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Preliminary evaluation of ASCAT-SWI and SMOS SM soil moisture products against in-situ observations in the Brazilian Caatinga biome

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Abstract

In recent years, there has been increasing interest in remote sensing the temporal dynamics of soil moisture contents in large agricultural areas, such as those located in the Cattinga biome of the Northeast Brazil (NEB). In this context, validation is critical for accurate and credible satellite-based products usage. The aim of this work is to present the results of the quality assessment of the Surface Soil Moisture (SSM) estimates derived from the microwave sensors on board of the Soil Moisture and Ocean Salinity (SMOS) satellite and the METOP satellite series. Dataset for both platforms are disseminated through the SMOS SSM and ASCAT-SWI operational products, respectively. SMOS SMM and ASCAT-SWI time series were compared to in situ SSM data taken in two sites from the Alagoan semiarid where the Caatinga biome is dominant from February 2012 to October 2013 at a bimonthly time scale. The Spearman's rho (r), Bias, and Root Mean Square Error (RMSE) were used as statistical metrics. Results revealed a poor performance for both products, but the SWI showed relatively good agreement in terms of trend when the soil moisture content in the upper layers was near to zero because of severe drought conditions. SWI could be useful for monitoring the variation of the SSM in rainfed crop areas of the Caatinga biome affected by severe droughts.

Keywords: surface soil moisture, SMOS, ASCAT SWI, Caatinga, Northeast Brazil.

1. Introduction

Surface soil moisture (SSM) is the moisture content in the upper few centimeters of the soil (i.e., roughly 1-2 cm). The importance of its monitoring derives from the fact that it influences the water cycle by controlling the partition of rainfall between land (infiltration, percolation, and runoff) and the atmosphere (evaporation and plant transpiration). Therefore, its assessment is vital for operational applications, such as agricultural drought tracking (Rossato and Angelis, 2013; Ferreira et al., 2014; Schirmbeck et al., 2017), climate modeling (Loew et al., 2013), flood forecasting (Brocca et al., 2010) and environmental studies (Zucco et al., 2014).

Currently available methods for monitoring the in situ SSM, such as gravimetric, neutron scattering, electrical resistance and time domain reflectometry are very accurate, but they have an use very limited because of their point-based nature, reduced spatial extent, and the high variability of soils (Walker et al., 2004; Cho et al., 2015). Nevertheless, that restriction has been gradually overcome due to advance in the development of satellite technology and retrieval algorithms for estimation of SSM from space (Kornelsen and Coulibaly, 2013). Most of satellite platforms used to retrieve SSM use microwave sensors and can be categorized into: i) passive e.g., Soil Moisture and Ocean Salinity (SMOS) (Kerr et al., 2016); ii) active e.g., Advanced SCATterometer (ASCAT) (Paulik et al., 2014); and iii) passive-active e.g., Soil Moisture Active Passive (SMAP) (Sun et al., 2017; O'Neill et al., 2016). Passive sensors (i.e., radiometers) detect the naturally emitted microwave radiation within their field of view, whereas active sensors (i.e., scatterometers) have their own source of energy and basically measure the ratio between the transmitted and received electromagnetic radiation (Pierdicca et al., 2013; Kerr, 2007).

The ASCAT is a C-band active microwave remote sensing instrument flown on board of the polar orbiting Meteorological Operational (METOP) satellite series. The nominal resolution of the ASCAT SSM measurements is 50 km. It is operated at a frequency of 5.3 GHz in VV polarization (Wagner et al., 2013). Backscatter measurements from this sensor are transformed into SSM estimates with the TU WIEN method developed for the European Remote Sensing Active Microwave Instrument Wind Scatterometer instruments (Wagner, 1998; Naeimi et al., 2009). This dataset is operationally disseminated by EUMETSAT and as reprocessed time series by Vienna University of Technology (Bartalis et al., 2008). The European Copernicus Global Land Service uses this dataset to produce an operational Soil Water Index (SWI) (Paulik et al., 2014).

The SMOS satellite launched in November 2009 by European Space Agency (ESA) is an L-band passive microwave satellite that measures the thermal emission from the Earth with a Microwave Imaging Radiometer using Aperture Synthesis (MIRAS), which is a synthetic aperture radiometer with multiangular and full polarimetric capabilities (Al-Yaari et al., 2014). The nominal resolution of the SSM estimates from SMOS is 40 km, while its operation frequency is 1.4 GHz. The SMOS SSM retrieval algorithm is based on the iterative minimization of the difference of a forward model and the brightness temperatures sensed by SMOS as described in Kerr et al. (2010). The SMOS SSM L2 dataset is operationally distributed by the ESA SMOS Online Dissemination Service, although some European Research Centers such as the SMOS Barcelona Expert Centre (SMOS BEC) are dedicated to developing products based on SMOS SSM L2 (Kerr et al., 2001; McMullan et al., 2008).

The SMOS SSM and ASCAT-derived SWI products have shown great potential for agricultural drought monitoring among other operational applications, but very few works have been published using these datasets in worldwide; especially in Brazil. Rossato et al. (2017) stated that the SMOS-derived data infers accurate values of SSM over some densely vegetated Brazilian regions such as Votuporanga and Pacui. In Northeast Brazil (NEB), Ferreira et al. (2014) demonstrated the feasibility of SMOS SSM for determining local-scale SSM changes in the Ceará state. Cho et al. (2015) validated the ASCAT-derived SWI data by comparing with in situ SSM measured at Santa Rita do Passa Quatro (State of Sao Paulo, Brazil), and proved that it has good agreements with ground measurements though systematic errors were noted. Paredes-Trejo and Barbosa (2017) found that the Soil Water Deficit Index derived from SSM SMOS L2 (SWDIS) has a reasonably good overall performance in terms of the drought-weeks detection and capture of the SSM temporal dynamic in lowlands of the NEB.

In this work, the focus is specifically on the Caatinga biome of Northeast Brazil. This biome was chosen because it has been hit by recurrent droughts, which usually trigger serious impacts on water supply, rainfed agriculture, livestock and some drought-prone ecosystems (Paredes et al., 2015; Barbosa and Kumar, 2016). In this context, one could expect that the SSM sensed from satellite-based microwave sensors would help to face drought situations in that semiarid region. In view of this, the accuracy of SSM estimates from both SMOS SSM and ASCAT-derived SWI was assessed by comparing them against in situ data.

2. Materials and methodology

The study was carried out in two sites in the Alagoan semiarid, which are located in 9.47° N, 37.89° W (Olho D'Água do Casado; A1), and 9.44° N, 37.90° W (Delmiro Gouveia; A2), respectively (Figure 1). Both sites show the presence of xerophytic and deciduous species such as Murici (*Byrsonima gardneriana* A. Juss). Its climate is semiarid and characterized by a mean annual precipitation of 546 mm yr^{-1} with a rainy season from November to April (Araujo et al., 2016; Santos et al., 2017). The soil has been classified as Neossolos and shows high content of sand in its upper layer (Souza, 2011).

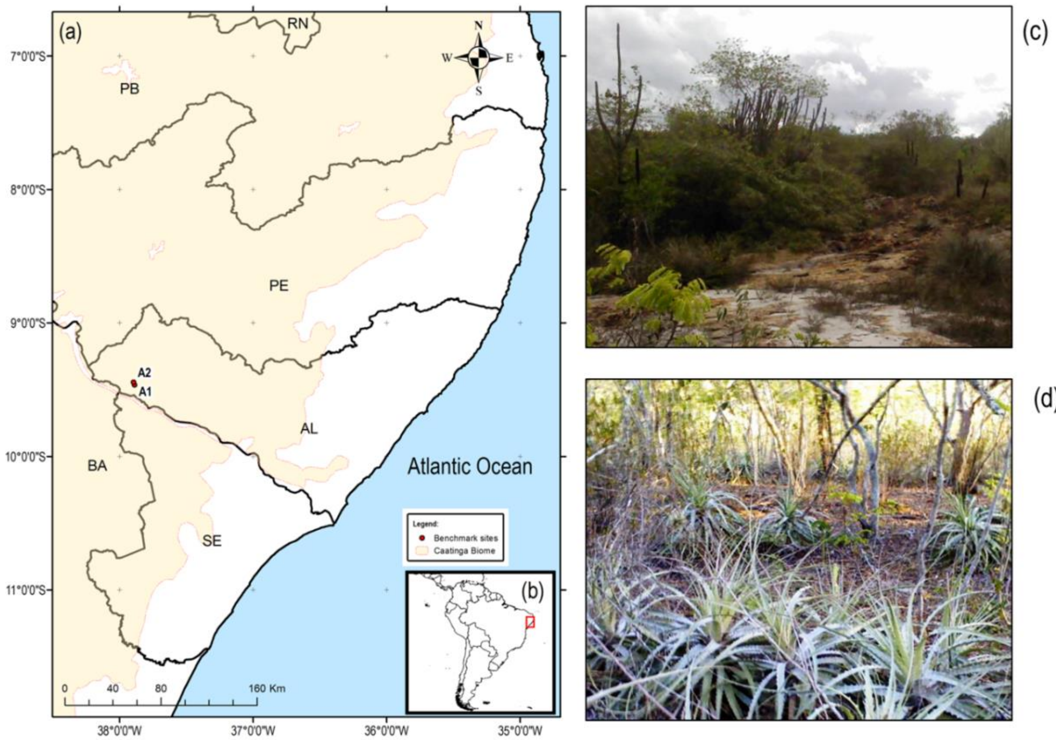

Figure 1 – Study unit showing the location of the benchmark sites in the state of Alagoas (**a**); its geographical location in South America (**b**); and two photographs taken in February 2012 by Geovânia dos Santos at the sites A1 (9° 27’ 53’’ S, 37° 53’ 21’’ W) (**c**); and A2 (9° 26’ 38’’ S, 37° 53’ 49’’ W) (**d**).

The in situ SSM measurements were obtained at a depth of 10 cm during afternoon hours in the benchmark sites from 17 February 2012 to 20 October 2013 using a bimonthly sampling. At each site, unaltered soil samples were taken at 20 different points within a sample area of about one hectare. The gravimetric method was employed at each soil sample to estimate the SSM (Allen, 2000). Finally, results were averaged and grouped by benchmark site and date (i.e., 11 observations per site).

The Soil Moisture Level 3 product for both descending and ascending orbits created and disseminated by the SMOS BEC was used to retrieval the SSM for each site on each sampling date. The arithmetic average of the two orbits was calculated to minimize the effect of gaps in retrieval. The SMOS BEC has implemented several quality filters during its creation (Gonzalez-Zamora et al., 2015) (available at http://cp34-bec.cmima.csic.es). Consequently, it can be considered adequate to obtain good estimates of SSM such as demonstrated in previous studies carried out in non-Brazilian territories with similar climatic conditions to the semiarid region of the NEB (Sanchez et al., 2012; Gumuzzio et al., 2016).

The version 3 of the global daily SWI operational product disseminated by the Copernicus Global Land service was used to infer moisture conditions in different soil depths for each benchmark site and date. The SWI algorithm uses an two-layer infiltration model describing the relation between SSM retrieved from the ASCAT instruments on board the METOP satellites and profile soil moisture as a function of time (Wagner et al., 1999). The SWI was formulated as follows:

$$SWI(t_n) = \frac{\sum_{i=1}^{n} SSM(t_i)\, e^{-\frac{t_n - t_i}{T}}}{\sum_{i=1}^{n} e^{-\frac{t_n - t_i}{T}}} \qquad (1)$$

so that for $t_i \leq t_n$, t_n is the observation time of the current measurement and t_i are the observation times of the previous measurements (both given in Julian days). This model supposes that the water content of the deeper layer is controlled by the past moisture conditions in the surface layer and thus the precipitation history (Ceballos et al., 2005). The used T parameter for the SWI calculation is T=L/C (see equation 1), where L is the depth of the reservoir layer and C is an area-representative pseudo-diffusivity constant, which means that a high (low) T describes a deeper (upper) soil layer (Albergel et al., 2008). Since the calculation of the SWI values requires the availability of historic SSM time series data, a computational adaption of this SWI algorithm was proposed by Albergel et al. (2008). The operational version of the SWI product is available for eight different T values (1, 5, 10, 15, 20, 40, 60, and 100) together with their respective quality flags (QFLAG) (available at http://land.copernicus.vgt.vito.be/). This quality flag is related to the number of available SSM measurements used for calculating SWI for a T value at time t_i. For this study, the SWI values with QFLAG ≤ 50% were rejected. SWI images with T > 15 were also omitted, because the in situ SSM measurements encompass for the 0-10 cm soil layers.

A modified Atmospheric Water Deficit (AWD) suggested by Martinez-Fernández et al. (2015) was used, where the AWD is calculated as the 7-day running sum of precipitation minus the 7-day running sum of potential evapotranspiration (Eto). Negative (positive) values indicate the presence of dry (wet) atmospheric conditions. The daily precipitation and ETo data were extracted for each benchmark site from a ground-based climate dataset developed by Xavier et al. (2015).

In order to assess the overall performance of the SMOS SSM and SWI products, the Spearman's rho (r) was used to quantify the strength of the monotonic relationship between the SSM estimates from both SWI and SMOS SSM against in situ SSM data at each site, whereas its statistical significance was tested on base to the algorithm AS 89. This non-parametric measure was chosen because it is less sensitive to outliers and non-normal data than the Pearson's rho. The Spearman's rho varies from -1 to 1 with a perfect score of one (Best and Roberts, 1975). The Bias and Root Mean Square Error (RMSE) were also used as statistical metrics. Bias measures the average trend of the estimated values to be larger or smaller than their observed ones. Positive values indicate overestimation bias, whereas negative values indicate underestimation bias. On the other side, RMSE is the root mean squared error between the satellite-derived soil moisture and SSM measured in situ. A smaller value indicates better performance (Entekhabi et al., 2010). The aforementioned metrics were computed using the version 0.3 of the hydroTSM R package developed by Zambrano-Bigiarini (2012).

3. Results and discussion

To explore the potential impact of the atmospheric dynamic on the upper soil moisture, a comparison analysis was made with the modified AWD and the in situ SSM measurements. As expected, a moderate coupling strength and statistically significant (for α = 0.10) between the antecedent hydrometeorological condition and soil moisture content was found (Figure 2). It is interesting to remark that the modified AWD exhibited persistently negative values, because the NEB suffered severe rainfall deficiencies in 2012 and 2013 (Marengo et al., 2017). This explains why the in situ SSM observations showed a considerable proportion of values of SSM near to zero (general median: 0.023 m^3 m^{-3}). On the other side, the predominantly sandy texture of the soils of the study area (sand content ≥ 90%) also could have contributed to a low water retention capacity in the superficial layers of the soil (Martinez-Fernández et al., 2015).

Figure 3 shows the SSM retrieved from SMOS compared against in situ SSM at each site for each sampling date. At first view, these estimates tend to overestimate the in situ SSM measurements (bias mean: 185%, RMSE mean: 0.07 m^3 m^{-3}). Note also that this feature is very noticeable when the values of the in situ SSM is less than 0.06 m^3 m^{-3}, suggesting that the estimates derived from the SMOS SSM product could be unrealistic in semiarid regions. About this behavior, Rodriguez-Fernandez et al. (2016) argued that semiarid regions show low intrinsic variability in the SMOS signal; therefore, the low correlation between the SMOS SSM estimates and in situ data could be due to the fact that the variance is not dominated by an annual cycle, but by noise, whose origin could be Radio Frequency Interference (RFI). In fact, Paredes-Trejo and Barbosa (2017) evidenced that the SMOS SSM signal can be considerably compromised by RFI in the semiarid region of northeast Brazil, in particular where the soil water content is very low. These results suggest that the SSM is poorly captured by the SMOS SSM product, mainly in regions where the water content of the upper layer is highly sensitive to severe droughts.

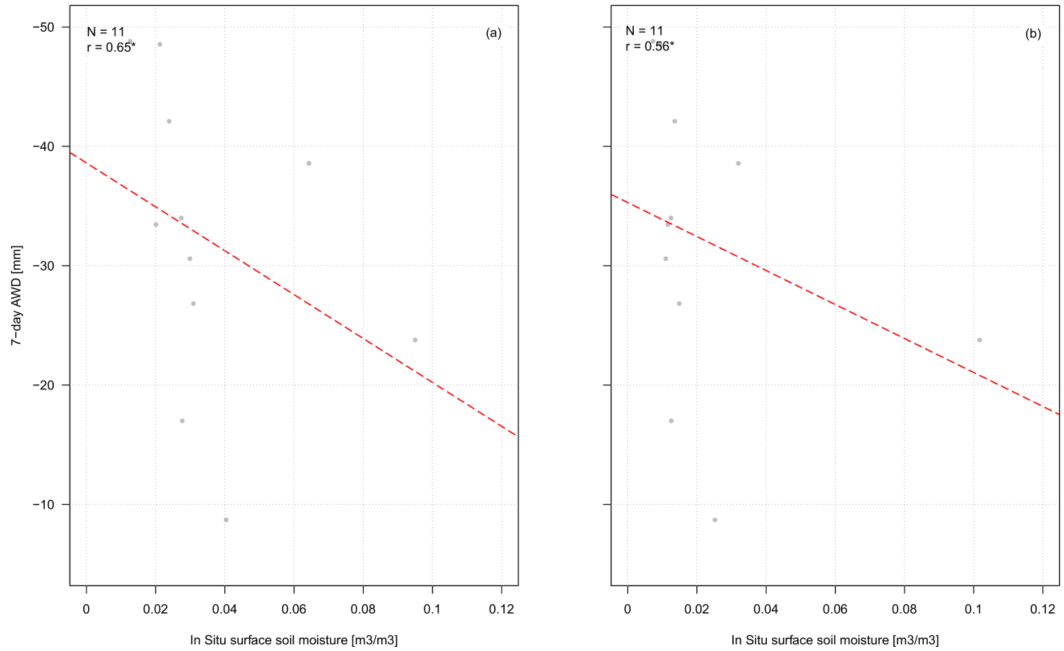

Figure 2 – Modified AWD and in situ SSM measurements from 17 February 2012 to 20 October 2013 at bimonthly time scale for: (**a**) the A1 site; and (**b**) the A2 site. Dashed red line depicts the linear regression best fit. N is the amount of paired values, and r is the Spearman's rho. * indicates that the Spearman's rho is statistically significant at the 10% level. Locations of sites are shown in Figure 1.

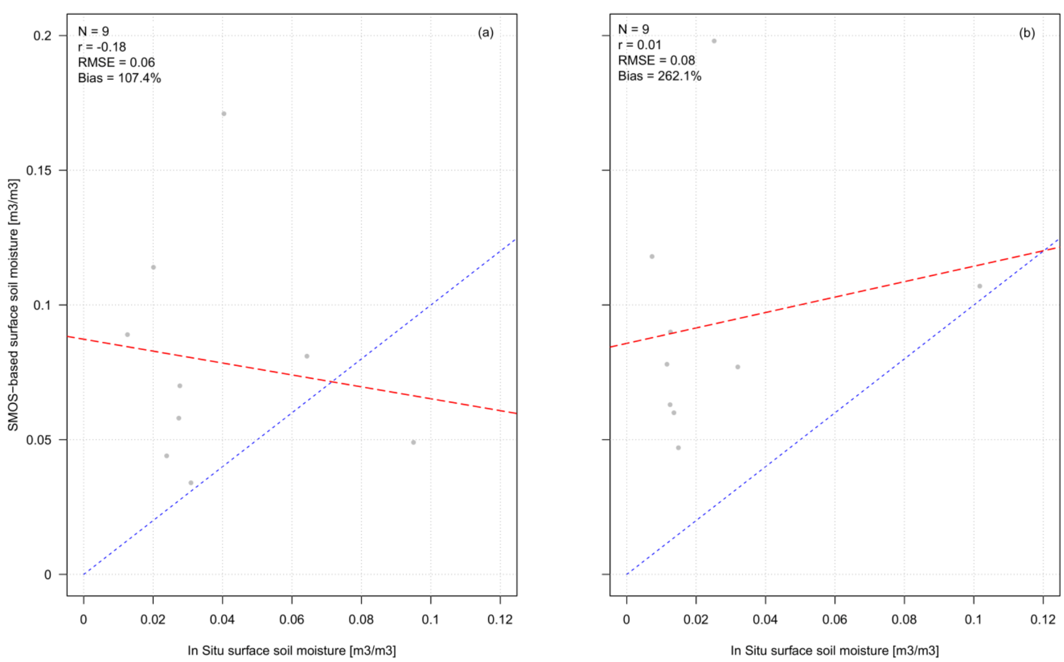

Figure 3 – As Figure 2, but for the SSM retrieved from SMOS, (**a**) the A1 site; and (**b**) the A2 site. Dashed blue line indicates 1:1 correspondence. RMSE is the root mean squared error in the same units of the SMOS SSM and in situ SSM, and Bias is the percentage of bias between both variables.

A point-to-point comparison was applied to explore the overall association between the SSM estimates derived from SWI against in situ SSM measurements. The SWI-in situ SSM pairs for the benchmark sites are shown in Figures 4 and 5. It can be seen that the four T parameters used for calculating SWI showed similar results in terms of coefficient of RMSE (ranged from 17 to 25%). If the analysis is strictly based on this metric, one can assume the SSM for the analyzed sites is not adequately captured by the SWI product. However, in most cases, the monotonic relationship was better than those obtained by the SSM retrieved from SMOS. Furthermore, an aspect less evident is fact that the association between the SWI and the in situ SSM measurements shows a slight improvement when the values of the in situ SSM are less than 3%. That means that, in those places where the SSM is often low (e.g., as at the benchmark sites of this work), the SWI values could be useful for capturing trends related to the water content of the surface layer.

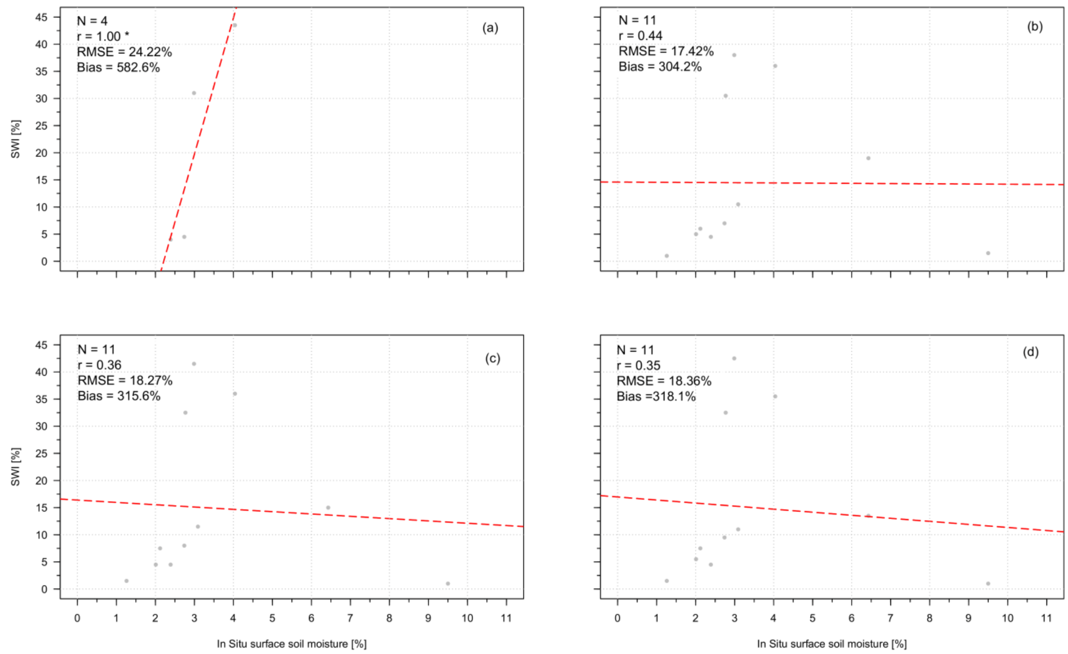

Figure 4 – As Figure 2, but for the SWI time series at the A1 site, (**a**) for T = 1; (**b**) for T = 5; (**c**) for T = 10, and (**d**) for T = 15.

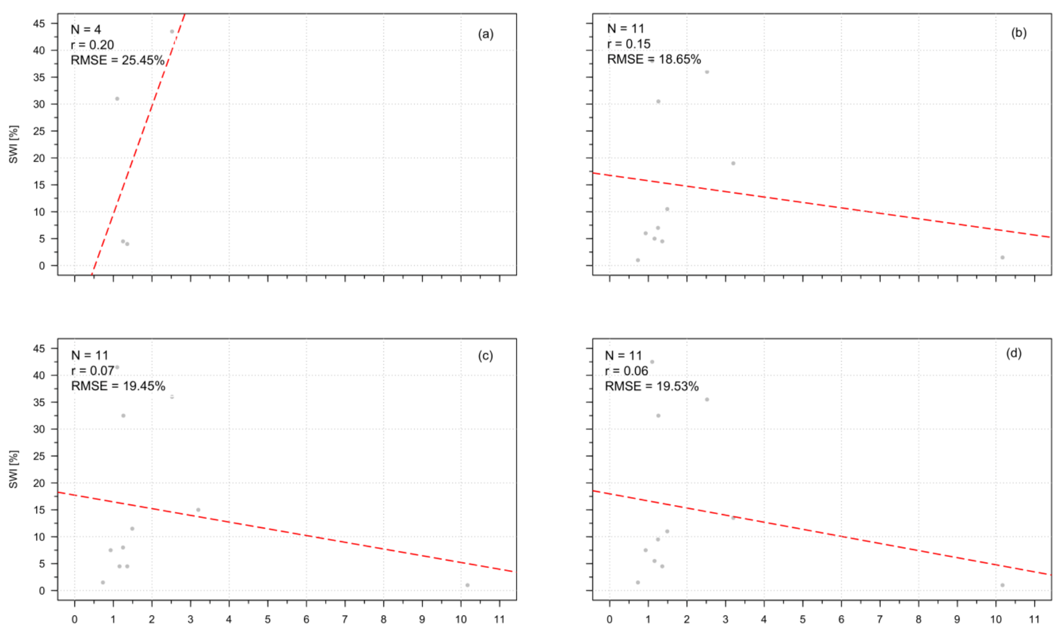

Figure 5 – As Figure 2, but for the SWI time series at the A2 site, (**a**) for T = 1; (**b**) for T = 5; (**c**) for T = 10, and (**d**) for T = 15

The relative overestimation of the in situ SSM measurements have been referred in previous SMOS/SWI validation works in different semiarid biomes and attributed to the smaller dynamic range of soil moisture in these areas (Tomer et al., 2015; Rodriguez-Fernández et al., 2016). Nevertheless, despite the results revealed high values of Bias and RMSE for both products, there are some operational services such as tracking agricultural drought in near-real time, where the general trend of SSM values is more relevant than their field observations (Enenkel et al., 2016). In this context, the SWI product would provide soil moisture estimates more reliable than the SMOS SM product.

For this study, it is convenient to emphasize that the use of time series with smaller timescale (e.g., daily) and longer duration could have led to different results, therefore these findings should be considered as preliminary. About this point, in the near future it will be necessary to install soil moisture networks around the NEB that provide complete databases with long term series of observations.

4. Conclusions

SMOS SSM and SWI datasets were compared to in situ SSM data taken from two sites of the Alagoan semiarid region where the Caatinga biome is dominant. The SMOS SSM was derived from the BEC SMOS L3 operational product disseminated by the SMOS Barcelona Expert Centre, whereas the time series of SWI were extracted from the third version of the global daily SWI operational product disseminated by the Copernicus Global Land service. The results obtained here are similar to those referred for some semiarid regions by previous works. The validation against in situ observations reveals a poor performance for both products, but the SWI shows relatively good agreement in terms of trend when the soil moisture content in the upper layers is near to zero due to severe drought conditions. The results suggested that the SWI could be useful for capturing trends related to soil water balance. Nevertheless, these findings should be considered as preliminary because only 22 soil samples of in situ SSM were available.

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