Comparison between SMOS, VUA, ASCAT, and ECMWF soil moisture products over four watersheds in U.S.

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Comparison Between SMOS, VUA, ASCAT, and ECMWF Soil Moisture Products Over Four Watersheds in U.S.

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***Abstract*— As part of the Soil Moisture and Ocean Salinity (SMOS) validation process, a comparison of the skills of three satellites [SMOS, Advanced Microwave Scanning Radiometer-Earth Observing System (AMSR-E) or Advanced Microwave Scanning Radiometer, and Advanced Scatterometer (ASCAT)], and one-model European Centre for Medium Range Weather Forecasting (ECMWF) soil moisture products is conducted over four watersheds located in the U.S. The four products compared in for 2010 over four soil moisture networks were used for the calibration of AMSR-E. The results indicate that SMOS retrievals are closest to the ground measurements with a low average root mean square error of 0.061 m $^{3}\cdot$ m^{-3} for the morning overpass and 0.067 m $^{3}\cdot$ m^{-3} for the afternoon overpass, which represents an improvement by a factor of 2–3 compared with the other products. The ECMWF product has good correlation coefficients (around 0.78) but has a constant bias of 0.1–0.2 m $^{3}\cdot$ m^{-3} over the four networks. The land parameter retrieval model AMSR-E product gives reasonable results in terms of correlation (around 0.73) but has a variable seasonal bias over the year. The ASCAT soil moisture index is found to be very noisy and unstable.**

***Index Terms*— Soil moisture, Soil Moisture and Ocean Salinity (SMOS), validation.**

I. Introduction

SOIL moisture is an important variable in the study of seasonal climate evolution and prediction as it plays a major role in the mass and energy transfers between the soil and the atmosphere [1]. In land surface models, soil moisture is the key parameter in determining the evaporative fraction at the surface and the infiltration in the root zone. Soil moisture information is also essential for agriculture at a local scale and for water resources management at a regional scale. At the global scale, soil moisture is of great value for weather forecasting [2], climate change [3], and monitoring extreme events such as floods.

Recently, satellite missions specially designed for soil moisture monitoring are implemented (Soil Moisture and Ocean Salinity (SMOS) [4]) and proposed (Soil Moisture Active Passive (SMAP) [5]). SMOS was successfully launched by the European Space Agency in November 2009 and SMAP is scheduled for launch in October 2014 by the National Aeronautics and Space Administration. Both satellite instruments are designed to acquire data at the most suitable frequency for soil moisture retrieval (1.4 GHz [6]).

Several approaches are developed to retrieve soil moisture using the higher frequencies that are the only option until now. These include passive Scanning Multispectral Microwave Radiometer (SMMR, 1978–1987 [7]), passive Special Sensor Microwave/Imager (SSM/I, 1987 [7]), passive Advanced Microwave Scanning Radiometer-Earth Observing System (AMSR-E, 2002) [7], [8], WindSat (passive instrument, 2003 [9]), and active Advanced Scatterometer (ASCAT, 1991) [10]). Although their lowest frequencies (5–20 GHz) are not the most suitable for soil moisture retrievals because of their high sensitivity to the vegetation and the atmosphere, they provide valuable data since 1978.

All of the products above are obtained at a relatively coarse resolution, typically around 50 km, and relating them to point measurements for validation purposes is not always straightforward especially at a global scale. Therefore, it is necessary to validate coarse scale soil moisture estimates with model outputs or *in situ* observations from dense networks that represent area average soil moisture conditions. For SMOS, the initial validation is performed on a number of sites [11] and [12]. However, it is also necessary to compare the new SMOS product to already existing products. Here, we use alternative satellite products and outputs from a model-based system. We use *in situ* data to establish the performance and reliability of each product.

The following section describes the comparison of the four soil moisture data sets over four watersheds. The methodology used is described in Section III. Results from the comparison with ground measurements are analyzed

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in Section IV. Finally, some conclusions are summarized in the last section.

II. Data

A. Satellite-Based Soil Moisture Products

1) SMOS: The SMOS [4] satellite was launched in November 2009. This is the first satellite specially dedicated to soil moisture retrieval with an L-band passive radiometer (1.4 GHz [6]). SMOS provides global coverage in less than three days with a 43-km resolution. The satellite is polar orbiting with equator crossing times of 6:00 A.M. [local solar time (LST), ascending] and 6:00 P.M. (LST, descending). It is assumed that at L-band the signal is mainly influenced by the soil moisture contained in the first 5 cm of the soil on average over low vegetated areas.

SMOS acquires brightness temperatures at multiple incidence angles, from 0° to 55° with full-polarization mode. The angular signature is a key element of the algorithm that retrieves the soil moisture and the vegetation optical depth, which expresses the quantity of signal that is absorbed by the vegetation layer, through the minimization of a cost function between modeled (L-band microwave emission of the biosphere model [13]) and acquired brightness temperatures [14]. The novelty of the SMOS algorithm is that the heterogeneity inside the field of view of the radiometer is considered. Around each node of the SMOS grid, an extended grid of 123×123 km at a 4-km resolution, called the working area, is defined to quantify the heterogeneity seen by the radiometer. Each working area node belongs to one of the ten following landcover classes (aggregated from ECOCLIMAP landcover ecosystems, [15]): vegetation, forest, wetland, saline water, fresh water, barren, permanent ice, urban area, frost, and snow. In the SMOS algorithm, a specific radiative transfer model is associated with each class and it is thus possible to quantify the contribution of each of these classes. Considering the antenna pattern of the instrument, a weighting function is applied. The soil moisture and the vegetation optical depth are then retrieved over the relevant fractions, i.e., vegetated areas and forest (e.g., no retrieval is performed if the main class is waterbody). More information can be found in [14] and in the algorithm theoretical basis document [16]. These retrieval products are known as level 2 products [14] and are available on the icosahedral snyder equal area (ISEA)-4h9 grid, [17]. The nodes of this grid are equally spaced at 15 km. In this paper, the SMOS products used came from the reprocessing campaign using the version 5.01 of the level 2 soil moisture processor.

2) ASCAT: The ASCAT was launched in October 2006 on the MetOp-A satellite as a follow-on to the European Remote Sensing (ERS) satellites with the SCAT scatterometer that started operating in 1991. Since its launch, it is acquiring data at C-band (5.3 GHz). The scatterometer is composed of six beams: three on each side of the satellite track with azimuth angles of 45°, 90°, and 135° azimuth angles (incidence angles are in a range of 25°–64°), which generates two swaths of 550 km each with a spatial resolution of 25 or 50 km. The crossing times are 9:30 P.M. LST for the ascending orbit and 9:30 A.M. LST for the descending orbit.

In this paper, the ASCAT 25-km soil moisture product is downloaded from the Eumetsat data center and retrieval is performed using the Technische Universität Wien soil moisture algorithm [10], [18] that uses wet and dry references from the ERS satellites between 1992 and 2007 to retrieve an index ranging from 0 (dry) to 1 (wet) that represents the relative soil moisture of the first 2 cm of the soil.

3) AMSR-E: The AMSR-E was launched in June 2002 on the Aqua satellite and stopped producing data in October 2011. This radiometer acquired data with a single 55° incidence angle at six different frequencies: 6.9, 10.7, 18.7, 23.8, 36.5, and 89.0 GHz, all dual polarized. The crossing times are 1:30 A.M. (LST, descending) and 1:30 P.M. (LST, ascending). The footprint of the antenna is around 43×75 km at 6.9 GHz and 29×51 km at 10.7 GHz with a spatial resolution of 60 km at 6.9 GHz and 50 km at 10.7 GHz [19].

There are several products available that used AMSR-E data to estimate soil moisture. Many studies already shown that the official product from the National Snow and Ice Data Center is not able to reproduce low values of soil moisture [20]–[23]. The soil moisture product from the Vrije University of Amsterdam (VUA) [7] is therefore chosen in this paper.

The land parameter retrieval model [7] from the VUA retrieves the soil moisture and the vegetation optical depth using the combination of the C- and X-band AMSR-E channels and the 36.5-GHz channel to estimate the surface temperature. X-band observations are used in the areas of the world where C-band observations are affected by radio frequency interferences (RFIs). This algorithm is based on a microwave radiative transfer model with *a priori* information about soil characteristics. The operational VUA product is available on a 0.25° grid only for the descending orbit. The distributed data over this grid are quality checked and the data that are flagged are filtered out because of high topography or extreme weather conditions, such as snow, that would decrease the observed brightness temperatures and result in higher soil moisture estimates. The VUA product used in this paper is the version 3 product.

B. Model-Based Soil Moisture Product European Centre for Medium Range Weather Forecasting (ECMWF)

The ECMWF provides medium range global forecasts and this process produces some environmental variables that include soil temperature, evaporation, and soil moisture.

The SMOS level 2 processor uses a custom made climate data product from ECMWF that is used to set the initial values in the cost function solution and to model the contributions to the signal of the different parts of the scene seen by the radiometer. This is a forecast product generated 3–15 h in advance and every 3 h (at 3:00 A.M., 6:00 A.M., 9:00 A.M., and so on). It is considered an internal SMOS product as it is interpolated at SMOS overpass times and over the SMOS grid. Thus, this custom ECMWF product has the same spatial and temporal resolutions as SMOS and will be used in this paper.

The ECMWF soil moisture represents the top 7 cm below the surface.

ECMWWF auxiliary product information can be found in [4], [14], or [16].

C. In Situ Measurements

Four watersheds located in the United States are selected for this paper: Walnut Gulch (WG) in Arizona, Little Washita (LW) in Oklahoma, Little River (LR) in Georgia, and Reynolds Creeks in Idaho. They represent different types of climate (from semiarid to humid) and land use and are in operation since 2002 [24].

WG is located in southeast Arizona. Most of this watershed is covered by shrubs and grass, which is typical of the region. The annual mean temperature is 17.6 °C at Tombstone and the annual mean precipitation is 320 mm, mainly from high intensity convective thunderstorms in the late summer. The upper most 10 cm of the soil profile contains up to 60% gravel and the underlying horizons usually contains less than 40% gravels.

LW is located in southwest Oklahoma in the southern Great Plains region of the U.S. The climate is subhumid with an average annual rainfall of 750 mm, which falls mainly during the spring and fall seasons. Topography is moderately rolling with a maximum relief of less than 200 m and land use is dominated by rangeland and pasture (63%).

LR is located in southern Georgia near Tifton. With an average annual precipitation of 1200 mm, the climate is humid. This watershed is typical of the heavily vegetated slow-moving stream systems in the coastal plain region of the U.S. The topography over this watershed is relatively flat. Approximately 40% of the watershed is forest with 40% crops and 15% pasture.

RC is located in a mountainous area of southwest Idaho. The topography is high with a relief of over 1000 m that results in diverse climates, soils, and vegetation typical of this part of the Rocky Mountains. The climate is considered to be semiarid with an annual precipitation of 500 mm. Approximately 75% of the annual precipitation at high elevation is snow whereas only 25% is snow at low elevation.

Surface soil moisture and temperature sensors (0–5 cm) are acquiring data since 2002 for the four watersheds. The data used in this paper are the averages of the sensors located in each watershed (with the weighting coefficients derived from a Thiessen polygon). These averages are based on the same sets of sensors from 2002. The *in situ* soil moisture data set was distributed for the period of 2001–2011 and because of a significant change in the station configuration in 2005–2006, only a limited number of stations is considered reliable for the entire period (14/8/8/15 sensors for WG/LW/LR/RC, respectively). Therefore, even though we only use the 2010 data in this paper, only data from the stations considered reliable for the entire period are used. In addition, several sensors are disregarded because of poor or suspicious performances as follows: 1) sensors with periods of missing data are removed and only locations with continuous data are used in the analysis; 2) the sensors are calibrated and

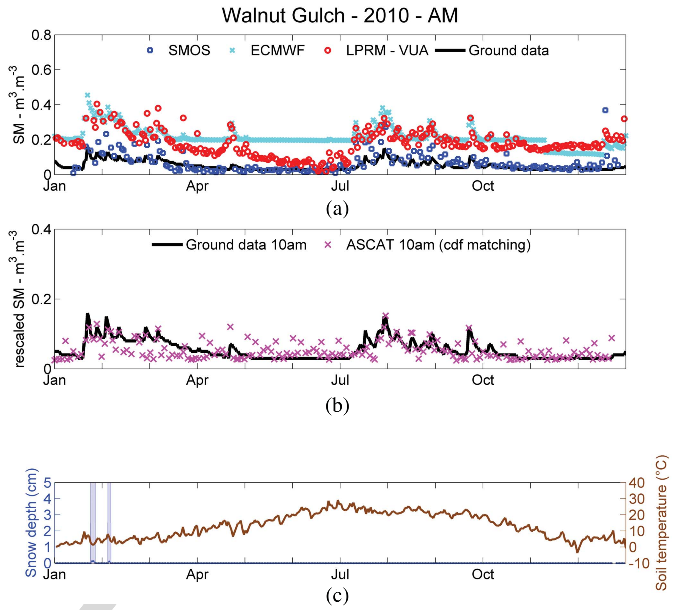

Fig. 1. (a) Time series of 2010 morning soil moisture over WG retrieved by SMOS, ECMWF, VUA, and *in situ* measurements. (b) Linearly scaled ASCAT soil moisture and *in situ* measurements. (c) Snow depth from ECMWF with measured soil temperature. Snowing and freezing days: blue shadows on (c).

checked during a field experiment and sensors/locations that did not agree well with the *in situ* observations are removed; 3) a temporal stability analysis is performed with all the *in situ* data and bad locations are removed; and 4) the sensors that did not respond well (visually) to precipitation events are removed. Soil moisture data are acquired every 30 min (hourly for RC). LW and LR watersheds are equipped with precipitation sensors that recorded data every 30 min. Table I shows the characteristics of each watershed.

D. Snow Cover and Soil Temperature Information

Additional information on the snow presence over each watershed is used in this paper. The ECMWF snow cover variable is used to remove data during days of snow cover and freezing events. Like the ECMWF soil moisture product, the snow depth is available at SMOS resolution and overpass time. It is natively available on a 0.225° grid every 3 h and is interpolated spatially and temporally to match SMOS requirements for use in the SMOS algorithm. The snow depth represents the amount of snow in centimeter present at the surface of the ground.

The soil temperature is also measured by the ground stations. Like the soil moisture, the temperature values from the different stations are given averaged over each watershed.

III. Data Preprocessing and Methodology

VUA and ASCAT grid products are first linearly interpolated on the SMOS grid. The distributed *in situ* soil moisture measurements are an average of different sensors representing an area that is comparable with a satellite footprint [24]. The networks of the four watersheds are specially designed for this purpose and the *in situ* data are furnished with a list of SMOS nodes that are covered by these networks. By averaging the

TABLE I
WATERSHED CHARACTERISTICS: NUMBER OF STATIONS MEASURING SOIL MOISTURE AT 5 cm, CLIMATE, ANNUAL RAINFALL, TOPOGRAPHY, AND MAIN SOIL USE [24]

Watershed	Nb. Stations	Climate	Annual Precip. (mm)	Topography	Soil Use
WG	14	Semiarid	320	Rolling	Range
LW	8	Subhumid	750	Rolling	Range/wheat
LR	8	Humid	1200	Flat	Row crop/forest
RC	15	Semiarid	500	Mountainous	Range

retrieved soil moisture values from these specific nodes, it is then possible to fairly compare this average with the *in situ* measurements. This method is already used to compare SMOS soil moisture to ground measurements in [12].

In order for the comparison to be fair, statistics are computed for the common dates and for the nonsnowing/freezing dates considering the five data sets: SMOS, ECMWF, VUA, ASCAT, and the ground measurements. Because of a change in the ECMWF system in November 2010, the statistics did not consider the data after this date. The statistics are therefore representative of the period from January 1 to November 9. After filtering, the number of available dates is 48/57/44/50 for the morning overpass comparison of WG/LW/LR/RC and 61/72/50/70 for the afternoon overpass comparison. There are more dates for the afternoon comparison as the VUA data set is not available in the afternoon and thus not considered. Days of snow cover are determined with the snow depth variable from ECMWF: when the snow depth is greater than 0 cm, data from that day are not considered. Days with freezing events are determined with the soil temperature variable: when the soil temperature is lower than −3 °C, the soil is considered to be frozen and the day is not considered. These days of snow cover and/or freezing events are shown in Figs. 1–4 on the bottom panels by the shaded zones. Statistics are then computed with the *in situ* soil moisture measured at the satellite overpasses.

Linear correlation coefficient (R), standard error of estimate (SEE) between derived soil moisture and *in situ* measurements SEE, bias and root mean square error (RMSE) are computed for each data set with the ground measurements over each watershed at the corresponding overpass times. The SEE measures the difference in the variability between two data sets, if SEE = 0 the two data sets have the same variability without considering any existing bias. The bias is the difference between the annual means of the two data sets. The RMSE considers both the bias and the difference in the variability and it is recalled that $\mathrm{RMSE}^2 = \mathrm{SEE}^2 + \mathrm{bias}^2$. R measures the intensity of a possible linear relationship between the two data sets. As there are very few points considered for these statistical computations, 95% confidence intervals are also computed for the correlation coefficient and the SEE.

Previously, the ASCAT soil moisture product is an index varying between zero and one and cannot be directly compared with ground measurements and the other data sets. A linear rescaling is therefore performed on ASCAT data between the minimum and the maximum values of the *in situ* data for each watershed (the snowing and the freezing days are filtered out beforehand). However, by performing this rescaling, the ASCAT statistical results are improved unfairly in comparison with the other data sets because the bias is removed by the

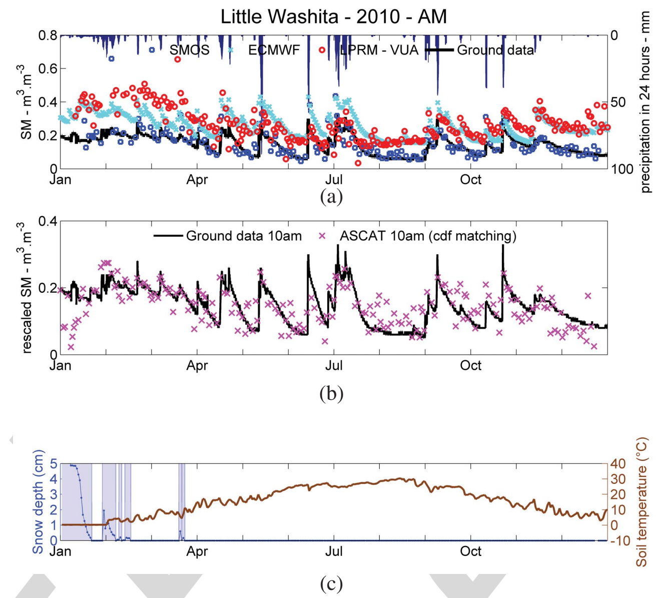

Fig. 2. (a) Time series of 2010 morning soil moisture over LW retrieved by SMOS, ECMWF, VUA, and *in situ* soil moisture and precipitation measurements. (b) Linearly scaled ASCAT soil moisture and *in situ* measurements. (c) Snow depth from ECMWF with measured soil temperature. Snowing and freezing days: blue shadows on (c).

rescaling. Therefore, apart from the correlation coefficient, the SEE, bias, and RMSE values are not calculated.

IV. RESULTS AND DISCUSSION

A. Comparison With Ground Measurements

The time series over 2010 of SMOS, ECMWF, VUA, and ASCAT soil moisture products are shown in Figs. 1–4 for each watershed along with the ground measurements. In addition, complementary information (snow depth and soil temperature) is added to each time series and precipitation as well for LW and LR.

Table II and Figs. 5 and 6 show the statistical scores of the comparison between the four data sets (SMOS, ECMWF, VUA, and ASCAT) and the *in situ* measurements over the four watersheds. The correlation coefficient (R), the SEE, the bias, and the RMSE are computed separately for the morning and afternoon overpasses.

1) Walnut Gulch: WG is the driest site of this paper. The *in situ* soil moisture measurements are rarely above 0.10 $m^3 \cdot m^{-3}$ (Fig. 1). For the morning overpasses, SMOS have the best results with a very good correlation coefficient ($R = 0.87$) associated to the lowest bias (0.029 $m^3 \cdot m^{-3}$) and the lowest RMSE (0.054 $m^3 \cdot m^{-3}$) of the tested data sets (Table II). For the afternoon overpasses, SMOS and ECMWF

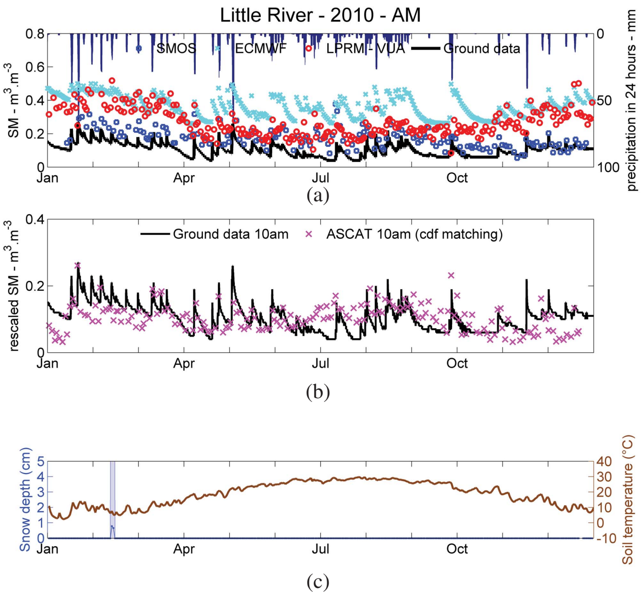

Fig. 3. (a) Time series of 2010 morning soil moisture over LR retrieved by SMOS, ECMWF, VUA, and *in situ* soil moisture and precipitation measurements. (b) Linearly scaled ASCAT soil moisture and *in situ* measurements. (c) Snow depth from ECMWF with measured soil temperature. Snowing and freezing days: blue shadows on (c).

are significantly better than VUA or ASCAT in terms of correlation (0.70 and 0.77) but SMOS is better than all the other products regarding the bias (0.014 m^3·m^{-3}) and the RMSE (0.054 m^3· m^{-3}), see Table II. Over this watershed, the SMOS product improved the bias by a factor of 8 and the RMSE by a factor of 3 when compared with the ECMWF and the VUA products, while keeping an equivalent or better correlation coefficient.

Observing more closely at the seasonal trends, SMOS tends to underestimate the soil moisture during the dry season (March–July) and performed better during the winter dry season (October–December) than during the rest of the year. However, the SMOS time series follow correctly the *in situ* soil moisture time series.

The ECMWF product exhibits the highest bias with the *in situ* measurements (Figs. 1–5). However, ECMWF is closer to the *in situ* measurements after mid November than before when the surface model is revised, which reduced ECMWF soil moisture positive bias in dry areas. ECMWF bias is lower than VUA bias after mid November. The ECMWF soil moisture followed correctly the *in situ* measurements even though some soil moisture increases are not observed. Most of the ECMWF bias is due to its high minimum soil moisture level at around 0.20 m^3·m^{-3} before mid November and 0.12 m^3·m^{-3} after.

In Fig. 1, VUA is close to the ground measurements in June when the soil is at its driest point and the soil temperature is very high and no rain event occurred (no change in the soil moisture time series). The largest VUA bias (0.15 m^3·m^{-3}) is found in winter (October–February) when the vegetation is assumed to be less and when the temperature is lower.

The ASCAT time series is very noisy and even though the increases in soil moisture are apparent (Fig. 5), the dry season is not well-described when the soil moisture is low and stable.

2) Little Washita: The LW site have the largest range of *in situ* soil moisture (0.1–0.3 m^3· m^{-3}, Fig. 2). There are very little data considered in January and February because of the snow and freezing events during this period. For the morning overpasses, SMOS and ECMWF have better correlation coefficients but they are not significantly better than VUA and ASCAT because their 95% confidence intervals overlap. With a bias of 0.013 m^3· m^{-3} and a RMSE of 0.048 m^3· m^{-3}, the SMOS product is closer to the ground measurements than the other products (Table II). For the afternoon overpasses, SMOS and ECMWF products are comparable in terms of correlation (0.62 and 0.70, respectively). However, SMOS has a very low bias (0.017 m^3· m^{-3}) and this resulted in a RMSE value of 0.072 m^3· m^{-3} (Table II). Over the LW watershed, SMOS improved the bias between retrieved or modeled soil moisture and *in situ* measurements by a factor of 5 and the RMSE by a factor of 1.5 for a statistically equivalent correlation (i.e., even if the correlation coefficients are not the same, their confidence intervals overlap, Table II).

Fig. 2 shows that the SMOS, VUA, and ECMWF products described correctly all the rain events except at the beginning of the year (January–April) when there are consecutive small rainfalls and the SMOS and VUA products became more scattered. The rain events of May–July are particularly well-reproduced by SMOS and ECMWF with expected decreases from the infiltration and evaporation processes. However, the first SMOS retrieval after a rain event is overestimated most of the time.

The ECMWF product presents good results in terms of correlation (0.85 for the morning and 0.70 for the afternoon) but this product is still penalized by its general bias throughout the year (around 0.10 m^3·m^{-3}) that can be clearly identified on Fig. 5.

VUA exhibits a variable bias: above 0.20 m^3·m^{-3} in January and February and near zero in June and July, respectively. As observed in WG, the lowest bias is found when the vegetation is supposed to be fully developed and when the temperature is at its maximum. During this period, the VUA product is closer to the ground measurements than the ECMWF product. Rain events are well-observed by this product but this nonstable bias prevents VUA from having a very good correlation coefficient.

As observed for WG, the ASCAT soil moisture index is again very noisy in LW. ASCAT have its best performance with good soil moisture dynamics during the periods of February–June and November and December (Fig. 2).

3) Little River: LR is the site with the highest frequency of rain events resulting in small variations in the soil moisture time series (Fig. 3). For the morning overpasses, the SMOS and ECMWF products are equivalent in terms of correlation (around 0.72). The SMOS product have the lowest bias (0.088 m^3·m^{-3}) and the lowest RMSE (0.095 m^3·m^{-3}) of all products (Table II). For the afternoon overpasses, even though the SMOS correlation coefficient interval overlaps a little on the ECMWF confidence interval, it can be assumed the ECMWF product has the best correlation coefficient (0.84). However, SMOS is still closer to the ground measurements than the other products with a bias of 0.073 m^3·m^{-3} and a RMSE of 0.088 m^3·m^{-3} (Table II). Over the LR watershed

TABLE II

STATISTICAL RESULTS OVER FOUR WATERSHEDS OF SMOS, ECMWF, AMSR-E, AND ASCAT COMPARED WITH *IN SITU* MEASUREMENTS. ASCAT DATA ARE LINEARLY NORMALIZED (ASCATN) IN RANGE OF *IN SITU* MEASUREMENTS. ALL RESULTS ARE STATISTICALLY SIGNIFICANT WITH p-VALUE LESS THAN 0.05. FIG. 6 IS MORE VISUALIZED VERSION OF THESE STATISTICS WITH ERROR BARS ADDED

		Morning					Afternoon				
		R	SEE	Bias	RMSE	Dates	R	SEE	Bias	RMSE	Dates
WG	SMOS	**0.87**	0.046	**0.029**	**0.054**	50	0.70	0.053	**0.014**	**0.054**	61
	ECMWF	0.70	**0.031**	0.169	0.172		0.77	**0.033**	0.166	0.169	
	VUA	0.79	0.062	0.125	0.140		-	-	-	-	
	ASCATn	0.60	-	-	-		0.46	-	-	-	
LW	SMOS	0.83	0.047	**0.013**	**0.048**	59	0.62	0.071	**0.017**	**0.072**	35
	ECMWF	0.85	**0.042**	0.111	0.118		0.70	**0.051**	0.094	0.107	
	VUA	0.69	0.063	0.110	0.127		-	-	-	-	
	ASCATn	0.74	-	-	-		0.53	-	-	-	
LR	SMOS	0.73	**0.037**	**0.088**	**0.095**	48	0.66	0.049	**0.073**	**0.088**	53
	ECMWF	0.71	0.048	0.257	0.262		**0.84**	**0.039**	0.267	0.270	
	VUA	0.59	0.060	0.151	0.162		-	-	-	-	
	ASCATn	0.51	-	-	-		0.38	-	-	-	
RC	SMOS	0.79	0.038	**−0.030**	0.048	54	0.60	0.055	**−0.003**	0.055	74
	ECMWF	**0.89**	0.031	0.070	0.076		**0.82**	**0.035**	0.061	0.070	
	VUA	0.84	0.065	0.057	0.087		-	-	-	-	
	ASCATn	0.70	-	-	-		0.48	-	-	-	

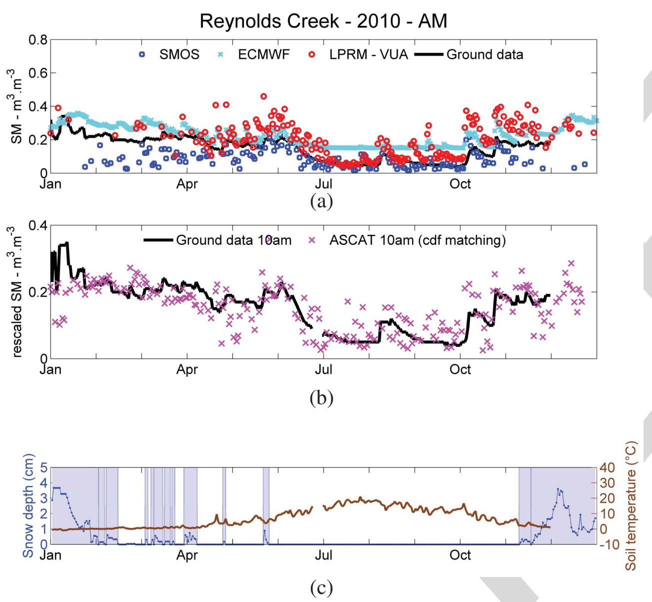

Fig. 4. (a) Time series of 2010 morning soil moisture over RC retrieved by SMOS, ECMWF, VUA, and *in situ* measurements. (b) Linearly scaled ASCAT soil moisture and *in situ* measurements. (c) Snow depth from ECMWF with measured soil temperature. Snowing and freezing days: blue shadows on (c).

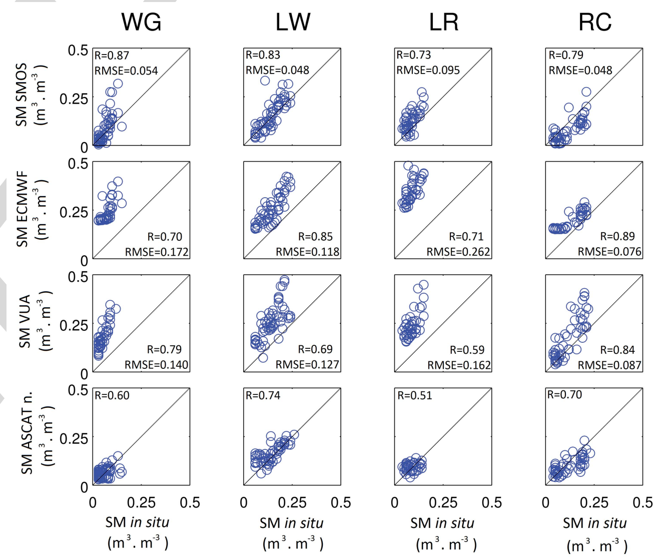

Fig. 5. Only morning overpasses: scatter plots of soil moisture derived from SMOS, ECMWF, VUA, and ASCAT compared with ground measurements in 2010 over four sites. Fourth line: for ASCAT row, scaled soil moistures are compared. More statistics are in Table II and Fig. 6.

SMOS improved the bias by a factor of 3 and the RMSE by a factor of 2 but did not succeed in having an equivalent correlation level in the afternoon.

By observing the evolution of the soil moisture time series in Fig. 3, small repetitive rain events in the first half of the year are observed with difficulty by the satellite products that resulted in scattered retrievals around the ground measurements. From September, SMOS is closer to the *in situ* measurements than during the rest of the year, certainly because there are less rain events. LR is the site where SMOS is the furthest from its mission goal in terms of error. However, this watershed is the most heterogeneous site of this experiment with a lot of forests and wetlands, whose contributions to the signal must be estimated to retrieve only the soil moisture value for the vegetated area of this watershed and this is not easily done.

The ECMWF product has again a high and stable bias throughout the year (around 0.26 $m^3 \cdot m^{-3}$) but it modeled very well all the rain events. Nevertheless, the soil moisture ranges described during these rainfalls are too large compared with the ground measurements (0.20 $m^3 \cdot m^{-3}$ for ECMWF against 0.05 $m^3 \cdot m^{-3}$ for the *in situ*), especially in September and October.

VUA also have its highest bias in LR (0.16–0.30 $m^3 \cdot m^{-3}$). As observed for LW, the bias is lower when the vegetation is denser and when the surface temperatures reached their highest value.

TABLE III
MEAN PROBABILITY OF RFI OCCURRENCES ON SMOS ACQUISITION IN 2010 OVER FOUR WATERSHEDS

	Walnut Gulch	Little Washita	Little River	Reynolds Creek
Morning	0.09%	0.00%	0.38%	2.23%
Afternoon	0.37%	0.38%	0.82%	0.36%

ASCAT soil moisture retrievals reflected well the *in situ* evolution for the period March–June. However, after the month of June, the data became noisier and did not follow the observed soil moisture dynamics. The ground soil moisture decreased in June and July, whereas the ASCAT index increased. This is represented as a wide cloud of points when compared directly with the ground data (Fig. 5). The associated R value is then not representative of this cloud.

4) Reynolds Creek: RC is located in a mountainous region. It represents a challenging set of conditions for the satellite soil moisture retrievals because of the topography and the snow/freezing conditions during the winter season (Fig. 4). For the morning overpasses, all the products are equivalent in terms of correlation. Regarding the bias, SMOS underestimated the soil moisture whereas ECMWF and VUA overestimated it. The RMSE values are found lower over RC for the ECMWF and the VUA products (0.076 $m^3{\cdot}m^{-3}$ and 0.087 $m^3{\cdot}m^{-3}$, respectively) than over the other test sites (Table II). For the afternoon overpasses, ECMWF correlation (0.82) is significantly better than SMOS and ASCAT. SMOS have the lowest bias (-0.003 $m^3{\cdot}m^{-3}$) but still have a value of RMSE of 0.055 $m^3{\cdot}m^{-3}$ (Table II).

With the exception of the beginning of the year the general temporal evolution of all soil moisture products followed correctly the trend of the *in situ* data.

RC is the only site where SMOS underestimated the ground measurements (Fig. 5). However, when looking at the period when there is no snow or possibly frozen soil (April–October), SMOS appeared to perform properly and the bias decreased. This can be explained, when the soil is frozen, decreases in the dielectric constant occur and the soil appears as dry [25]. Dry snow is expected to be transparent at L-band [26].

ECMWF exhibits a smaller bias for RC than for the other watersheds, especially during the spring and the fall seasons. However, during the summer, ECMWF seems to have reached a high minimum soil moisture level as its modeled soil moisture values are stable around 0.20 $m^3{\cdot}m^{-3}$ whereas the ground measurements are around 0.05 $m^3{\cdot}m^{-3}$ (Figs. 4 and 5).

The VUA soil moisture time series in May and June is noisy which might be because of vegetation growth. But between June and October, when the vegetation is denser, the VUA product followed the *in situ* measurements very well with almost no bias.

After the last snow event in late March, the ASCAT product followed correctly the *in situ* measurements and have a good correlation for the morning overpasses ($R = 0.70$).

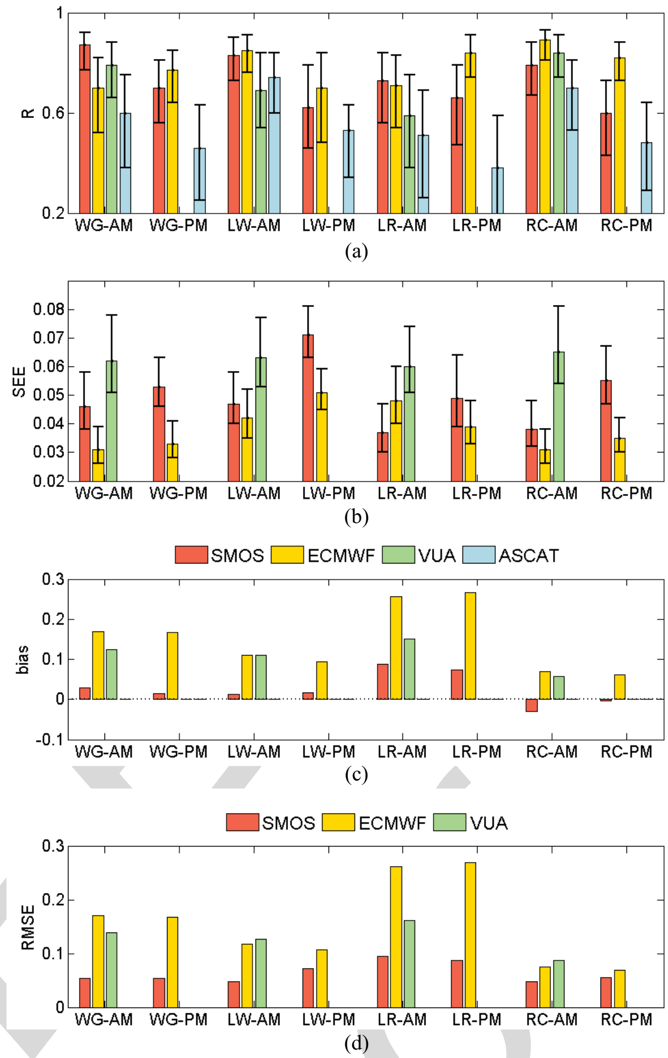

Fig. 6. Statistics regarding comparison between soil moisture from SMOS, ECMWF, VUA, and linearly normalized ASCAT and *in situ* measurements. Four subfigures correspond. (a) Correlation coefficient R. (b) SEE. (c) Bias. (d) RMSE over each watershed. Morning and afternoon comparisons are treated separately and 95% confidence intervals are indicated for R and SEE.

B. Comparison Between the Ascending and the Descending Orbits

Statistical scores for the afternoon overpasses (Table II, Fig. 6) show a lower correlation and a larger scattering for the satellite soil moisture products. The SMOS correlation coefficient have an average across all watersheds of 0.80 in the morning for a SEE of 0.042 $m^3{\cdot}\ m^{-3}$ and a correlation of 0.65 in the afternoon for a SEE of 0.057 $m^3{\cdot}\ m^{-3}$. For the morning overpasses, the ASCAT product has an average correlation of 0.64 and 0.46 for the afternoon.

The SMOS penetration depth is assumed to be between 2 and 5 cm (depending on the soil properties and moisture conditions, [4], [27]) and at 6:00 A.M. when the soil is in a hydraulic quasi-equilibrium, SMOS can be fairly compared with the 5-cm soil moisture measurements [27]. At 6:00 P.M. the soil is not in equilibrium and if SMOS is measuring the soil moisture from the top 3 cm of the soil, the differences with the 5 cm ground measurements will be higher at 6:00 P.M.

than at 6:00 A.M. [27] recommended using morning measurements when comparing with space observations because of the day-time decoupling that could occur in the afternoon because of the nonhydraulic equilibrium of the soil. The same explanations apply for the ASCAT results at 9:30 A.M. and at 9:30 P.M. These results are consistent with the results of [28].

Another possible explanation for these differences between the morning and the afternoon results is still related to the nonequilibrium of the soil and it concerns the assumptions are made concerning the soil surface temperature. It is assumed that the soil and the vegetation temperatures are approximately equal, which is a fair assumption during the night or early morning but during the day, the vegetation temperature is expected to be closer to the air temperature than to the soil temperature. This assumption of equal vegetation and effective soil temperatures can lead to less accurate satellite soil moisture retrievals in the afternoon.

Regarding SMOS results, one last possibility could be the presence of RFIs that are only seen during the descending orbits when the satellite is going in the afternoon from north to south and is pointing in the southwest direction. From the RFI contamination probability maps derived from the mixed polarized acquisitions (real and imaginary parts [16], [29]), it is possible to compute for each watershed the mean probability of RFI occurrences (Table III). Except over RC, the probability of RFI contamination is higher for the afternoon overpasses even if they are still very low compared with highly contaminated regions such as Asia. This difference in RFI contamination between the morning and the afternoon overpasses might partially explain why SMOS results are better in the morning.

V. Conclusion

SMOS data were compared with *in situ* observations and other satellite data and model outputs. SMOS, VUA, ECMWF, and ASCAT soil moisture retrievals were compared with the *in situ* measurements and intercompared over four different sites in the U.S. under various climate conditions and soil characteristics.

Over the four test sites, no specific product had a significantly better correlation with the ground measurements. Since this paper only covers the year 2010, 35–74 common dates were considered to compute the statistics and resulted in substantial confidence intervals that made all products equivalent in terms of correlation. The statistical parameters used to differentiate the four data sets were the SEE, the bias, and logically the RMSE. Over most of the watersheds, ECMWF had a significantly lower SEE (0.039 $m^3\cdot m^{-3}$ in average) than SMOS (0.049 $m^3\cdot m^{-3}$ in average) and VUA (0.063 $m^3\cdot m^{-3}$ for the morning only), representing a less scattered data set. ECMWF soil moisture time evolution was very close to the ground measurements with clear identifications of the rainfall events and the soil drainage afterward. However, SMOS had clearly the lowest bias with an average of 0.032 $m^3\cdot m^{-3}$ whereas ECMWF had a mean bias of 0.150 $m^3\cdot m^{-3}$ and VUA of 0.129 $m^3\cdot m^{-3}$. SMOS also had the lowest RMSE over all the sites except RC. SMOS had a mean RMSE of 0.064 $m^3\cdot m^{-3}$ whereas ECMWF had a mean RMSE of 0.156 $m^3\cdot m^{-3}$ and VUA of 0.129 $m^3\cdot m^{-3}$ (for the morning only). Therefore, although the SMOS mission accuracy objective of 0.040 $m^3\cdot m^{-3}$ was not reached over these four watersheds in 2010, SMOS improved the total RMSE by a factor of at least 2 on average in 2010 for an equivalent correlation compared with the other soil moisture products.

The time series analysis revealed a positive constant bias in the ECMWF data set: 0.17/0.10/ 0.26/0.07 $m^3\cdot m^{-3}$, respectively for the WG/LW/LR/RC watersheds. Even after mid-November when the surface model and analysis were revised, this bias was still present over all the watersheds but had decreased over WG (data after mid-November were not considered in the statistical results). Despite very good correlation coefficients, this minimum level was a major obstacle in using ECMWF for the four test sites. VUA also had a bias but was not constant and appeared to evolve with the seasons. The bias was higher when the vegetation and the soil temperature were low (during winter) and tended to decrease when the vegetation was supposed to be denser and the soil temperature increasing to its maximum in the summer, resulting in a quasi-null bias. This evolution of the VUA bias throughout the year was assumed to be linked to a physical parameter such as the vegetation or the temperature since it evolved with the seasons and because the AMSR-E frequencies (6.9 and 10.7 GHz) were more sensitive to the vegetation layer than SMOS at 1.4 GHz. It was also possible that this bias was due to the soil effective temperature that was modeled through the 36-GHz brightness temperature or to another assumption that was made in the VUA algorithm. The ASCAT soil moisture index was very noisy in comparison with the other products and even though some rain events were obvious in the retrievals, the *in situ* soil moisture dynamics were not well-represented for any of the watersheds. Active microwave observations were very sensitive to surface roughness and WG, for example, had sandy soils with significant amount of gravel. These soil characteristics resulted in a greater surface roughness which could explain partially the poor results of ASCAT.

The comparison of the statistical performances of the products between the morning and the afternoon revealed that the ECMWF model did not show significant differences whereas the satellite SMOS and ASCAT products showed several differences: $R = 0.80/0.65$, $SEE = 0.042/0.057$ $m^3\cdot m^{-3}$, bias $=$ 0.040/0.027 $m^3\cdot m^{-3}$, RMSE $=$ 0.061/0.067 $m^3\cdot m^{-3}$ for SMOS, and $R = 0.64/0.46$ for ASCAT (A.M./P.M. in average over the four watersheds). These differences in performance can be explained that in the morning, the soil was in hydraulic quasi-equilibrium. On the other hand for the afternoon, this comparison might not be as correct as for the morning. Another explanation could be the inaccurate modeling of the soil and the vegetation temperatures in the retrieval algorithm. They were assumed to be equal and this assumption might not be true in the afternoon when the vegetation temperature was expected to be closer to the air temperature than to the soil temperature. The last possible explanation for SMOS performance difference concerned the RFI. The occurrence probabilities of

RFI in 2010 were higher in the afternoon than in the morning except over RC.

The results of this paper concur with the different studies that were realized in the frame of the SMOS soil moisture product validation [11], [12], [14], [30]. SMOS soil moisture retrievals were already very close to the ground measurements but need to be improved to meet its scientific goal of an error less than 0.04 $m^3 \cdot m^{-3}$. In this perspective, a new version of the level 2 soil moisture processor (v5.51) was already in place since March 2012 and allowed to switch between the Dobson and the Mironov constant dielectric model and this version showed promising first results.

The main advantage in comparing satellite products was the possibility of comparing with global coverage and further studies will be developed in this direction in the near future.

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References

[1] "Implementation plan for the global observing system for climate in support of the UNFCCC," World Meteorological Organ., Intergovern. Oceanogr. Commission, United Nations Environ. Progr., International Council Science, Geneva, Switzerland, Tech. Rep. 1244, 2010.

[2] M. Drusch, "Initializing numerical weather predictions models with satellite derived surface soil moisture: Data assimilation experiments with ECMWF's integrated forecast system and the TMI soil moisture data set," *J. Geophys. Res.*, vol. 113, no. D3, p. D03102, Feb. 2007.

[3] H. Douville and F. Chauvin, "Relevance of soil moisture for seasonal climate predictions: A preliminary study," *Climate Dynamics*, vol. 16, nos. 10–11, pp. 719–736, Oct. 2000.

[4] Y. Kerr, P. Waldteufel, J. Wigneron, S. Delwart, F. Cabot, J. Boutin, M. Escorihuela, J. Font, N. Reul, C. Gruhier, S. Juglea, M. Drinkwater, A. Hahne, M. Martin-Neira, and S. Mecklenburg, "The SMOS mission: New tool for monitoring key elements of the global water cycle," *Proc. IEEE*, vol. 98, no. 5, pp. 666–687, May 2010.

[5] D. Entekhabi, E. Njoku, P. E. O. Neill, K. Kellogg, W. Crow, W. Edelstein, J. Entin, S. Goodman, T. Jackson, J. Johnson, J. Kimball, J. Piepmeier, R. Koster, N. Martin, K. McDonald, M. Moghaddam, S. Moran, R. Reichle, J. Shi, M. Spencer, S. Thurman, L. Tsang, and J. Zyl, "The soil moisture active passive (smap) mission," *Proc. IEEE*, vol. 98, no. 5, pp. 704–716, May 2010.

[6] Y. Kerr, P. Waldteufel, J. Wigneron, J. Martinuzzi, J. Font, and M. Berger, "Soil moisture retrieval from space: The soil moisture and ocean salinity (SMOS) mission," *IEEE Trans. Geosci. Remote Sens.*, vol. 39, no. 8, pp. 1729–1735, Aug. 2001.

[7] M. Owe, R. de Jeu, and J. Walker, "A methodology for surface soil moisture and vegetation optical depth retrieval using the microwave polarization difference index," *IEEE Trans. Geosci. Remote Sens.*, vol. 39, no. 8, pp. 1643–1654, Aug. 2001.

[8] E. Njoku, T. Jackson, V. Lakshmi, T. Chan, and S. Nghiem, "Soil moisture retrieval from ASMR-E," *IEEE Trans. Geosci. Remote Sens.*, vol. 41, no. 2, pp. 215–229, Feb. 2003.

[9] L. Li, P. Gaiser, B. Gao, R. Bevilacqua, T. Jackson, E. Njoku, C. Rüdiger, J. Calvet, and R. Bindlish, "Windsat global soil moisture retrieval and validation," *IEEE Trans. Geosci. Remote Sens.*, vol. 48, no. 5, pp. 2224–2241, May 2010.

[10] V. Naeimi, K. Scipal, Z. Bartalis, and S. H. W. Wagner, "An improved soil moisture retrieval algorithm for ERS and METOP scatterometer observations," *IEEE Trans. Geosci. Remote Sens.*, vol. 47, no. 7, pp. 1999–2013, Jul. 2009.

[11] A. A. Bitar, D. Leroux, Y. Kerr, O. Merlin, P. Richaume, A. Sahoo, and E. Wood, "Evaluation of SMOS soil moisture products over continental U.S. Using SCAN/SNOTEL network," *IEEE Trans. Geosci. Remote Sens.*, vol. 50, no. 5, pp. 1572–1586, May 2012.

[12] T. Jackson, R. Bindlish, M. Cosh, T. Zhao, P. Starks, D. Bosch, M. Seyfried, S. Moran, Y. Kerr, and D. Leroux, "Validation of soil moisture ocean salinity (SMOS) soil moisture over watershed networks in the U.S.," *IEEE Trans. Geosci. Remote Sens.*, vol. 50, no. 5, pp. 1530–1543, May 2012.

[13] J. Wigneron, Y. Kerr, P. Waldteufel, K. Saleh, M. Escorihuela, P. Richaume, P. Ferrazzoli, P. de Rosnay, R. Gurney, J. Calvet, J. Grant, M. Guglielmetti, B. Hornbuckle, C. Mätzler, T. Pellarin, and M. Schwank, "L-band microwave emission of the biosphere (L-MEB) model: Description and calibration against experimental data sets over crop fields," *Remote Sens. Environ.*, vol. 107, no. 4, pp. 639–655, Apr. 2007.

[14] Y. Kerr, P. Waldteufel, P. Richaume, J. Wigneron, P. Ferrazzoli, A. Mahmoodi, A. Al Bitar, F. Cabot, C. Gruhier, S. Juglea, D. Leroux, A. Mialon, and S. Delwart, "The SMOS soil moisture retrieval algorithm," *IEEE Trans. Geosci. Remote Sens.*, vol. 50, no. 5, pp. 1384–1403, May 2012.

[15] V. Masson, J.-L. Champeau, F. Chauvin, C. Meriguet, and R. Lacaze, "A global data base of land surface parameters at 1-km resolution in meteorological and climate models," *J. Climate*, vol. 16, no. 9, pp. 1261–1282, May 2003.

[16] "Algorithm theoretical basis document," Tech. Rep. 3.d, CESBIO, Toulouse, France, IPSL, Paris, France, INRA-EPHYSE, Bordeaux, France, Reading University, Reading, England, Tor Vergata University, Rome, Italy, 2010.

[17] D. Carr, R. Kahn, K. Sahr, and T. Olsen, "Isea discrete global grids," *Stat. Comput. Stat. Graph. Newlett.*, vol. 8, nos. 2–3, pp. 31–39, 1997.

[18] W. Wagner, G. Lemoine, and H. Rott, "A method for estimating soil moisture from ERS scatterometer and soil data," *Remote Sens. Environ.*, vol. 70, no. 2, pp. 191–207, Nov. 1999.

[19] "AMSR-E data users handbook," Japan Aerospace Exploration Agency (JAXA), Washington, DC, USA, Tech. Rep. NCX-030021, Mar. 2006.

[20] C. Gruhier, P. de Rosnay, Y. Kerr, E. Mougin, E. Ceschia, J. Calvet, and P. Richaume, "Evaluation of AMSR-E soil moisture product based on ground measurements over temperate and semi-arid regions," *Geophys. Res. Lett.*, vol. 35, no. 10, p. L10405, May 2008.

[21] C. Rudiger, J. C. Calvet, C. Gruhier, T. Holmes, R. de Jeu, and W. Wagner, "An intercomparison of ERS-Scat and AMSR-E soil moisture observations with model simulations over france," *Amer. Meteorol. Soc.*, vol. 10, no. 2, pp. 431–447, Apr. 2009.

[22] C. Draper, J. Walker, P. Steinle, R. de Jeu, and T. Holmes, "An evaluation of AMSR-E derived soil moisture over Australia," *Remote Sens. Environ.*, vol. 113, no. 4, pp. 703–710, Apr. 2009.

[23] C. Gruhier, P. de Rosnay, S. Hasenauer, T. Holmes, R. de Jeu, Y. Kerr, E. Mougin, E. Njoku, F. Timouk, W. Wagner, and M. Zribi, "Soil moisture active and passive microwave products: Intercomparison and evaluation over a sahelian site," *Hydrol. Earth Syst. Sci.*, vol. 14, no. 1, pp. 141–156, Jan. 2010.

[24] T. Jackson, M. Cosh, R. Bindlish, P. Starks, D. Bosch, M. Seyfried, D. Goodrich, M. Moran, and J. Du, "Validation of advanced microwave scanning radiometer soil moisture products," *IEEE Trans. Geosci. Remote Sens.*, vol. 48, no. 12, pp. 4256–4272, Dec. 2010.

[25] C. Matzler, "Passive microwave signatures of landscapes in winter," *Meteorol. Atmospheric Phys.*, vol. 54, nos. 1–4, pp. 241–260, 1994.

[26] R. Armstrong and M. Brodzik, "A twenty year record of global snow cover fluctuations derived from passive microwave remote sensing data," in *Proc. 5th Conf. Polar Meteorol. Oceanography, Amer. Meteorol. Soc.*, Dallas, TX, USA, 1999, pp. 113–117.

[27] T. Jackson, "Profile soil moisture from space measurements," *J. Irrigat. Drainage Divis., ASCE*, vol. 106, pp. 81–92, Mar. 1980.

[28] C. Albergel, C. Rüdiger, D. Carrer, J. Calvet, N. Fritz, V. Naeimi, Z. Bartalis, and S. Hasenauer, "An evaluation of ascat surface soil moisture products with in-situ observations in southwestern france," *Hydrol. Earth Syst. Sci.*, vol. 13, no. 2, pp. 115–124, 2009.

[29] R. Oliva, E. Daganzo-Eusebio, Y. Kerr, S. Mecklenburg, S. Nieto, P. Richaume, and C. Gruhier, "SMOS radio frequency interference scenario: Status and actions taken to improve the RFI environment in the 1400–1427 MHz passive band," *IEEE Trans. Geosci. Remote Sens.*, vol. 50, no. 5, pp. 1427–1439, May 2012.

[30] C. Albergel, P. de Rosnay, C. Gruhier, J. Munoz-Sabater, S. H. L. Isaksen, Y. Kerr, and W. Wagner, "Evaluation of remotely sensed and modelled soil moisture products using global ground-based in situ observations," *Remote Sens. Environ.*, vol. 118, pp. 215–226, Mar. 2012.

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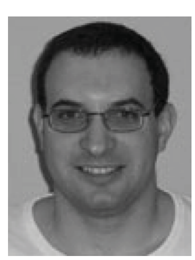

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Comparison Between SMOS, VUA, ASCAT, and ECMWF Soil Moisture Products Over Four Watersheds in U.S.

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***Abstract*— As part of the Soil Moisture and Ocean Salinity (SMOS) validation process, a comparison of the skills of three satellites [SMOS, Advanced Microwave Scanning Radiometer-Earth Observing System (AMSR-E) or Advanced Microwave Scanning Radiometer, and Advanced Scatterometer (ASCAT)], and one-model European Centre for Medium Range Weather Forecasting (ECMWF) soil moisture products is conducted over four watersheds located in the U.S. The four products compared in for 2010 over four soil moisture networks were used for the calibration of AMSR-E. The results indicate that SMOS retrievals are closest to the ground measurements with a low average root mean square error of 0.061 m $^{3}\cdot$ m^{-3} for the morning overpass and 0.067 m $^{3}\cdot$ m^{-3} for the afternoon overpass, which represents an improvement by a factor of 2–3 compared with the other products. The ECMWF product has good correlation coefficients (around 0.78) but has a constant bias of 0.1–0.2 m $^{3}\cdot$ m^{-3} over the four networks. The land parameter retrieval model AMSR-E product gives reasonable results in terms of correlation (around 0.73) but has a variable seasonal bias over the year. The ASCAT soil moisture index is found to be very noisy and unstable.**

***Index Terms*— Soil moisture, Soil Moisture and Ocean Salinity (SMOS), validation.**

I. Introduction

SOIL moisture is an important variable in the study of seasonal climate evolution and prediction as it plays a major role in the mass and energy transfers between the soil and the atmosphere [1]. In land surface models, soil moisture is the key parameter in determining the evaporative fraction at the surface and the infiltration in the root zone. Soil moisture information is also essential for agriculture at a local scale and for water resources management at a regional scale. At the global scale, soil moisture is of great value for weather forecasting [2], climate change [3], and monitoring extreme events such as floods.

Recently, satellite missions specially designed for soil moisture monitoring are implemented (Soil Moisture and Ocean Salinity (SMOS) [4]) and proposed (Soil Moisture Active Passive (SMAP) [5]). SMOS was successfully launched by the European Space Agency in November 2009 and SMAP is scheduled for launch in October 2014 by the National Aeronautics and Space Administration. Both satellite instruments are designed to acquire data at the most suitable frequency for soil moisture retrieval (1.4 GHz [6]).

Several approaches are developed to retrieve soil moisture using the higher frequencies that are the only option until now. These include passive Scanning Multispectral Microwave Radiometer (SMMR, 1978–1987 [7]), passive Special Sensor Microwave/Imager (SSM/I, 1987 [7]), passive Advanced Microwave Scanning Radiometer-Earth Observing System (AMSR-E, 2002) [7], [8], WindSat (passive instrument, 2003 [9]), and active Advanced Scatterometer (ASCAT, 1991) [10]). Although their lowest frequencies (5–20 GHz) are not the most suitable for soil moisture retrievals because of their high sensitivity to the vegetation and the atmosphere, they provide valuable data since 1978.

All of the products above are obtained at a relatively coarse resolution, typically around 50 km, and relating them to point measurements for validation purposes is not always straightforward especially at a global scale. Therefore, it is necessary to validate coarse scale soil moisture estimates with model outputs or *in situ* observations from dense networks that represent area average soil moisture conditions. For SMOS, the initial validation is performed on a number of sites [11] and [12]. However, it is also necessary to compare the new SMOS product to already existing products. Here, we use alternative satellite products and outputs from a model-based system. We use *in situ* data to establish the performance and reliability of each product.

The following section describes the comparison of the four soil moisture data sets over four watersheds. The methodology used is described in Section III. Results from the comparison with ground measurements are analyzed

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in Section IV. Finally, some conclusions are summarized in the last section.

II. Data

A. Satellite-Based Soil Moisture Products

1) SMOS: The SMOS [4] satellite was launched in November 2009. This is the first satellite specially dedicated to soil moisture retrieval with an L-band passive radiometer (1.4 GHz [6]). SMOS provides global coverage in less than three days with a 43-km resolution. The satellite is polar orbiting with equator crossing times of 6:00 A.M. [local solar time (LST), ascending] and 6:00 P.M. (LST, descending). It is assumed that at L-band the signal is mainly influenced by the soil moisture contained in the first 5 cm of the soil on average over low vegetated areas.

SMOS acquires brightness temperatures at multiple incidence angles, from 0° to 55° with full-polarization mode. The angular signature is a key element of the algorithm that retrieves the soil moisture and the vegetation optical depth, which expresses the quantity of signal that is absorbed by the vegetation layer, through the minimization of a cost function between modeled (L-band microwave emission of the biosphere model [13]) and acquired brightness temperatures [14]. The novelty of the SMOS algorithm is that the heterogeneity inside the field of view of the radiometer is considered. Around each node of the SMOS grid, an extended grid of 123×123 km at a 4-km resolution, called the working area, is defined to quantify the heterogeneity seen by the radiometer. Each working area node belongs to one of the ten following landcover classes (aggregated from ECOCLIMAP landcover ecosystems, [15]): vegetation, forest, wetland, saline water, fresh water, barren, permanent ice, urban area, frost, and snow. In the SMOS algorithm, a specific radiative transfer model is associated with each class and it is thus possible to quantify the contribution of each of these classes. Considering the antenna pattern of the instrument, a weighting function is applied. The soil moisture and the vegetation optical depth are then retrieved over the relevant fractions, i.e., vegetated areas and forest (e.g., no retrieval is performed if the main class is waterbody). More information can be found in [14] and in the algorithm theoretical basis document [16]. These retrieval products are known as level 2 products [14] and are available on the icosahedral snyder equal area (ISEA)-4h9 grid, [17]. The nodes of this grid are equally spaced at 15 km. In this paper, the SMOS products used came from the reprocessing campaign using the version 5.01 of the level 2 soil moisture processor.

2) ASCAT: The ASCAT was launched in October 2006 on the MetOp-A satellite as a follow-on to the European Remote Sensing (ERS) satellites with the SCAT scatterometer that started operating in 1991. Since its launch, it is acquiring data at C-band (5.3 GHz). The scatterometer is composed of six beams: three on each side of the satellite track with azimuth angles of 45°, 90°, and 135° azimuth angles (incidence angles are in a range of 25°–64°), which generates two swaths of 550 km each with a spatial resolution of 25 or 50 km. The crossing times are 9:30 P.M. LST for the ascending orbit and 9:30 A.M. LST for the descending orbit.

In this paper, the ASCAT 25-km soil moisture product is downloaded from the Eumetsat data center and retrieval is performed using the Technische Universität Wien soil moisture algorithm [10], [18] that uses wet and dry references from the ERS satellites between 1992 and 2007 to retrieve an index ranging from 0 (dry) to 1 (wet) that represents the relative soil moisture of the first 2 cm of the soil.

3) AMSR-E: The AMSR-E was launched in June 2002 on the Aqua satellite and stopped producing data in October 2011. This radiometer acquired data with a single 55° incidence angle at six different frequencies: 6.9, 10.7, 18.7, 23.8, 36.5, and 89.0 GHz, all dual polarized. The crossing times are 1:30 A.M. (LST, descending) and 1:30 P.M. (LST, ascending). The footprint of the antenna is around 43×75 km at 6.9 GHz and 29×51 km at 10.7 GHz with a spatial resolution of 60 km at 6.9 GHz and 50 km at 10.7 GHz [19].

There are several products available that used AMSR-E data to estimate soil moisture. Many studies already shown that the official product from the National Snow and Ice Data Center is not able to reproduce low values of soil moisture [20]–[23]. The soil moisture product from the Vrije University of Amsterdam (VUA) [7] is therefore chosen in this paper.

The land parameter retrieval model [7] from the VUA retrieves the soil moisture and the vegetation optical depth using the combination of the C- and X-band AMSR-E channels and the 36.5-GHz channel to estimate the surface temperature. X-band observations are used in the areas of the world where C-band observations are affected by radio frequency interferences (RFIs). This algorithm is based on a microwave radiative transfer model with *a priori* information about soil characteristics. The operational VUA product is available on a 0.25° grid only for the descending orbit. The distributed data over this grid are quality checked and the data that are flagged are filtered out because of high topography or extreme weather conditions, such as snow, that would decrease the observed brightness temperatures and result in higher soil moisture estimates. The VUA product used in this paper is the version 3 product.

B. Model-Based Soil Moisture Product European Centre for Medium Range Weather Forecasting (ECMWF)

The ECMWF provides medium range global forecasts and this process produces some environmental variables that include soil temperature, evaporation, and soil moisture.

The SMOS level 2 processor uses a custom made climate data product from ECMWF that is used to set the initial values in the cost function solution and to model the contributions to the signal of the different parts of the scene seen by the radiometer. This is a forecast product generated 3–15 h in advance and every 3 h (at 3:00 A.M., 6:00 A.M., 9:00 A.M., and so on). It is considered an internal SMOS product as it is interpolated at SMOS overpass times and over the SMOS grid. Thus, this custom ECMWF product has the same spatial and temporal resolutions as SMOS and will be used in this paper.

The ECMWF soil moisture represents the top 7 cm below the surface.

ECMWWF auxiliary product information can be found in [4], [14], or [16].

C. In Situ Measurements

Four watersheds located in the United States are selected for this paper: Walnut Gulch (WG) in Arizona, Little Washita (LW) in Oklahoma, Little River (LR) in Georgia, and Reynolds Creeks in Idaho. They represent different types of climate (from semiarid to humid) and land use and are in operation since 2002 [24].

WG is located in southeast Arizona. Most of this watershed is covered by shrubs and grass, which is typical of the region. The annual mean temperature is 17.6 °C at Tombstone and the annual mean precipitation is 320 mm, mainly from high intensity convective thunderstorms in the late summer. The upper most 10 cm of the soil profile contains up to 60% gravel and the underlying horizons usually contains less than 40% gravels.

LW is located in southwest Oklahoma in the southern Great Plains region of the U.S. The climate is subhumid with an average annual rainfall of 750 mm, which falls mainly during the spring and fall seasons. Topography is moderately rolling with a maximum relief of less than 200 m and land use is dominated by rangeland and pasture (63%).

LR is located in southern Georgia near Tifton. With an average annual precipitation of 1200 mm, the climate is humid. This watershed is typical of the heavily vegetated slow-moving stream systems in the coastal plain region of the U.S. The topography over this watershed is relatively flat. Approximately 40% of the watershed is forest with 40% crops and 15% pasture.

RC is located in a mountainous area of southwest Idaho. The topography is high with a relief of over 1000 m that results in diverse climates, soils, and vegetation typical of this part of the Rocky Mountains. The climate is considered to be semiarid with an annual precipitation of 500 mm. Approximately 75% of the annual precipitation at high elevation is snow whereas only 25% is snow at low elevation.

Surface soil moisture and temperature sensors (0–5 cm) are acquiring data since 2002 for the four watersheds. The data used in this paper are the averages of the sensors located in each watershed (with the weighting coefficients derived from a Thiessen polygon). These averages are based on the same sets of sensors from 2002. The *in situ* soil moisture data set was distributed for the period of 2001–2011 and because of a significant change in the station configuration in 2005–2006, only a limited number of stations is considered reliable for the entire period (14/8/8/15 sensors for WG/LW/LR/RC, respectively). Therefore, even though we only use the 2010 data in this paper, only data from the stations considered reliable for the entire period are used. In addition, several sensors are disregarded because of poor or suspicious performances as follows: 1) sensors with periods of missing data are removed and only locations with continuous data are used in the analysis; 2) the sensors are calibrated and

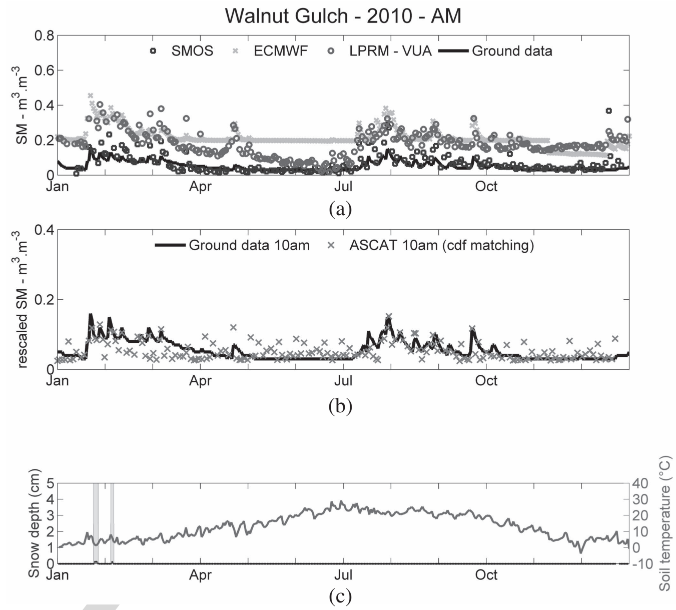

Fig. 1. (a) Time series of 2010 morning soil moisture over WG retrieved by SMOS, ECMWF, VUA, and *in situ* measurements. (b) Linearly scaled ASCAT soil moisture and *in situ* measurements. (c) Snow depth from ECMWF with measured soil temperature. Snowing and freezing days: blue shadows on (c).

checked during a field experiment and sensors/locations that did not agree well with the *in situ* observations are removed; 3) a temporal stability analysis is performed with all the *in situ* data and bad locations are removed; and 4) the sensors that did not respond well (visually) to precipitation events are removed. Soil moisture data are acquired every 30 min (hourly for RC). LW and LR watersheds are equipped with precipitation sensors that recorded data every 30 min. Table I shows the characteristics of each watershed.

D. Snow Cover and Soil Temperature Information

Additional information on the snow presence over each watershed is used in this paper. The ECMWF snow cover variable is used to remove data during days of snow cover and freezing events. Like the ECMWF soil moisture product, the snow depth is available at SMOS resolution and overpass time. It is natively available on a 0.225° grid every 3 h and is interpolated spatially and temporally to match SMOS requirements for use in the SMOS algorithm. The snow depth represents the amount of snow in centimeter present at the surface of the ground.

The soil temperature is also measured by the ground stations. Like the soil moisture, the temperature values from the different stations are given averaged over each watershed.

III. Data Preprocessing and Methodology

VUA and ASCAT grid products are first linearly interpolated on the SMOS grid. The distributed *in situ* soil moisture measurements are an average of different sensors representing an area that is comparable with a satellite footprint [24]. The networks of the four watersheds are specially designed for this purpose and the *in situ* data are furnished with a list of SMOS nodes that are covered by these networks. By averaging the

TABLE I

WATERSHED CHARACTERISTICS: NUMBER OF STATIONS MEASURING SOIL MOISTURE AT 5 cm, CLIMATE, ANNUAL RAINFALL, TOPOGRAPHY, AND MAIN SOIL USE [24]

Watershed	Nb. Stations	Climate	Annual Precip. (mm)	Topography	Soil Use
WG	14	Semiarid	320	Rolling	Range
LW	8	Subhumid	750	Rolling	Range/wheat
LR	8	Humid	1200	Flat	Row crop/forest
RC	15	Semiarid	500	Mountainous	Range

retrieved soil moisture values from these specific nodes, it is then possible to fairly compare this average with the *in situ* measurements. This method is already used to compare SMOS soil moisture to ground measurements in [12].

In order for the comparison to be fair, statistics are computed for the common dates and for the nonsnowing/freezing dates considering the five data sets: SMOS, ECMWF, VUA, ASCAT, and the ground measurements. Because of a change in the ECMWF system in November 2010, the statistics did not consider the data after this date. The statistics are therefore representative of the period from January 1 to November 9. After filtering, the number of available dates is 48/57/44/50 for the morning overpass comparison of WG/LW/LR/RC and 61/72/50/70 for the afternoon overpass comparison. There are more dates for the afternoon comparison as the VUA data set is not available in the afternoon and thus not considered. Days of snow cover are determined with the snow depth variable from ECMWF: when the snow depth is greater than 0 cm, data from that day are not considered. Days with freezing events are determined with the soil temperature variable: when the soil temperature is lower than −3 °C, the soil is considered to be frozen and the day is not considered. These days of snow cover and/or freezing events are shown in Figs. 1–4 on the bottom panels by the shaded zones. Statistics are then computed with the *in situ* soil moisture measured at the satellite overpasses.

Linear correlation coefficient (R), standard error of estimate (SEE) between derived soil moisture and *in situ* measurements SEE, bias and root mean square error (RMSE) are computed for each data set with the ground measurements over each watershed at the corresponding overpass times. The SEE measures the difference in the variability between two data sets, if SEE = 0 the two data sets have the same variability without considering any existing bias. The bias is the difference between the annual means of the two data sets. The RMSE considers both the bias and the difference in the variability and it is recalled that $\text{RMSE}^2 = \text{SEE}^2 + \text{bias}^2$. R measures the intensity of a possible linear relationship between the two data sets. As there are very few points considered for these statistical computations, 95% confidence intervals are also computed for the correlation coefficient and the SEE.

Previously, the ASCAT soil moisture product is an index varying between zero and one and cannot be directly compared with ground measurements and the other data sets. A linear rescaling is therefore performed on ASCAT data between the minimum and the maximum values of the *in situ* data for each watershed (the snowing and the freezing days are filtered out beforehand). However, by performing this rescaling, the ASCAT statistical results are improved unfairly in comparison with the other data sets because the bias is removed by the rescaling. Therefore, apart from the correlation coefficient, the SEE, bias, and RMSE values are not calculated.

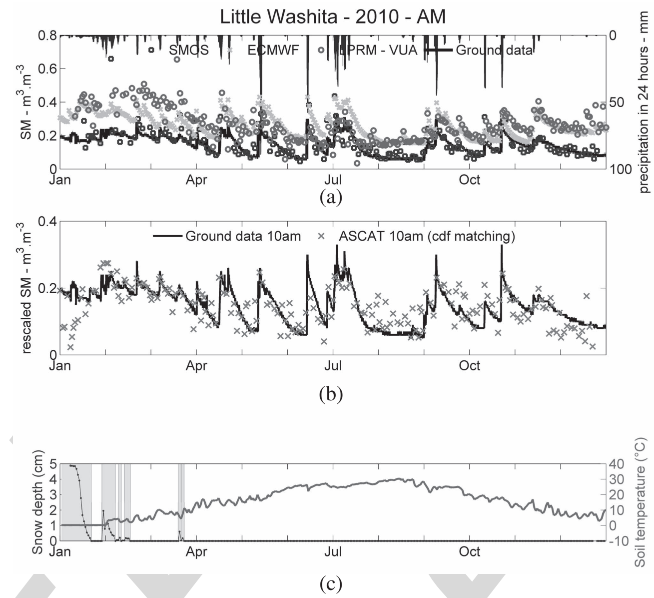

Fig. 2. (a) Time series of 2010 morning soil moisture over LW retrieved by SMOS, ECMWF, VUA, and *in situ* soil moisture and precipitation measurements. (b) Linearly scaled ASCAT soil moisture and *in situ* measurements. (c) Snow depth from ECMWF with measured soil temperature. Snowing and freezing days: blue shadows on (c).

IV. RESULTS AND DISCUSSION

A. Comparison With Ground Measurements

The time series over 2010 of SMOS, ECMWF, VUA, and ASCAT soil moisture products are shown in Figs. 1–4 for each watershed along with the ground measurements. In addition, complementary information (snow depth and soil temperature) is added to each time series and precipitation as well for LW and LR.

Table II and Figs. 5 and 6 show the statistical scores of the comparison between the four data sets (SMOS, ECMWF, VUA, and ASCAT) and the *in situ* measurements over the four watersheds. The correlation coefficient (R), the SEE, the bias, and the RMSE are computed separately for the morning and afternoon overpasses.

1) Walnut Gulch: WG is the driest site of this paper. The *in situ* soil moisture measurements are rarely above 0.10 $m^3 \cdot m^{-3}$ (Fig. 1). For the morning overpasses, SMOS have the best results with a very good correlation coefficient ($R = 0.87$) associated to the lowest bias (0.029 $m^3 \cdot m^{-3}$) and the lowest RMSE (0.054 $m^3 \cdot m^{-3}$) of the tested data sets (Table II). For the afternoon overpasses, SMOS and ECMWF

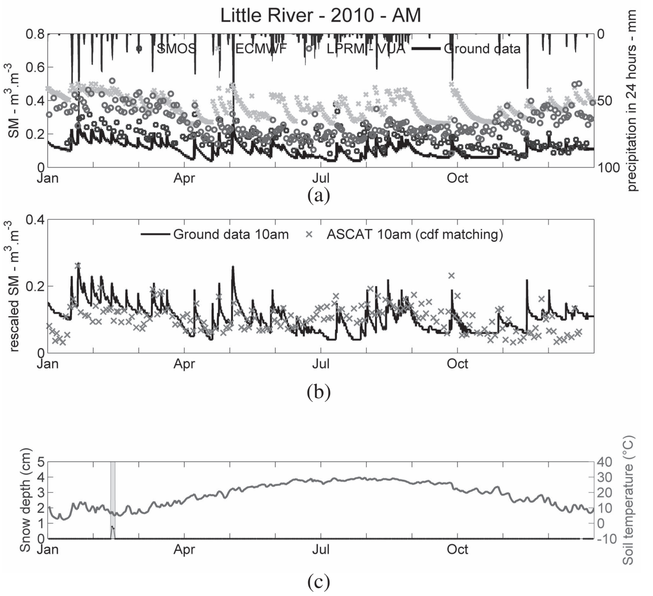

Fig. 3. (a) Time series of 2010 morning soil moisture over LR retrieved by SMOS, ECMWF, VUA, and *in situ* soil moisture and precipitation measurements. (b) Linearly scaled ASCAT soil moisture and *in situ* measurements. (c) Snow depth from ECMWF with measured soil temperature. Snowing and freezing days: blue shadows on (c).

are significantly better than VUA or ASCAT in terms of correlation (0.70 and 0.77) but SMOS is better than all the other products regarding the bias (0.014 $m^3 \cdot m^{-3}$) and the RMSE (0.054 $m^3 \cdot m^{-3}$), see Table II. Over this watershed, the SMOS product improved the bias by a factor of 8 and the RMSE by a factor of 3 when compared with the ECMWF and the VUA products, while keeping an equivalent or better correlation coefficient.

Observing more closely at the seasonal trends, SMOS tends to underestimate the soil moisture during the dry season (March–July) and performed better during the winter dry season (October–December) than during the rest of the year. However, the SMOS time series follow correctly the *in situ* soil moisture time series.

The ECMWF product exhibits the highest bias with the *in situ* measurements (Figs. 1–5). However, ECMWF is closer to the *in situ* measurements after mid November than before when the surface model is revised, which reduced ECMWF soil moisture positive bias in dry areas. ECMWF bias is lower than VUA bias after mid November. The ECMWF soil moisture followed correctly the *in situ* measurements even though some soil moisture increases are not observed. Most of the ECMWF bias is due to its high minimum soil moisture level at around 0.20 $m^3 \cdot m^{-3}$ before mid November and 0.12 $m^3 \cdot m^{-3}$ after.

In Fig. 1, VUA is close to the ground measurements in June when the soil is at its driest point and the soil temperature is very high and no rain event occurred (no change in the soil moisture time series). The largest VUA bias (0.15 $m^3 \cdot m^{-3}$) is found in winter (October–February) when the vegetation is assumed to be less and when the temperature is lower.

The ASCAT time series is very noisy and even though the increases in soil moisture are apparent (Fig. 5), the dry season is not well-described when the soil moisture is low and stable.

2) Little Washita: The LW site have the largest range of *in situ* soil moisture (0.1–0.3 $m^3 \cdot m^{-3}$, Fig. 2). There are very little data considered in January and February because of the snow and freezing events during this period. For the morning overpasses, SMOS and ECMWF have better correlation coefficients but they are not significantly better than VUA and ASCAT because their 95% confidence intervals overlap. With a bias of 0.013 $m^3 \cdot m^{-3}$ and a RMSE of 0.048 $m^3 \cdot m^{-3}$, the SMOS product is closer to the ground measurements than the other products (Table II). For the afternoon overpasses, SMOS and ECMWF products are comparable in terms of correlation (0.62 and 0.70, respectively). However, SMOS has a very low bias (0.017 $m^3 \cdot m^{-3}$) and this resulted in a RMSE value of 0.072 $m^3 \cdot m^{-3}$ (Table II). Over the LW watershed, SMOS improved the bias between retrieved or modeled soil moisture and *in situ* measurements by a factor of 5 and the RMSE by a factor of 1.5 for a statistically equivalent correlation (i.e., even if the correlation coefficients are not the same, their confidence intervals overlap, Table II).

Fig. 2 shows that the SMOS, VUA, and ECMWF products described correctly all the rain events except at the beginning of the year (January–April) when there are consecutive small rainfalls and the SMOS and VUA products became more scattered. The rain events of May–July are particularly well-reproduced by SMOS and ECMWF with expected decreases from the infiltration and evaporation processes. However, the first SMOS retrieval after a rain event is overestimated most of the time.

The ECMWF product presents good results in terms of correlation (0.85 for the morning and 0.70 for the afternoon) but this product is still penalized by its general bias throughout the year (around 0.10 $m^3 \cdot m^{-3}$) that can be clearly identified on Fig. 5.

VUA exhibits a variable bias: above 0.20 $m^3 \cdot m^{-3}$ in January and February and near zero in June and July, respectively. As observed in WG, the lowest bias is found when the vegetation is supposed to be fully developed and when the temperature is at its maximum. During this period, the VUA product is closer to the ground measurements than the ECMWF product. Rain events are well-observed by this product but this nonstable bias prevents VUA from having a very good correlation coefficient.

As observed for WG, the ASCAT soil moisture index is again very noisy in LW. ASCAT have its best performance with good soil moisture dynamics during the periods of February–June and November and December (Fig. 2).

3) Little River: LR is the site with the highest frequency of rain events resulting in small variations in the soil moisture time series (Fig. 3). For the morning overpasses, the SMOS and ECMWF products are equivalent in terms of correlation (around 0.72). The SMOS product have the lowest bias (0.088 $m^3 \cdot m^{-3}$) and the lowest RMSE (0.095 $m^3 \cdot m^{-3}$) of all products (Table II). For the afternoon overpasses, even though the SMOS correlation coefficient interval overlaps a little on the ECMWF confidence interval, it can be assumed the ECMWF product has the best correlation coefficient (0.84). However, SMOS is still closer to the ground measurements than the other products with a bias of 0.073 $m^3 \cdot m^{-3}$ and a RMSE of 0.088 $m^3 \cdot m^{-3}$ (Table II). Over the LR watershed

TABLE II

STATISTICAL RESULTS OVER FOUR WATERSHEDS OF SMOS, ECMWF, AMSR-E, AND ASCAT COMPARED WITH *IN SITU* MEASUREMENTS. ASCAT DATA ARE LINEARLY NORMALIZED (ASCATN) IN RANGE OF *IN SITU* MEASUREMENTS. ALL RESULTS ARE STATISTICALLY SIGNIFICANT WITH p-VALUE LESS THAN 0.05. FIG. 6 IS MORE VISUALIZED VERSION OF THESE STATISTICS WITH ERROR BARS ADDED

		Morning					Afternoon				
		R	SEE	Bias	RMSE	Dates	R	SEE	Bias	RMSE	Dates
WG	SMOS	**0.87**	0.046	**0.029**	**0.054**	50	0.70	0.053	**0.014**	**0.054**	61
	ECMWF	0.70	**0.031**	0.169	0.172		0.77	**0.033**	0.166	0.169	
	VUA	0.79	0.062	0.125	0.140		-	-	-	-	
	ASCATn	0.60	-	-	-		0.46	-	-	-	
LW	SMOS	0.83	0.047	**0.013**	**0.048**	59	0.62	0.071	**0.017**	**0.072**	35
	ECMWF	0.85	**0.042**	0.111	0.118		0.70	**0.051**	0.094	0.107	
	VUA	0.69	0.063	0.110	0.127		-	-	-	-	
	ASCATn	0.74	-	-	-		0.53	-	-	-	
LR	SMOS	0.73	**0.037**	**0.088**	**0.095**	48	0.66	0.049	**0.073**	**0.088**	53
	ECMWF	0.71	0.048	0.257	0.262		**0.84**	**0.039**	0.267	0.270	
	VUA	0.59	0.060	0.151	0.162		-	-	-	-	
	ASCATn	0.51	-	-	-		0.38	-	-	-	
RC	SMOS	0.79	0.038	−**0.030**	0.048	54	0.60	0.055	−**0.003**	0.055	74
	ECMWF	**0.89**	0.031	0.070	0.076		**0.82**	**0.035**	0.061	0.070	
	VUA	0.84	0.065	0.057	0.087		-	-	-	-	
	ASCATn	0.70	-	-	-		0.48	-	-	-	

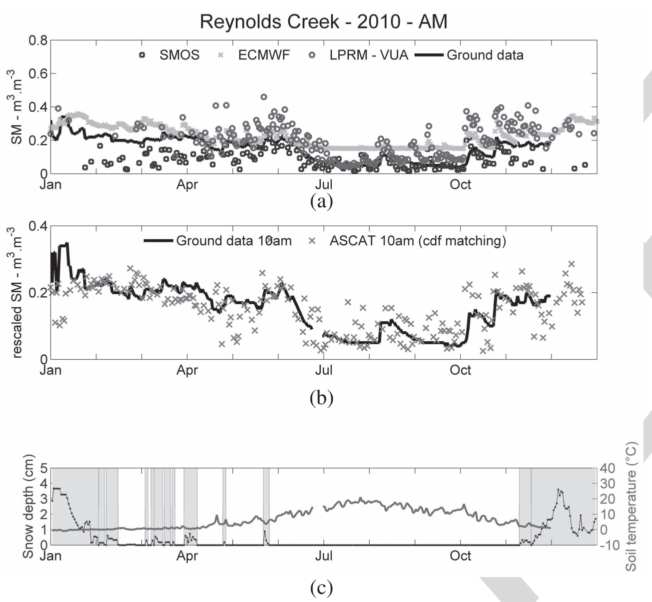

Fig. 4. (a) Time series of 2010 morning soil moisture over RC retrieved by SMOS, ECMWF, VUA, and *in situ* measurements. (b) Linearly scaled ASCAT soil moisture and *in situ* measurements. (c) Snow depth from ECMWF with measured soil temperature. Snowing and freezing days: blue shadows on (c).

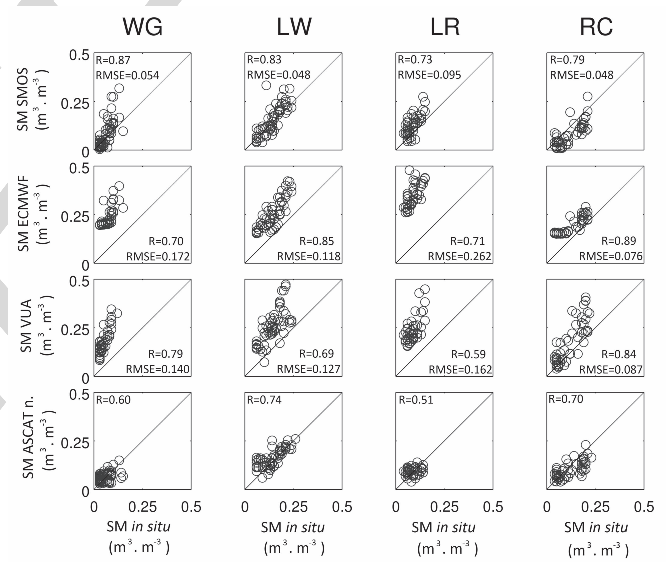

Fig. 5. Only morning overpasses: scatter plots of soil moisture derived from SMOS, ECMWF, VUA, and ASCAT compared with ground measurements in 2010 over four sites. Fourth line: for ASCAT row, scaled soil moistures are compared. More statistics are in Table II and Fig. 6.

SMOS improved the bias by a factor of 3 and the RMSE by a factor of 2 but did not succeed in having an equivalent correlation level in the afternoon.

By observing the evolution of the soil moisture time series in Fig. 3, small repetitive rain events in the first half of the year are observed with difficulty by the satellite products that resulted in scattered retrievals around the ground measurements. From September, SMOS is closer to the *in situ* measurements than during the rest of the year, certainly because there are less rain events. LR is the site where SMOS is the furthest from its mission goal in terms of error. However, this watershed is the most heterogeneous site of this experiment with a lot of forests and wetlands, whose contributions to the signal must be estimated to retrieve only the soil moisture value for the vegetated area of this watershed and this is not easily done.

The ECMWF product has again a high and stable bias throughout the year (around 0.26 $m^3 \cdot m^{-3}$) but it modeled very well all the rain events. Nevertheless, the soil moisture ranges described during these rainfalls are too large compared with the ground measurements (0.20 $m^3 \cdot m^{-3}$ for ECMWF against 0.05 $m^3 \cdot m^{-3}$ for the *in situ*), especially in September and October.

VUA also have its highest bias in LR (0.16–0.30 $m^3 \cdot m^{-3}$). As observed for LW, the bias is lower when the vegetation is denser and when the surface temperatures reached their highest value.

TABLE III
MEAN PROBABILITY OF RFI OCCURRENCES ON SMOS ACQUISITION IN 2010 OVER FOUR WATERSHEDS

	Walnut Gulch	Little Washita	Little River	Reynolds Creek
Morning	0.09%	0.00%	0.38%	2.23%
Afternoon	0.37%	0.38%	0.82%	0.36%

ASCAT soil moisture retrievals reflected well the *in situ* evolution for the period March–June. However, after the month of June, the data became noisier and did not follow the observed soil moisture dynamics. The ground soil moisture decreased in June and July, whereas the ASCAT index increased. This is represented as a wide cloud of points when compared directly with the ground data (Fig. 5). The associated R value is then not representative of this cloud.

4) Reynolds Creek: RC is located in a mountainous region. It represents a challenging set of conditions for the satellite soil moisture retrievals because of the topography and the snow/freezing conditions during the winter season (Fig. 4). For the morning overpasses, all the products are equivalent in terms of correlation. Regarding the bias, SMOS underestimated the soil moisture whereas ECMWF and VUA overestimated it. The RMSE values are found lower over RC for the ECMWF and the VUA products (0.076 $m^3 \cdot m^{-3}$ and 0.087 $m^3 \cdot m^{-3}$, respectively) than over the other test sites (Table II). For the afternoon overpasses, ECMWF correlation (0.82) is significantly better than SMOS and ASCAT. SMOS have the lowest bias (-0.003 $m^3 \cdot m^{-3}$) but still have a value of RMSE of 0.055 $m^3 \cdot m^{-3}$ (Table II).

With the exception of the beginning of the year the general temporal evolution of all soil moisture products followed correctly the trend of the *in situ* data.

RC is the only site where SMOS underestimated the ground measurements (Fig. 5). However, when looking at the period when there is no snow or possibly frozen soil (April–October), SMOS appeared to perform properly and the bias decreased. This can be explained, when the soil is frozen, decreases in the dielectric constant occur and the soil appears as dry [25]. Dry snow is expected to be transparent at L-band [26].

ECMWF exhibits a smaller bias for RC than for the other watersheds, especially during the spring and the fall seasons. However, during the summer, ECMWF seems to have reached a high minimum soil moisture level as its modeled soil moisture values are stable around 0.20 $m^3 \cdot m^{-3}$ whereas the ground measurements are around 0.05 $m^3 \cdot m^{-3}$ (Figs. 4 and 5).

The VUA soil moisture time series in May and June is noisy which might be because of vegetation growth. But between June and October, when the vegetation is denser, the VUA product followed the *in situ* measurements very well with almost no bias.

After the last snow event in late March, the ASCAT product followed correctly the *in situ* measurements and have a good correlation for the morning overpasses ($R = 0.70$).

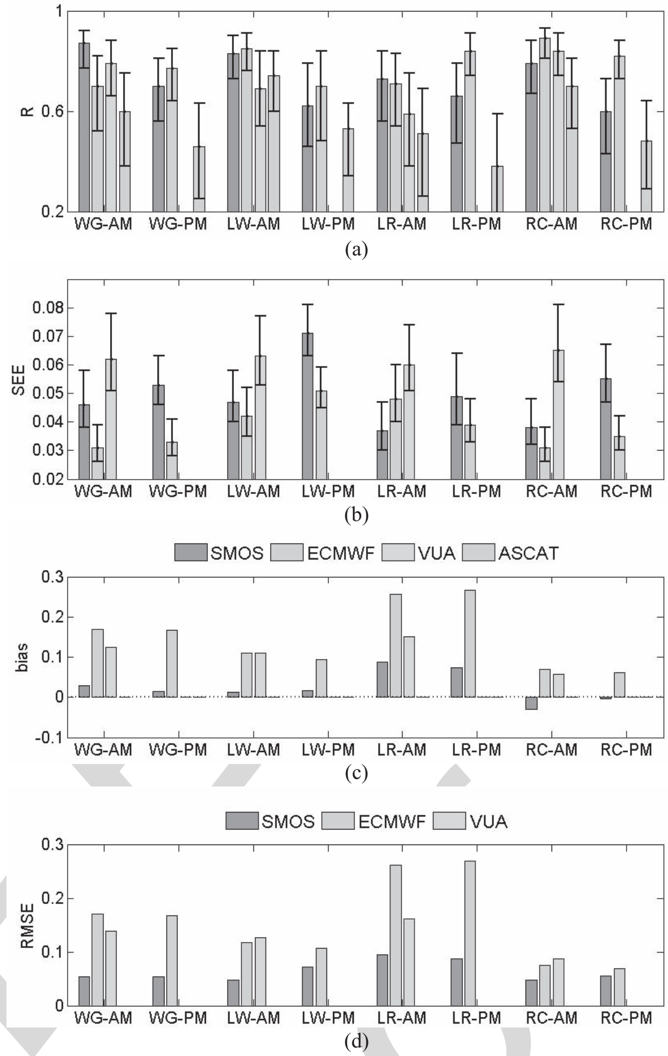

Fig. 6. Statistics regarding comparison between soil moisture from SMOS, ECMWF, VUA, and linearly normalized ASCAT and *in situ* measurements. Four subfigures correspond. (a) Correlation coefficient R. (b) SEE. (c) Bias. (d) RMSE over each watershed. Morning and afternoon comparisons are treated separately and 95% confidence intervals are indicated for R and SEE.

B. Comparison Between the Ascending and the Descending Orbits

Statistical scores for the afternoon overpasses (Table II, Fig. 6) show a lower correlation and a larger scattering for the satellite soil moisture products. The SMOS correlation coefficient have an average across all watersheds of 0.80 in the morning for a SEE of 0.042 $m^3 \cdot m^{-3}$ and a correlation of 0.65 in the afternoon for a SEE of 0.057 $m^3 \cdot m^{-3}$. For the morning overpasses, the ASCAT product has an average correlation of 0.64 and 0.46 for the afternoon.

The SMOS penetration depth is assumed to be between 2 and 5 cm (depending on the soil properties and moisture conditions, [4], [27]) and at 6:00 A.M. when the soil is in a hydraulic quasi-equilibrium, SMOS can be fairly compared with the 5-cm soil moisture measurements [27]. At 6:00 P.M. the soil is not in equilibrium and if SMOS is measuring the soil moisture from the top 3 cm of the soil, the differences with the 5 cm ground measurements will be higher at 6:00 P.M.

than at 6:00 A.M. [27] recommended using morning measurements when comparing with space observations because of the day-time decoupling that could occur in the afternoon because of the nonhydraulic equilibrium of the soil. The same explanations apply for the ASCAT results at 9:30 A.M. and at 9:30 P.M. These results are consistent with the results of [28].

Another possible explanation for these differences between the morning and the afternoon results is still related to the nonequilibrium of the soil and it concerns the assumptions are made concerning the soil surface temperature. It is assumed that the soil and the vegetation temperatures are approximately equal, which is a fair assumption during the night or early morning but during the day, the vegetation temperature is expected to be closer to the air temperature than to the soil temperature. This assumption of equal vegetation and effective soil temperatures can lead to less accurate satellite soil moisture retrievals in the afternoon.

Regarding SMOS results, one last possibility could be the presence of RFIs that are only seen during the descending orbits when the satellite is going in the afternoon from north to south and is pointing in the southwest direction. From the RFI contamination probability maps derived from the mixed polarized acquisitions (real and imaginary parts [16], [29]), it is possible to compute for each watershed the mean probability of RFI occurrences (Table III). Except over RC, the probability of RFI contamination is higher for the afternoon overpasses even if they are still very low compared with highly contaminated regions such as Asia. This difference in RFI contamination between the morning and the afternoon overpasses might partially explain why SMOS results are better in the morning.

V. CONCLUSION

SMOS data were compared with *in situ* observations and other satellite data and model outputs. SMOS, VUA, ECMWF, and ASCAT soil moisture retrievals were compared with the *in situ* measurements and intercompared over four different sites in the U.S. under various climate conditions and soil characteristics.

Over the four test sites, no specific product had a significantly better correlation with the ground measurements. Since this paper only covers the year 2010, 35–74 common dates were considered to compute the statistics and resulted in substantial confidence intervals that made all products equivalent in terms of correlation. The statistical parameters used to differentiate the four data sets were the SEE, the bias, and logically the RMSE. Over most of the watersheds, ECMWF had a significantly lower SEE (0.039 $m^3 \cdot m^{-3}$ in average) than SMOS (0.049 $m^3 \cdot m^{-3}$ in average) and VUA (0.063 $m^3 \cdot m^{-3}$ for the morning only), representing a less scattered data set. ECMWF soil moisture time evolution was very close to the ground measurements with clear identifications of the rainfall events and the soil drainage afterward. However, SMOS had clearly the lowest bias with an average of 0.032 $m^3 \cdot m^{-3}$ whereas ECMWF had a mean bias of 0.150 $m^3 \cdot m^{-3}$ and VUA of 0.129 $m^3 \cdot m^{-3}$. SMOS also had the lowest RMSE over all the sites except RC. SMOS had a mean RMSE of 0.064 $m^3 \cdot m^{-3}$ whereas ECMWF had a mean RMSE of 0.156 $m^3 \cdot m^{-3}$ and VUA of 0.129 $m^3 \cdot m^{-3}$ (for the morning only). Therefore, although the SMOS mission accuracy objective of 0.040 $m^3 \cdot m^{-3}$ was not reached over these four watersheds in 2010, SMOS improved the total RMSE by a factor of at least 2 on average in 2010 for an equivalent correlation compared with the other soil moisture products.

The time series analysis revealed a positive constant bias in the ECMWF data set: 0.17/0.10/ 0.26/0.07 $m^3 \cdot m^{-3}$, respectively for the WG/LW/LR/RC watersheds. Even after mid-November when the surface model and analysis were revised, this bias was still present over all the watersheds but had decreased over WG (data after mid-November were not considered in the statistical results). Despite very good correlation coefficients, this minimum level was a major obstacle in using ECMWF for the four test sites. VUA also had a bias but was not constant and appeared to evolve with the seasons. The bias was higher when the vegetation and the soil temperature were low (during winter) and tended to decrease when the vegetation was supposed to be denser and the soil temperature increasing to its maximum in the summer, resulting in a quasi-null bias. This evolution of the VUA bias throughout the year was assumed to be linked to a physical parameter such as the vegetation or the temperature since it evolved with the seasons and because the AMSR-E frequencies (6.9 and 10.7 GHz) were more sensitive to the vegetation layer than SMOS at 1.4 GHz. It was also possible that this bias was due to the soil effective temperature that was modeled through the 36-GHz brightness temperature or to another assumption that was made in the VUA algorithm. The ASCAT soil moisture index was very noisy in comparison with the other products and even though some rain events were obvious in the retrievals, the *in situ* soil moisture dynamics were not well-represented for any of the watersheds. Active microwave observations were very sensitive to surface roughness and WG, for example, had sandy soils with significant amount of gravel. These soil characteristics resulted in a greater surface roughness which could explain partially the poor results of ASCAT.

The comparison of the statistical performances of the products between the morning and the afternoon revealed that the ECMWF model did not show significant differences whereas the satellite SMOS and ASCAT products showed several differences: $R = 0.80/0.65$, $SEE = 0.042/0.057$ $m^3 \cdot m^{-3}$, bias $=$ 0.040/0.027 $m^3 \cdot m^{-3}$, RMSE $=$ 0.061/0.067 $m^3 \cdot m^{-3}$ for SMOS, and $R = 0.64/0.46$ for ASCAT (A.M./P.M. in average over the four watersheds). These differences in performance can be explained that in the morning, the soil was in hydraulic quasi-equilibrium. On the other hand for the afternoon, this comparison might not be as correct as for the morning. Another explanation could be the inaccurate modeling of the soil and the vegetation temperatures in the retrieval algorithm. They were assumed to be equal and this assumption might not be true in the afternoon when the vegetation temperature was expected to be closer to the air temperature than to the soil temperature. The last possible explanation for SMOS performance difference concerned the RFI. The occurrence probabilities of

RFI in 2010 were higher in the afternoon than in the morning except over RC.

The results of this paper concur with the different studies that were realized in the frame of the SMOS soil moisture product validation [11], [12], [14], [30]. SMOS soil moisture retrievals were already very close to the ground measurements but need to be improved to meet its scientific goal of an error less than 0.04 $m^3 \cdot m^{-3}$. In this perspective, a new version of the level 2 soil moisture processor (v5.51) was already in place since March 2012 and allowed to switch between the Dobson and the Mironov constant dielectric model and this version showed promising first results.

The main advantage in comparing satellite products was the possibility of comparing with global coverage and further studies will be developed in this direction in the near future.

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REFERENCES

[1] "Implementation plan for the global observing system for climate in support of the UNFCCC," World Meteorological Organ., Intergovern. Oceanogr. Commission, United Nations Environ. Progr., International Council Science, Geneva, Switzerland, Tech. Rep. 1244, 2010.

[2] M. Drusch, "Initializing numerical weather predictions models with satellite derived surface soil moisture: Data assimilation experiments with ECMWF's integrated forecast system and the TMI soil moisture data set," *J. Geophys. Res.*, vol. 113, no. D3, p. D03102, Feb. 2007.

[3] H. Douville and F. Chauvin, "Relevance of soil moisture for seasonal climate predictions: A preliminary study," *Climate Dynamics*, vol. 16, nos. 10–11, pp. 719–736, Oct. 2000.

[4] Y. Kerr, P. Waldteufel, J. Wigneron, S. Delwart, F. Cabot, J. Boutin, M. Escorihuela, J. Font, N. Reul, C. Gruhier, S. Juglea, M. Drinkwater, A. Hahne, M. Martin-Neira, and S. Mecklenburg, "The SMOS mission: New tool for monitoring key elements of the global water cycle," *Proc. IEEE*, vol. 98, no. 5, pp. 666–687, May 2010.

[5] D. Entekhabi, E. Njoku, P. E. O. Neill, K. Kellogg, W. Crow, W. Edelstein, J. Entin, S. Goodman, T. Jackson, J. Johnson, J. Kimball, J. Piepmeier, R. Koster, N. Martin, K. McDonald, M. Moghaddam, S. Moran, R. Reichle, J. Shi, M. Spencer, S. Thurman, L. Tsang, and J. Zyl, "The soil moisture active passive (smap) mission," *Proc. IEEE*, vol. 98, no. 5, pp. 704–716, May 2010.

[6] Y. Kerr, P. Waldteufel, J. Wigneron, J. Martinuzzi, J. Font, and M. Berger, "Soil moisture retrieval from space: The soil moisture and ocean salinity (SMOS) mission," *IEEE Trans. Geosci. Remote Sens.*, vol. 39, no. 8, pp. 1729–1735, Aug. 2001.

[7] M. Owe, R. de Jeu, and J. Walker, "A methodology for surface soil moisture and vegetation optical depth retrieval using the microwave polarization difference index," *IEEE Trans. Geosci. Remote Sens.*, vol. 39, no. 8, pp. 1643–1654, Aug. 2001.

[8] E. Njoku, T. Jackson, V. Lakshmi, T. Chan, and S. Nghiem, "Soil moisture retrieval from ASMR-E," *IEEE Trans. Geosci. Remote Sens.*, vol. 41, no. 2, pp. 215–229, Feb. 2003.

[9] L. Li, P. Gaiser, B. Gao, R. Bevilacqua, T. Jackson, E. Njoku, C. Rüdiger, J. Calvet, and R. Bindlish, "Windsat global soil moisture retrieval and validation," *IEEE Trans. Geosci. Remote Sens.*, vol. 48, no. 5, pp. 2224–2241, May 2010.

[10] V. Naeimi, K. Scipal, Z. Bartalis, and S. H. W. Wagner, "An improved soil moisture retrieval algorithm for ERS and METOP scatterometer observations," *IEEE Trans. Geosci. Remote Sens.*, vol. 47, no. 7, pp. 1999–2013, Jul. 2009.

[11] A. A. Bitar, D. Leroux, Y. Kerr, O. Merlin, P. Richaume, A. Sahoo, and E. Wood, "Evaluation of SMOS soil moisture products over continental U.S. Using SCAN/SNOTEL network," *IEEE Trans. Geosci. Remote Sens.*, vol. 50, no. 5, pp. 1572–1586, May 2012.

[12] T. Jackson, R. Bindlish, M. Cosh, T. Zhao, P. Starks, D. Bosch, M. Seyfried, S. Moran, Y. Kerr, and D. Leroux, "Validation of soil moisture ocean salinity (SMOS) soil moisture over watershed networks in the U.S.," *IEEE Trans. Geosci. Remote Sens.*, vol. 50, no. 5, pp. 1530–1543, May 2012.

[13] J. Wigneron, Y. Kerr, P. Waldteufel, K. Saleh, M. Escorihuela, P. Richaume, P. Ferrazzoli, P. de Rosnay, R. Gurney, J. Calvet, J. Grant, M. Guglielmetti, B. Hornbuckle, C. Mätzler, T. Pellarin, and M. Schwank, "L-band microwave emission of the biosphere (L-MEB) model: Description and calibration against experimental data sets over crop fields," *Remote Sens. Environ.*, vol. 107, no. 4, pp. 639–655, Apr. 2007.

[14] Y. Kerr, P. Waldteufel, P. Richaume, J. Wigneron, P. Ferrazzoli, A. Mahmoodi, A. Al Bitar, F. Cabot, C. Gruhier, S. Juglea, D. Leroux, A. Mialon, and S. Delwart, "The SMOS soil moisture retrieval algorithm," *IEEE Trans. Geosci. Remote Sens.*, vol. 50, no. 5, pp. 1384–1403, May 2012.

[15] V. Masson, J.-L. Champeau, F. Chauvin, C. Meriguet, and R. Lacaze, "A global data base of land surface parameters at 1-km resolution in meteorological and climate models," *J. Climate*, vol. 16, no. 9, pp. 1261–1282, May 2003.

[16] "Algorithm theoretical basis document," Tech. Rep. 3.d, CESBIO, Toulouse, France, IPSL, Paris, France, INRA-EPHYSE, Bordeaux, France, Reading University, Reading, England, Tor Vergata University, Rome, Italy, 2010.

[17] D. Carr, R. Kahn, K. Sahr, and T. Olsen, "Isea discrete global grids," *Stat. Comput. Stat. Graph. Newlett.*, vol. 8, nos. 2–3, pp. 31–39, 1997.

[18] W. Wagner, G. Lemoine, and H. Rott, "A method for estimating soil moisture from ERS scatterometer and soil data," *Remote Sens. Environ.*, vol. 70, no. 2, pp. 191–207, Nov. 1999.

[19] "AMSR-E data users handbook," Japan Aerospace Exploration Agency (JAXA), Washington, DC, USA, Tech. Rep. NCX-030021, Mar. 2006.

[20] C. Gruhier, P. de Rosnay, Y. Kerr, E. Mougin, E. Ceschia, J. Calvet, and P. Richaume, "Evaluation of AMSR-E soil moisture product based on ground measurements over temperate and semi-arid regions," *Geophys. Res. Lett.*, vol. 35, no. 10, p. L10405, May 2008.

[21] C. Rudiger, J. C. Calvet, C. Gruhier, T. Holmes, R. de Jeu, and W. Wagner, "An intercomparison of ERS-Scat and AMSR-E soil moisture observations with model simulations over france," *Amer. Meteorol. Soc.*, vol. 10, no. 2, pp. 431–447, Apr. 2009.

[22] C. Draper, J. Walker, P. Steinle, R. de Jeu, and T. Holmes, "An evaluation of AMSR-E derived soil moisture over Australia," *Remote Sens. Environ.*, vol. 113, no. 4, pp. 703–710, Apr. 2009.

[23] C. Gruhier, P. de Rosnay, S. Hasenauer, T. Holmes, R. de Jeu, Y. Kerr, E. Mougin, E. Njoku, F. Timouk, W. Wagner, and M. Zribi, "Soil moisture active and passive microwave products: Intercomparison and evaluation over a sahelian site," *Hydrol. Earth Syst. Sci.*, vol. 14, no. 1, pp. 141–156, Jan. 2010.

[24] T. Jackson, M. Cosh, R. Bindlish, P. Starks, D. Bosch, M. Seyfried, D. Goodrich, M. Moran, and J. Du, "Validation of advanced microwave scanning radiometer soil moisture products," *IEEE Trans. Geosci. Remote Sens.*, vol. 48, no. 12, pp. 4256–4272, Dec. 2010.

[25] C. Matzler, "Passive microwave signatures of landscapes in winter," *Meteorol. Atmospheric Phys.*, vol. 54, nos. 1–4, pp. 241–260, 1994.

[26] R. Armstrong and M. Brodzik, "A twenty year record of global snow cover fluctuations derived from passive microwave remote sensing data," in *Proc. 5th Conf. Polar Meteorol. Oceanography, Amer. Meteorol. Soc.*, Dallas, TX, USA, 1999, pp. 113–117.

[27] T. Jackson, "Profile soil moisture from space measurements," *J. Irrigat. Drainage Divis., ASCE*, vol. 106, pp. 81–92, Mar. 1980.

[28] C. Albergel, C. Rüdiger, D. Carrer, J. Calvet, N. Fritz, V. Naeimi, Z. Bartalis, and S. Hasenauer, "An evaluation of ascat surface soil moisture products with in-situ observations in southwestern france," *Hydrol. Earth Syst. Sci.*, vol. 13, no. 2, pp. 115–124, 2009.

[29] R. Oliva, E. Daganzo-Eusebio, Y. Kerr, S. Mecklenburg, S. Nieto, P. Richaume, and C. Gruhier, "SMOS radio frequency interference scenario: Status and actions taken to improve the RFI environment in the 1400–1427 MHz passive band," *IEEE Trans. Geosci. Remote Sens.*, vol. 50, no. 5, pp. 1427–1439, May 2012.

[30] C. Albergel, P. de Rosnay, C. Gruhier, J. Munoz-Sabater, S. H. L. Isaksen, Y. Kerr, and W. Wagner, "Evaluation of remotely sensed and modelled soil moisture products using global ground-based in situ observations," *Remote Sens. Environ.*, vol. 118, pp. 215–226, Mar. 2012.

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