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SMOS-derived soil moisture anomalies and drought indices: a comparative analysis using *in situ* measurements

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Abstract:

The objective of this analysis is to demonstrate the feasibility of using a composite L2 Soil Moisture and Ocean Salinity (SMOS) soil moisture product for determining drought conditions by taking advantage of its spatial and temporal resolutions. The work investigates the potential relationships between soil moisture anomalies and two drought indices, the Standardized Precipitation Index and the Standardized Precipitation Evapotranspiration Index, both calculated on a ten-day basis. As the two drought indices can be applied to different time scales for precipitation series, the influence of time scale on the drought definition is also studied. The anomalies were calculated both for the *in situ* soil moisture by REMEDHUS (Soil Moisture Measurement Stations Network, Spain) and from the SMOS L2 soil moisture product. In general, *in situ* anomalies exhibit higher correlation coefficients for the drought indices than those of SMOS, except for the shortest time scale. As expected, the short-term remotely sensed anomalies have a high response to precipitation events. This effect may be due to the greater sensitivity of SMOS data to rainfall, as well as to the spatial averaged nature of its observations. The optimal time scale was 1 month for the SMOS values and ranged between 30 and 50 days for the *in situ* values. The use of evapotranspiration in the calculation of the indices did not improve the description of the anomalies. The relationship between indices and soil moisture conditions provides encouraging results. Indeed, this method generates preliminary but valuable insights for future satellite products. Copyright © 2014 John Wiley & Sons, Ltd.

KEY WORDS SMOS; anomalies; soil moisture; SPI; SPEI

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INTRODUCTION

Soil moisture is a key component of the hydrological cycle, which determines run-off generation and groundwater recharge (Western *et al*., 2002). It also largely affects the functioning of the ecosystem (Sitch *et al*., 2003) as well as forest activity and growth (Pastor and Post, 1986). In the context of agriculture, soil moisture influences the yield production as excessive and scarce soil moisture can expose plants to oxygen deficiencies and drought stresses, respectively (Raich and Tufekcioglu, 2000). For these reasons, the accurate estimation of soil moisture variability as a function of time and space is highly relevant to several hydrological, ecological and agricultural applications. Great efforts have been made to estimate soil moisture, and due to the difficulties inherent to *in situ* measurements, the remote sensing approach has become a convincing alternative because of its spatial and temporal coverage. The strategy involves developing new remote sensing soil moisture products to enhance future drought monitoring. Because of the difficulty of extending point-based soil moisture observations to larger areas, microwave remote sensing represents an alternative approach for describing on a continuous spatial basis the soil water content (Schmugge *et al*., 2002). Spatial passive missions operating at frequencies above 5 GHz, such as the Microwave Imager from the Tropical Rainfall Measuring Mission (Gao *et al*., 2006), among others, can be used for soil moisture observations, even though none of these missions are dedicated soil moisture missions (Rüdiger *et al*., 2009). Active microwave products from instruments measuring radar backscatter, such as the Advanced Scatterometer onboard METOP-A, its predecessor scatterometer on board the European Remote Sensing Satellite (ERS-1&2) and the ENVISAT Advanced Synthetic Aperture Radar, also demonstrate the relevance of surface soil moisture retrieval data from space that can be used by the scientific community (Wagner *et al*., 1999; Bartalis *et al*., 2007; Rüdiger *et al*., 2009; Albergel *et al*., 2012).

Satellite missions focusing on soil moisture observations based on the most suitable L-band wavelength for

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soil moisture retrieval are currently underway, including the Soil Moisture and Ocean Salinity (SMOS) (Kerr *et al.*, 2010; Kerr *et al.*, 2012; Mecklenburg *et al.*, 2012) from the European Space Agency (ESA) and the future Soil Moisture Active Passive from National Aeronautics and Space Administration (Entekhabi *et al.*, 2010).

After the end of its commissioning phase in May 2010, the SMOS mission is being continuously providing data products for more than 2 years. The hydrological community is taking advantage of the level-2 soil moisture product, which is also being used to produce a series of composite L3 soil moisture products at different temporal and spatial resolutions (Piles *et al.*, 2011). The next generation of L4 products includes end-level products obtained using a combination of SMOS data as well as physical or statistical models or other remote sensors. One example of such products is the fire risk maps from the SMOS Barcelona Expert Center (http://www.smos-bec.icm.csic.es/fire_risk_maps).

Some studies have validated the SMOS-derived soil moisture product L2 using *in situ* data (dall'Amico *et al.*, 2012; Jackson *et al.*, 2012; Lacava *et al.*, 2012; Sánchez *et al.*, 2012a). Nevertheless, the SMOS validation is difficult, given the local character of soil moisture measurements used for validation, which may not exhibit the high spatial variability, as well as the low spatial resolution of the SMOS data, wherein soil moisture conditions are averaged over large areas. Current long-term consistent soil moisture time series, based on active and passive data, as the Soil Moisture of the Climate Change Initiative project from the ESA could be a useful alternative to compare remotely sensed soil moisture (Liu *et al.*, 2012).

Another indirect approach for validation is the use of indices obtained using meteorological parameters, which summarizes the general variability of moisture conditions in the region and exhibits a good correlation with soil moisture measurements (Sims *et al.*, 2002; Dai, 2011; Vicente-Serrano *et al.*, 2012). For example, a recent study comparing SMOS-derived soil moisture spatial patterns with the terrain, vegetation and climatic factors in the REMEDHUS site in Spain (Sánchez *et al.*, 2012b) showed that the Antecedent Precipitation Index (Choudhury *et al.*, 1994) had a better match with the soil moisture spatial distribution in comparison with the topographic attributes or land use.

Following the suggestions of Albergel *et al.* (2012), a soil moisture anomalies (SMA) analysis was performed in order to evaluate the ability of SMOS and *in situ* datasets to capture short-term scale soil surface water variations. Because no equivalent data are available for comparison with the satellite SMA, a comparison can be made by using different definitions of soil moisture proxies, as discussed by Champagne *et al.* (2011).

In this study, we utilized field soil moisture data collected at the REMEDHUS site and meteorological drought indices to evaluate the SMOS SMA. Thus, our research attempts to demonstrate the ability of SMOS L2 SMA to detect wet or dry conditions compared with meteorological indices obtained by climate databases. Such indices are widely used for quantifying and monitoring drought conditions (Heim, 2002; Svoboda *et al.*, 2002). The potential of the SMOS-derived SMA composite for quantifying soil moisture extreme conditions is powered by the high temporal resolution and global spatial coverage of the satellite data.

Although a variety of climate drought indices are available (Sivakumar *et al.*, 2010), two indices have been used in this study: the Standardized Precipitation Index (SPI) (McKee *et al.*, 1993) and the Standardized Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano *et al.*, 2010). The SPI is only based on precipitation data, and it has been accepted by the World Meteorological Organization as a reference drought index because it is able to identify different types of drought that are calculated on different time scales (Hayes *et al.*, 2011). The SPEI follows the same principle as the SPI, but it combines data on precipitation and evapotranspiration and exhibits a better relationship with hydrological variables, such as soil moisture, than the SPI on a global scale (Vicente-Serrano *et al.*, 2012).

The main objective of this study is to demonstrate the feasibility of using a composite L2 SMOS soil moisture product for determining drought conditions by taking advantage of its spatial and temporal resolutions. To do this, we compared SMA from the SMOS L2 soil moisture product and *in situ* soil moisture measurements with two drought indices, the SPI and the SPEI.

STUDY AREA AND DATASET

The REMEDHUS network (Martínez-Fernández and Ceballos, 2005; Sánchez *et al.*, 2010) is located within a 1300 km^2 area (41.1°–41.5°N; 5.1°–5.7°W) (Figure 1). This area is nearly flat (less than 10% slope), and it ranges from 700 to 900 m a.s.l. The climate is Continental–Mediterranean, with approximately 400 mm of average annual precipitation. The mean temperature is 12 °C, with long, cold winters and hot summers. The average annual reference evapotranspiration for this period is 1025 mm according Food and Agriculture Organization-56 Penman–Monteith method. The land cover class of all SMOS cells in the retrieval is mainly vegetated soil (nominal land use: low vegetation of grass and crops) for the purpose of this study, which is in line with the chiefly land use in the REMEDHUS area (Wagner *et al.*, 2007). For this reason, only 16 stations that fall within this category were used.

The monitoring network performs continuous soil moisture measurements using Hydra probes (Stevens® Water Monitoring System, Inc.) integrating over a depth

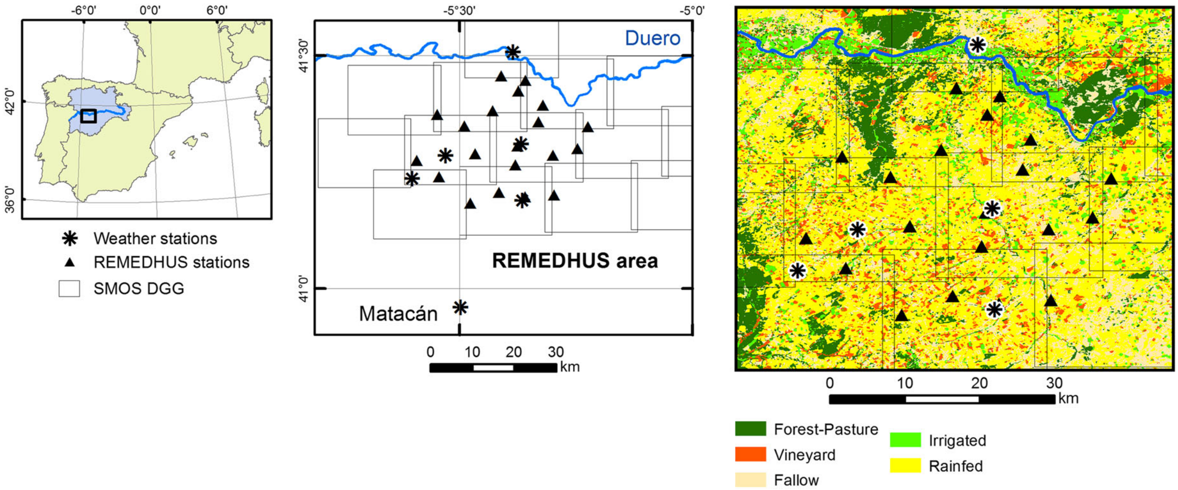

Figure 1. Spatial distribution of weather and soil moisture stations over the Soil Moisture and Ocean Salinity discrete global grid cells covering REMEDHUS. Only 16 REMEDHUS stations have been used. Land cover map is also shown

of 0–5 cm. REMEDHUS provides a continuous measurement of soil moisture each hour. The network and database are managed using a remote data transfer system (general packet radio services modems). This network, together with intensive field campaigns, has shown high performance in Cal/Val studies that utilize passive and active microwave sensors for soil moisture retrieval (Ceballos *et al*., 2005; Brocca *et al*., 2011; Sánchez *et al*., 2012a). In addition, this network is a partner of the International Soil Moisture Network (Dorigo *et al*., 2011).

Data from five automatic weather stations within the network (Cañizal, Carrizal, Granja, Villamor and Toro) have been used as the basis for drought indexes (Table I and Figure 1). The Matacán station belongs to the Spanish Meteorological Agency weather network and is located 40 km away from the study area. Because Matacán provided a historical dataset (65 years), it allowed for a more complete analysis of the statistical distribution of the temporal series. The REMEDHUS weather station data span much shorter periods (Table I). The 10-day precipitation series of Matacán exhibited correlation coefficients in the range of 0.81–0.92 with the weather stations located in REMEDHUS, whereas the 10-day series of reference evapotranspiration between the Matacán and the REMEDHUS stations exhibited correlations in the range of 0.96–0.99.

SMOS L2 soil moisture

The SMOS L2 product has a nominal average spatial resolution of 43 km (Barre *et al*., 2008). However, L2 contains geolocated products generated by the ESA on the Icosahedral Snyder Equal Area projection and resampled over a discrete global grid (DGG) with fixed latitude and longitude coordinates for the centre of each grid cell, as identified by a Grid_Point_ID and equispaced by 15 km. The temporal sampling of the mission is 1–3 days, with morning and evening overpasses (ascending and descending, respectively). Each grid node has a numeric identifier that is used in the subsequent analysis. Even though the DGG cells are hexagonal, a rectangular grid in the following figures is considered for simplicity.

Table I. Locations and precipitation of weather stations used in this work

Weather Station	Coordinates (WGS84) Long, Lat	Precipitation (mm) 2010	Precipitation (mm) 2011	Period of data
Cañizal	−5.364855, 41.189362	480.4	297.0	2007–2011
Carrizal	−5.529793, 41.285543	555.8	315.4	2010–2011
Granja	−5.367322, 41.310975	414.2	228.8	2007–2011
Toro	−5.385031, 41.508399	438.2	248.5	2007–2011
Villamor	−5.601760, 41.236445	591.0	319.4	2001–2011
Mean	—	473.2	266.8	—
Matacán	−5.498333, 40.959444	414.7	246.8	1945–2011

Soil Moisture and Ocean Salinity L2 soil moisture data for all of 2010 and 2011 were used for this study, which includes 430 days with data. The data reported herein are from the last reprocessing at the time of our analyses, i.e. the reprocessed MIR_SMUDP2 (L2 Soil Moisture User Data Product) dataset version 5.01. This product has been generated with processor version 5.01, which includes data acquired from 12 January 2010 to 31 December 2011. The use of a unique version of reprocessing guarantees similar expected quality standards for the entire dataset. To evaluate the quality of the L2 data, all files contain information about the quality of each retrieved parameter (data quality index which is the theoretical retrieval *a posteriori* standard deviation). Data with a data quality index value above a threshold of $0.06\,\mathrm{m^3\,m^{-3}}$ were excluded and led to the filtering of obvious outliers (dall'Amico *et al*., 2012). This limit is less constraining than that used in other works (e.g. Wanders *et al*., 2012) but resulted useful for filtering radio frequency interference (RFI) disturbances in a period with a large RFI uncertainty in the area. In addition, data have also been filtered for RFIs, which adversely affect the SMOS data. Data degradation due to RFIs is one of the major sources of deterioration in the quality of SMOS data (Mecklenburg *et al*., 2012). The possibility of having RFI-corrupted data has been previously assessed using the Confidence Flags of the MIR_ SMUDP2 data type. The RFI flags allowed one to filter out the measurements acquired on REMEDHUS that exceed the user-given threshold of probability of having RFIs, which in turn is computed using the ancillary data from the AUX_DGGRFI file (Current RFI Probability at the DGG point from the L2 Soil Moisture product). The valid range of this probability is [0.0, 1.0]. Values >1.0 could indicate possible data corruption in the AUX_DGGRFI, as stated in the SMOS Level 2 and Auxiliary Data Products Specifications.

Once compared with the *in situ* observations, no clear difference in the performance between morning and evening overpasses could be detected in the SMOS data. To increase the temporal resolution of the product, both ascending and descending overpasses data were used in the SMOS L2 series.

METHODS

SMA

In a first step, a simple soil moisture comparison was performed between soil moisture data sets (Figure 2). *In situ* and L2 data were normalized (between 0 and 1) using their own maximum and minimum values over the period of study (Albergel *et al*., 2012). This procedure can prevent differences in the datasets that manifest as differences in texture and in soil depth measured by satellite and *in situ* sensors.

To capture the short-term scale soil surface variations, anomaly time series were computed for both datasets. The SMA time series were computed using a ten-day-moving window for the soil moisture value. After trying various periods to evaluate the depiction of drought, a ten-day interval was chosen for the SMA calculation, as it appeared to the best choice in terms of time resolution of the drought indices. When shorter intervals were used, the robustness of the statistical fit decreased. On the other hand, using longer intervals did not seem appropriate due to the limited period of the SMOS dataset. To calculate the SMA, the average and standard deviation were calculated from the full data record for each set of *in situ* and satellite observation data sets, covering two full years. Next, each observation (from *in situ* or satellite) was normalized to the average and standard deviation of that data set. This method (Crow *et al*., 2005; Rüdiger *et al*., 2009) eliminates the effect of differences in means and standard deviation between data sets and provides a better estimate of the sensitivity to certain conditions than a comparison of absolute or normalized values.

The SMA has been calculated only for the REMEDHUS stations that coincide with the nominal land use within the L2 product for the area ($n = 16$), as well as for the 14 SMOS DGG cells (Figure 1). The ten-day composite SMA both from L2 and the *in situ* dataset was compared with the drought indices described in the subsequent section. The correlation test was reported as non-significant when the *p*-value is greater than 0.05.

The SPI

The SPI was proposed by McKee *et al*. (1993) and has been used more frequently during the two last decades

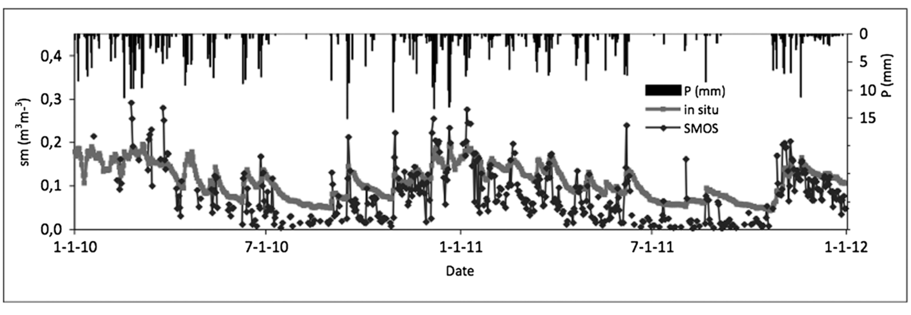

Figure 2. Daily *in situ* and Soil Moisture and Ocean Salinity soil moisture at REMEDHUS in 2010 and 2011. Daily mean precipitation is also shown

(e.g. Hayes *et al.*, 1999; Lloyd-Hughes and Saunders, 2002; Vicente-Serrano, 2006a; Hirschi, 2011). The SPI is based on the conversion of precipitation data to probabilities based on long-term precipitation records computed on different time scales. Probabilities are transformed into standardized series with an average of 0 and a standard deviation of 1. Among the different probability models used to fit the precipitation series, the Pearson III distribution shows enhanced adaptability to precipitation series at different time scales (Guttman 1999; Vicente-Serrano 2006b; Quiring 2009). Therefore, here we use the algorithm described by Vicente-Serrano (2006b) to calculate the SPI values based on the Pearson III distribution and L-moments approach to obtain the distribution parameters. The SPI at a temporal resolution of 10 days is calculated and compared with the SMOS data. However, the time scale at which soil moisture variability is responding to precipitation in the study domain is not known *a priori* (e.g. in a region, soil moisture may show high frequency variability and respond immediately to precipitation events, whilst soil moisture in other region may show a slow response and respond better to the cumulative precipitation recorded in a period of *n* days or months). Consequently, antecedent rainfall of longer time intervals has been considered in the calculation of the SPI index. Time scales from 10 days to 48 months have been incorporated in the analysis. Given the short period of climatic data available in the REMEDHUS Network (11 years), the Matacán station (65 years of data) was used to obtain the Pearson III probability distribution parameters, which were applied to the series of the REMEDHUS Network stations.

The SPEI

The main criticism of the SPI is that its calculation is based only on precipitation data. The index does not consider other variables that can influence drought severity, mainly the evapotranspiration. It is widely recognized that evapotranspiration affects soil moisture availability and, consequently, the vegetation water content, which directly affects agricultural droughts. The SPEI, based on precipitation and reference evapotranspiration (Et_0), includes the concept of atmospheric water demand in the calculation of a multi-scalar drought index (Vicente-Serrano *et al.*, 2010). The SPEI is based on a monthly climatic water balance (precipitation minus reference evapotranspiration), which is adjusted using a three-parameter log–logistic distribution. The values are accumulated at different time scales, using the same approach as with the SPI, and converted to standard deviations with respect to the average values.

Reference evapotranspiration data are obtained for each weather station in REMEDHUS using the Penman–Monteith approach (Allen *et al.*, 1998), which is considered a reference method by the International Commission for Irrigation, the Food and Agriculture Organization of the United Nations and the American Society of Civil Engineers. The necessary parameters for the application of this method were not available in the Matacán station. Therefore, for data from the Matacán station, we applied the empirical equation formulated by Hargreaves and Samani (1985), which is recommended for scarce datasets (Droogers and Allen, 2002). Correlations between the Et_0 values obtained from Hargreave's and Penman–Monteith methods were very good (correlation coefficient, $R \approx 0.99$) for all the stations, meaning, it is possible to utilize the long-term parameters necessary to calculate the SPEI from the Matacán station. The SPEI was also obtained at a 10-day resolution and on a time scale ranging from 10 days to 48 months.

Finally, for a quantitative comparison between drought indices and SMA from the SMOS and *in situ* measurements, the Pearson's R coefficient was computed for each dataset pair. The *p*-value was used to establish the statistical significance, wherein the significance level of $\alpha = 0.05$ was considered significant, although a *p*-value of 0.01 was also obtained.

RESULTS

SMOS vs in situ soil moisture measurements

A brief analysis of the relationships between area-averaged SMOS cells and *in situ* measurements was performed. The area-averaged temporal evolution of the two soil moisture datasets, together with the amount of precipitation, is compared in Figure 2. The dynamic range of SMOS is more severe than that of the *in situ* data, due to SMOS lower penetration depth. Still, it demonstrates a marked flashiness related to the rain events in the SMOS soil moisture. The similarity between the SMOS-derived soil moisture and the *in situ* measurements, as well as the good performance of the SMOS soil moisture in representing the temporal variability of the soil moisture measurements, is evident. However, an underestimation is observed in the absolute SMOS soil moisture values. In addition, a higher reactivity to precipitation events was observed in the SMOS dataset in comparison with the *in situ* soil moisture data. This SMOS sensitivity to rain events spurs the idea of its comparison with the drought indices.

For the whole area, the mean correlation between *in situ* and SMOS datasets during the period of study was 0.73 ($RMSD = 0.042\ m^3\ m^{-3}$, $bias = -0.031\ m^3\ m^{-3}$), which is in line with a previous study on the SMOS validation in the network (Sánchez *et al.*, 2012a) and is in agreement with the accuracy requirements of the mission for the soil moisture product ($RMSE < 0.04\ m^3\ m^{-3}$).

SMOS and in situ SMA vs SPI and SPEI: time scale analysis

To determine the most suitable time scale for the drought indices to represent the temporal variability of the SMA, different time scales were selected, corresponding

Table II. Correlation coefficients between Standardized Precipitation Index and Standardized Precipitation Evapotranspiration Index and the corresponding Soil Moisture and Ocean Salinity cells/REMEDHUS stations soil moisture anomalies, calculated for every weather station on a 10-day time scale with intervals ranging from 10 to 120 days

R *in situ*	10		20		30		40		50		60		70		80		90		100		110		120	
	SPI	SPEI	SPI	SPEI	SPI	SPEI	SPI	SPEI	SPI	SPEI	SPI	SPEI	SPI	SPEI	SPI	SPEI	SPI	SPEI	SPI	SPEI	SPI	SPEI	SPI	SPEI
Matacán	0.33	0.53	0.62	0.75	0.71	0.82	0.71	0.85	0.68	0.83	0.67	0.80	0.66	0.76	0.62	0.71	0.60	0.67	0.56	0.61	0.52	0.56	0.47	0.51
Cañizal	0.21	0.58	0.57	0.80	0.66	0.84	0.68	0.85	0.67	0.79	0.69	0.76	0.68	0.71	0.67	0.67	0.67	0.65	0.66	0.62	0.64	0.59	0.60	0.54
Carrizal	0.31	0.41	0.55	0.61	0.57	0.56	0.61	0.50	0.60	0.40	0.60	0.31	0.56	0.24	0.50	0.15	0.51	0.13	0.49	0.10	0.48	0.07	0.44	0.00
Granja	0.22	0.39	0.61	0.55	0.69	0.56	0.69	0.53	0.69	0.50	0.72	0.45	0.71	0.41	0.69	0.37	0.69	0.36	0.69	0.36	0.67	0.35	0.63	0.32
Villamor	0.29	0.50	0.67	0.72	0.70	0.71	0.68	0.67	0.62	0.60	0.59	0.53	0.59	0.48	0.56	0.45	0.57	0.44	0.57	0.45	0.56	0.45	0.54	0.43
Toro	0.29	0.44	0.70	0.65	0.74	0.68	0.73	0.68	0.71	0.66	0.69	0.62	0.66	0.59	0.63	0.57	0.62	0.57	0.60	0.57	0.57	0.56	0.52	0.54
R SMOS	10		20		30		40		50		60		70		80		90		100		110		120	
	SPI	SPEI	SPI	SPEI	SPI	SPEI	SPI	SPEI	SPI	SPEI	SPI	SPEI	SPI	SPEI	SPI	SPEI	SPI	SPEI	SPI	SPEI	SPI	SPEI	SPI	SPEI
Matacán	0.54	0.66	0.63	0.74	0.66	0.76	0.61	0.75	0.59	0.69	0.52	0.61	0.53	0.58	0.52	0.55	0.51	0.53	0.45	0.48	0.41	0.42	0.38	0.38
Cañizal	0.46	0.72	0.56	0.73	0.61	0.74	0.59	0.70	0.57	0.64	0.53	0.56	0.55	0.53	0.55	0.52	0.56	0.51	0.53	0.47	0.49	0.43	0.47	0.39
Carrizal	0.51	0.54	0.52	0.53	0.52	0.45	0.51	0.36	0.48	0.27	0.44	0.17	0.40	0.07	0.39	0.04	0.38	0.02	0.31	−0.06	0.30	−0.09	0.30	−0.11
Granja	0.44	0.53	0.62	0.53	0.65	0.52	0.60	0.44	0.58	0.38	0.57	0.31	0.58	0.29	0.57	0.28	0.57	0.29	0.55	0.28	0.51	0.26	0.48	0.24
Villamor	0.54	0.66	0.61	0.64	0.61	0.59	0.55	0.51	0.49	0.42	0.44	0.34	0.45	0.31	0.46	0.33	0.48	0.35	0.45	0.34	0.42	0.33	0.41	0.32
Toro	0.48	0.59	0.67	0.65	0.68	0.66	0.63	0.61	0.58	0.55	0.54	0.49	0.52	0.47	0.50	0.47	0.49	0.48	0.46	0.47	0.41	0.44	0.36	0.41

The following thresholds on the *p*-values are used: (i) NS (non-significant) for *p*-value greater than 0.05 (dark grey), (ii) between 0.05 and 0.01 (light grey) and (iii) below 0.01.
SMOS, Soil Moisture and Ocean Salinity; SPI, Standardized Precipitation Index; SPEI, Standardized Precipitation Evapotranspiration Index.

to 10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 110 and 120 days (i.e. these intervals of antecedent climate conditions analysed). A temporal analysis was performed using the five automatic weather stations in the REMEDHUS network and considering the average of the measurements. The comparison was also made using the SMOS-averaged and the REMEDHUS-averaged SMA (Table II), revealing the influence of antecedent climatic conditions, using the correlations as a measurement of the outstanding memory (persistence) of soil moisture.

Table II provides information about the correlations of the different weather stations. A good fit was found in terms of statistical significance for both datasets, as only 5% of the correlations have a *p*-value >0.05 for both datasets. In general, higher correlations were obtained for the *in situ* SMA with respect to the SMOS data. This is likely due to the different penetration depths of SMOS and the *in situ* probes. Stronger correlations are found for the drought time scales of 30–60 days for the *in situ* SMA and 20–40 days for the SMOS SMA. At these time scales, the correlations tend to be similar between the SPI and SPEI, with some differences between the weather stations. These observations highlight the difficulty of making *in situ* comparisons based on data collected on very different spatial scales. The low values of Carrizal station can be justified by the fact that its precipitation series is not long enough to provide consistent calculations.

Figure 3 shows the correlation between the time series of the 10-day SPI, SPEI, SMOS and the *in situ* SMA, averaging the values across the entire REMEDHUS site. Stronger correlations are recorded for drought time scales of 30–60 days for the *in situ* SMA and between 30 and 50 days for the SMOS SMA. This confirms that soil moisture variability is driven by antecedent climate conditions and that the main soil moisture response is not only related to the immediate weather conditions. For

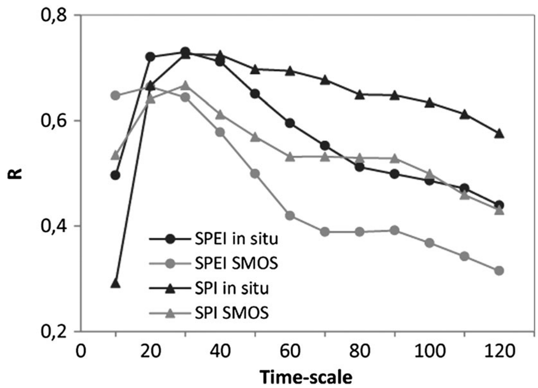

Figure 3. Correlation coefficients between the drought indices and soil moisture anomalies along different time scales, for both Soil Moisture and Ocean Salinity (SMOS) and *in situ* averaged data. Black, *in situ* measurements; grey, SMOS measurements; dots, Standardized Precipitation Evapotranspiration Index (SPEI); triangles, Standardized Precipitation Index (SPI)

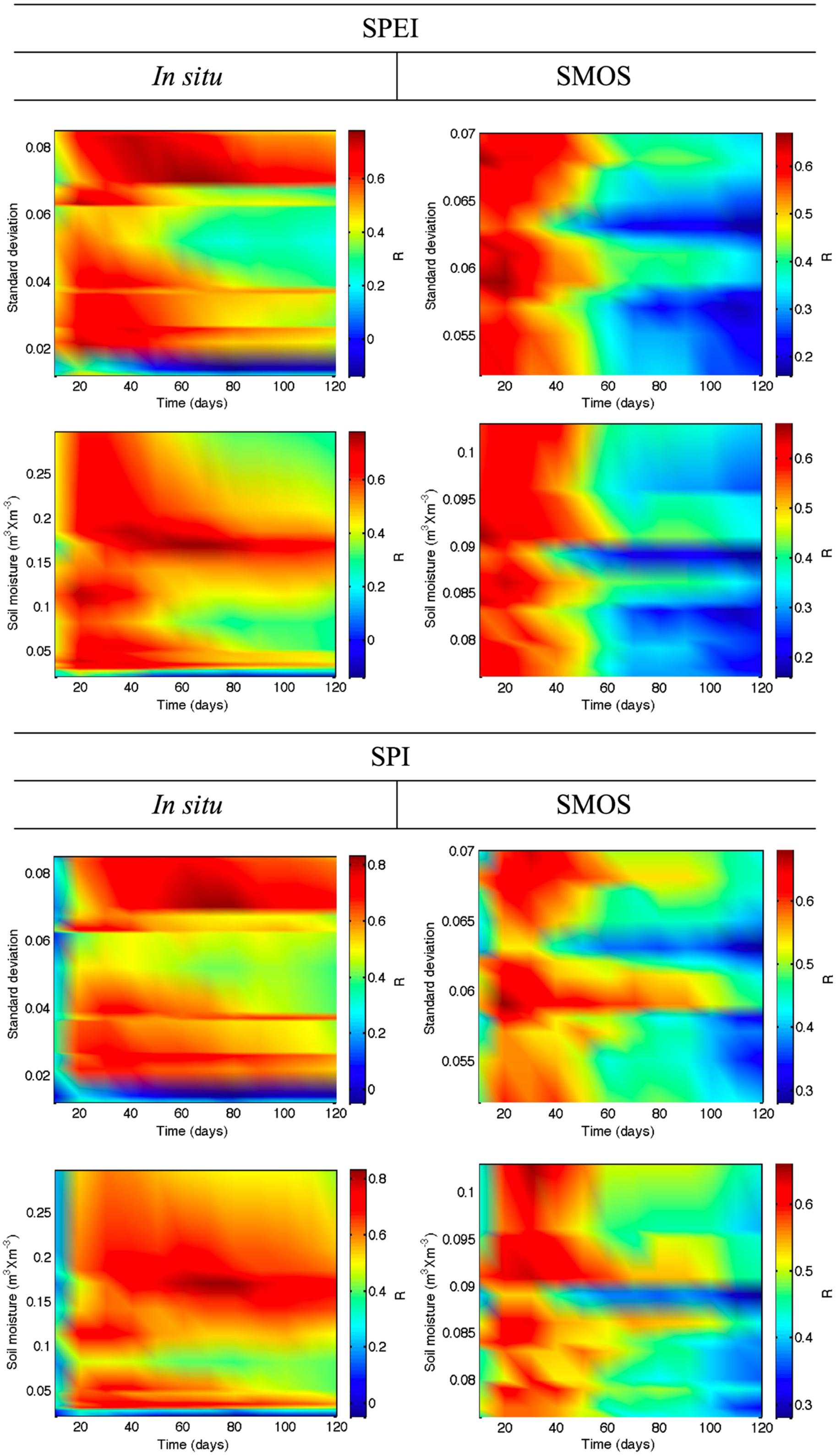

Figure 4. Mean correlation coefficients between soil moisture anomalies (sort by standard deviations and soil moisture contents) and drought indices along the different time scales

time scales longer than 60 days, the response of the soil moisture variability decreases noticeably. For the *in situ* SMA, both SPI and SPEI correlations are stronger, showing that differences between the SMOS and *in situ* SMA correlations are not only influenced by the time scales upon which maximum correlations are obtained but also with the magnitude of the correlations. Nevertheless, in both cases, the SPEI tends to exhibit higher correlations than the SPI. The differences tend to be lower for the time scales at which maximum correlations are recorded.

Finally, a comparison between each station and cell with the average drought indices was performed (Figure 4). In this figure, the values of the correlation (R) between SMA and drought indices within the different time scales are presented. The temporal pattern is clearer for the SMOS series, showing that the correlation is worse for more than a 60-day time interval. This period may be indicative of the time scale of precipitation extremes that the SMOS SMA can capture. For each dataset, the attempt is to visualize if the correlation is related to the soil moisture content and standard deviation, i.e. if highest correlations are in correspondence of low/high soil moisture contents or standard deviations. For the *in situ* dataset, no appreciable link was found. As seen in Figure 4, for the SMOS dataset, there is a traceable similarity between the soil moisture data and the standard deviation time patterns with respect to the correlations with the indices. However, it must be noted that this similarity is actually due to the scarce standard variation and low averaged soil moisture content in the SMOS series.

DISCUSSION AND CONCLUSIONS

This study compared the variability of *in situ* soil moisture measurements, SMOS L2 surface soil moisture and two drought indices based on climatic information and revealed the utility of the SMOS products for assessing the temporal variability of soil moisture on a regional scale. Significant correlations between the drought indices, *in situ*, and SMOS SMA were found. As expected, higher correlations were obtained for the *in situ* measurements relative to the SMOS dataset. Nevertheless, independent of the dataset, both drought indices were good proxies of the soil moisture variability.

The main novelty of our approach was the use of two drought indices for comparison with the SMA. Given the difficulty of performing robust soil moisture measurements for long time series, very few studies have compared drought indices with actual soil moisture variability (Vicente-Serrano *et al.*, 2012). The study was executed using the REMEDHUS site (central Iberian Peninsula), which contains high quality soil moisture and meteorological observations. A statistically significant performance of the SMOS SMA for reproducing *in situ* measurements was found, even though a slight underestimation was assumed in the use of current L2 processed versions (dall'Amico *et al.*, 2012; Dente *et al.*, 2012; Sánchez *et al.*, 2012a). This good performance can be supported by the presence of sparse and homogeneous vegetation cover in the area, fitting the nominal class proposed in the algorithm, and due to the limited topographic effects in this area (Sánchez *et al.*, 2012a).

The SPI and the SPEI exhibit better performance in terms of reproducing the variability of the soil moisture on a global scale (Vicente-Serrano *et al.*, 2012). In our case, after a previous attempt using the daily interval for the calculation of these indices and the SMA, a ten-day resolution was chosen to represent the *in situ* and SMOS SMA due to its greater correlation with SPI and SPEI. More extended intervals (e.g. monthly) are not useful here due to the limited period of the SMOS dataset.

The SMA reflects the cumulative precipitation anomalies and is known to provide memory in the climate and hydrological system (Anderson *et al.*, 2012). The water retained in the soil after a rainfall event is temporally more persistent than the rainfall event itself (Koster and Suarez, 2001) and has a greater persistence during periods of low precipitation (Huang *et al.* 1996). This 'memory' effect was demonstrated herein when using indices at different time scales. The flexibility of using multiple time scales to calculate drought indices is highly relevant for selecting the most appropriate time interval at which soil moisture responds to the climate variability. Soil moisture data tend to respond better to short time scales of both SPI and SPEI. For the ten-day antecedent time scale of the indices, SMOS SMA exhibits higher correlation coefficients compared with drought indices than *in situ* data (Figure 3). Increasing the time scale changes the trend such that the *in situ* SMA is better matched to the drought indices, demonstrating the capability of the ground observations to provide a better description of the soil moisture resilience. The SMOS data tend to respond to drought indices on shorter time scales than the *in situ* measurements, even though this response could be misinterpreted due to the SMOS lower penetration depths compared with the *in situ* measurements and the different depths and scales of each dataset. With respect to the SMOS SMA, the optimal antecedent period for the ten-day SPI and SPEI that best suited the SMA is 20–30 days. However, for the *in situ* SMA, the best correlation is between 30 and 50 days. These time scales are shorter than those characterized for stream flows, reservoir storages and groundwater (Szalai *et al.*, 2000; Vicente-Serrano and López-Moreno, 2005; Fiorillo and Guadagno, 2010; Lorenzo-Lacruz *et al.*, 2010). Typically, short time scales of hydrological drought indices are associated with agricultural droughts that are directly driven by shortages in the soil moisture (e.g. McKee *et al.*, 1993; Hayes *et al.*, 1999), although no previously published work has demonstrated this response using *in situ* measurements. Our results clearly illustrate this point, confirming that although medium (6–9 month) and long time scales (12–24 month) are very useful for monitoring stream flow droughts (e.g. Vicente-Serrano and López-Moreno, 2005; Lorenzo-Lacruz *et al.*, 2010), shorter time scales exhibit good performance in reproducing the temporal variability in soil moisture.

The better correlation of the SMOS SMA at the shortest time scale could be explained by the fact that the depth of soil that contributes to the radiometer observation becomes shallow when the near surface is wet during and shortly after a precipitation event (Jackson *et al.*, 2012). After some elapsed time, the soil moisture is distributed more uniformly throughout the soil profile. In other words, when it is raining, the remote-derived soil moisture content is higher than the observed at 0–5 cm depth. Other issue includes the spatial scale of the estimations. REMEDHUS area is equal to the SMOS footprint. Although the DGG cells are resampled to 15 km, the actual spatial resolution is broader, in contrast with the individual *in situ* monitoring sites, which lead to negligible spatial variations in the SMOS data.

There are no remarkable differences between the use of the SPI and the SPEI for analysing the variability of soil moisture on a local scale in the different observatories. This may be driven by the difficulty of recording the influence of the involved climatic variables on a local scale, at which particular soil characteristics and topographic conditions may be affecting the relationships. On a regional scale, it was revealed that soil moisture variability tends to better respond to the SPEI than the SPI, considering both the SMOS and *in situ* measurements. Vicente-Serrano *et al.* (2012) compared the performance of different drought indices to reproduce the variability of soil moisture observatories located around the world. They showed that, in general, the SPEI outperforms the capacity of the SPI for monitoring the SMA. Although precipitation is the main variable for explaining the soil moisture variability, evapotranspiration included in the SPEI may also be an important variable for explaining soil moisture changes. Thus, there is indirect evidence based on stream flow data that suggests the influence of evapotranspiration on soil moisture, mainly driven by global warming processes (Walter *et al.*, 2004; Brocca *et al.*, 2008; Cai and Cowan, 2008; Lespinas *et al.*, 2010).

In conclusion, this study provides preliminary but valuable insights for future SMOS products. Satellite soil moisture data and reasonably simple indices of surface soil moisture conditions could be used as an additional piece of information for assessing drought conditions that are typically quantified using climate indices on the regional scale. Conversely, the drought indices time series are suitable as proxies of soil moisture conditions in the top layer, especially when computed over periods of 20–50 days, coinciding with several works that examine the potential of the SMA for predicting precipitation over regions where the land memory is long and soil moisture–precipitation coupling is strong (Wang *et al.*, 2007). Time scales of longer than 60 days for the drought indices decrease the strength of the relationships with the SMA, especially for the SMOS dataset. The methodology applied in this study provides empirical evidence about the usefulness of drought indices for monitoring the SMA and vice versa, demonstrating that the SMA mostly responds to short drought time scales.

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