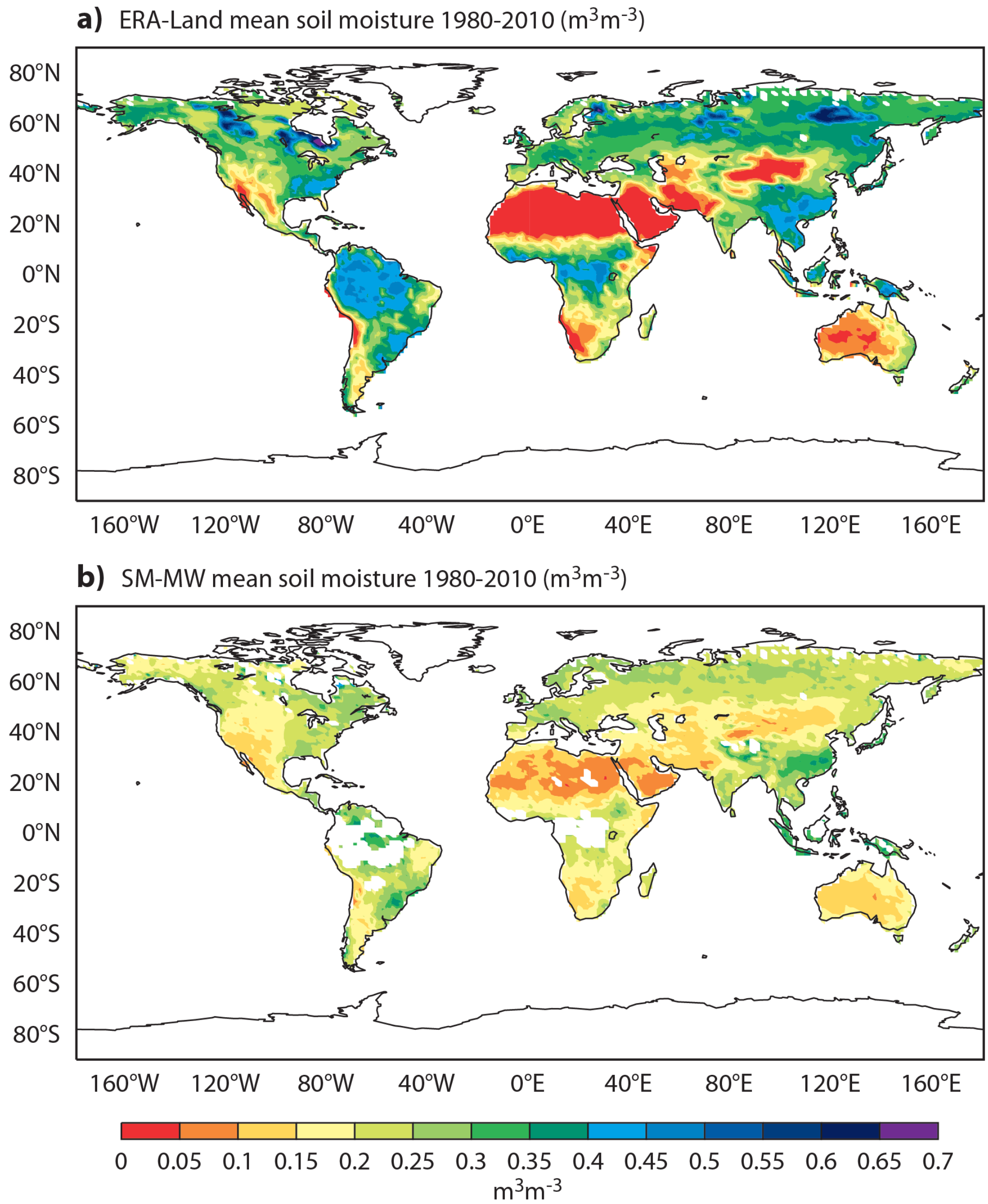

Figure 1: ERA-Land (a) and SM-MW (b) mean surface soil moisture over 1980-2010

2.1.1 In situ measurements

This study makes use of in situ soil moisture measurements obtained through the International Soil Moisture Network (ISMN, http://www.ipf.tuwien.ac.at/insitu/, Dorigo et al. 2011, 2012b), a data hosting centre where globally-available ground-based soil moisture measurements are collected, harmonized and made available to users. Data from 11 networks are considered for 2010: NRCS-SCAN (Natural Resources Conservation Service - Soil Climate Analysis Network) and SNOTEL (SNOwpack TELemetry) over the United States (177 and 348 stations), SMOSMANIA (Soil Moisture Observing System-Meteorological Automatic Network Integrated Application) and SMOSMANIA-E in France (12 and 9 stations), REMEDHUS (REd de MEDición de la HUmedad del Suelo) and VAS (Valencia Anchor Stations) in Spain (20 and 2 stations), MAQU in China (20 stations), OZNET in Australia (38 stations), AMMA (African Monsoon Multidisciplinary Analyses) in western Africa (3 stations), UMBRIA in Italy (3 stations) and HOBE (Hydrological Observatory) in Denmark. Data at 5 cm (10 cm for the MAQU network) are used and the year 2010 is retained for the comparison. Table 1 gives a full list of reference for each network. For the specific 2010 year, 620 stations are available. ERA-Land ability to represent soil moisture is also assessed for 2007, 2008 and 2009 using networks that have data for those years (numbers of stations might differ). All the considered networks used in this study also measure temperature, it permits to remove observations potentially affected by frozen condition. Daily averaged observations of surface soil moisture are used.

Table 1: Comparison of surface soil moisture with in situ observations for ERA-Land in 2010. Mean correlations (R), root mean square differences (RMSD), bias (in situ measurements minus products) are given for each network. Scores are given for significant correlations with p-values <0.05. For each R estimate a 95% Confidence Interval (CI) was calculated using a Fisher Z transform.

ERA-Land Vs. ground measurements	**N stations with significant R values**	**Averaged R values (95%CI)**	**Averaged RMSD (m^3m^{-3})**	**Averaged Bias (m^3m^{-3})**
SMOSMANIA (France) Albergel et al., 2008, Calvet et al. 2007	12 over 12	0.84(±0.03)	0.098	-0.066
SMOSMANIA-E (France) Parrens et al., 2012	9 over 9	0.71(±0.05)	0.168	-0.076
VAS (Spain) http://nimbus.uv.es	2 over 2	0.78(±0.05)	0.136	-0.128
AMMA (western Africa) Pellarin et al., 2009	2 over 3	0.64(±0.06)	0.053	-0.040
HOBE (Denmark) Birsher et al., 2012	29 over 30	0.68(±0.07)	0.074	-0.030
MAQU (China) Su et al., 2011	17 over 20	0.57(±0.11)	0.093	-0.044
OZNET (Australia) Smith et al., 2012	37 over 38	0.77(±0.05)	0.126	-0.105
REMEDHUS (Spain) Ceballos et al., 2005	19 over 20	0.72(±0.05)	0.171	-0.147
SCAN (USA) Schaefer and Paetzold, 2010	135 over 177	0.65(±0.08)	0.094	-0.014
SNOTEL (USA) Schaefer and Paetzold, 2010	235 over 306	0.63(±0.09)	0.119	-0.054
UMBRIA (Italy) Brocca et al., 2009	3 over 3	0.75(±0.09)	0.137	-0.131
ALL NETWORKS	**500 over 620**	**0.66(±0.08)**	**0.118**	**-0.063**

2.1.2 ERA-Land reanalysis

The recent improvements in the LSM scheme used in the operational Integrated Forecast System (IFS) of ECMWF, in particular with respect to soil moisture (Balsamo et al., 2009; Albergel et al. 2012c), provided the motivation for producing an updated land surface reanalysis of ERA-Interim using offline (land-only) simulations; ERA-Land (Balsamo et al., 2012). It has been generated at ECMWF and benefits from the most recent land modelling improvements; the ERA-Interim near-surface meteorology has been used to force the improved H-TESSEL LSM (Balsamo et al. 2009).

Compared to the TESSEL LSM used in ERA-Interim (Van den Hurk et al. 2000), the H-TESSEL LSM used in ERA-Land has a better match to soil moisture observations (Balsamo et al. 2009; de Rosnay et al., 2012a, Albergel et al. 2012c). It benefits from an improved hydrology; the formulation of the soil hydrological conductivity and diffusivity was revised to be spatially variable according to a global soil texture map (FAO/UNESCO Digital Soil Map of the World, DSMW, FAO, 2003). In addition, surface runoff is based on variable infiltration capacity. There is a new snow scheme (Dutra et al., 2010) and a multi-year satellite based vegetation climatology (Boussetta et al., 2010). Also, the formulation of the bare soil evaporation has been revisited to allow a smooth transition between vegetated and non-vegetated areas and to realign the formulation of bare ground evaporation with studies in the literature (Albergel et al., 2012b). All these modifications were found to improve the representation of soil moisture. Land surface fields obtained from ERA-Land were also shown to be a good choice for initializing the latest seasonal forecasting system (System-4, Molteni et al. 2011). Like ERA-Interim, ERA-Land has a spatial resolution of about 80 km (T255) and analyses are available for 00:00, 06:00, 12:00 and 18:00 UTC. It considers four layers of soil (0–7, 7–28, 28–100 and 100–289 cm). In this study, daily averaged surface soil moisture from ERA-Land first soil layer (0–7 cm) is used.

2.1.3 Remotely-sensed data

Near surface soil moisture can be estimated at a global scale based on active and passive satellite microwave remote sensing with adequate spatial-temporal resolution and accuracy: sensor using low frequency microwave from 1 to 10 GHz are particularly sensitive to surface soil moisture (Schmugge, 1983, Calvet et al., 2011). Over the past decades remotely sensed surface soil moisture datasets were obtained from scatterometer observations from the Active Microwave Instrument on board the two European Remote Sensing satellites (ERS-AMI, 5.3GHz) and the Advanced Scatterometer on MetOp (ASCAT 5.255 GHz, e.g. Scipal et al. 2002; Bartalis et al. 2007), or on observations from various multi-frequency radiometers including the Advanced Microwave Scanning Radiometer for the Earth Observing System (AMSR-E from 6.9 to 89.0 GHz, Njoku et al. 2003; Owe et al. 2008), the Scanning Multichannel Microwave Radiometer (SMMR 6.6 GHz and above, Owe et al., 2001) and the Special Sensor Microwave Imager (SSM/I at 19 GHz and above, Owe et al. 2008), the TRMM Microwave Imager (TMI) on the Tropical Rainfall Measuring Mission (TRMM), at 10.7 GHz and above (Gao et al. 2006; Owe et al. 2008), and WindSat (from 6.8 to 37 GHz, Li et al. 2010; Parinussa et al. 2012). More recently the Soil Moisture and Ocean Salinity mission (SMOS), the first dedicated soil moisture mission, was launched (in L-band ~1.42 GHz, Kerr et al. 2010; Mecklenburg et al. 2012) while within the next few years novel dedicated soil moisture missions like SMAP (Entekhabi et al. 2010) and SAOCOM (http://www.conae.gov.ar/eng/satelites/saocom.html) are expected to complete the list of soil moisture datasets available from space. Also, the continuity of existing products is guaranteed by the recent launch of AMSR-2 (http://www.jaxa.jp/projects/sat/gcom_w/index_e.html) in spring 2012 as follow-up mission of AMSR-E, and by the ASCAT sensor on the operational MetOp-B platform launched in September 2012. Many studies have highlighted the good agreement between those data sets and ground-based observations over different biomes and climate conditions (e.g. Albergel et al. 2009, 2010, 2012a; Draper et al. 2009; Gruhier et al. 2010; Brocca et al. 2011; Parrens et al., 2012).

Recently, the European Space Agency Water Cycle Multi-mission Observation Strategy (ESA-WACMOS) project and Climate Change Initiative (CCI, http://www.esa-soilmoisture-cci.org) have supported the generation of a soil moisture product based on multiple microwave sources from space. The first version of the combined product, SM-MW, was released in June 2012 by the Vienna University of Technology and the VU University of Amsterdam. SM-MW was generated using active and passive soil moisture products, derived from SMMR, SSM/I, TMI and ASMR-E (for the passive products), and the ERS AMI and ASCAT scatterometers (for the active products as in Liu et al. 2011, 2012; Wagner et al. 2012).

2.2 Evaluation strategy

The nearest neighbour approach was retained to match grid point location of soil moisture from ERA-Land with that of (i) ground measurements from the eleven networks used in this study and (ii) SM-MW. Datasets potentially affected by frozen condition were masked using a soil temperature threshold of 4 degrees ºC. ERA-Land ability to reproduce soil moisture variability is first assessed using ground measurement based on the correlation coefficient (R), the root mean square differences (RMSD) and the Bias (in situ minus ERA-Land).

The same metrics are also applied between SM-MW and ERA-Land. Only cases where the p-value is below 0.05 (significant correlation), are retained. Pixels with non-significant R values are excluded from the computation of the average metric. As in Draper et al. (2012) for each R estimate a 95% Confidence Interval (CI) was calculated using a Fisher Z transform. Whereas p-value gives an indication on the significance of the correlation, the 95% CI permits to identify periods or areas that are significantly better than others.

The whole period 1980-2010 is first investigated, then correlations are calculated for 3-yr periods from 1980-1982 to 2007-2009. R values are given for each period considered individually (only pixels with significant R), and also considering pixels with significant level of correlations for each periods. The different products used to develop SM-MW vary over space and time (Liu et al. 2012) and differences in the microwave observation channels and sampling densities are expected to influence the quality of the different periods. To illustrate their potential effects on SM-MW quality, the evaluation is repeated for the following sub-periods, as in Dorigo et al. (2013):

- 1 January 1980 – 31 August 1987: based SMMR observations only,
- 1 September 1987 – 30 June 1991: based on SSM/I only,
- 1 July 1991 – 31 December 1997: based on a combination of SSM/I and ERS AMI,
- 1 January 1998 – June 2002: based on a combination of TMI and AMI between 40°N and 40°S, and a combination of SSM/I and ERS AMI elsewhere,

- 1 July 2002 – 31 December 2006: based on a combination of AMSR-E and ERS AMI,
- 1 January 2007 – 31 December 2010: based on a combination of AMSR-E and ASCAT.

For those six periods, and to avoid seasonal effects, time series of anomalies from a moving monthly average were also calculated. The difference from the mean is calculated using a sliding window of five weeks all over the periods, and the difference is scaled to the standard deviation. For each soil moisture estimate at day (i), a period F is defined, with F=[i-17, i+17] (corresponding to a five-week window). If at least five measurements are available in this period, the average soil moisture value and the standard deviation over each time window are calculated (Albergel et al., 2010).

3 Results

3.1 ERA-Land vs. in situ measurements

This section presents the results of the comparison between in situ observations and ERA-Land. For all the stations used in this study, a first visual quality check was performed. When suspicious data were observed (e.g. non-physical jumps in the time series), they were discarded. Additional quality control was required for the stations from the NRCS-SCAN and SNOTEL networks; as indicated in their website, data are provisional and subject to revision, very little control is applied to measurements. Dharssi et al. (2011) used a simple process to identify stations where sensors might be dysfunctional. Stations are rejected based on the scores obtained when compared to their experiments (in term of correlations, RMSDs and biases). A similar process is applied based only on the correlation level. Stations for which ERA-Land have a correlation less than 0.3 are rejected (as in Dharssi et al., 2011). This rather strict process has removed some good stations too (e.g. in areas where the model might not realistically represent soil moisture, Albergel et al., 2013). Also, only stations with significant R values were retained leading to a total of 500 stations (over 620) for 2010. The results are presented in Table 1, on average R(95%CI), RMSD and Bias are; 0.66(±0.08) [(ranging from 0.57(±0.11) for the MAQU network in China to 0.84(±0.03) for the SMOSMANIA network in France], 0.118 m^3m^{-3} and -0.063 m^3m^{-3}. About 65% of the stations (323 over 500) have R values greater than 0.6, the negatives biases shown in Table 1 (in situ minus ERA-Land) indicate that ERA-Land tends to overestimate soil moisture. Results are in line with previous study evaluating ECMWF soil moisture; ERA-Land has good skills in capturing surface soil moisture variability and tends however to overestimate soil moisture. Table 2 presents the same scores for years 2007, 2008, 2009 (2010, also) for networks that have data over 2007-2010 (SMOSMANIA, AMMA, REMEDHUS, OZNET, SCAN and SNOTEL). From Table 2 one may appreciate the consistency of ERA-Land, e.g. for the stations of the REMEDHUS networks, averaged R values are; 0.74(±0.05), 0.75(±0.04), 0.78(±0.04) and 0.72(±0.05) for 2007, 2008, 2009 and 2010, respectively.

Table 2: Same as Table 1 for networks that have data in 2007, 2008, 2009 and 2010.

		N stations with significant R values	R values (95%CI)	RMSD (m^3m^{-3})	Bias (m^3m^{-3})
SMOSMANIA (France) Albergel et al., 2008, Calvet et al., 2007	2007	12	0.78(±0.04)	0.094	-0.065
	2008	12	0.80(±0.04)	0.089	-0.056
	2009	12	0.85(±0.03)	0.083	-0.048
	2010	12	0.84(±0.03)	0.098	-0.066
AMMA (Western Africa) Pellarin et al., 2009	2007	7	0.78(±0.04)	0.160	-0.154
	2008	5	0.74(±0.05)	0.087	-0.077
	2009	4	0.70(±0.04)	0.100	-0.091
	2010	2	0.64(±0.06)	0.053	-0.04
OZNET (Australia) Smith et al., 2012	2007	33	0.76(±0.05)	0.118	-0.099
	2008	36	0.69(±0.06)	0.124	-0.112
	2009	31	0.66(±0.05)	0.131	-0.112
	2010	37	0.77(±0.05)	0.126	-0.105
REMEDHUS (spain) Ceballos et al., 2005	2007	18	0.74(±0.05)	0.157	-0.125
	2008	17	0.75(±0.04)	0.163	-0.129
	2009	19	0.78(±0.04)	0.148	-0.120
	2010	19	0.72(±0.05)	0.171	-0.147
SCAN (USA) Schaefer and Paetzold, 2010	2007	101	0.69(±0.07)	0.125	-0.056
	2008	99	0.67(±0.06)	0.124	-0.054
	2009	99	0.64(±0.08)	0.131	-0.051
	2010	135	0.65(±0.08)	0.094	-0.014
SNOTEL (USA) Schaefer and Paetzold, 2010	2007	197	0.63(±0.09)	0.112	-0.028
	2008	185	0.60(±0.10)	0.114	-0.044
	2009	225	0.63(±0.09)	0.119	-0.038
	2010	235	0.63(±0.09)	0.119	-0.054

3.2 SM-MW vs ERA-Land for 1980-2010 and 3-year sub-periods

Figure 2 presents; (a) the correlations values obtained from the comparison between SM-MW and ERA-Land over 1980-2010, only significant correlations are considered (p-value<0.05), (b) the size of the 95% CI and (c) the number of data used for the comparison (sample size). On average the R (95%CI) value is 0.44(±0.07), they are however areas with much better R values. As seen of fig2.a. relatively low R values at higher latitudes (North hemisphere, 50ºN and above) clearly penalise the global average. Also it corresponds to areas with higher 95% CI (fig2.b) and less SM-MW data available for the comparison (fig2.c). Poor scores are also obtained over desert areas (e.g. Sahara, Kalahari in south east Africa) and in high elevation areas (e.g. European Alpes, Tibetan plateau). Best R values are obtained in the sub-Saharan region, over the whole Australia, the southern part of Africa, western South America (e.g. Brazil) and more generally in areas with a strong annual cycle and higher density data (Figure 2.c). Table 3 presents scores per latitudinal band (20º range). It clearly shows that best R values are found in the tropics and around the equator; 0.52(±0.02) [0º-20ºN] and 0.60(±0.03)

[20ºS-0º] than at higher latitudes, for instance 0.37(±0.05) [40ºN-60ºN]. This is also visible on figure 3.a presenting a latitudinal plot of R values for 1980-2010 (thick black line). Figure 2 (a, b, c) and figure 3.a are is in line with findings from Dorigo et al. (2010, 2013) who stated that from a retrieval point of view, SM-MW products are more likely to be best in semi-arid regions where (i) retrievals are most accurate and (ii) observation density is highest.

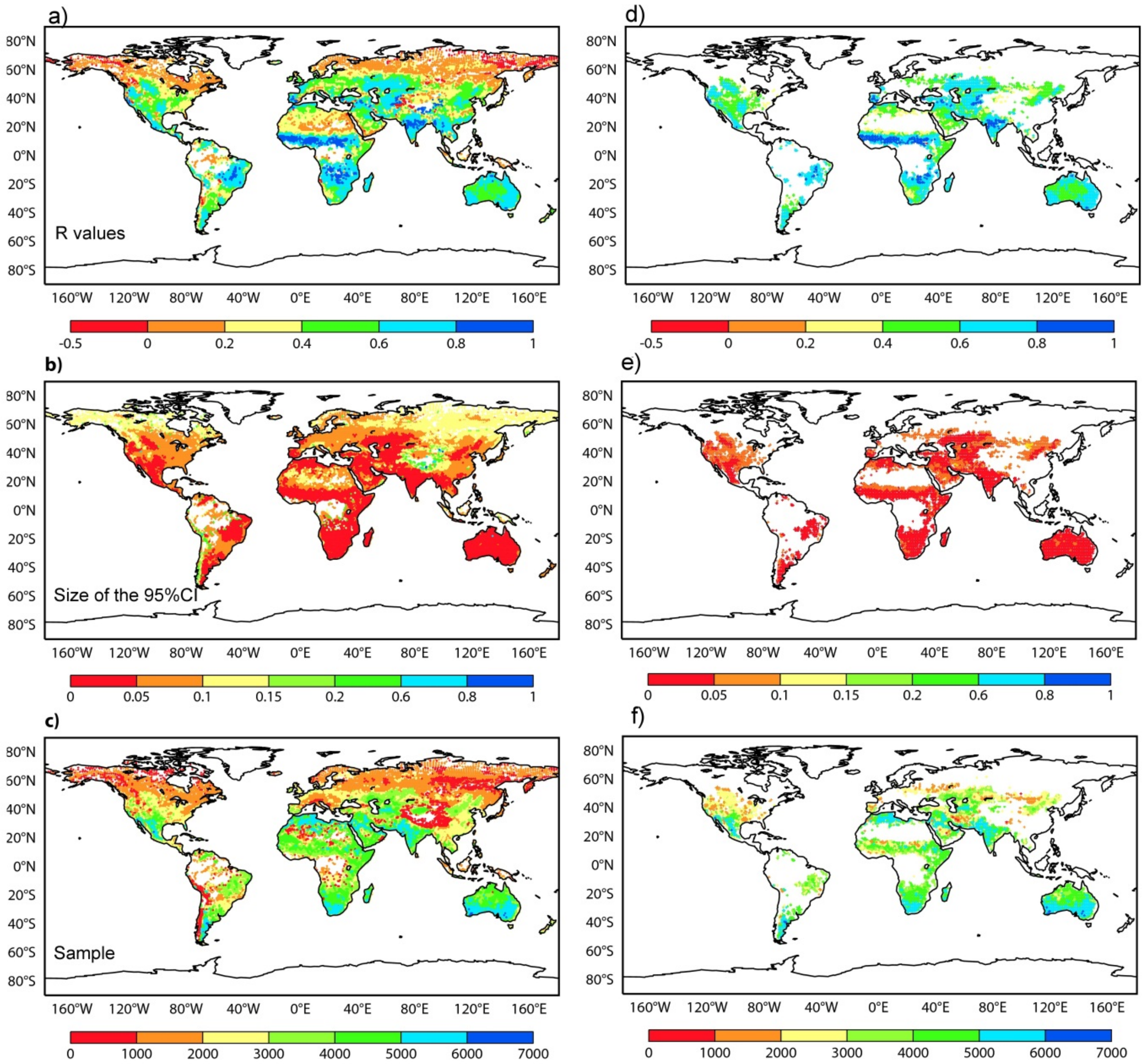

Figure 2: a) Correlations value between SM-MW and ERA-Land over 1980-2010 (only significant correlations are considered, p-value<0.05), b) size of the 95% confidence interval (CI) and c) number of data used for the comparison (Sample), d), e) and f) same as a), b) and c) when considering correlations that are consistently significant for every 3-yr sub-periods (from 1980-1982 to 2007-2009).

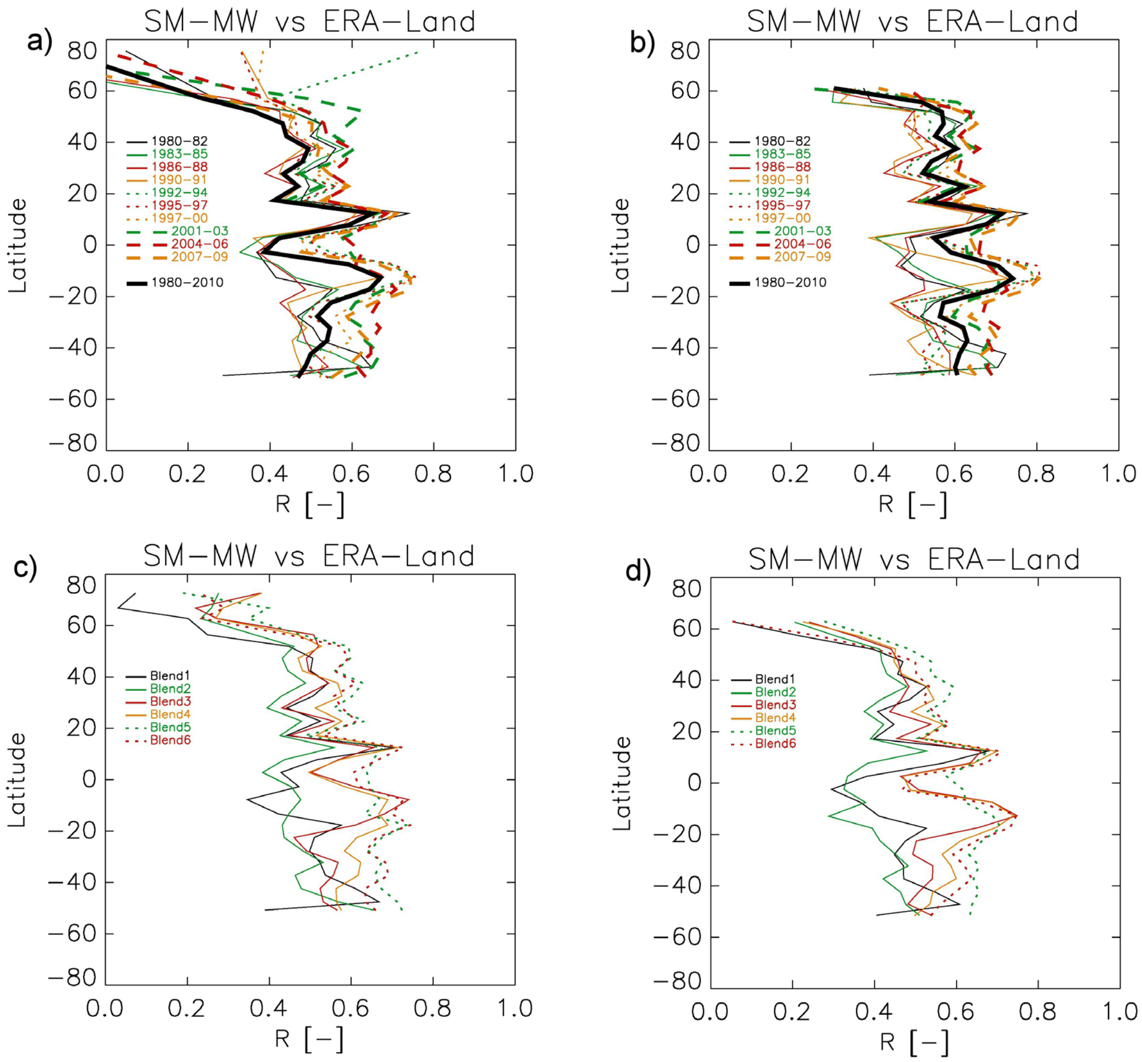

Figure 3: latitudinal plot of correlations between SM-MW and ERA-Land for 1980-2010 and each 3-yr sub-period (from 1980-1982 to 2007-2009), a) significant correlations (p-value<0.05) for each sub-period considered individually, b) only pixels that have significant correlation value (p-value<0.05) for each sub period, c) and d) same as a) and b) for period as defined in section 2.2.; 1 January 1980 – 31 August 1987 (based SMMR observations only), 1 September 1987 – 30 June 1991 (based on SSM/I only), 1 July 1991 – 31 December 1997 (based on a combination of SSM/I and ERS-AMI), 1 January 1998 – June 2002 (based on a combination of TMI and ERS-AMI between 40°N and 40°S, and a combination of SSM/I and AMI elsewhere), 1 July 2002 – 31 December 2006 (based on a combination of AMSR-E and ERS-AMI), 1 January 2007 – 31 December 2010 (based on a combination of AMSR-E and ASCAT).

Table 3: Scores (N pixels with significant R values, averaged R values and averaged sample) for the comparison between SM-MW and ERA-Land over 1980-2010.

Latitudinal range	N pixels with significant R values (p-values<0.05)		Averaged R values (95%CI)		Averaged N sample	
	For 1980-2010	For each 3-yr sub-periods	For 1980-2010	For each 3-yr sub-periods	For 1980-2010	For each 3-yr sub-periods
60ºN-80ºN	1434	2	0.09(±0.05)	0.30(±0.02)	1236	2258
40ºN-60ºN	4664	1303	0.37(±0.05)	0.56(±0.02)	1904	2828
20ºN-40ºN	4614	1917	0.47(±0.05)	0.57(±0.02)	2922	3829
0º-20ºN	2505	1181	0.52(±0.02)	0.65(±0.02)	3130	3729
20ºS-0º	1948	649	0.60(±0.03)	0.70(±0.02)	2786	3782
40ºS-20ºS	2210	1359	0.54(±0.03)	0.58(±0.02)	3821	4664
60ºS-40ºS	141	71	0.49(±0.03)	0.61(±0.02)	3284	4899

Figure 4 presents ten maps of R values corresponding to the ten 3-yr sub period (from 1980-1982 to 2007-2009) and Figure 5 (top in black) illustrates the R values along with their 95% CI. A simple look to figures 4 and 5 permits to notice the quality over time of SM-MW variability (with respect to ERA-Land). Also an improvement in R values is observed from 2001-2003, particularly in the South Hemisphere (latitudinal plot on figure 3.a). Averaged R values (95%CI) are 0.49(±0.12), 0.50(±012), 0.45(±0.12), 0.47(±0.12), 0.52(±0.11), 0.50(±0.10), 0.52(±0.09), 0.57(±0.09), 0.57(±0.09), and 0.52(±0.05) from 1980-1982 to 2007-2009 (Figure 5 top in black). The small decrease in the R value in the 2007-2009 period is due to the addition of high-latitude (50ºN and above) and high-elevation (e.g. European Alps) areas in SM-MW (introduction of data from ASCAT). For these areas, where SM-MW data were not available previously, low correlation between ERA-Land and SM-MW is obtained and, hence, the average correlation decreases. One may also note the decrease in the 95%CI that is related to the increasing number of SM-MW data available for the comparison in the most recent period.

For investigating SM-MW consistency over time, a more coherent comparison is to consider the same pixels for all periods (i.e. pixels with significant R values for all the periods) as illustrated on figure 2 (d, e and f) for the R values, size of the 95% CI and sample size. It removed most of the value above 60ºN (see also Table 3). Averaged R values (95%CI) are then 0.59(±0.11) in 1980-1982, 0.57(±0.11) in 1983-1985, 0.52(±0.10) in 1986-1988, 0.52(±0.10) in 1989-1991, 0.57(±0.08) in 1992-1994, 0.56(±0.08) in 1995-1997, 0.61(±0.06) in 1998-2000, 0.62(±0.07) in 2001-2003, 0.66(±0.05) in 2004-2006, 0.66(±0.04) in 2007-2009. An average correlation of 0.60(±0.02) is obtained for 1980-2010. Figure 3.b presents a latitudinal plot of R values under these conditions, for each sub-period and for the whole 1980-2010, also. Best R values are obtained in the latest periods (particularly true for the South Hemisphere), however Figure 5 (top in green) permits to appreciate the consistency over time of SM-MW product; if R values are slightly lower in the very first periods the difference is not significant (see 95%CI on Figure 5 top in green). In this configuration, biases and RMSD are of similar magnitude (order of ~1.10^{-3} and ~1.10^{-1} m^3m^{-3}) for the different period, scores are reported in Table 4. Also, the average number of SM-MW data available per pixels increases over time, 144, 146, 210, 286, 322, 341, 469, 440, 534 and 899 for each sub-period.

Table 4: Scores for the comparison between SM-MW and ERA-Land, only pixels that have significant correlation value (p-value<0.05) for each sub period are considered

	1980-82	1983-85	1986-88	1989-91	1992-94	1995-97	1998-00	2001-03	2003-05	2006-09	1980-2010
R (95%CI)	0.59 (±0.11)	0.57 (±0.11)	0.52 (±0.10)	0.52 (±0.10)	0.57 (±0.08)	0.56 (±0.08)	0.61 (±0.06)	0.62 (±0.07)	0.66 (±0.05)	0.66 (±0.04)	0.60 (±0.02)
RMSD m^3m^{-3}	0.100	0.101	0.104	0.105	0.103	0.104	0.098	0.096	0.095	0.094	0.099
Bias m^3m^{-3}	0.005	0.008	0.004	0.005	0.002	0.008	0.006	0.008	0.007	0.003	0.005

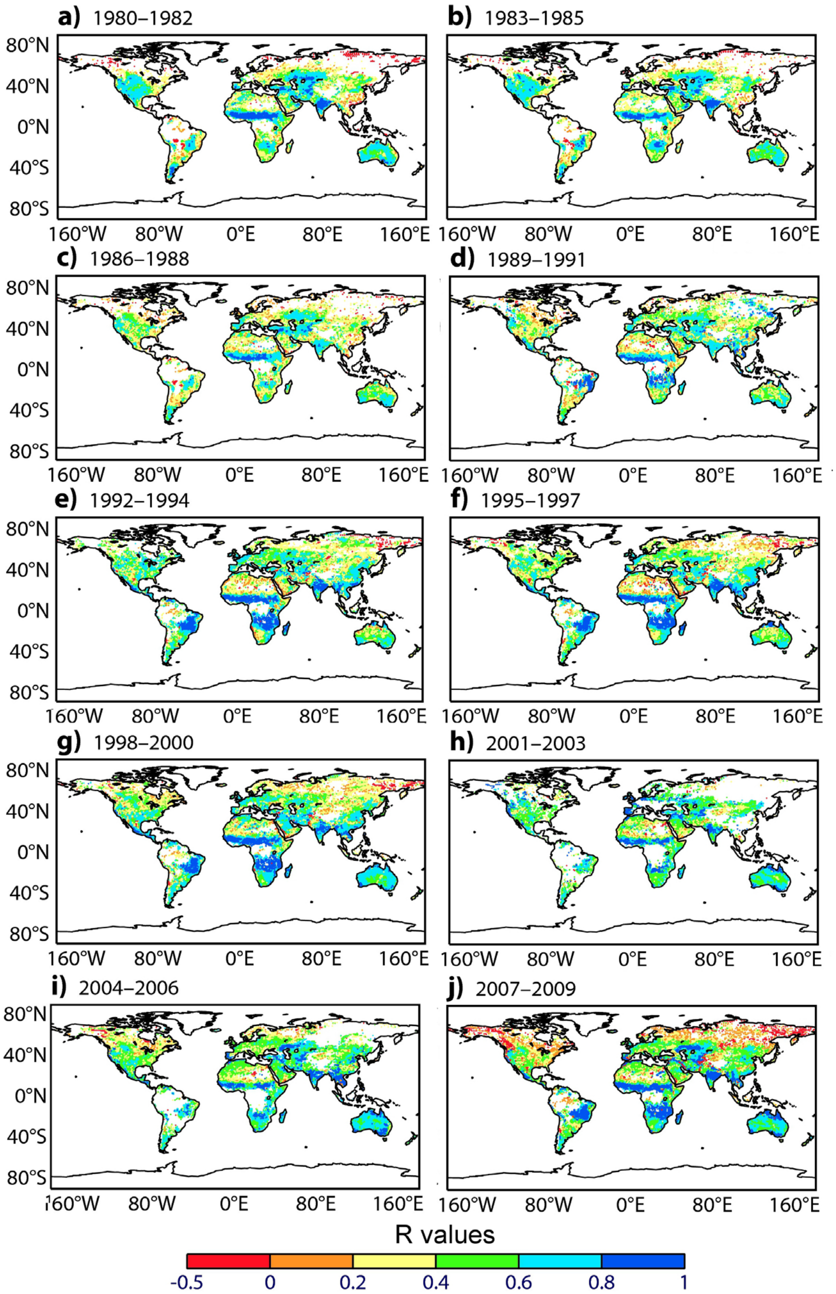

Figure 4: Correlations value between SM-MW and ERA-Land (only significant level of correlations, p-value<0.05) for the 10 3-yr sub periods considered individually in this study (from 1980-1982 to 2007-2009).

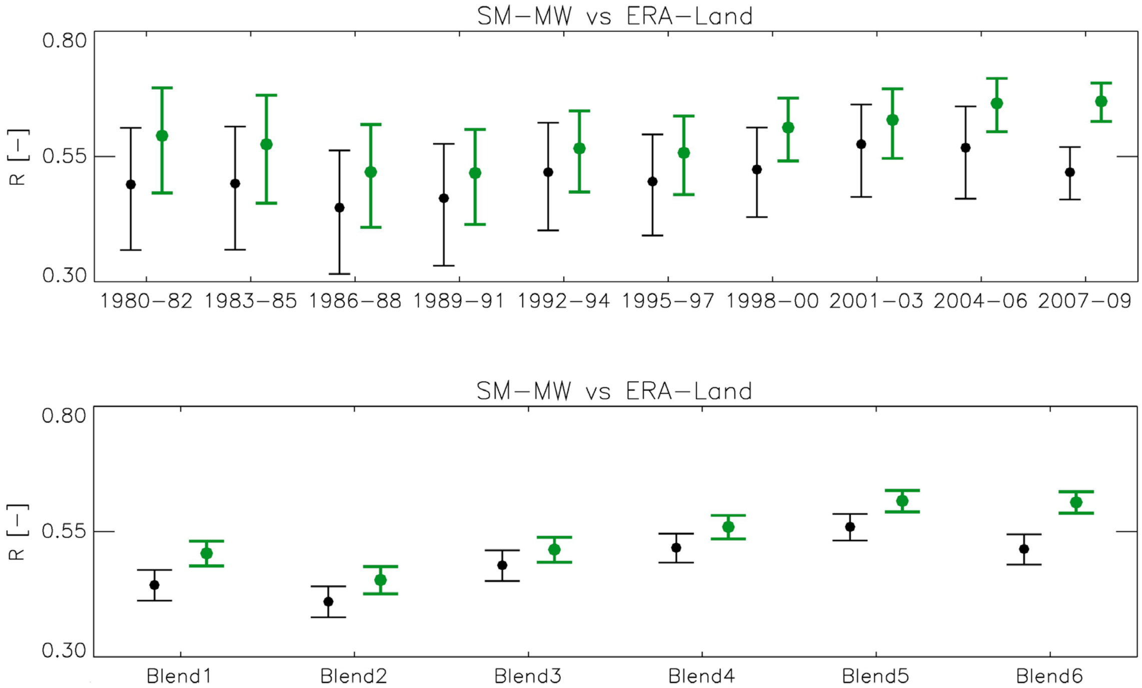

Figure 5: Averaged correlation values, R, (95% confidence Intervals) between SM-MW and ERA-Land for each 3-yr sub-periods within 1980-2010 (top) and for the 6 blended periods defined in section 2.2.Evaluation strategy. Black dots represent each period considered individually (only pixels with significant R values, p-values<0.05), green dots represent for each periods pixels which have significant R values for all periods.

Table 5 presents the percentage of R values ranked in 5 bins of increasing values [good (R>0.7), fair (0.5<R<0.7), poor (0.3<R<0.5) and inadequate (0<R<0.3 and R<0)] for the comparison between SM-MW and ERA-Land, for 1980-2010, 45.0% of the R values are above 0.5. Considering pixels that have significant R for each sub-period, it is 77.5%.

Table 5: percentage of correlations values ranked in 5 bins of increasing values [good (R>0.7), fair (0.5<R<0.7), poor (0.3<R<0.5) and inadequate (0<R<0.3 and R<0)] for the comparison between SM-MW and ERA-Land for 3-yr sub period and for 1980-2010 also. Values in parenthesis are when pixels present significant correlations values for all the 10 3-yr sub-period.

In %	R < 0	0 < R < 0.3	0.3 < R < 0.5	0.5 < R < 0.7	0.7 < R
1980-1982	3.2(0.0)	13.6(4.5)	31.3(25.1)	33.4(41.3)	18.5(29)
1983-1985	2.0(0.0)	14.9(6.4)	31.3(25.9)	34.6(42.0)	17.2(25.6)
1986-1988	1.6(0.0)	18.2(7.5)	42.0(39.4)	29.8(39.5)	8.5(13.5)
1989-1991	1.5(0.1)	17.7(8.5)	38.4(39.3)	29.7(38.4)	12.6(13.7)
1992-1994	1.7(0.1)	11.0(5.6)	32.0(32.1)	35.2(38.1)	20.1(24.2)
1995-1997	1.8(0.0)	14.2(6.5)	33.7(33.4)	31.7(37.0)	18.7(23.1)
1998-2000	1.5(0.0)	12.5(3.0)	28.1(20.9)	36.5(46.8)	21.3(29.3)
2001-2003	0.8(0.0)	7.3(2.8)	21.7(15.7)	43.1(49.7)	27.0(31.9)
2004-2006	0.9(0.0)	8.2(1.0)	23.7(11.2)	39.5(46.5)	27.6(41.2)
2007-2009	5.0(0.0)	15.0(2.2)	19.0(11.0)	34.0(43.7)	27.0(43.1)
1980-2010	**2.0(0.0)**	**25.0(0.6)**	**27.0(21.9)**	**32.0(53.4)**	**13.0(24.1)**

3.3 SM-MW vs. ERA-Land per blending periods

The analysis presented in section 3.2 for the whole 1980-2010 and 3-yr sub-periods was repeated for the separate blended periods specified in section 2.2 (Evaluation strategy). Considering pixels with significant level of R, individually for each period, averaged values are; 0.44(±0.03), 0.41(±0.03), 0.48(±0.03), 0.52(±0.03), 0.56(±0.03) and 0.52(±0.03) for the blended periods from 1 to 6, respectively. They are; 0.51(±0.02), 0.45(±0.03), 0.51(±0.03), 0.56(±0.03), 0.61(±0.03), 0.61(±0.03) when considering pixels that have significant R values for each blended periods. As for the 3-yr sub-periods, biases and RMSD (not shown) are of similar magnitude (order of $\sim 1.10^{-3}$ and $\sim 1.10^{-1}$ m^3m^{-3}). The second period (1 September 1987 – 30 June 1991) is based on SSM/I (19.3GHz) inputs only. At Ku band, radiance emitted from the soil surface is strongly attenuated by the vegetation canopy, leading to an increased uncertainty of the retrievals over sparsely vegetated areas and to a progressive masking over areas with moderate to dense vegetation (such as tropical and boreal forests, as in Figure 6.b). R value for this period is smaller than for the other periods, even than the first one that uses inputs from SMMR (C band, 6.6GHz), only (as in figure6.a). In the subsequent third period (1 July 1991 – 31 December 1997) the additional introduction of the ERS-AMI C-band data (5.3GHz) tends to fill this gap (as in Figure 6.c). Dorigo et al. (2013) noticed that introduction of the circular non-polar orbiting TRMM TMI (X band, 10.7 GHz) in 1998 leads to an increased observation density over the low and mid-latitudes while the observation density at higher latitudes remains similar to that of the preceding period. Slightly better correlations were found for this fourth period (1 January 1998 – June 2002, Figure 6.d) than for the previous periods. Finally the two last periods (1 July 2002 – 31 December 2006, based on a combination of AMSR-E [6.9/10.7 GHz] and ERS-AMI; 1 January 2007 – 31 December 2010, based on a combination of AMSR-E and ASCAT [5.3GHz]) present similar R values (Figure 6.e and f). Latitudinal plots on Figure 3.c and d illustrate the positive impact of the introduction of new sources of data over time and space in SM-MW product (with respect to ERA-Land). It confirms that the use of C-band is more suitable for soil moisture retrieval than X and Ku band. In particular the use of ERS-AMI C-band data from the third blended period, and then from AMSR-E and ASCAT presents a clear improvement (more visible in the South Hemisphere). Finally figure 7 presents histograms of the R values (configuration with significant R values for all blended period) as well as their cumulative distribution function (CDF). A simple look to figure 7 permits to notice the added value of each source of data (but SSM/I) introduced to SM-MW; 50% of the R values are above 0.52, 0.45, 0.51, 0.57, 0.63 and 0.63 for blended period 1 to 6, respectively.

Correlations values on anomaly time series are presented on figure 8 using latitudinal plots, as for figure 3. Figure 8(left) illustrates correlations for the six blended periods considered individually (significant cases only) and Figure 8(right) cases that have significant correlations for all the periods. In this configuration, averaged value are; 0.34, 0.31, 0.34, 0.39, 0.49 and 0.45. If there is a clear added value from the satellites used in the two latest periods, it is also possible to note that latitudes presenting high values of correlations on volumetric time series due to a strong seasonal cycle (e.g. 0º-25ºN on figure 3d) have smaller values when considering anomaly time series (i.e. ability to represent the soil moisture short term variability).

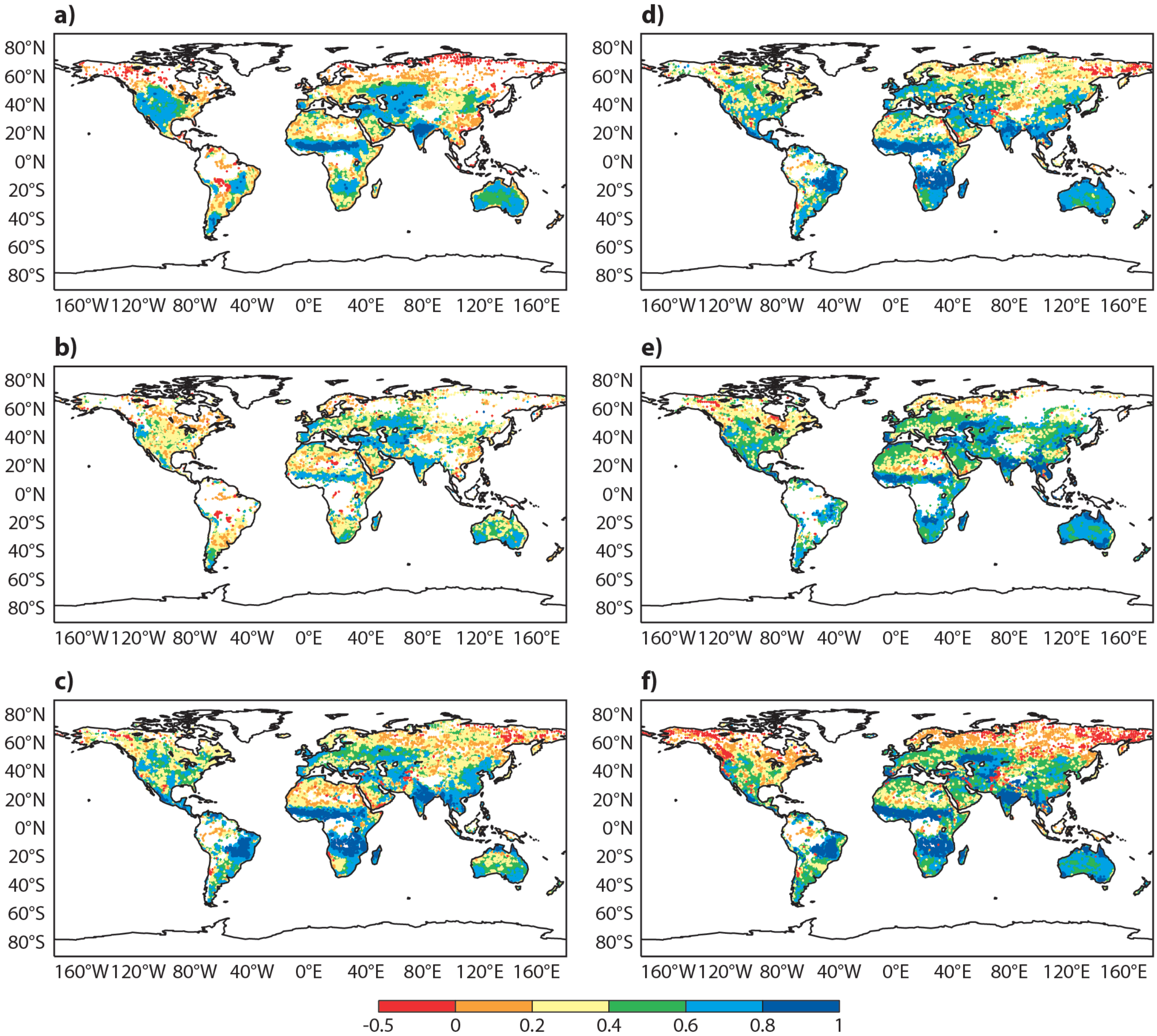

Figure 6: Correlations value between SM-MW and ERA-Land (only significant level of correlations, p-value<0.05) for the 6 blended period as defined in section 2.2; a) 1 January 1980 – 31 August 1987 (based SMMR observations only), b) 1 September 1987 – 30 June 1991 (based on SSM/I only), c) 1 July 1991 – 31 December 1997 (based on a combination of SSM/I and ERS-AMI), d) 1 January 1998 – June 2002 (based on a combination of TMI and AMI between 40°N and 40°S, and a combination of SSM/I and ERS-AMI elsewhere), e) 1 July 2002 – 31 December 2006 (based on a combination of AMSR-E and ERS-AMI), f) 1 January 2007 – 31 December 2010 (based on a combination of AMSR-E and ASCAT).

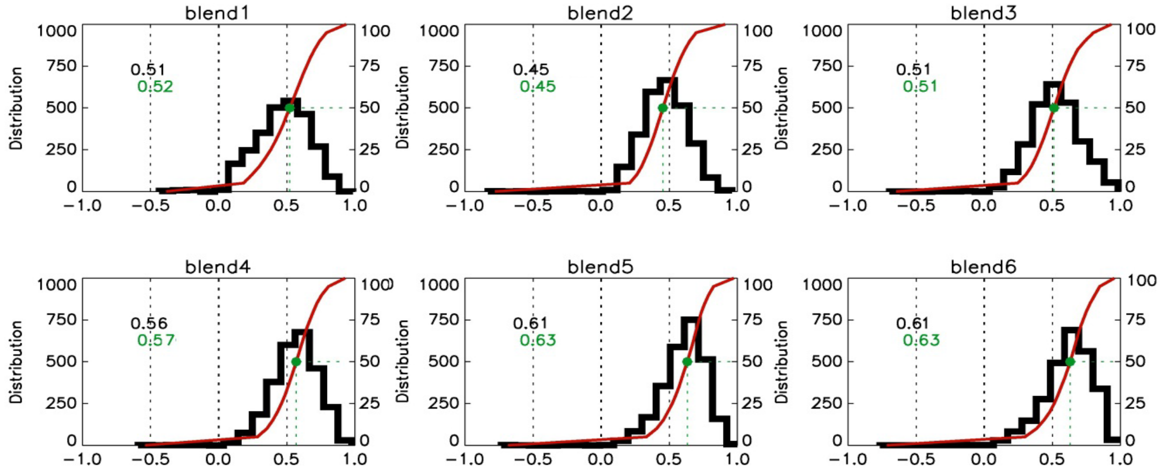

Figure 7: Histograms of correlations values between SM-MW and ERA-Land for each of the 6 blended periods as defined in section 2.2.Evaluation strategy, averaged value is reported in black. Only pixels that have significant level of correlations values for each period are considered. Red curve is the cumulative distribution function (right y-axis, in %) of the correlations. Green dots represent the median value, i.e. 50% of the correlations are above this value (also reported in green).

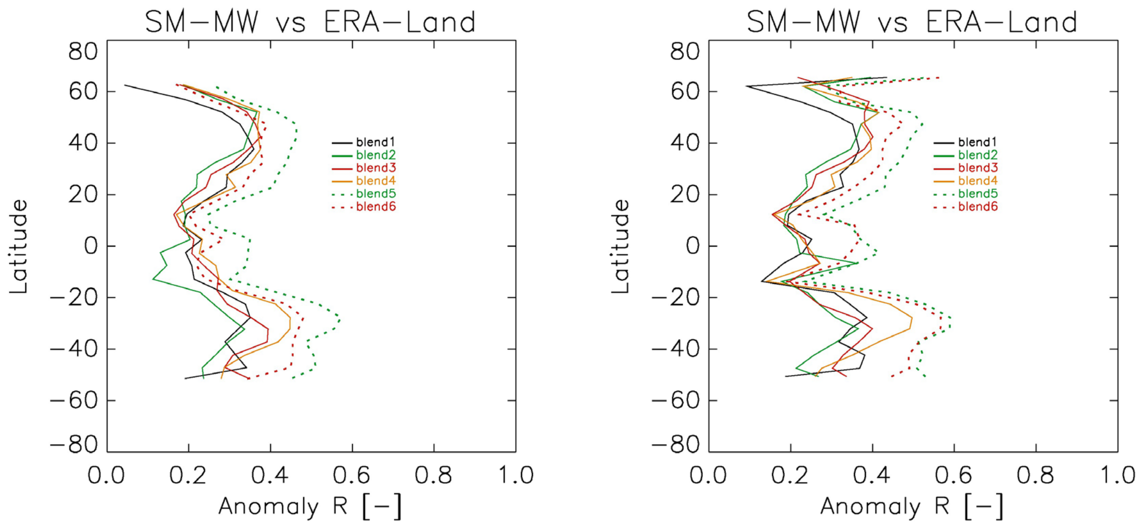

Figure 8: Same as figure 3 c and d for the anomaly time series from a moving monthly average.

4 Discussions

Spatial variability of soil moisture is very high at any spatial scale from local to regional. Precipitation, evapotranspiration, soil texture, topography, vegetation and land use could either enhance or reduce the spatial variability of soil moisture depending on how it is distributed and combined with other factors (Famiglietti et al., 2008). In this study ERA-Land was used as a term of comparison to evaluate trends' consistency in SM-MW obtained from multi-sensor remote sensing. ERA-Land uses a frozen version of the latest ECMWF land surface model and it was shown to capture reasonably well surface soil moisture annual variability although it tends to overestimate the in situ observations (negative biases and high RMSD). ERA-Land was also evaluated for its atmospheric fluxes (Balsamo et al. 2012, Boussetta et al. 2013) and provides initial conditions to the monthly and seasonal forecasting systems at ECMWF ensuring internal model consistency. Differences in soil properties could imply important variations in the mean and variance on soil moisture, even over small distances. Saleem and Salvucci (2002), Koster et al. (2009, 2011) suggested that the true information content of modelled soil moisture (e.g. from ERA-Land) does not necessarily rely on their absolute magnitudes but instead on their time variation (with this signal being less affected by soil texture uncertainties). Soil moisture represents the time-integrated impacts of antecedent meteorological forcing on the hydrological state of the soil system within the model. Modelled soil moisture have their own dynamic range, linked for instance to their soil physiographic parameters (wilting point and field capacity) associated to each soil texture. While it is recognised that no single metric or statistic can capture all the attributes of environmental variables, the correlation coefficient is the most relevant to compare Earth Observations soil moisture data and model outputs. Bias and RMSD were also computed in this study to identify possible drift between the two datasets.

Good level of correlations were found between SM-MW and ERA-Land over 1980-2010 and in each subsequent 3-yr sub-periods when considering pixels that have significant level of correlations for all periods; 0.59(±0.11) in 1980-1982, 0.57(±0.11) in 1983-1985, 0.52(±0.10) in 1986-1988, 0.52(±0.10) in 1989-1991, 0.57(±0.08) in 1992-1994, 0.56(±0.08) in 1995-1997, 0.61(±0.06) in 1998-2000, 0.62(±0.07) in 2001-2003, 0.66(±0.05) in 2004-2006, 0.66(±0.04) in 2007-2009. An average correlation of 0.60(±0.02) is obtained for 1980-2010. SM-MW variability is consistent over time; if slightly better R values are obtained in the latest periods; the difference is not significant. Considering pixels that have significant R values for each period individually, slightly lower correlations are found for 2007-2009 (as in Dorigo et al. 2013). This can be explained by the addition of data at high-latitude and high-elevation (e.g. European Alps) areas in SM-MW where the quality of the retrieval is lower. As highlighted by Dorigo et al. (2010, 2013); from a retrieval point of view, SM-MW products are more likely to be best in semi-arid regions where (i) retrievals are most accurate and (ii) observation density is highest. It is confirmed by figure 2 (a, b, c).

Similar analysis using the six blended periods as defined in section 2.2 were useful to identify the potential impact of the different products used to develop SM-MW. It confirms that better results are obtained with C band than with X band and Ku band and that the latest C-bands products AMSR-E, ASCAT provide a better retrieval than the first SMMR dataset. The second period (1 September 1987 – 30 June 1991), based on SSM/I (passive microwave product at Ku band 19.3GHz) inputs only, presents the lowest scores. At SSM/I wavelength, radiance emitted from the soil surface is strongly attenuated by the vegetation canopy, leading to an increased uncertainty of the retrievals over sparsely vegetated and resulting to less data being available. That explains the better R values obtained with SMMR for the previous period (1 January 1980 – 31 August 1987, passive microwave at C band, 6.6GHz), although the observation density is smaller, it has a better coverage (figure 6a and b). There is a general decrease in SM-MW coverage (and observations density) for the fifth blended period (1 July 2002 – 31 December 2006, based on a combination of AMSR-E and ERS AMI) attributed to the substitution over many areas of the passive observations with scatterometer products that have a lower daily coverage (see figure 6.e.). Based on in situ measurements, Dorigo et al. (2013) found a small decrease in performance with respect to the introduction of ASCAT in SM-MW. They partly attributed this decrease to the use of new ground measurements networks in areas where microwave retrieval are difficult (northern latitude, peat land, densely vegetated areas, complex topography…). It was not observed at a global scale using ERA-Land as a reference and the same pixels that present significant R values for all the 3-yr sub-periods.

The use of model data to monitor soil moisture retrieval from remote sensing has however some limitations since the interpretation of the results is hampered by the accuracy of the reference data set (model itself and its inputs such as the atmospheric forcing). Albergel et al. (2010, 2012c) have highlighted some non-realistic representation of soil moisture in ECMWF products that might be caused by shortcomings in the soil characteristics and pedotransfer functions that are employed, as well as by the difficulty of representing the spatial heterogeneity of these properties. For instance, a wrong representation of the soil texture could lead to a poor representation of soil moisture when compared to in situ data. Comparison in those areas (e.g. over the Tibetan plateau, Albergel et al., 2013) might lead to poor level of correlations. ECMWF is currently using a soil texture map from the Food and Agricultural Organization (FAO) dataset (FAO, 2003) and the implementation of a new map such as the new comprehensive Harmonized World Soil Database (HWSD) (FAO, 2009) could lead to better results. Albergel et al. (2013) found very similar trend between ERA-Land and SM-MW soil moisture over 1988-2010, it gives more strength to the comparison. However, while we assume ERA-Land quality to be constant over time one may note that the atmospheric observing system used in the atmospheric reanalyses has undergone changes over time (e.g. Robertson et al., 2011, Dee et al., 2011). That impacts the long term consistency of the surface meteorological forcing of ERA-Land.

Also, soil moisture time series show a strong seasonal pattern that could artificially increase the agreement between satellite and model output soil moisture in terms of R. To avoid seasonal effects, the analysis of anomaly time-series was also carried out. Correlations on anomaly time series (SM-MW and ERA-Land) were investigated in this study for the six blended periods described in section 2.2. Based on pixels that have significant R values on anomaly time series for each blended periods, averaged values are respectively 0.34, 0.31, 0.34, 0.39, 0.49 and 0.45. The good level of correlation of the volumetric time series (0.51, 0.45, 0.51, 0.56, 0.61 and 0.61) is explained by seasonal variations, which are suppressed in monthly anomalies. When a model output is applied as a reference to monitor satellite derived soil moisture, this score is particularly sensitive to the meteorological forcing (e.g. quality of the precipitation) used in the model. Albergel et al. (2012a) found that over areas such as Western Africa correlations on volumetric time series are mainly driven by the annual cycle and the representation of the soil moisture short term variability by ECMWF's products is poor when compared to ground measurements.

5 Conclusions

In this study, soil moisture from ERA-Land revised version of the land surface components of ERA-Interim re-analysis from ECMWF was used to monitor SM-MW dataset from remote sensing. ERA-Land was found to represent soil moisture variability well, when compared to in situ measurements of soil moisture 620 stations from 11 networks across the world for 2012, averaged correlation (95% confidence interval), root mean square difference and bias values; 0.66(±0.08) [(ranging from 0.57(±0.11) for the MAQU network in China to 0.84(±0.03) for the SMOSMANIA network in France], 0.118 m^3m^{-3} and -0.063 m^3m^{-3}.The good quality of ERA-Land soil moisture, its global coverage, frozen configuration and large scale nature makes it suitable for the monitoring of satellite retrieved soil moisture. The findings from Dorigo et al. (2013) who used ground-based observations of 932 sites from 29 different historical and active monitoring networks worldwide from the International Soil Moisture Network to evaluate SM-MW were confirmed by this study. While the number of dense in situ networks was too limited in space and time for them to provide a representative global picture of SM-MW datasets, the use of ERA-Land makes it possible. This study provides several insights into the use of Land Surface Model to evaluate satellite retrieved surface soil moisture and also from SM-MW itself:

- LSM, which are forced with high quality atmospheric forcing data and which were shown to adequately capture the soil moisture temporal dynamic, can be used to complement the evaluation of satellite retrieved surface soil moisture and monitor their variability. The large scale nature of LSM estimates is more representative of the scales of remotely sensed products and their global scale availability permits to extend the typical validation approach based on in situ measurements in areas (periods) where no data are available.

- Even if different products varying over space and time, and with differences in the microwave observation channels and sampling densities, are used to develop SM-MW, its variability is relatively stable over 1980-2010,

- SM-MW performs slightly better for period based on C band observations than X band and Ku band.

In particular a very good agreement is obtained in the tropics and close to the Equator, all over Australia and south Russia while poor correlations are obtained at high latitude (North hemisphere, 50ºN and above). Dorigo et al. (2013) found SM-MW to be relatively stable over 1980-2010 despite a decrease in scores for the most recent period where better retrievals are expected. They partly attributed it to the use of new ground measurements networks in areas where soil moisture retrieval is difficult. In contrast using a global scale dataset such as ERA-Land as a reference it was possible to carry out a more coherent comparison and to consider locations that have significant correlations values for each 3-yr sub periods within 1980-2010 only. Averaged R (95%CI) values between SM-MW and ERA-Land are 0.59(±0.11) in 1980-1982, 0.57(±0.11) in 1983-1985, 0.52(±0.10) in 1986-1988, 0.52(±0.10) in 1989-1991, 0.57(±0.08) in 1992-1994, 0.56(±0.08) in 1995-1997, 0.61(±0.06) in 1998-2000, 0.62(±0.07) in 2001-2003, 0.66(±0.05) in 2004-2006, 0.66(±0.04) in 2007-2009. An average correlation of 0.60(±0.02) is obtained for 1980-2010. Similar score to that of the previous period is obtained for 2007-2009, with a smaller 95%CI also. Considered individually however, a small decrease is indeed noticed in the latest 2007-2009 period, however having a global scale analysis permits to see that it corresponds to the addition of data in high latitude and high elevation that were not present in the previous period and that have poor R values (e.g. north Siberia and Alaska, south-eastern part of south America, European Alpes see figures 4 and 6). These areas are characterised by a smaller density of SM-MW data and a retrieval of smaller quality. It is of interest to better understand models and satellite data behaviours at high latitude where poor correlations values were obtained. The correlation was found to be more relevant than other standard metrics (root mean square differences, bias…) to evaluate the difference between SM-MW and ERA-Land. However, the definition of a better suited measure of accuracy to characterise the quality of soil moisture data is still a challenge (e.g. in semi-arid areas were soil moisture has a very low variability). Finally, additional work will focus on the use of ERA-Land as inputs of methods such as error propagation that can provide a more global view of the uncertainty of retrieved soil moisture. Techniques such as the triple collocation method (Stoffelen 1998) assess the uncertainty of soil moisture estimates resulting from errors in the input variables. Also, investigating specific areas of the World (e.g. agricultural/forested areas) will permit to better understand the impact of the land cover on the soil moisture retrieval from space.

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