Detailed response to Reviewer 2

The authors thank the reviewer #2 for his/her fair and very constructive review of the manuscript. Considering the comments of the reviewers, some parts have been rewritten to clarify our objectives and results. Here is a detailed description of our responses to the review's issues. Reviewer comments are reported in red.
To help the reviewers, the revised manuscript has been provided in this file with major modifications highlighted in bold. The responses are referred in line numbers corresponding to this revised manuscript version.

Main comment

The paper is about using the PERSIANN rainfall product to simulate soil moisture over the Valencia Anchor Station in Spain. The context is the SMOS calibration/validation process. The use of satellite precipitation products to force hydrological models is quite a recent field of research which has to be developed as more and more satellite products will be available in the coming years and have to be evaluated and validated according to the requirements of hydrological modelling studies. In that sense the paper is in an original and interesting context. However the paper has too many weaknesses. In my opinion it has to be significantly improved before thinking about a publication in HESS.

I'm particularly concerned by the three following aspects:
1. The objectives of the paper are not clear at all 2. Conclusions are not always convincing and not supported by the discussion of the results which seems to have been rushed. 3. Some explanations and illustrations are missing to understand the methodology and to analyse the results.
Considering the remarks of the reviewer, we have considerably improved the paper, by rewriting some parts that were confusing, and by adding more results and figures. The manuscript title was also changed a little. The conclusion was completely reworked.

These three points are detailed hereafter:
Point 1.
The context of the paper is the calibration/validation (cal/val) activities of SMOS but this does not make a scientific objective on its own. What are the scientific questions?
–>If the objective of the paper is to provide a reference soil moisture to be compared to the SMOS estimates for the cal/val process: - What are the scientific issues that the authors will have to face during the CAL/VAL process? - Do these issues justify the use of a hydrological model? Why not using the data from the soil moisture probes (mentioned p.1146 l.11)? - p.1148 l18-19 the authors "obtained good estimation of the distribution of soil moisture over the entire VAS area" which means for me that the rain gage network provides a sufficient information to be used routinely for the cal/val process. So why using satellite precipitation data?
Yes, you are right. The objective of this paper is to provide a reference soil moisture to be compared to the SMOS estimates for the Cal/Val process. During SMOS Cal/Val activities, the instrument measurements have to be validated. For this purpose we must have a continuous field of soil moisture over an area slightly larger than the actual pixel (3dB footprint) so that we can

apply the antenna pattern on it. To make such a large field of soil moisture ground measurements are not tractable so we rely on a limited set of ground sites and spatialize the soil moisture information with use of a SVAT coupled to a set of forcings and a very good knowledge of soil types and land use. At SMOS pixel scale (50x50 km²), 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. As in situ observations are not always available, the use of a satellite rainfall database is needed. In this framework the PERSIANN database was tested so as to be used as input to a SVAT model. Once the soil moisture fields are known, it is possible to compute satellite level brightness temperatures (to check calibration for instance) or to compare to satellite products. Moreover, as the model runs with a reasonably fine time step (1h) we can always have values at the time of overpass. This study is the necessary step towards simulating SMOS brightness temperature.

–>If the objective is to evaluate the performance of a hydrological model for different rainfall inputs: - How do the authors define the performance? Do they have any soil moisture reference that they could use (see my comment on soil moisture probes)? It seems that the authors assume that soil moisture simulated by using rain gages data is the reference. How can we trust this assumption? - The results should be discussed according to the hydrological processes and the way they are represented in the model. However are provided neither a description of the model, nor a fine description of the main processes in the studied region that could help the reader in understanding the sensitivity of soil moisture to rainfall variability.
No, the purpose of this study is not to evaluate the performance of a hydrological model for different rainfall inputs.

–>If the question is to "improve the soil moisture modelling in situations where there are few or no rain gauge data to allow reliable estimates of spatial rainfall" (as written p.1146 l27-27) - Some aspects are missing to comprehensively address this issue. For which network configuration is it preferable to use satellite data instead of rain gages data? Is a there a critical density of rain gages under which satellite data must be preferred?
Difficult to evaluate as it depends on its location through the instrument footprint. As SMOS measures the surface emission at different incident angles, a dense sampling and knowledge of the surface is important. For instance, for one incidence angle a rain gauge can have an important influence on the measured signal. The same rain gauge has lesser impact on the measured signal if the incidence angle is changed.

More generally are there some critical scales in space but also in time to be taken into account to properly simulate the soil moisture?
We must be able to capture the daily cycle. The surface soil moisture changes very rapidly in less than 2 hours. SMOS acquires data at about 6 am and 6 pm (local solar time). For example, the soil moisture at 8 am can be different than that at 6 am even more in semi arid region as in Spain.
The spatial distribution is more difficult to evaluate as one must consider the antenna pattern of the instrument. It is a weighted function due to the instrument. The emission received by SMOS is stronger in the middle of its antenna pattern than in the border of it.

The last sentence of the abstract suggests that these scale issues are addressed in the paper: "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 soil moisture distribution."

However this question is actually not quantitatively treated. Some crucial information is missing: what is the temporal resolution of the PERSIANN product used?
The PERSIANN database is on an hourly basis (L138).

What is the time resolution of rain gage data? What is the time step required by SURFEX-ISBA?
According to the dataset, in the 4 fully equipped meteorological stations located into the VAS 50x50 km² area, the measured data are registered on a 30/60 min basis. In addition, among the rain gauges, some of them are recording the weather information daily. In order to run the SVAT model with a suitable temporal resolution, standard diurnal cycles were reconstructed from the daily data.
The model is run at an hourly basis which corresponds to the PERSIANN database which is convenient. It avoids temporal interpolation of the precipitation database.

Point 2.
I'm not always convinced by the results and conclusions of the paper.
–>Rainfall comparison
The robustness of the presented results is criticisable as the analysis is carried out for only one year and with only one satellite pixel and two rain gages. It would be useful to see at least the behaviour of year 2007.
Figure 1 and 2 are not sufficient for a clear comparison. I would expect scatter plots and/or distributions of the rainfall intensities or a contingency table with non-rainy and rainy days. Moreover the colorbar chosen for the plots is not suitable as non-rainy and rainy periods are not distinguishable.
We agree with your comment, new tables and figures are provided within the new version of the manuscript. A new comparison using all the available meteorological data over the VAS area and their nearest PERSIANN points was performed and introduced in the manuscript (Table 1 – page 18 and Fig. 2 – page 23).
Fig. 1 from the old version of the manuscript was replaced by Table 2 (page 19) where a statistical analysis between Caudete de las Fuentes1 (CA FU1) rain gauge and of its nine PERSIANN neighbours (PP) for 2006 and 2007 is presented. Also, Fig.3 (page 24) was added and here we can observe the coordinates of the data used (CA FU1 and PP) in the statistical analysis.
The Fig. 2 from the old version of the manuscript was also replaced by a scatterplot which contains a statistical analysis for 2006 and 2007 (Fig. 5 - page 26).

–>Soil moisture simulation
Over the Valencia area the main problem of PERSIANN rainfall estimations seems to be the significant overestimation of rainfall from September to October. This overestimation directly impacts the simulated soil moisture which is significantly overestimated from September to October. The point here is that September-October period is the rainy season which is obviously critical in a hydrological context. Mediterranean regions experience extreme events (rainy events and flash floods) mostly during this period. In my point of view, the estimation of rain and soil moisture for these two months should be a prior target. This aspect is a bit underestimated by the authors. The authors do mention the discordances during this period of time, but they mainly base their conclusions on the good accordance between satellite and rain gages from May to August, which is actually the dry season.
We had to be sure that the seasonal cycle was coherent between the 2 database.

I find thus quite optimistic to conclude about the "potential" (p.1155 l. 3), of the PERSIANN product for soil moisture simulation both for point and areal simulation. I don't agree with the conclusions of Section 4.2 (p.1152 l. 17-18). Where is the demonstration of the interest of using PERSIANN together with rain gauges?
We wanted to check if the PERSIANN database was in agreement with rain gauge: dynamic, spatial and temporal resolution. By "potential" we wanted to say that even if some important differences exist in terms of precipitation (as you noticed), the simulated surface soil moisture is in most part of the year within the range of expected soil moisture for this area. However, by comparing with SMOS real data we will be able to set which precipitation database is the more convenient to use for our purpose.

A deeper and more objective discussion is expected about the significance of the results obtained in Section 4.1 and 4.2.
New analysis were performed and discussed within the new version of the manuscript (see section 4.2).

Point 3.
–>What is the contribution of the study according to the existing literature? A review is missing. Only 4 papers are reported as similar studies. There are many studies dealing with the issues of using satellite rainfall for hydrological modelling, not only in Southern Africa.
New references concerning the application of satellite rainfall products in hydrological models (L70 – L78) were added in the text.

–>A minimum presentation of the Valencia Anchor Station would be expected to clearly understand the study. Two important illustrations are missing: - a description of the climate and particularly the seasonal variability of rainfall. - a map with the rain gage network and the satellite grid is missing. Table 1 is not reader-friendly.
We agree with your comment. The seasonal variability of rainfall over the VAS area was introduced in the text by a figure representing a monthly comparison between all the meteorological stations/rain gauges and their nearest PERSIANN points (Fig. 2 – page 23).
A map with all meteorological stations/rain gauges available over the VAS area as well as the PERSIANN grid was added in the manuscript. (see Fig. 1 – page 22). Table 1 from the old version of the manuscript was replaced by Fig. 3 – page 24.

–>The choice of the satellite rainfall product is not clear. Why PERSIANN? What about using other satellite products? It is not clear which one of the satellite rainfall products of the PERSIANN database is used, PERSIANN CCS is mentioned p.1145 l. 6. Is it the product used? What are its specific characteristics?
The choice of PERSIANN-CCS estimates is because there are among the satellite rainfall databases with the highest spatial (0.04x0.04°) and temporal (1 hour) resolution (added in the text L137 – L139). The paragraph 2.2 (L225 – L139) presents PERSIANN – CCS specific characteristics.

–>Some descriptions of the hydrological models are missing. The paper is too dependent from Juglea et al., 2010. What are the differences between SURFEX and ISBA?
What is the time step of the simulations?

The model used is SURFEX (stands for surface externalisée – Le Moigne et al.,2009) and was developed at the National Center for Meteorological Research (CNRM) at Météo-France. It gathers all the developments and improvements made in surface schemes, containing four different modules: ISBA (Interactions between Soil-Biosphere-Atmosphere), Sea and ocean, TEB (Town Energy Balance) and Lake. In this article only the module for the soil and vegetation – ISBA (Noilhan and Planton, 1989) was used. ISBA is a SVAT scheme which describes the exchanges of heat and water between the low-level atmosphere, the vegetation and the soil. The simulation step was 1 hour.

–>As a direct consequence of the unclear paper objectives, I really don't understand the objective of Section 4.4. Why making a comparison with AMSR-E? This section is not discussed and does not even support the conclusions of the paper.
The abstract as well as the conclusion of the paper were rewritten to clarify our objectives and results. In fact, the AMSR-E data were used to verify which of the spatialized soil moisture data (obtained using in situ observation or using PERSIANN satellite estimates) can reproduce better the soil moisture behaviour at SMOS scale. In this context, the use of the PERSIANN database was tested through the soil moisture obtained using a SVAT model.

Other comments

p.1145 l. 10. It's not obvious to me. Do you have a reference? What about the effect of soil characteristics?
The soil characteristics have, of course, an important influence in the soil moisture variability.
However, precipitation amounts and occurrence are considered as an important factor in controlling spatial and temporal patterns of the soil moisture (Grayson et al., 2006), especially when using a SVAT model. Due to its high variability in space and time as well as its highly intermittent occurrence, having an accurate idea of the precipitation occurrence and amount is an important issue so as to obtain a good estimation of soil moisture variability.
Differences in rainfall amounts can produce considerable impacts on seasonal weather and climate forecasts when used for land surface model initialization. This indicates the importance of using the most accurate precipitation database, as large differences are in most of the cases directly translated into equally high errors in soil moisture.

p. 1147 l. 1-2. Is there a reason to use Inverse Distance Weighted compared to other interpolation techniques (nearest neighbour, kriging,: : :)?
The IDW method was used because of the small number of the meteorological stations over the entire VAS area as well as because of their distribution. A cross-validation analysis was done between the IDW and kriging, by computing different test for different dates and for different meteorological stations/rain gauges. The differences between the use of IDW or kriging were not significant so the choice of a sophisticated technique like the kriging was not justified.

p. 1147 l. 9. What is meant by "optimum"?
A trade off between the simulation time and the needs in spatial data was found by dividing the 50x50km² area into 25 grid surfaces of 10x10km2 each. Again, comparison with SMOS data will help us defining the best configuration for our purpose.

p 1147 l. 18. What is “a good estimation of the distribution of soil moisture”? Please give some illustration of the simulation performances?

In a previous study we have calibrated and validated the SVAT model using in situ measurements (Juglea et al., 2010). That allows us to have an idea of the soil moisture distribution over the entire test site for any season/year.

p. 1149 l. 18. the nearest PERSIANN pixel?

The clarification concerning the choice of the nearest PERSIANN pixel was made in the text L299.

p. 1151 l. 5. Please remove “Anyway”. I don’t agree with this explanation. On contrary, spatial aggregation leads to an underestimation of rainfall intensities.

Sorry for this inconvenient, the word “anyway” was deleted. Your comment is right, spatial aggregation leads to an underestimation of rainfall intensities. However, scale differences between precipitation can induce differences in rainfall occurrences.

p. 1151 l. 27-28. Please rephrase.

Agree with your comment. The sentence was replaced by: “The soil moisture comparison outlined in Fig. 7 indicates a wide range of accuracies when comparing several soil moisture data obtained using different precipitation estimates. These differences depend on season, being marked especially at the end of the year, when, as in the case of the rainfall amounts, an important disagreement is observed.” (L324 – L327).

p. 1154 l. 23-24. “Anyway” sounds weird for a scientific discussion. Please discuss objectively your results.

Sorry for this inconvenient, the word “anyway” was deleted and the text was modified accordingly.

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Soil moisture modelling of a SMOS pixel : interest of using the PERSIANN database over the Valencia Anchor Station

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Abstract.

In the framework of Soil Moisture and Ocean Salinity (SMOS) Calibration/Validation activities, this study presents the interest of using the PERSIANN -CCS[1] database into hydrological applications with the goal of accurately simulating a whole SMOS pixel by representing the spatial and temporal heterogeneity of the soil moisture fields over a wide area ($50\times50\,km^2$). The study is focused over Valencia Anchor Station (VAS) experimental site, in Spain, which is one of the main test sites in Europe for the SMOS Calibration/Validation (Cal/Val) activities. At SMOS pixel scale ($50\times50\,km^2$), 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. To quantify the gain of using PERSIANN instead of distributing sparse rain gauge measurements, point-like and areal comparisons between in situ observations and satellite rainfall is done. An overestimation of the satellite rainfall amounts is observed in most of the cases but the precipitation patterns are in general retrieved.

To simulate the high variability in space and time of surface soil moisture, a Soil Vegetation Atmosphere Transfer (SVAT) model - ISBA (Interactions between Soil Biosphere Atmosphere) is used. 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 is depicted by a comparison between different soil moisture data. Point-like and spatialized simulated data using meteorological observations or PERSIANN - CCS database as well as ground measure-

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

ments are used. It is shown that a good consistency is reached in most part of the year, the precipitation differences having less impact upon the simulated soil moisture. The behaviour of surface soil moisture at SMOS scale is verified by the use of remote sensing data from the Advanced Microwave Scanning Radiometer on Earth observing System (AMSR-E). We show that the PERSIANN database provides useful information at temporal and spatial scales in the context of soil moisture retrieval.

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 $0.04\,\mathrm{m^3\,m^{-3}}$ and a temporal resolution of 2-3 days (Kerr et al., 2001). **The SMOS mission is based on a dual polarized L-band (1.4 GHz) radiometer using aperture synthesis (two-dimensional [2-D] interferometer) so as to achieve a maximum spatial resolution of 55 km over land (43 km on average over the field of view), providing multi-angular dual polarized (or fully polarized) brightness temperatures over the globe (Kerr et al., 2001).**

The validation and calibration of the SMOS measurements is a crucial phase of the mission. In this context, a representative value of a whole SMOS pixel which can be compared to a satellite product at any overpass time is needed. To achieve this goal, it is essential to characterize and monitor an area slightly larger than the actual pixel (3dB footprint) in terms of soil moisture/brightness temperature. The Valencia Anchor Station (VAS) experimental site was selected as a key site providing in situ measurements over an area as wide as a SMOS pixel (Lopez-Baeza et al., 2005a; Delwart et al., 2007).

Observing the spatial distribution of soil moisture at the catchment scale is a difficult task requiring dense sampling to achieve a good accuracy. Distributed soil moisture fields over the entire VAS area are obtained by the use of a Soil-Vegetation-Atmosphere-Transfer (SVAT) scheme called SURFEX (Externalized Surface) – module ISBA (Interactions between Soil-Biosphere-Atmosphere) (Noilhan and Planton, 1989; Noilhan and Mahfouf, 1996). The ability to reproduce the high temporal and spatial heterogeneity of soil moisture fields at SMOS pixel scale using sparse in situ measurements over Valencia Anchor Station was investigated by Juglea et al. (2010). At SMOS pixel scale ($50\times50\,\mathrm{km^2}$) 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. The potential of using high spatial resolution $0.04\times0.04°$

PERSIANN-CCS (Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks-Cloud Classification System – http://chrs.web.uci.edu/persiann) satellite rainfall data (Hong et al., 2004) in the framework of the SMOS Calibration/Validation (Cal/Val) activities is reported in this paper. The advantage of using the PERSIANN-CCS 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 rainfall. Actually, the PERSIANN-CCS estimates are among the satellite rainfall databases with the highest spatial ($0.04 \times 0.04°$) and temporal (1 hour) resolution.

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 the choice of the 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 is 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). **Collischonn et al. (2008) evaluated the rainfall estimates of the Tropical Rainfall Measuring Mission (TRMM) satellite over the Tapajos river basin in Amazon. Gottschalck et al. (2005) studied the impact of different precipitation products on soil state and Ming et al. (2010) forced a Land Surface Model with both satellite estimates and in-situ measurements to test how well they can predict hydrologic states and fluxes useful for water resource applications. Both studies were carried out over the continental United State region. In this paper, we force a SVAT scheme with both satellite and ground reference data over the Valencia Anchor Station (VAS) area. Firstly, an evaluation of the skill of the PERSIANN products to replicate the variability of gauge rainfall amounts and occurrence at point and areal scale is performed. Then, the capacity of PERSIANN satellite rainfalls to be used as input to a hydrological model is tested. ISBA is used to simulate the spatial and temporal heterogeneity of the soil moisture fields at point and spatialized scale. Comparisons between simulated soil moisture and ground measurements are performed.**

Satellite remote sensing approaches open the possibility to provide spatially integrated information on soil moisture over large areas. Several papers investigated these soil moisture remote sensing products (Wagner et al., 2007; Rüdiger et al., 2009; Gruhier et al., 2010). In this framework, the spatialized soil moisture product obtained using PERSIANN rainfall data is tested by comparing with the spatialized soil moisture 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).

2 Studied area and data

2.1 Valencia Anchor Station

The Valencia Anchor Station site is located in the South East of Spain, about 80 km inland to the West of Valencia. It was selected by ESA with the main objective to characterize a large-scale reference area. It is dedicated specifically to the validation and calibration of low spatial resolution Earth Observation data and products. The site, defined within the natural region of the Utiel-Requena Plateau, represents a reasonably homogeneous area of about 50×50 km^2 (Lopez-Baeza et al., 2008), mainly dedicated to vineyard crops (about 75% cover), and other Mediterranean land uses (shrubs, oaks, pine, olive and almond trees, etc). From a microwave point of view, the area remains as a ploughed bare soil for about half a year.

VAS 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. Over the VAS area (50×50 km^2) 22 meteorological stations, 4 fully equipped and 18 rain gauges, are randomly and not uniformly distributed (Fig. 1). **The 4 fully equipped stations provide meteorological data: air temperature and humidity at screen level, atmospheric pressure, precipitation, wind speed and direction and solar and atmospheric radiation.**

Over the 50×50 km^2 area in situ soil moisture measurements are available. In this study, soil moisture data recorded during a campaign called Melbex 2 (39.526°N, 1.288°W - Mediterranean Ecosystem L-Band characterization Experiment 2) are used. The campaign was carried out from April 2007 to December 2007 to observe the surface emission of vineyards (Cano et al., 2008). The soil is characterized as sandy clay loam, with a texture composed of 45% sand and 26% clay. The soil moisture measurements were carried out every 10 min using capacitive probes. In the area, the soil was ploughed at least 3 times during the growing period of vineyards.

Surface static fields (vegetation fraction, roughness, leaf area index (LAI), soil texture, and others) are accessible. 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 LAI data comes from the MODIS instrument (Moderate Resolution Imaging Spectroradiometer; http://modis.gsfc.nasa.gov/) at 1 km spatial resolution provided on a daily and 8-day basis.** An accurate map representing the spatial distribution of clay and sand (Millan-Scheiding et al., 2008) at 10 m resolution covering all the 50×50 km^2 area is available.

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 $0.04 \times 0.04°$ resolution (Hong et al., 2004). Instead of extracting local texture information in PERSIANN (Hsu et al., 1997, 1999; Sorooshian et al., 2000), PERSIANN-CCS extracts information from the whole cloud patch and provides multiple infrared brightness temperature versus rainfall rate (Tb-R) relationships for different cloud classification types.

The product used in this study is PERSIANN - CCS, hereafter referenced as PERSIANN. It is at $0.04 \times 0.04°$ spatial resolution in an hourly basis. It covers $60°$ S to $60°$ N globally and over the VAS area 221 PERSIANN points are distributed (see Fig. 1).

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 $55°$ (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. The data used in this study are AMSR-E Level 3 soil moisture and brightness temperature at 6.9 GHz (Njoku, 2004), and were provided by the National Snow and Ice Data Center (NSIDC). 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). Using the brightness temperature at 6.9 GHz in horizontal (h) and vertical (v) polarizations, we computed the polarization ratio using:

$$\mathrm{PR} = \frac{Tb_v - Tb_h}{Tb_v + Tb_h} \tag{1}$$

It 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). The AMSR-E brightness temperature and soil moisture products are re-sampled to a global cylindrical 25km Equal-Area Scalable Earth Grid (EASE-Grid) cell spacing (Njoku, 2004). Two AMSR-E pixels are covering the VAS area. The average of these two pixels is considered to be representative for the $50 \times 50\,\mathrm{km}^2$ area.

3 Methodology – ISBA modelling

The model used to generate the temporal behaviour of the soil moisture from atmospheric forcing and initial conditions is called SURFEX (stands for surface externalisée – Le Moigne et al., 2009) and was developed at the National Center for Meteorological Research (CNRM) at Météo-France. It gathers all the developments and improvements made in surface schemes, containing four different modules: ISBA (Interactions between Soil-Biosphere-Atmosphere), Sea and ocean, TEB (Town Energy Balance) and Lake. In this article only the module for the soil and vegetation - ISBA (Interactions between Soil-Biosphere-Atmosphere) (Noilhan and Planton, 1989; Noilhan and Mahfouf, 1996) is used. 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 parametrization can be found in Juglea et al. (2010). **The atmospheric forcing, needed to run the ISBA model, is composed of: air temperature and humidity at screen level, atmospheric pressure, precipitation, wind speed and direction and solar and atmospheric radiation.**

The soil moisture modelling is done in two steps: one consisted in 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.

– Point procedure

The point procedure consists into forcing the ISBA model in different points by using in situ meteorological observations and PERSIANN points. Data from two rain gauges 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) are used for this study. The nearest PERSIANN points used for this local study is the point PP149 (1.26° W, 39.54° N). A common set of characteristics of the surface and atmospheric forcing are used for the three simulations (CA FU/CA FU1/PP149). However, as the goal of this approach is to evaluate the influence of the precipitation patterns and amounts over the simulated soil moisture, rainfall data are considered different for each study case. **Analysis of the obtained soil moisture as well as comparisons with ground measurements are presented in the paragraph 4.2.1**.

– Spatialized procedure

In order to reproduce the high temporal and spatial heterogeneity of soil moisture fields over the entire VAS area, the 50×50 km^2 is divided into 25 areas of 10×10 km^2 each. Fig. 1 presents the spatial distribution of the available meteorological stations/rain gauges over the

VAS 50×50 km^2 area. As an irregular distribution of the stations can be noticed (for example in the center of the area there is no data) an interpolation (Inverse Distance Weighted – IDW) using all the available meteorological stations is performed over the 10×10 km^2 grid as described in Juglea et al., 2010. To achieve an homogeneous sampling of the soil moisture over the entire area and so a spatialized soil moisture comparable with SMOS data, the SVAT model is driven at an hourly basis by interpolated atmospheric forcings and land surface data from VAS. Spatially distributed fields and forcing enable to simulate soil moisture spatial and temporal behaviour. **Once the soil moisture fields are known over the 50×50 km^2 grid, it is possible to compare to satellite products. Spatialized soil moisture values outputted from SVAT are averaged to produce a mean value of soil moisture representative over the 50×50 km^2 area (VAS).**

The VAS area covers 221 PERSIANN points. The temperature, atmospheric pressure, wind speed, wind direction and the relative humidity are interpolated (IDW) over the 4×4 km^2 grid using the 4 complete meteorological stations. The downwelling shortwave fluxes are extracted over the same grid from the Land-SAF (http://www.meteo.pt/landsaf/) radiation product while the longwave fluxes are calculated using the interpolated data and the formulation from Brutsaert (1975) which uses only inputs of measured surface air temperature and moisture amount. The roughness and the fraction of vegetation (ECOCLIMAP) and the LAI (MODIS), are at 1 km resolution. Due to their different spatial resolutions when compared to the 4×4 km^2 grid, these products are aggregated through a spatial mean. Texture maps (sand and clay) are available at 10m resolution. In this case, the aggregation to the 4×4 km^2 is done by considering the main class of texture into the grid cell. In order to evaluate the PERSIANN database, the SVAT model is also driven by the 221 satellite rainfall estimates and the data from the VAS area. All the PERSIANN points covering the VAS site lead to 221 soil moisture points, from which the average is computed.

To check the behaviour of both spatialized soil moisture data (using in situ observations – VAS or satellite estimates – PERSIANN), a comparison with existing products derived from AMSR-E is performed. In the paragraph 4.2.2, equivalences between the simulated soil moisture using different input data as well as comparisons of spatialized soil moisture and remote sensing products from AMSR-E are discussed. .

4 Results

In order to test the ability of the PERSIANN satellite rainfalls to be used as an input of a hydrological model so as to accurately simulate a whole SMOS pixel, an evaluation of the product is undertaken. Firstly, rain rates comparisons at point/areal scale between in situ observations and the PERSIANN points is done. Secondly, ISBA is used to simulate the spatial and temporal heterogeneity of the soil moisture fields at point and spatialized scale. Comparisons between

simulated soil moisture and ground measurements as well as comparisons between spatialized soil moisture data using meteorological observations from VAS/ PERSIANN database are depicted next. To test which spatialized soil moisture (VAS or PERSIANN) behaviour is best, a two year comparison with AMSR-E data products is performed. The soil moisture simulations are extracted for the time steps close to the overpass times of the satellites. As AMSR-E penetration depth is of about 2 cm, the simulated soil moisture integrated over the first 2 cm is considered. The results are detailed in the next section.

4.1 Rainfall comparison

In this section, the skill of the PERSIANN products to replicate the gauged variability of rainfall amounts and occurrence is investigated for 2006 and 2007. **Fig. 2 presents monthly comparisons between all the meteorological stations within the 50$\times$50 km^2 VAS area and their nearest PERSIANN points (PP) for 2007. Although there is a general agreement in rainfall patterns, the precipitation values produced by PERSIANN substantially overestimate the rainfall amounts in comparison with the gauges. If from March to August comparable rainfall amounts and variability are observed, in winter PERSIANN overestimates the amount of rainfall. This overestimation is more noticeable during 2006 (not showed), when the rain gauges records an amount of rainfall smaller than 50 mm/month in September whereas the PERSIANN products systematically exceeds 150 mm/month. For 2007, the same important differences are observed for the month of January and February. Table 1 summarizes the results for the entire VAS catchment and lists both the root-mean square error (RMSE) and the mean bias (Mbias) of daily precipitation between each in situ rainfall observation and PERSIANN points. It shows that the PERSIANN product indicates in most of the considered cases equivalent spatial and temporal error over the VAS area. As PERSIANN data seriously overestimate the rainfall a further calibration and adjustment of the satellite data using in situ observations can be suggested.**

In order to encounter the spatial variability of the PERSIANN product, a representative rain gauge called Caudete de las Fuentes 1 (CA FU1) is analysed more in depth. The coordinates of this rain gauge are depicted in Fig. 3, where all the PERSIANN (PP) neighbours points chosen for the comparison are also presented. The precipitation events occurring during the years 2006 and 2007 at the CA FU1 rain gauge and at the nearest PERSIANN points are analysed and Table 2 summarizes the differences in terms of RMSE and Mbias. **In this case also, substantial differences between the different rainfall data in terms of range and temporal variability are observed.** 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 is observed in September 2006, 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. During the months of June, July and August (2006, 2007) the amount of rainfall is comparable for both cases. Among this period the CA FU1 rain gauge records rainfall amounts at around 45 mm while the PERSIANN points shows rainfall amounts of about 70 mm.

The fact that the satellite data represent areal rainfall, while the gauge data represent point rainfall can also induce precipitation differences. **In this context, an interpolated (IDW) rainfall product obtained using all the available in situ observation over VAS is used. This product is representative over a 10×10 km^2 area. Fig. 4 presents the location as well as the differences when comparing the interpolated rainfall (10×10 km^2) with the spatial mean of the 12 PERSIANN points available within the same grid. To encounter the spatial resolution differences, a comparison of the interpolated rainfall and each PERSIANN point available within the 10×10 km^2 grid is performed. The analysis is done for 2007 at a daily scale. A slight improvement in terms of RMSE and R^2 is obtained when comparing data at the same spatial resolution. For instance, when comparing the interpolated rainfall with each nearest PP no correlation is observed and the RMSE value is above 6.73 mm/day in most cases. In the case of comparing the satellite based estimates spatially averaged and the interpolated precipitation, R^2 = 0.23 -/- and the RMSE is about 5.32 mm/day. This results highlight the importance of comparing equivalent spatial products, meaning that the scaling issue has to be considered.** It should be noted also the fact that the PERSIANN system involves no local calibration in producing its rainfall estimates. This means that the PERSIANN product can be improved by taking into account the characteristics of the considered region. 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/interpolated data, a low correlation being obtained. This can also be due to the important variability of the precipitation occurrence over the VAS area. This variability can be seen by comparing at a daily scale the chosen rain gauge CA FU1 with other in situ rain gauge situated at about 4 km (Caudete de las Fuentes – CA FU) - see Fig. 3 to localize both rain gauges. Despite their proximity, the recorded rainfall at the two stations for 2006 is not highly correlated (R^2 = 0.36 -/-) neither (see Fig. 5).

4.2 Soil moisture

4.2.1 Point to point comparison between soil moisture data

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. Precipitation is considered as an important factor in controlling spatial and temporal patterns of soil moisture, especially in arid and semiarid regions (Grayson et al., 2006). In this context, the SVAT model is driven using different precipitation database: from the CA FU and CA FU1 rain gauges and also from the PERSIANN point PP149. **The in situ soil moisture considered was recorded during Melbex 2 campaign, from April 2007 to December 2007.**

In order to observe the difference that the precipitation events can induce on the modelling of soil moisture, Fig. 6 illustrates a comparison at an hourly scale between the three simulated soil moisture data (CA FU, CA FU1 and PP149) and ground measurements. The considered period is from June to December 2007 and the soil moisture is representative over 5 cm depth. The SVAT simulations indicate that there is a considerable impact on land surface states when using different precipitation forcing. The simulations using CA FU, CA FU1 or PP149, all show some differences from the observed soil moisture. The RMSE values are ranging from 0.02 $m^3\,m^{-3}$ for CA FU1, 0.05 $m^3\,m^{-3}$ for PP149 and 0.06 $m^3\,m^{-3}$ for CA FU. The pattern of differences, however, varies considerably. For instance, the CA FU simulation depicts dryer soil moisture values within the considered period. The precipitation total amount recorded along the considered period is of 189.85 mm. The CA FU recorded rainfall amount is comparable with the amount of rainfall recorded at CA FU1 rain gauge of 172.08 mm. However, the precipitation occurrence registered from CA FU is more widely distributed in time, causing a longer period of dry soil moisture values. The PP149 runs indicate generally a much wetter soil than the measured one. This pattern is consistent with the overestimation of late fall and winter precipitation by the satellite products. A total rainfall amount of 324.08 mm within the considered period is encountered, almost twice than the total rain gauges amount. The CA FU1 simulation, on the other hand, illustrates substantially less error from the observed soil moisture.

A more detailed analysis over a longer period is performed using the simulated soil moisture data. Fig. 7 compares the soil moisture data simulated at 5 cm depth at an hourly resolution for 2006 and 2007. The statistical analysis of the comparison between the three configurations is summarized in Table 4. **The soil moisture comparison outlined in Fig. 7 indicates a wide range of accuracies when comparing several soil moisture data obtained using different precipitation estimates. These differences depend on season**, being marked especially at the end of the year, when, as in the case of the rainfall amounts, an important disagreement is observed. For 2006, when comparing the soil moisture using the CA FU1 rain gauge and the PP149 an RMSE value of 0.07 $m^3\,m^{-3}$ (RMSE = 0.06 $m^3\,m^{-3}$ between soil moisture CA FU rain gauge/ PP149) is obtained. If only the period from January to the end of August 2006 is considered a noticeable improvement of the results is observed. An RMSE of 0.03 $m^3\,m^{-3}$ is found between CA FU1/ PP149 (respectively 0.03 $m^3\,m^{-3}$ – CA FU/ PP149). The correlation values are also better, reaching 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). **The greatest differences are generally observed during the late fall and winter season**. To understand these differences obtained at the end of the year, a more detailed analysis is done for

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 $\mathrm{m}^3\,\mathrm{m}^{-3}$. 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 $\mathrm{m}^3\,\mathrm{m}^{-3}$. **The same difference is obtained also in the case of using CA FU rain gauge. From September to December, an RMSE of 0.09 $\mathrm{m}^3\,\mathrm{m}^{-3}$ is found between CA FU1/ PP149 (respectively 0.11 $\mathrm{m}^3\,\mathrm{m}^{-3}$ – CA FU/ PP149) and the correlation values of 0.49 -/- for CA FU1/ PP149 and 0.42 -/- for CA FU/ PP149. For 2007, the simulated soil moisture using PP149 is slightly higher than the other soil moisture data, causing a little degradation of the scores. However, at the end the year, from September to December, the impact of the precipitation is less significant than for 2006, an RMSE of 0.06 $\mathrm{m}^3\,\mathrm{m}^{-3}$ is found between CA FU1/ PP149 (respectively 0.10 $\mathrm{m}^3\,\mathrm{m}^{-3}$ – CA FU/ PP149). The correlation values are also better, attending values of 0.55 -/- for CA FU1/ PP149 and 0.45 -/- for CA FU/ PP149.**

In the previous section, when comparing the rain gauges against the satellite estimates, we obtain also some discrepancies. 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 – $50\times50\,\mathrm{km}^2$.

4.2.2 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 for 2006 and 2007. Fig. 8 compares the two spatialized soil moisture data: VAS and PERSIANN at 5 cm depth. **In order to better understand the seasonal variations of the impact of the PERSIANN precipitation products on the simulated soil moisture, we focused on a monthly analysis.** In the first part of the year both amplitude and variation of the soil moisture are retrieved. For 2006, from the beginning of the year until May, an RMSE value equal to 0.03 $\mathrm{m}^3\,\mathrm{m}^{-3}$ 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 $\mathrm{m}^3\,\mathrm{m}^{-3}$ and the R^2 = 0.60 -/-. During all this period, from the beginning of the year to the end of the summer, a good agreement between both data is observed (RMSE = 0.03 $\mathrm{m}^3\,\mathrm{m}^{-3}$ and R^2 = 0.83 -/-). Although the simulated soil moisture using satellite estimates generally perform well, there are some exceptions, however. At the end of the year (from September), when the precipitation amount is the most different, the RMSE value is higher than the rest of the year (RMSE = 0.08 $\mathrm{m}^3\,\mathrm{m}^{-3}$) and the correlation coefficient is lower compared to the other periods R^2 = 0.56 -/-. For 2007 the spatialized soil moisture statistics are within the same range as for 2006. At the beginning of the year, from January to the end of May the RMSE = 0.06 $\mathrm{m}^3\,\mathrm{m}^{-3}$ (R^2 = 0.68 -/-), from June to the end of August the RMSE

= 0.04 $m^3\,m^{-3}$ (R^2 = 0.82 -/-) and at the end of the year, from September to December the RMSE = 0.06 $m^3\,m^{-3}$ (R^2 = 0.65 -/-). The precipitation differences at the end of the year 2007 are less significant, inducing less errors in the simulated soil moisture.

Point to point comparison between soil moisture data are influenced by the rainfall events and occurrence differences. The use of spatialized data (average of several simulated grid points) attenuate these influences, leading to more consistent soil moisture results.

4.2.3 Comparison with AMSR-E data

Two soil moisture data basis representative over the Valencia Anchor Station ($50\times50\,km^2$ area) are considered (VAS and PERSIANN) and tested by a comparison with remotely sensed data from AMSR-E. Soil moisture (Njoku L3) and the polarization ratio at 6.7 GHz products are considered. 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 simulated soil moisture representative over 2 cm depth is considered. **As the AMSR-E soil moisture product shows biases and very small amplitude (Rüdiger et al., 2009; Gruhier et al., 2010), a normalization between [0, 1] is done for all the soil moisture data within this paragraph. The normalized AMSR-E soil moisture data display a very high variation. The comparison was done for 2006 and 2007.** Fig. 9 compares the three soil moisture products and the Table 4 summarizes the differences encountered within the considered product. All statistics presented in the following sections are calculated for the normalized soil moisture values and are, therefore, dimensionless. In general we can observe that the dynamics of the soil moisture are well captured during the whole year. During the first part of the year, the AMSR-E product and modelled spatialized soil moisture estimate levels are comparable. **In the middle of the year, as the AMSR-E signal is perturbed by the vegetation, the comparison is done with the polarization ratio. The AMSR-E soil moisture product shows only low correlations with any of the VAS or PERSIANN datasets. The spatialized soil moisture is found to be in better agreement with the polarization ratio which shows a good representation of the dynamic behaviour of the soil moisture content. A good correlation exists between the three datasets (VAS, PERSIANN and AMSR-E polarization ratio), with a range of the correlation coefficient from 0.40 -/- to 0.67 -/- for both 2006 and 2007. During the spring and summer season for 2006 and 2007 the three products compare well. The higher agreement during this period is important because it shows that although the PERSIANN products overestimate the total rainfall during the year, during this period precipitation are accurately represented by this satellite estimates. Although there is a general agreement in soil moisture patterns, the high** precipitation satellite estimates during the late fall and winter induce an overestimation of PERSIANN soil moisture compared with AMSR-E products and VAS data. 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 Calibration and Validation activities of the Soil Moisture and Ocean Salinity mission, obtaining a brightness temperature comparable with the instrument measurements is an important issue. A good knowledge of soil moisture over a large area is then necessary. Precipitation amounts and occurrence are considered as an important factor in controlling spatial and temporal patterns of the soil moisture. Due to its high variability in space and time as well as its highly intermittent occurrence, measuring precipitation requires dense sampling to achieve a good accuracy. The study is performed over the Valencia Anchor Station (2006–2007) which provides in situ data at large scale. Meanwhile, the sparse distribution of the gauges within the area can be a limit to our approach. In this context, this paper investigates the ability of PERSIANN rainfall estimates to give access to a higher spatial and temporal distribution of the precipitation.

An evaluation of PERSIANN rainfall amount and occurrence was undertaken. Local meteorological station/gauge data and the PERSIANN estimates do not compare very well. During the summer season, when the precipitation occurrence and amounts are less important, patterns in rainfall are better reproduced. However, during late fall and winter substantial differences between the different rainfall data in terms of range and temporal variability are observed. This can be explained by the variability of the rainfall over the VAS region and also by the scale difference of the databases. Whereas rain gauges record the rainfall at a point, the PERSIANN satellite estimates integrate the amount of rain over a wider area. Although important local differences exist, averages at equivalent scale show results in better agreement.

Used as input to a SVAT model – ISBA – the PERSIANN product has an important impact when it is used in local modelling. However, the differences in soil moisture are much lesser than the differences in precipitation forcing. Nevertheless, there are periods (late fall and winter) when the soil moisture differences are of equivalent magnitude to that of the precipitation forcing. A wide range of accuracies when comparing several soil moisture data obtained using different precipitation estimates is observed. These differences depend on the season, being marked especially at the end of the year, when, as in the case of the rainfall, an important disagreement is observed.

Two spatialized soil moisture information representative over the $50\times50\,\mathrm{km}^2$ are obtained using ISBA coupled to a set of forcings and a good knowledge of soil types and land use. One

spatialized soil moisture is obtained using the gauge data combined through an areal interpolation approach (IDW) and another spatialized soil moisture data obtained using PERSIANN satellite rainfall estimates. The simulated soil moisture using satellite estimates generally performs well, both amplitude and variation being retrieved. However, at the end of the year (from September), when the precipitation amounts are the most different, the RMSE value is higher than the rest of the year. This spatialized approach significantly improves the results. To check the validity of both spatialized soil moisture data, a comparison with AMSR-E product is performed. Although AMSR-E surface soil moisture product is not able to capture the absolute value, it provides reliable information on surface soil moisture temporal variability, at seasonal and rainy events scale. In general we can observe that the dynamics of the soil moisture are well captured during the whole year by both spatialized soil moisture databases (VAS and PERSIANN). From April to September, during the vegetation growing season the AMSR-E signal is very perturbed inducing an important error in the soil moisture product. The use of the polarization ratio at 6.9 GHz provides a better agreement with simulated soil moisture. The spatialized soil moisture obtained using the VAS in situ observation is, in general, more in accordance with the AMSR-E products than the spatialized soil moisture data obtained using PERSIANN satellite estimates.

The rainfall differences reported above are sometimes consequent and can produce considerable impacts on seasonal weather and climate forecasts when used for land surface model initialization. This indicates the importance of using the most accurate precipitation database, as large differences are in most of the cases directly translated into equally high errors in soil moisture. The satellite derived rainfall estimates seem to have potential to contribute to extending model simulations and water resource estimations into the future. Further work will imply simulation of the SMOS brightness temperature using the simulated soil moisture obtained from the presented work. Comparison with SMOS data will give us more information about which precipitation database to be considered in our approach.

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Table 1. List of all the meteorological stations/ rain gauges (1st column) and their nearest PERSIANN points (2nd column) available over the VAS area. The root-mean square error (RMSE) and the mean bias (Mbias) of daily precipitation between each in situ rainfall observations and PERSIANN points are calculated for 2006 and 2007.

Station Name	PERSIANN point	2006 RMSE mm/day	2006 Mbias mm/day	2007 RMSE mm/day	2007 Mbias mm/day
CASAS DE VES	28	5.69	0.80	6.04	0.90
CASAS IBANEZ	42	6.96	0.90	6.95	1.11
VILLAMALEA	56	6.13	0.77	6.57	1.02
REQUENA LA PORTERA COOP.	102	6.04	0.82	6.43	1.11
REQUENA CAMPO ARCIS	100	4.79	0.77	5.82	1.06
DEL MORO CHJ	130	5.82	0.76	5.92	0.94
REQUENA	136	5.31	0.81	6.31	1.19
CAUDETE DE LAS FUENTES	148	5.58	0.73	5.95	1.03
MINGLANILLA	141	5.70	0.34	5.98	0.79
PRESA DE CONTRERAS	143	6.15	1.08	6.72	0.76
UTIEL CHJ	167	5.83	0.76	6.92	1.59
UTIEL	167	6.03	0.69	6.93	1.55
UTIEL (LA CUBERA)	166	5.61	0.71	6.38	1.69
CAMPORROBLES COOPERATIVA	196	5.86	0.75	5.53	0.70
CAMPO ARCIS	100	4.75	0.77	5.22	1.00
CERRITO REQUENA	119	5.55	0.78	5.53	1.08
VAS	165	5.71	0.91	5.26	1.02
GRAJA DE INIESTA	122	4.54	0.62	5.43	0.80
CONTRERAS	143	6.03	0.86	6.53	0.82
CAUDETE DE LAS FUENTES 1	149	5.52	0.68	5.93	1.23
VILLAMALEA 1	72	4.80	0.75	6.20	1.01
CERRO	24	4.87	0.76	5.48	1.01

Table 2. Daily statistical analysis between Caudete de las Fuentes1 (CA FU1) rain gauge and of its nine PERSIANN neighbours (PP) for 2006 and 2007.

Rain gauge CA FU1/PERSIANN point	2006 RMSE mm/day	2006 Mbias mm/day	2007 RMSE mm/day	2007 Mbias mm/day
CA FU1/PP131	5.64	0.71	5.19	1.02
CA FU1/PP132	5.44	0.69	5.70	1.06
CA FU1/PP133	5.79	0.84	5.79	1.25
CA FU1/PP148	5.60	0.69	5.36	1.04
CA FU1/PP149	5.53	0.68	5.93	1.24
CA FU1/PP150	5.61	0.74	6.35	1.45
CA FU1/PP165	5.66	0.71	5.31	1.09
CA FU1/PP166	5.62	0.74	6.12	1.35
CA FU1/PP167	5.64	0.79	6.42	1.61

Table 3. Statistical analysis between simulated local soil moisture at 5 cm depth using Caudete de las Fuentes (CA FU), Caudete de las Fuentes1 (CA FU1) and the PERSIANN point PP149. The study is performed for 2006 and 2007.

		CA FU/PP149	CA FU1/ PP149	CA FU1/CA FU
2006	RMSE $\mathrm{m^3\,m^{-3}}$	0.07	0.06	0.03
	R^2 -/-	0.55	0.50	0.87
	Mbias $\mathrm{m^3\,m^{-3}}$	0.04	0.02	-0.02
	Eff -/-	-0.75	0.08	0.74
2007	RMSE $\mathrm{m^3\,m^{-3}}$	0.09	0.06	0.05
	R^2 -/-	0.54	0.61	0.81
	Mbias $\mathrm{m^3\,m^{-3}}$	0.07	0.04	-0.04
	Eff -/-	-2.23	0.23	0.50

Table 4. Statistical analysis between SM VAS (spatialized soil moisture obtained using in situ observations), SM PERSIANN (spatialized soil moisture data obtained using PERSIANN satellite rainfall estimates), SM AMSR-E (AMSR-E soil moisture product) and PR AMSR-E (AMSR-E polarization ratio 6.9 GHz). The comparison is made for 2006 and 2007.

		RMSE -/-	R^2 -/-
2006	SM VAS/SM AMSR-E	0.24	0.07
	SM PERSIANN/SM AMSR-E	0.26	0.01
	SM VAS/PR AMSR-E 6.9 GHz	0.17	0.50
	SM PERSIANN/PR AMSR-E 6.9 GHz	0.17	0.41
2007	SM VAS/SM AMSR-E	0.19	0.38
	SM PERSIANN/SM AMSR-E	0.20	0.24
	SM VAS/PR AMSR-E 6.9 GHz	0.13	0.67
	SM PERSIANN/PR AMSR-E 6.9 GHz	0.14	0.53

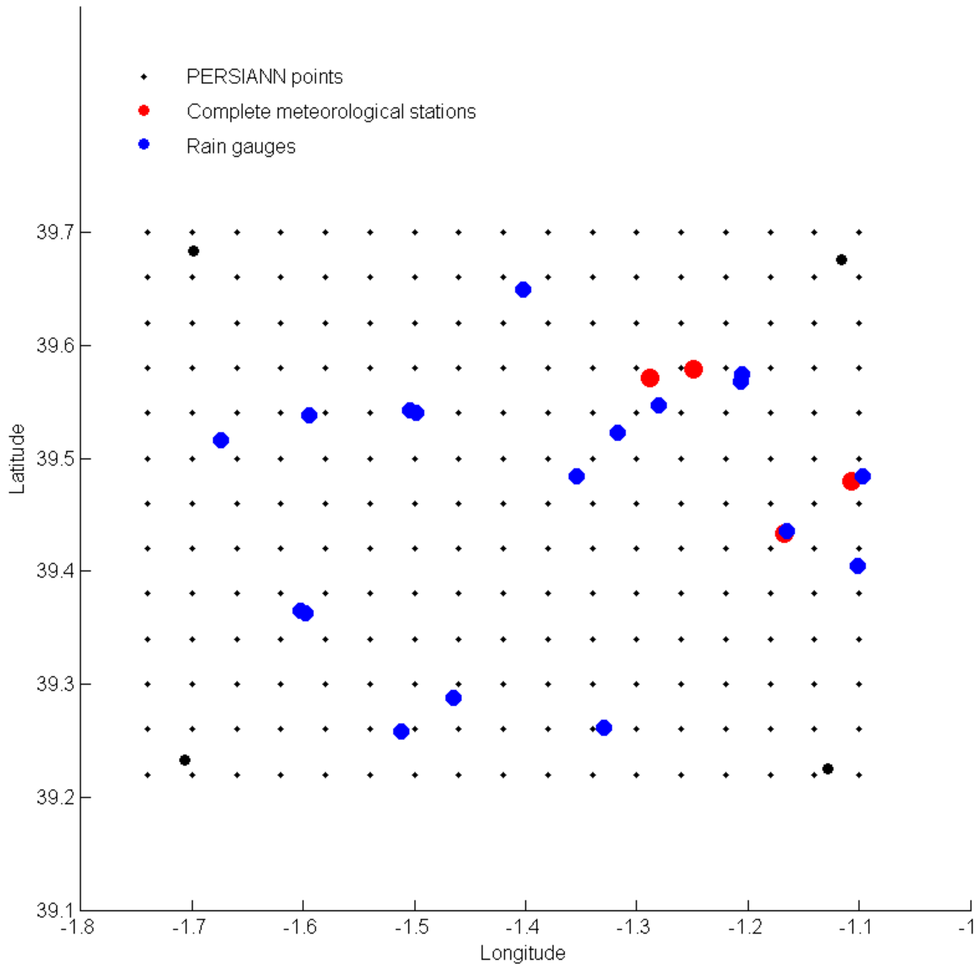

Fig. 1. Distribution of the in situ meteorological stations (red dots) and rain gauges (blue dots) over the $50 \times 50\,\mathrm{km}^2$ VAS area (the four large black dots representing its limits). The PERSIANN points are represented in small black dots.

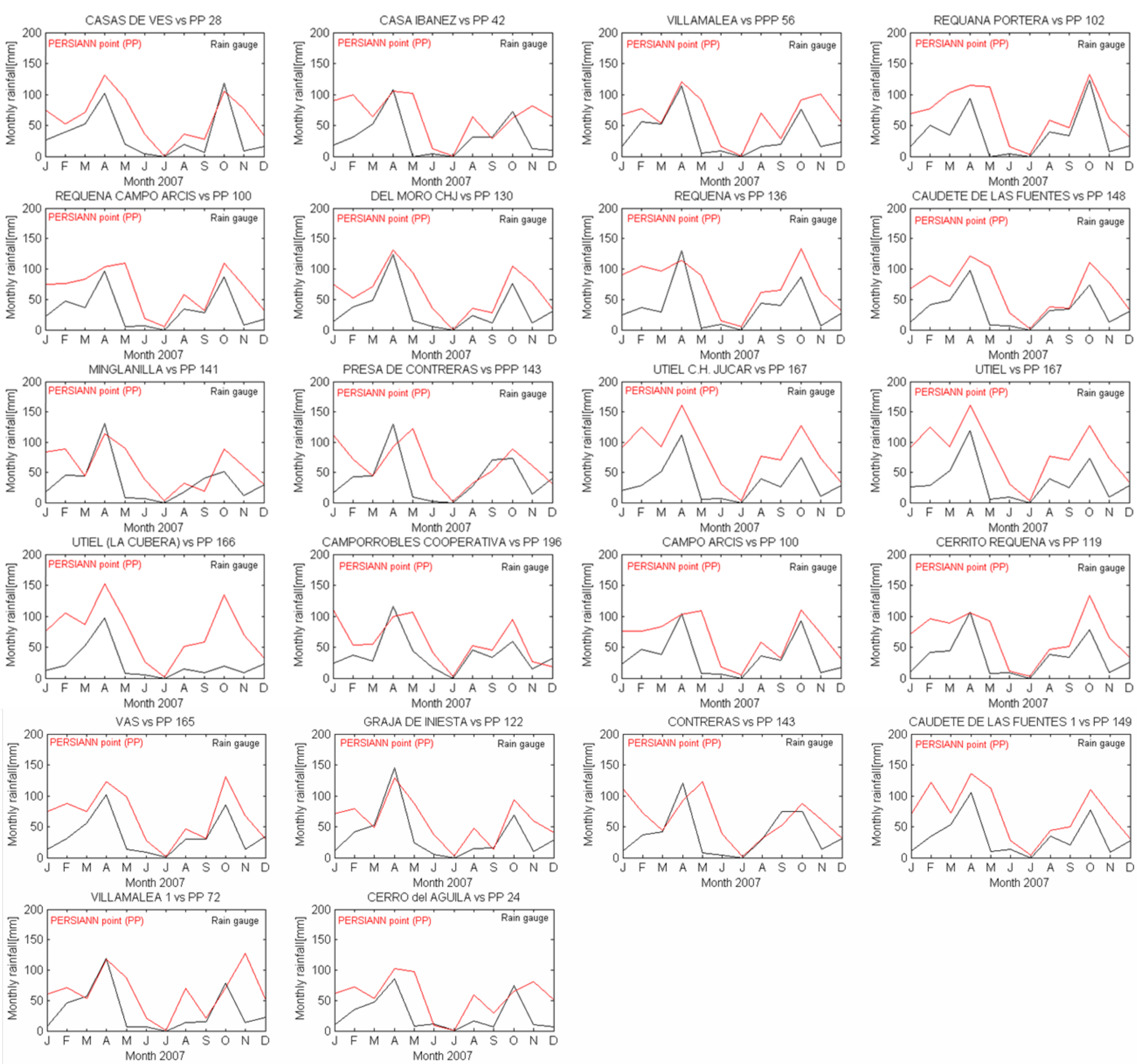

Fig. 2. Monthly comparisons between all the meteorological stations/rain gauges (black line) within the $50\times50\,\mathrm{km}^2$ VAS area and their nearest PERSIANN points (red lines) for 2007.

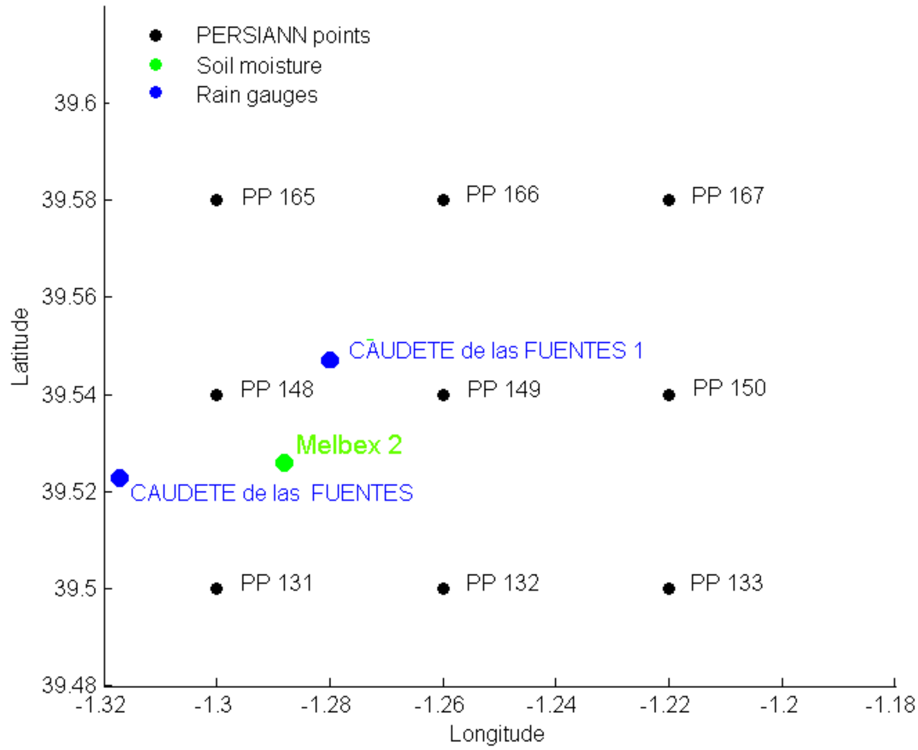

Fig. 3. Coordinates of Caudete de las Fuentes (CA FU) and Caudete de las Fuentes 1 rain gauges (blue dots) and their PERSIANN neighbors (black dots and their number of reference). The site of Melbex 2 soil moisture campaign is represented by the green dot.

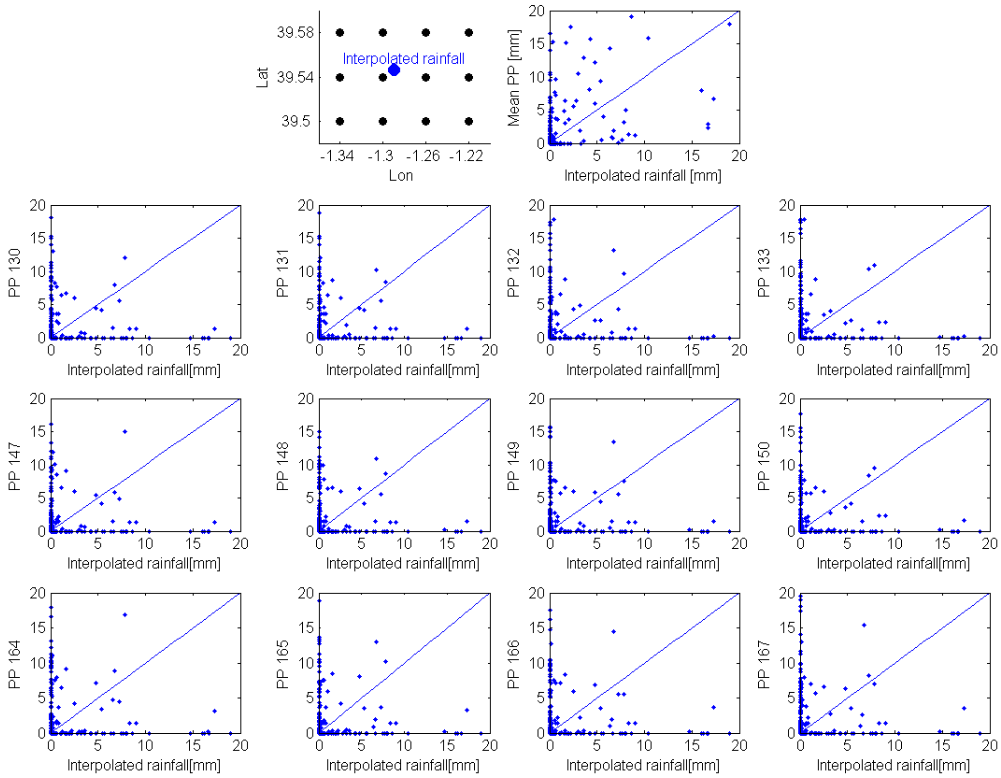

Fig. 4. Comparison between interpolated rainfall product (X axis) and PERSIANN points (Y axis). The interpolated rainfall is representative over a $10\times10\,\mathrm{km}^2$ area and is obtained using in situ observations over VAS. The mean PP represents the spatial average of the 12 PERSIANN points available within the same grid as the interpolated rainfall. The top left figure provides a map (longitude X axis, latitude Y axis) representing the interpolated rainfall and the PERSIANN points, while the top right figure represents the comparison between the interpolated rainfall and the PERSIANN mean. The 2nd, 3rd and 4th rows present comparisons of the interpolated rainfall (X axis) and each PERSIANN point (Y axis). The analysis is done for 2007 at a daily scale.

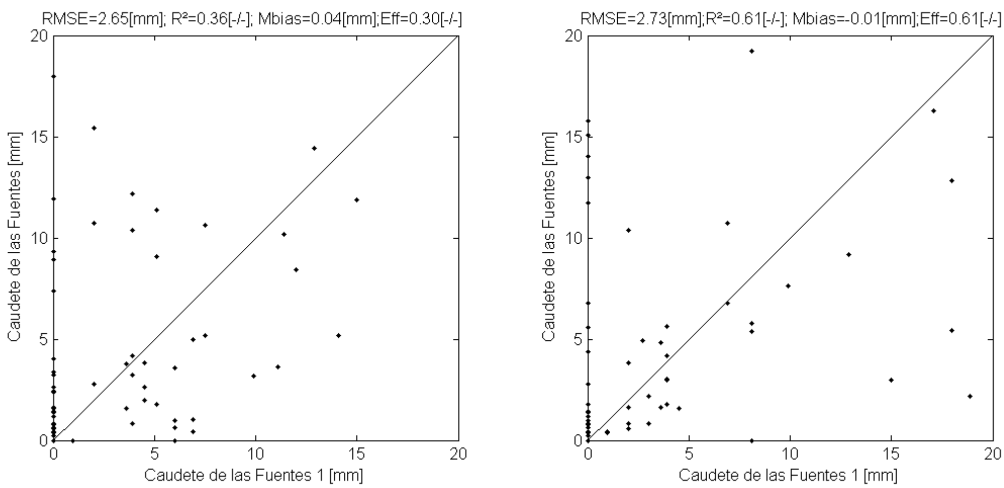

Fig. 5. Precipitation events at Caudete de las Fuentes (Y axis) versus Caudete de las Fuentes 1 (X axis) rain gauges for 2006 (left hand figure) and 2007 (right hand figure). See Fig. 3 to localize both gauges.

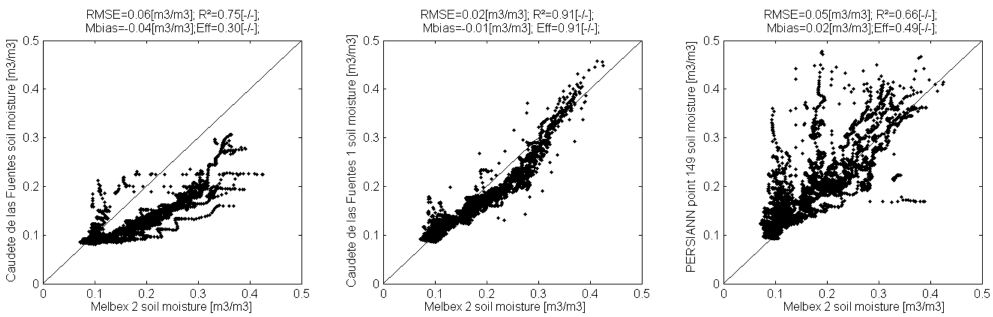

Fig. 6. Simulated soil moisture at 5 cm depth using Caudete de las Fuentes rain gauge (Y axis, left hand figure), Caudete de las Fuentes 1 rain gauge (Y axis, middle figure) and the PERSIANN point 149 (Y axis, right hand figure) compared to Melbex 2 in situ soil moisture (X axis) from the 1 June to 31 December 2007.

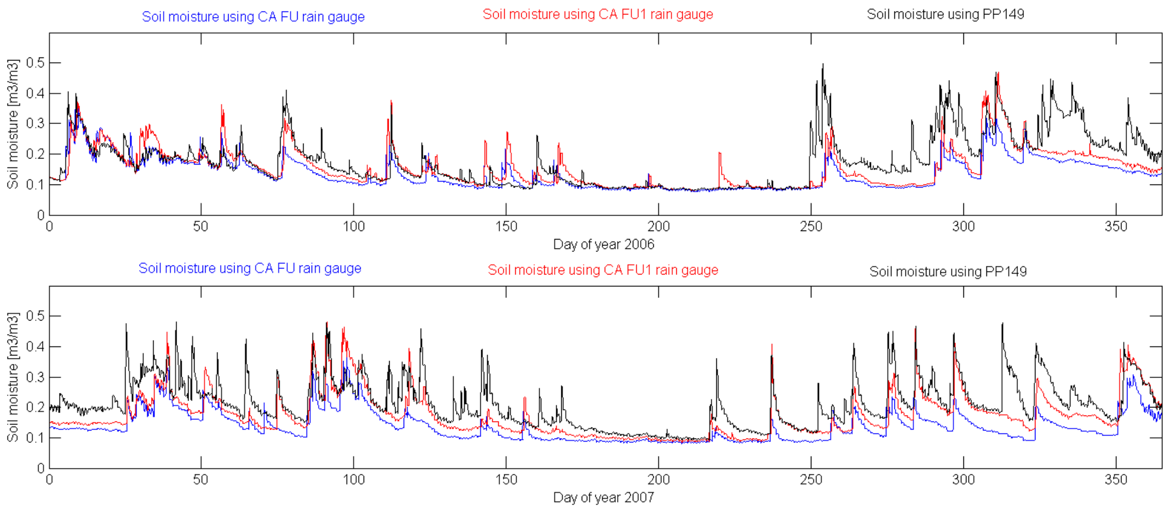

Fig. 7. Comparison between simulated soil moisture at 5 cm depth using Caudete de las Fuentes rain gauge (blue line), Caudete de las Fuentes 1 rain gauge (red line) and the PERSIANN point PP149 (black line). The comparison is made for 2006 (upper figure) and 2007 (bottom figure).

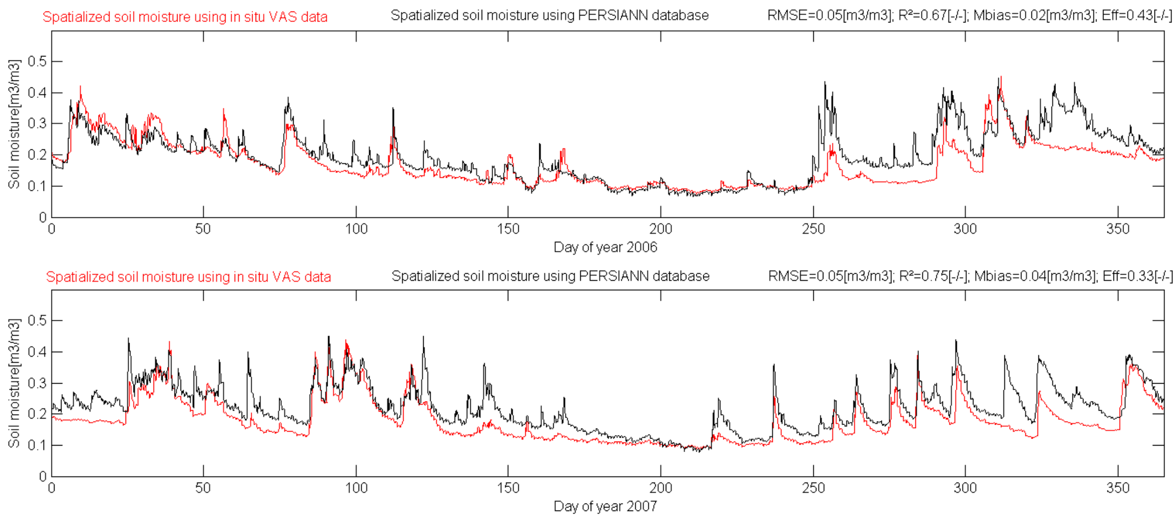

Fig. 8. Comparison between spatialized soil moisture databases obtained using in situ observations from VAS area (red line) and the PERSIANN satellite rainfall estimates (black line) for 2006 (upper figure) and 2007 (bottom figure).

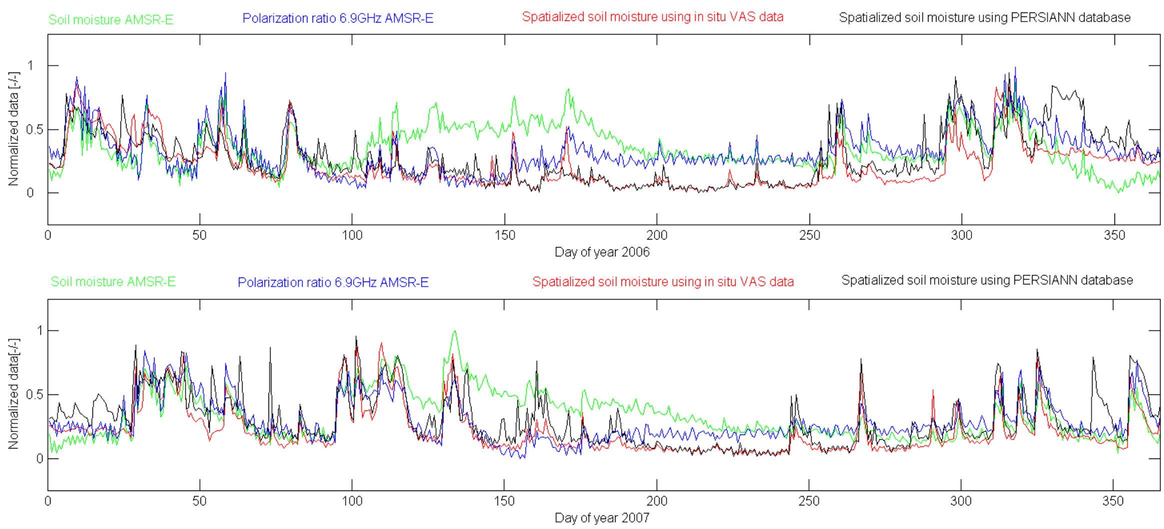

Fig. 9. Comparison between spatialized soil moisture using in situ observations(red line), spatialized soil moisture using PERSIANN datadase (black line), AMSR-E soil moisture product (green line) and AMSR-E polarization ratio at 6.9 GHz (blue line). The comparison is made for 2006 (upper figure) and 2007 (bottom figure). The data are normalized between [0, 1].