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Evaluation of PERSIANN database in the framework of SMOS Calibration/Validation activities over Valencia Anchor Station

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Abstract

Soil moisture is a key parameter for land surface water resource and climate change monitoring. ESA's Soil Moisture and Ocean Salinity (SMOS) mission will deliver, as one of its main goals, global fields of surface soil moisture with an accuracy better than $0.04\,m^3\,m^{-3}$. SMOS relies on an L-band (1.4 GHz) interferometric radiometer. Within the context of the preparation for this mission over land, the Valencia Anchor Station (VAS) experimental site, in Spain, was selected to be one of the main test sites in Europe for the SMOS Calibration/Validation (Cal/Val) activities.

This study presents preliminary analysis of PERSIANN in the framework of SMOS Cal/Val activities at the Valencia Anchor Station. The PERSIANN database is an automated system for Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks. The real interest of using the PERSIANN database into the hydrologic applications is mainly with the goal of having access to the spatial and temporal distribution of precipitation over a significant area (typically here an area equivalent to a SMOS pixel). The goal of this study is to quantify the gain of using PERSIANN instead of distributing sparse rain gauge measurements. The interest of using satellite rainfall estimates as well as the influence that the precipitation events can induce on the modelling of the water content in the soil was depicted by a comparison between different soil moisture products. Having an accurate estimation of the amount and temporal/spatial distribution of precipitation is a critical issue so as to have a faithful representation of the soil moisture distribution.

1 Introduction

Numerous studies have shown that L-band radiometry is the most relevant remote sensing technique to monitor surface soil moisture over land surfaces and at global scale (Wang et al., 1990a; Schmugge et al., 1992; Jackson et al., 1995, 1999). In this framework, ESA's Soil Moisture and Ocean Salinity (SMOS) mission has, as one of its main goals, to map global fields of surface soil moisture with an accuracy better than 0.04 $m^3 m^{-3}$ and with a temporal resolution of 2–3 days (Kerr et al., 2001). SMOS carries a fully polarimetric L-band (1.4 GHz) radiometer (Kerr et al., 2001). The passive microwave observations are done at multiple viewing angles (between 0° and 55°), and with a spatial resolution ranging from 35 km at nadir up to 50 km.

The potential of using high spatial resolution 0.04×0.04° PERSIANN-CCS[1] satellite rainfall data (Hong et al., 2004) in the framework of the SMOS Calibration/Validation (Cal/Val) activities is reported in this paper. At SMOS pixel scale (50×50 km^2) soil moisture variability is mostly driven by atmospheric forcing effects, thus mainly being influenced by climatic conditions at large scale and precipitation. The estimation of water content in the soil requires an understanding of the spatial and temporal variability of the rainfall. In particular, rainfall data availability has been highlighted as a major constraint on the effective application of water resource models, and it has been argued that quality of rainfall inputs to the model is often more important than choice of model itself (Wilk et al., 2006). Spatial rainfall estimates derived from rain-gauges are widely used as input to hydrological models and as "ground truth" for satellite rainfall measurements (Seed and Austin, 1990). The incorporation of satellite-based rainfall estimates in hydrological modelling are expected to offer an alternative to ground based rainfall estimates. The use of satellite-based information to improve spatial rainfall estimates has been widely reported (Hsu et al., 1999; Sorooshian et al., 2000; Grimes and Diop, 2003).

However, few studies have investigated so far the application of these data sets in hydrological models. Studies were conducted to evaluate the performance of hydrological models using operational satellite rainfall estimates in southern Africa (Thorne et al., 2001; Hughes et al., 2006; Hughes, 2006; Wilk et al., 2006). The advantage of using the PERSIANN database is to improve the soil moisture modelling in situations where there are few or no rain-gauge data to allow reliable estimates of spatial

[1]Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks-Cloud Classification System – http://chrs.web.uci.edu/persiann

rainfall. The model used is called SURFEX (Externalized Surface) – module ISBA (Interactions between Soil-Biosphere-Atmosphere) (Noilhan and Planton, 1989; Noilhan and Mahfouf, 1996) and it is a Soil-Vegetation-Atmosphere-Transfer (SVAT) scheme. The accuracy of the soil moisture product obtained using PERSIANN rainfall data was tested by comparing with point and spatialized soil moisture data obtained using in situ rain gauges as well as with remote sensing products derived from AMSR-E (Advanced Microwave Scanning Radiometer of the Earth Observing System). The study is focused on the experimental site of Valencia Anchor Station, in Spain, which was chosen to be one of the main SMOS Cal/Val test sites in Europe (Lopez-Baeza et al., 2005a,b; Delwart et al., 2007). VAS is a large reference area, sufficiently equipped with ground soil moisture probes and fully characterized so as to contribute to SMOS land product validation.

2 Studied area and data validation

2.1 Valencia Anchor Station

A 50×50 km^2 area was selected in Spain, close to the town of Caudete de las Fuentes (39°33′32″ N, 1°16′37″ W), with the main objective of characterizing a large-scale reference Cal/Val area specifically dedicated to the validation of low spatial resolution Earth Observation data and products. The site, called Valencia Anchor Station, represents a reasonably homogeneous and flat area (Lopez-Baeza et al., 2002). It is a semiarid environment with low annual precipitation (around 400 mm) and is characterized by an extensive set of measurements at different levels (both in the atmosphere and in the soil) in order to derive surface energy fluxes. The main cover type is vineyards, about 56%, followed by trees, shrubs, forest, industrial and urban. Besides the vineyards growing season, the area remain mostly under bare soil conditions.

Over the VAS area (50×50 km^2) 22 meteorological stations, 4 fully equipped and 18 rain gauges, are randomly and not uniformly distributed. Due to this non uniformity (for example in the center of the area there is no data) an interpolation (Inverse Distance Weighted – IDW) of all the available meteorological stations was applied. For the interpolation, the 50×50 km^2 was divided into 25 areas of 10×10 km^2 each (see Juglea et al., 2010). The temperature, atmospheric pressure, wind speed, wind direction, relative humidity were interpolated using just the 4 complete meteorological stations. The shortwave was extracted from Meteosat, a geostationary weather satellite launched by the European Space Agency (ESA), while the longwave was calculated (Brutsaert, 1975). For the precipitations, all 22 stations were taking into account. At the end of the interpolation we have an optimum spatial and temporal distribution of the atmospheric forcing over the entire VAS area.

A detailed description of the vegetation characteristics is available at 1 km resolution, based on ECOCLIMAP, a surface parameter database derived from land cover and climatic maps (Masson et al., 2003). The parameters provided by Ecoclimap are originally provided at 1-km resolution and are aggregated to a resolution of 10 km, as the interpolation for the atmospheric forcing was done. A map of texture (clay and sand) at 10 m resolution covering all the 50×50 km^2 area was also considered (Millan-Scheiding et al., 2008).

The use of all these data allows obtaining a good estimation of the distribution of soil moisture over the entire VAS area (see Juglea et al., 2010).

2.2 PERSIANN database

The PERSIANN system for rainfall estimation is under development at The Center for Hydrometeorology and Remote Sensing at The University of California, Irvine. The fundamental algorithm is based on a neural network and can therefore be easily adapted to incorporate relevant information as it becomes available. The original system (Hsu et al., 1997) was based on geostationary infrared imagery and later extended (Hsu et al., 1999) to include the use of both infrared and daytime visible imagery. Further development of PERSIANN has included cloud image segmentation and classification for rainfall estimation at 0.04×0.04° resolution (Hong et al., 2004).

The PERSIANN product used is at 0.04×0.04° resolution and covers 60° S to 60° N globally. Over the VAS area 221 PERSIANN points are distributed. So as to obtain a representative distribution of the soil moisture over the entire VAS area, in situ data (temperature, atmospheric pressure, wind speed, wind direction, relative humidity) were also interpolated using the IDW method in order to obtain the same grid as the PERSIANN rainfall database.

2.3 AMSR-E data

The Advanced Microwave Scanning Radiometer (AMSR) of the Earth Observing System (EOS) is a passive microwave scanning radiometer, operating at six wavelengths with an incidence angle of 55° within the microwave spectrum (6.925, 10.65, 18.7, 23.8, 36.5, and 89 GHz) in horizontal and vertical polarizations. Launched on the Aqua satellite in May 2002, it operates in polar sun-synchronous orbit with equator crossing at 1:30 p.m. and 1:30 a.m. local solar time. Global coverage is achieved every two days or less depending on the latitude. The mean spatial resolution at 6.9 GHz is about 56 km with a swath width of 1445 km.

The data used in this study are from the National Snow and Ice Data Center (NSIDC) Level 3 AMSR-E dataset (Njoku, 2004). The daily averages of brightness temperature and soil moisture products are re-sampled to a global cylindrical 25 km Equal-Area Scalable Earth Grid (EASE-Grid) cell spacing (Njoku, 2004). For this study soil moisture and polarization ratio at 6.9 GHz are used. The polarization ratio normalizes out the surface temperature and leaves a quantity that depends primarily on soil moisture, vegetation and atmosphere (Kerr and Njoku, 1990; Njoku et al., 2003; Owe et al., 2001) and is defined as:

$$\mathrm{PR} = \frac{Tb_v - Tb_h}{Tb_v + Tb_h} \quad (1)$$

As the AMSR-E soil moisture product shows biases and very small amplitude, a normalization between [0, 1] was done. Two AMSR-E soil moisture sampled pixels are covering the VAS area. The average of these two pixels was considered to be representative for the $50\times50\,km^2$.

3 Methodology – ISBA modelling

The soil moisture modelling was done in two steps: firstly a point modelling followed by a spatialized one. The data processed is either in situ data from VAS area either remote sensed data from PERSIANN. The model used to generate from atmospheric forcing and initial conditions the temporal behaviour of the soil moisture is called SURFEX (Externalized Surface) – module ISBA (Interactions between Soil-Biosphere-Atmosphere) (Noilhan and Planton, 1989; Noilhan and Mahfouf, 1996). It is a Soil-Vegetation-Atmosphere Transfer (SVAT) scheme employed in the operational weather forecast models of Météo-France. ISBA simulates the interaction between the low-level atmosphere, the vegetation and the soil, by using a physically based method that solves the water and energy budgets of the soil-vegetation system. In this study, the modelling of the heat and water transfers into the soil is based on the diffusive scheme – ISBA-DIF (Boone, 2000; Boone et al., 2000). More details about the choice of the parameterisation can be found in Juglea et al. (2010).

The point procedure consisted into forcing the ISBA model in three different points by using data from two rain gauges as well as from their nearest PERSIANN point. The two rain gauges considered are called Caudete de las Fuentes (CA FU – 1.31° W, 39.52° N) and Caudete de las Fuentes 1 (CA FU1 – 1.27° W, 39.55° N). The nearest PERSIANN point from both rain gauges is the point PP149 (1.26° W, 39.54° N). The input of the ISBA model was considered the same for the three cases. The rain was the only parameter that changed from a modelling to another. The rain used was from three different places: CA FU, CA FU1 rain gauges and also from PP149. A comparison between the soil moisture data obtained is depicted in the Sect. 4.2.

So as to achieve a homogeneous sampling of the soil moisture over the entire area and so a spatialized soil moisture comparable with SMOS data, the SVAT model was driven by interpolated atmospheric forcing and land surface data from VAS. Spatially distributed fields and forcing enables to simulate soil moisture spatial and temporal behaviour and thus averaged soil moisture at any moment for the whole pixel ($50\times50\,km^2$). The soil moisture obtained was considered as representative over the $50\times50\,km^2$ area (VAS).

In order to evaluate the PERSIANN database, the SVAT model was also driven using satellite rainfall estimates. The VAS area covers 221 PERSIANN points. Used as inputs for the SVAT model, 221 soil moisture points were obtained. In this case also, the average of the 221 points was considered to be representative over the $50\times50\,km^2$ area (PERSIANN). A comparison between the obtained results is detailed in Sect. 4.3.

4 Results

4.1 Point to point comparison between precipitation: rain gauges located into the VAS area versus PERSIANN points

In this section, the ability of the PERSIANN products to replicate the gauged variability of rainfall amounts and occurrence is investigated. Comparisons between rain gauges and their nearest PERSIANN points were done. As the results are similar over the whole VAS area, a representative rain gauge called Caudete de las Fuentes 1 (CA FU1) is showed. The coordinates of this rain gauge can be found in Table 1, where all the PERSIANN (PP) neighbors points are also presented. The precipitations events occur during the year 2006 at the CA FU1 rain gauge and at the nearest PERSIANN points are depicted in Fig. 1. PERSIANN overestimates rainfall in general compared to the gauges, especially in the rainy seasons, which was also found over India by Brown (2006) and across Australia, the Pacific, parts of Asia by Sorooshian et al. (2000). The more significant difference can be observed in the month of September, when the amount of rainfall between the PERSIANN points and CA FU1 rain gauge is considerably different. If the CA FU1 rain gauge records a slight amount of rainfall, all the

PERSIANN points (PP) shows rainy events going beyond 20 mm/day. During the summer season, the rain gauge as well as the PERSIANN products compare well. We can observe that during the months of May, June, July and August the amount of rainfall is similar for both cases. The PERSIANN patterns in the occurrence of rainfall are better reflected than patterns in rainfall amounts. Anyway, these differences between the rain gauges and the satellite estimates can be due to the fact that the satellite data represent areal rainfall, while the gauge data represent point rainfall. It should be noted also the fact that the PERSIANN system involves no local calibration in producing its rainfall estimates. However, downscaling of remotely sensed data remains an issue and hence these satellite-based rainfall estimates do not compare very well with the gauge data, a low correlation being obtained. This can be due to the fact that the variability of the precipitation over the VAS area is important. This variability can be seen by comparing the chosen rain gauge CA FU1 with other in situ rain gauge situated at about 4 km (Caudete de las Fuentes – CA FU). Despite their proximity to each other, the recorded rainfall at the two stations is not very highly correlated (R^2=0.35) neither (see Fig. 2).

4.2 Point to point comparison between modelled soil moisture using data from the rain gauges and the nearest PERSIANN point

The objective of this comparison is to assess whether the satellite data can be used instead of gauge data as inputs to a hydrological model. The SVAT model was driven using different precipitation database: from the CA FU and CA FU1 rain gauges and also from their nearest PERSIANN point PP149. In order to observe the difference that the precipitation events can induce on the modelling of soil moisture a comparison between the three soil moisture data was done. Figure 3 compares the soil moisture data simulated at 5 cm depth. The statistical analysis of the comparison between the three configurations is summarized in Table 2. Some differences between the three sets of data can be observed. These differences are due mostly because of rainy events; which was already noticed in the case of comparing the precipitation occurrence. These differences are sometimes marked, especially at the end of the year, when, as in the case of the rainfall amounts, an important disagreement is observed. Comparing the soil moisture using the CA FU1 rain gauge and the PP149 for all the 2006 an RMSE value of 0.07 (RMSE=0.06 between soil moisture CA FU rain gauge/PP149) is obtained. If only the period from January until the end of August is considered a noticeable improvement of the results is observed. An RMSE of 0.03 is found between CA FU1/PP149 (respectively 0.03 – CA FU/PP149). The correlation values are also better, attending values of 0.76 (instead of 0.55) for the first case (CA FU/PP149) and 0.70 (instead of 0.51) for the second case (CA FU1/PP149). So as to understand the differences obtained at the end of the year a more detailed analysis was done over the month of September(days of the year from 244 to 273). If the PP149 is considered, a monthly precipitation average of 5.20 [mm/day] results into a monthly mean of soil moisture of 0.19 [m^3 m^{-3}]. In the case of CA FU1 rain gauge, a monthly precipitation average of 0.89 [mm/day] results into a monthly mean of soil moisture of 0.12 [m^3 m^{-3}]. The same difference is obtained also in the case of using CA FU rain gauge.

However, the use of the PERSIANN rainfall demonstrates the interest of using these satellite data instead or together with the rain gauges. In the previous section, when comparing the rain gauges against the satellite estimates, we obtain also some discrepancies. As already mentioned, we conclude that one of the factors that can cause these discrepancies can be due to the fact that the satellite data represent areal rainfall, while the gauge data represent point rainfall. In the following section the comparison is done between equivalent products, both representative over the VAS area – 50×50 km^2.

4.3 Spatialized soil moisture over VAS area

Two spatialized soil moisture data are compared: one spatialized soil moisture obtained using the gauge data combined through an areal interpolation approach (IDW) and another spatialized soil moisture data obtained using the satellite rainfall estimates.

The comparison between both data is made from 2006 to 2007 (see Table 3). For graphical convenience only the 2006 period is showed. Figure 4 compares the two spatialized soil moisture data: VAS and PERSIANN. A good agreement between both data can be observed (Table 3). In the first part of the year both amplitude and variation of the soil moisture are retrieved. From the beginning of the year until May, an RMSE value equal to 0.03 is found and a correlation coefficient of 0.74. The good statistics results are also obtained from first of June until the end of August when the RMSE value is very low 0.01 and the R^2=0.60. We can observe that during all this period, from the beginning of the year until the end of the summer, a very good agreement between both data is observed (RMSE=0.03 and R^2=0.83). However, at the end of the year (from September), when the precipitation amount was the most different, the RMSE value is higher than the rest of the year (RMSE=0.08) and the correlation coefficient is lower compared to the other periods of the year R^2=0.56.

Although point to point comparison between soil moisture local data are sometimes very influenced by the rainfall events and occurrence differences, the use of spatialized data can attenuate these influences, improving the soil moisture modelling. The results obtained demonstrate the ability of the PERSIANN data to be used into a spatialized purpose. The accuracy of the obtained spatialized soil moisture is tested by comparing with data products derived from AMSR-E. The results are detailed in the next section.

4.4 Comparison with AMSR-E data

In this section, the two spatialized soil moisture data (VAS and PERSIANN) are compared with remotely sensed data from AMSR-E. Soil moisture (Njoku L3) and the polarization ratio at 6.7 GHz are considered. The inversion algorithm for the AMSR-E soil moisture uses the 10.7 GHz and 18.7 GHz brightness temperature data (Njoku et al., 2003). The increased attenuation by vegetation and the superficial sensing depth for higher frequencies is a limit in the soil moisture retrieval from AMSR-E data. As the vegetation has an important influence on the measured signal at these frequencies, the polarization ratio is used. It provides a better agreement (than the soil moisture product from AMSR-E) with simulated soil moisture even in the vegetation growing period (Juglea et al., 2010). The penetration depth of AMSR-E sensor is considered to be of about 2 cm so the soil moisture for the first two simulated layers is considered. As the absolute values are very different, all the data used are normalized between [0,1].

Figure 5 compares the three soil moisture products. In general we can observe that the dynamics of the soil moisture are well captured during the whole year. In the middle of the year, as the AMSR-E signal is perturbed by the vegetation, the comparison is done mostly with the polarization ratio. The spatialized soil moisture is found to be in better agreement with the polarization ratio. At the end of the year, as in the case of the rainfall amount and occurrence, we encounter the largest differences between the three soil moisture products. For this period, the spatialized VAS data is more in agreement with the AMSR-E products than the spatialized PERSIANN data.

5 Conclusions

In the framework of ESA's Soil Moisture and Ocean Salinity mission, this paper investigates the ability of PERSIANN rainfall estimates to give access to the spatial and temporal distribution of the precipitation so as to be able to have a optimum distribution of the water content in the soil over an area equivalent with a SMOS pixel (50×50 km^2). The study has been performed for 2006–2007 over the Valencia Anchor Station, which was selected to be one of the main key test site for the SMOS Calibration/Validation activities.

Compared with local gauge data the PERSIANN satellite estimates do not compare very well mostly due to the variability of the rainfall observed over the VAS area. Anyway, patterns in rainfall occurrence and amounts are well reproduced during the summer season. Use as an input to a SVAT model – ISBA – the PERSIANN product has an important impact when it is used in local modelling. The PERSIANN data available over the VAS area were used also into a spatialized purpose at the input of ISBA. Results of the modelling are compared to the spatialized soil moisture (obtained using meteorological stations) as well as remotely sensed data (AMSR-E). We show that useful information at temporal at spatial scales are provided in the context of soil moisture retrieval. The satellite derived rainfall estimates do seem to have potential to contribute to extending model simulations and water resource estimations into the future. The general conclusion from this study is that satellite-based rainfall estimation products can represent the main seasonal and spatial features of rainfall. Results indicated the usefulness of PERSIANN rainfall estimates for supplying rainfall inputs where gauge measurements are not available.

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References

Boone, A.: Modelisation des processus hydrologiques dans le schema de surface ISBA: Inclusion d'un reservoir hydrologique, du gel et modelisation de la neige., PhD thesis, University

Paul Sabatier, Toulouse, France, 252 pp., 2000. 1149
Boone, A., Masson, V., Meyers, T., and Noilhan, J.: The influence of the inclusion of soil freezing on simulations by a soil-vegetation-atmosphere transfer scheme., J. Appl. Meteor., 39, 1544–1569, 2000. 1149
Brown, J. E. M.: An analysis of the performance of hybrid infrared and microwave satellite precipitation algorithms over India and adjacent regions, Rem. Sens. Environ., 101, 63–81, 2006. 1150
Brutsaert, W. H.: On a derivable formula for long-wave radiation from clear skies, Water Resour. Res., 11(2), 742–744, 1975. 1147
Delwart, S., Bouzinac, C., and Wursteisen, P.: Overall SMOS Cal/Val Plan and Requirements, SMOS 7th Workshop, Esrin, 2007. 1146
Grimes, D. and Diop, M.: Satellite-based rainfall estimation for river flow forecasting in Africa. Part 1. Rainfall estimates and hydrological forecasts., Hydrol. Sci. J., 48(4), 567–584, 2003. 1145
Hong, Y., Hsu, K., Gao, X., and Sorooshian, S.: Precipitation Estimation from Remotely Sensed Information using An Artificial Neural Network-Cloud Classification System., J. Appl. Met., 43, 1834–1852, 2004. 1145, 1147
Hsu, K., Gao, X., Sorooshian, S., and Gupta, H. V.: Precipitation estimation from remotely sensed information using artificial neural networks., J. Appl. Meteor., 36, 1176–1190, 1997. 1147
Hsu, K., Gupta, H., Gao, X., and Sorooshian, S.: Estimation of physical variables from multichannel remotely sensed imagery using a neural network: application to rainfall estimation., Water Resour. Res., 35(5), 1605–1618, 1999. 1145, 1147
Hughes, D., Andersson, L., Wilk, J., and Savenije, H.: Regional calibration of the Pitman model for the Okavango River, J. Hydrol., 331(1–2), 30–42, 2006. 1145
Hughes, D. A.: Comparison of satellite rainfall data with observations from gauging station networks., J. Hydrol., 327, 399–410, 2006. 1145
Jackson, T. J., LeVine, D., Swift, C., Schmugge, T. J., and Schiebe, F.: Large area mapping of soil moisture using the ESTAR passive microwave radiometer., Rem. Sens. Environ., 54(1), 27–37, 1995. 1144
Jackson, T. J., Le Vine, D. M., Hsu, A., Oldack, A., Starks, P., Swift, C., Isham, J., and Haken, M.: Soil moisture Mapping at regional scales using microwave radiometry: The southern great plains hydrology experiment, IEEE Trans. Geosc. Remote Sens., 37(5), 2136–2151,

1999. 1144
Juglea, S., Kerr, Y., Mialon, A., Wigneron, J.-P., Lopez-Baeza, E., Cano, A., Albitar, A., Millan-Scheiding, C., Carmen Antolin, M., and Delwart, S.: Modelling soil moisture at SMOS scale by use of a SVAT model over the Valencia Anchor Station, Hydrol. Earth Syst. Sci. Discuss., 7, 649–686, 2010, http://www.hydrol-earth-syst-sci-discuss.net/7/649/2010/. 1147, 1149, 1154
Kerr, Y. H. and Njoku, E. G.: A semi empirical model for interpreting microwave emission from semiarid surfaces as seeen from space, IEEE Trans. Geosc. Remote Sens., 28, 384–393, 1990. 1148
Kerr, Y. H., Waldteufel, P., Wigneron, J.-P., Martinuzzi, J.-M., Font, J., and Berger, M.: Soil moisture retrieval from Space: The soil moisture and ocean salinity (SMOS) mission, IEEE Trans. Geosc. Remote Sens., 39(8), 1729–1735, 2001. 1145
Lopez-Baeza, E., Antolin Tomas, C., Bodas Salcedo, A., Gimeno Ferrer, J. F., Saleh Contell, K., Ferrer, F., Castell Balaguer, N., Domenech Garcia, C., Sanchez Alandi, M. A., and Velazquez Blazquez, A.: The Valencia Anchor Station: A Reference Cal/Val Area for Low-Resolution Remote Sensing Data and Products., Recent Advances in Quantitative Remote Sensing, Torrente (Valencia), poster, 2002. 1146
Lopez-Baeza, E., Alonso, S., Comeron, A., Diaz-Pabon, R., Domenech, C., Gimeno-Ferrer, J., Jorge, J., Labajo, A., Pineda, N., Pino, D., Rius, A., Rocadenbosch, F., Saleh, K., Sicard, M., Tarruella, R., Torrobella, J., and Velazquez, A.: A High-Quality Dataset of Land-Surface and Atmospheric Measurements for the Comparison/Crosscalibration of Data From Large Scale Optical Earth Observation Sensors in Space. The Valencia Anchor Station., Proceedings of the Workshop on Inter-Comparison of Large Scale Optical and Infrared Sensors, ESA/ESTEC 12–14 October 2004, ESA-WPP-244, 2005a. 1146
Lopez-Baeza, E., Domenech, C., Gimeno-Ferrer, J., and Velazquez, A.: Proposal of a Water Cycle Observatory: The Reference Valencia and Alacant Anchor Stations for Remote Sensing Data and Products., XI Spanish Remote Sensing Congress, Puerto de la Cruz, Tenerife, 2005b. 1146
Masson, V., Champeaux, J.-L., Chauvin, F., Meriguet, C., and Lacaze, R.: A global database of land surface parameters at 1-km resolution in meteorological and climate models, J. Climate, 16(9), 1261–1282, 2003. 1147
Millan-Scheiding, C., Marco, J., Soriano, M., Torre, E., Torregrosa, G., Abalos, B., Requena, F., Cano, A., Antolin, C., and Lopez-Baeza, E.: VAS Soil and Vegetation Characterization,

SMOS meeting in Bordeaux, INRA, 30–31 October 2008. 1147
Njoku, E. G.: AMSR-E/AQUA daily L3 surface soil moisture, interpretive parms, & QC EASE-Grids, Boulder, CO, USA: National Snow and Ice Data Center, Digital Media, 2004. 1148
Njoku, E. G., Jackson, T., Lakshmi, V., Chan, T., and Nghiem, S.: Soil moisture retrieval from AMSR-E, IEEE Geosc. Remote Sens. Lett., 41(2), 215–229, 2003. 1148, 1153
Noilhan, J. and Mahfouf, J.-F.: The ISBA land surface parameterization scheme, Global Planet. Change, 13, 145–159, 1996. 1146, 1149
Noilhan, J. and Planton, S.: A simple parameterization of land surface fluxes processes for meteorological models, Mon. Weather Rev., 117, 536–549, 1989. 1146, 1149
Owe, M., De Jeu, R. A. M., and Walker, J. P.: A Methodology for Surface Soil Moisture and Vegetation Optical Depth Retrieval using the Microwave Polarization Difference index, IEEE Trans. Geosc. Remote Sens., 39(8), 1643–1654, 2001. 1148
Schmugge, T., Jackson, T., Kustas, T. J., and Wang, J. R.: Passive microwave remote sensing of soil moisture: results from HAPEX, FIFE and MONSOON'90, ISPRS Journal of Photogrammetry and Remote Sensing, 47, 127–143, 1992. 1144
Seed, A. and Austin, G.: Variability of summer Florida rainfall and its significance for the estimation of rainfall by gages, radar and satellite., J. Geophys. Res., 95, 2207–2216, 1990. 1145
Sorooshian, S., Hsu, K., Gao, X., Gupta, H., Imam, B., and Braithwaite, D.: Evaluation of PERSIANN system satellite-based estimates of tropical rainfall., B. Am. Meteorol. Soc., 81, 2035–2046, 2000. 1145, 1150
Thorne, V., Coakley, P., Grimes, D., and Dugdale, G.: Comparsion of TAMSAT and CPC rainfall estimates with rainfall, for southern Africa., Int. J. Remote Sens., 22(10), 1951–1974, 2001. 1145
Wang, J. R., Shiue, J., Schmugge, T., and Engman, E. T.: The L-band PBMR measurements of surface soil moisture in FIFE, IEEE Trans. Geosc. Remote Sens., 28, 906–914, 1990a. 1144
Wilk, J., Kniveton, D., Andersson, L., Layberry, R., Todd, M., Hughes, D., Ringrose, S., and Vanderpost, C.: Estimating rainfall and water balance over the Okavango River Basin for hydrological applications., J. Hydrol., 331(1–2), 18–29, 2006. 1145

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Table 1. Coordinates of Caudete de las Fuentes1 (CA FU1) rain gauge (in the center) and of its nine PERSIANN neighbours.

PP165 (1.30° W, 39.58° N)	PP166 (1.26° W, 39.58° N)	PP167 (1.22° W, 39.58° N)
PP148 (1.30° W, 39.54° N)	PP149 (1.26° W, 39.54° N) CA FU1 (1.27° W, 39.55° N)	PP150 (1.22° W, 39.54° N)
PP131 (1.30° W, 39.50° N)	PP132 (1.26° W, 39.50° N)	PP133 (1.22° W, 39.50° N)

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Table 2. Statistical analysis between different punctual soil moisture products derived using Caudete de las Fuentes (CA FU), Caudete de las Fuentes1 (CA FU1) and the PERSIANN point PP149 data.

	CA FU/PP149	CA FU1/ PP149	CA FU1/CA FU
RMSE	0.07	0.06	0.03
R^2	0.55	0.50	0.87

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Table 3. Statistical analysis between spatialized soil moisture data derived using VAS data and PERSIANN data for 2006 and 2007.

	2006	2007
RMSE	0.05	0.05
R^2	0.67	0.75

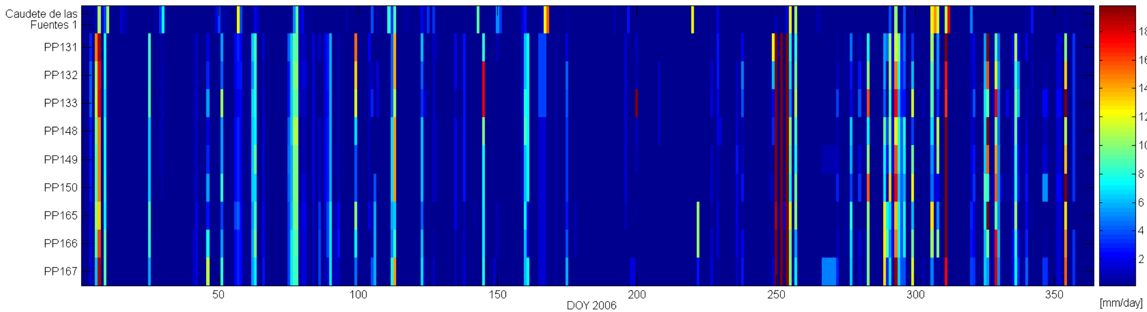

Fig. 1. Precipitations events at Caudete de las Fuetes1 rain gauge and at the nearest PERSIANN points during 2006.

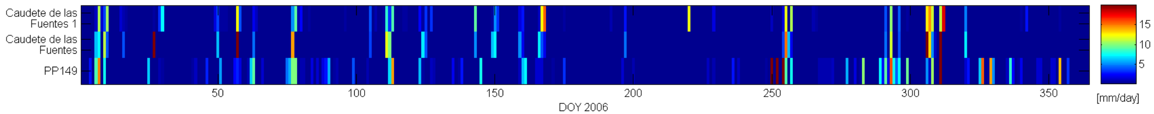

Fig. 2. Precipitations events at Caudete de las Fuentes1 (CA FU1), Caudete de las Fuentes (CA FU) rain gauges and the PERSIANN point PP149 during 2006.

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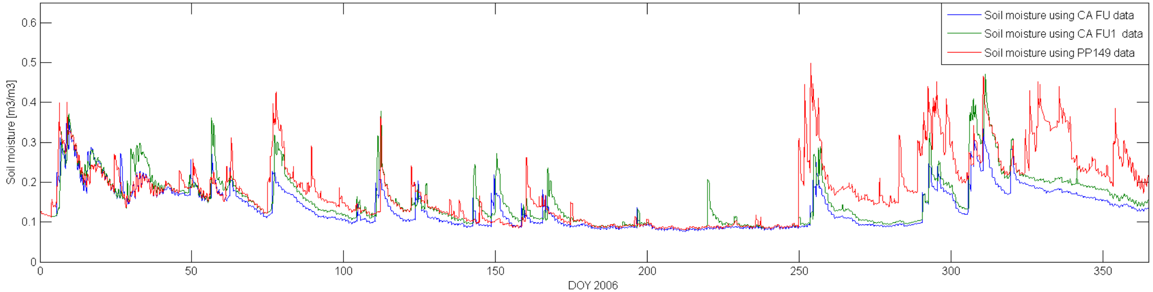

Fig. 3. Comparison between soil moisture data modelled using the precipitation data from CA FU, CA FU1 and the PERSIANN point PP149.

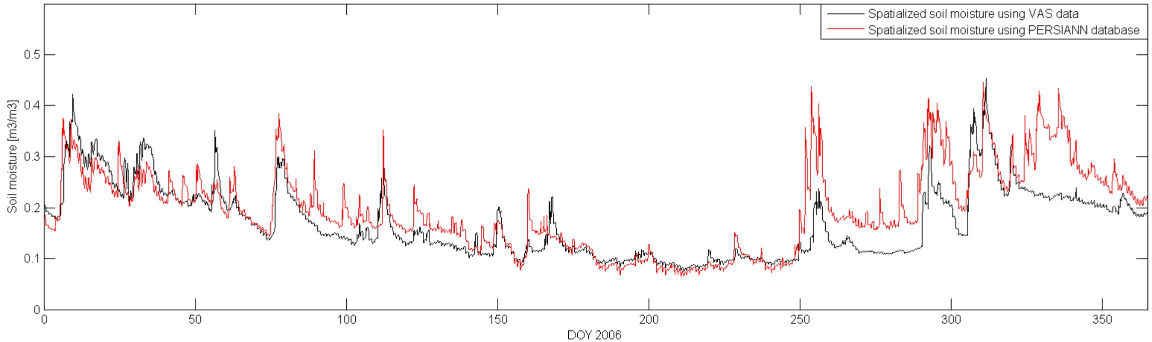

Fig. 4. Comparison between spatialized soil moisture data obtained using in situ measurements from VAS area and spatialized soil moisture data obtained using PERSIANN rainfall estimates.

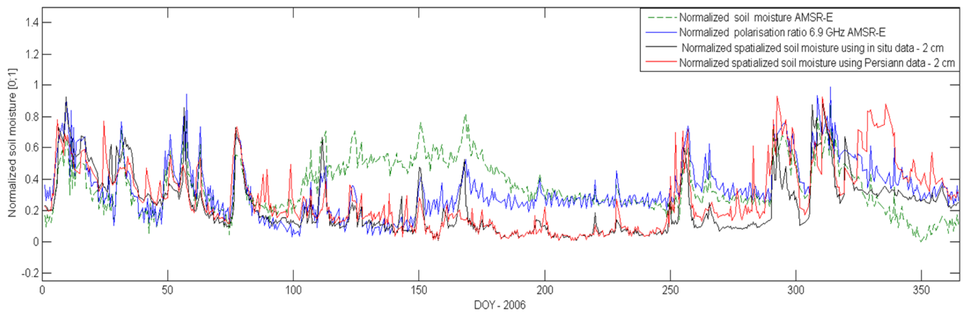

Fig. 5. Comparison between normalized spatialized soil moisture obtained using in situ data from VAS area and PERSIANN data and remote sensing products derived from AMSR-E.