Inter-comparison of hydrological model simulations with time series of SAR-derived soil moisture maps

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Abstract
A comparison between superficial soil moisture content, $m_v$ values predicted by the DREAM hydrologic model and those retrieved from time-series of ALOS/PALSAR and COSMO-SkyMed SAR data acquired in 2007 and 2010-2011 is presented. The area investigated is part of the Celone at Ponte Foggia–S. Severo river basin, which is a tributary of the Candelaro river, downstream of the S. Giusto Dam, in Puglia (Southern Italy). Results show a good agreement in terms of bias and rmse between the hydrologic modeled and SAR-retrieved $m_v$-values, and open new opportunities for the use of SAR-derived $m_v$-values to calibrate/validate hydrologic models in semi-arid areas.

Keywords: SAR, soil moisture retrieval, hydrological model, calibration, validation.

Introduction
Floods and droughts are the opposite extremes of the hydrological cycle that, in a semi-arid environment, crucially depend on the time and space variability of soil and land cover features both influencing the vertical and sub-horizontal water fluxes. The use of distributed hydrological models allows, in principle, the prediction of such extremes as well as the development of strategies for improving the management of water resources. In practice, their effectiveness is often significantly impaired by the high level of uncertainty associated with the model itself and its parameterization. In addition, traditional techniques for model calibration and validation, mainly based on time series of discharge measured in gauged basins, heavily suffer from the shortage of monitoring networks or the insufficient length of reliable records. Besides, it is often recognized a poor level of information about soil properties at the basin scale. Under these circumstances, over the last years, an alternative approach consisting in the use of Earth Observation (EO) data to estimate surface parameters, either to calibrate and validate or to be assimilated into hydrologic models,
is receiving increasing attention [Hall et al., 1995; Bach et al., 2000; Bach and Mauser, 2003; Hostache et al., 2009; Minacapilli et al., 2009; Schumann et al., 2009]. The reason is that EO data can provide estimates of hydrologic model state variables at a regional or continental scale and at a regular spatial and temporal resolution thus overcoming the limitations of more traditional techniques of calibration and validation. As an example, one of the state variables mostly used for the purpose of calibration or assimilation is the superficial volumetric soil moisture content, \( m_v \), [Pauwels et al., 2009; De Lathauwer et al., 2011, Timmermans et al., 2011; Giustarini et al., 2012] that is operationally derived from passive microwave systems at a coarse resolutions (i.e. beyond 15 km) and it can be also retrieved from Synthetic Aperture Radar (SAR) systems at a high resolution (i.e. below 1 km) [Loew et al., 2006; Paloscia et al., 2008; Mattia et., 2009; Pierdicca et al., 2010]. In fact, the use of SAR data for such an application has been until to date hindered by the long revisit time of most past and current spaceborne SAR systems that is not suited to monitor land parameters characterized by fast temporal dynamics, such as the superficial volumetric soil moisture content. However, important progresses in this field are expected from new SAR missions characterized by short revisit time such as the COSMO-SkyMed (CSK) constellation or the forthcoming Sentinel-1 (S-1) and ALOS-2 missions.

In this context, the objective of this paper is to compare estimates of the moisture content in the top 5 cm of soil, derived from a hydrologic model, with those retrieved from SAR systems at L- and X- band. The motivations underlying the study concern a future systematic assimilation of the SAR derived \( m_v \) into a hydrologic model, calibrated at regional scale, for improving the prediction and the monitoring of drought and/or flash flood events over semi-arid areas in Southern Italy.

The structure of the adopted semi-distributed hydrologic model, suitable for continuous hydrological simulations at daily and hourly time step, is derived from the DREAM (Distributed model for Runoff, Evapotranspiration, and Antecedent soil Moisture simulation) model proposed by Manfreda et al. [2005] and realized in a GIS-based approach; the DREAM model explicitly takes into account the spatial heterogeneity of hydrological processes exploiting a robust and physically based parameterization and allowing at the same time the use of prior information and measurable data for parameter estimation.

The river basin is partitioned over a grid of square cells (250 m x 250 m) for which data concerning elevation, land use and hydraulic soil properties are required. The model provides a distributed representation of vertical water fluxes (rainfall, interception, evapotranspiration and groundwater recharge) and a lumped representation of sub-horizontal fluxes (overland runoff, lateral flow and groundwater flow) at daily and hourly time step. Inputs are daily and hourly precipitation, \( P \) (mm), monthly crop reference evapotranspiration, \( ET_c \) (mm/day), and monthly Leaf Area Index, LAI (-).

The DREAM model provided the basis for the nested implementation of the Richards equation which has been used for evaluating vertical flows in the top soil layer (5 cm.). The Richards routine exploits the numerical solution proposed by Simunek et al. [2009] and runs, for each cell of the river basin, in a sub-module of 60 minutes with a vertical (i.e. depth) and temporal resolution of 1 cm and 1 s, respectively. However, the distinctive feature of the model, which consists of evaluating the lateral flow through a water content redistribution weighted by the topographic index, was preserved. The model was applied to the river basin of the Celone at Ponte Foggia-S. Severo, downstream of the S. Giusto dam.
and also downstream of the Celone at S. Vincenzo river station, a gauged sub-basin of the Candelaro river in Puglia, Southern Italy (Fig. 1). Over this area, time-series of SAR data at both L- and X- band were acquired in 2007 and 2010-2011 and transformed into time-series of soil moisture maps by means of the “Soil MOisture retrieval from multi-temporal SAR data” (SMOSAR) code, developed in view of the forthcoming European Space Agency (ESA) Sentinel-1 (S-1) mission [Mattia et al, 2011; Balenzano et al., 2012], and adapted to SAR data at X- [Satalino et al., 2012] and L-band [Satalino et al., 2010] SAR data.

The study area (grey area in Fig. 1) has an extension of about 73 km$^2$ and is obtained from the overlap of the Celone at Ponte Foggia-S. Severo river basin (red contour) with the area covered by satellite images (green rectangle).

The Celone at Ponte Foggia-S. Severo river basin, downstream of the Celone at S. Vincenzo river station, has an extension of 133 km$^2$ and a max altitude of 1016 m a.s.l.

The basin is located in a temperate Mediterranean region. The hydrologic regime is characterized by Mediterranean semiarid features like strong seasonality, intermittency and periodic occurrence of droughts and sudden floods. In particular, there is a dry period with negligible or null runoff lasting for more than three months on the average hydrologic year.

The paper is organized as follows. In the next section, the experimental data collected and analyzed in this research are briefly described. Then, the soil moisture retrieval using SAR data by SMOSAR algorithm and the selected hydrologic model are described. Finally, the comparison between the SAR-derived soil moisture maps and the hydrologic DREAM model simulations is described and discussed.

**Experimental data**
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A distinctive feature of the area is the intensive agricultural activity with a high percentage of soil destined to durum wheat (75% of the total basin area), followed by broad-leaved forest (5%), annual crops (4%), land principally occupied by agriculture with areas of natural vegetation (3%) and olive groves (2.7%).

The DREAM model was calibrated using data recorded at the Celone S. Vincenzo hydrometric river station (located upstream the S. Giusto Dam, see Fig. 1) for which continuous streamflow data are provided. The basin area of Celone at S. Vincenzo is 91 km². The DREAM runs were performed using 2 years of daily data from gauged sites located at Celone at S. Vincenzo (from 2007 to 2008). The soil moisture content at the beginning of the simulation period was arbitrarily assumed equal to the field capacity in all basin cells. Then, the first year was used for generating the initial conditions for the second year and only the second year was used to perform model calibration. The calibrated parameters were used, for the basin of Celone at Ponte Foggia-S. Severo (years 2007-2008 and 2010-2011) for which, on the contrary, the streamflow data are not available in the same years. On this area precipitation time series at daily scale, for the years 2007-2008 and years 2010-2011, are available for the sites Biccarì, Faeto, Orsara di Puglia, Orto di Zolfo and Troia, of the monitoring network of the Regional Hydrographic Service. For the hourly time scale the following time series are available: Biccarì (25/11/2006-06/05/2009 and 16/05/2009-21/11/2011), Faeto (16/10/2007-22/11/2011), Orsara di Puglia (13/10/2006-22/11/2011), Orto di Zolfo (14/05/2007 - 05/12/2007, 17/06/2008 - 25/07/2008 and 31/12/2001-22/11/2011), Troia (8/11/2007-21/11/2011).

The study area was covered by approximately weekly or bi-weekly acquisitions of ALOS/PALSAR and COSMO-SkyMed images in 2007 and 2010-2011, respectively. In particular, 8 PALSAR ScanSAR WB1 HH-polarized data acquired on 04/01/2007, 19/02/2007, 13/03/2007, 25/03/2007, 11/04/2007, 23/04/2007, 28/04/2007 and 10/05/2007 (i.e. DoY 4, 50, 72, 84, 101, 113, 118, 130) and 8 CSK StripMap PingPong HH-polarized images acquired on 08/07/2010, 24/07/2010, 01/08/2010 and 09/08/2010 (i.e. DoY 189, 205, 213, 221) and on 17/06/2011, 25/06/2011, 03/07/2011 and 11/07/2011 (i.e. DoY 168, 176, 184 and 192) were available. The SAR data were used to derive time series of soil moisture content maps by means of the SMOSAR software over an area of approximately 700 km² (green rectangle in Fig. 1).

**Soil moisture content retrieval from multi-temporal SAR data (SMOSAR)**

The most challenging difficulty of using single-date SAR data to retrieve $m_v$ is their multiple dependence on surface parameters (e.g. superficial soil moisture content, vegetation biomass, soil roughness and canopy structure) that makes ill-posed the problem and, then, difficult to be solved without using *a priori* information on surface parameters [Mattia et al., 2009]. In fact, a significant simplification can be achieved by using dense or quasi-dense time series of SAR data (i.e. revisit time within 6-12 days) rather than single-date images. This is because temporal changes of surface roughness, canopy structure and vegetation biomass take place at longer temporal scales than soil moisture changes (excluding cultivation practices). Therefore, SAR multi-temporal acquisitions with a short repeat cycle are expected to track changes in soil moisture content only, since other parameters affecting radar backscatter can be considered constant. This is the rationale of the SMOSAR code that transforms dense or
quasi-dense temporal series of SAR images (HH or VV) into superficial soil moisture maps at high resolution scale (approximately 1 km) over agricultural areas. The algorithm can be applied over bare or sparsely vegetated soils or vegetated areas whose radar response can be approximated by the direct soil response attenuated by the crop canopy, such as for instance the cereals-like crop response to the L-band radar signal. On the contrary, at X-band SMOSAR can be applied only to bare soil due to the reduced capability of the radar signal to pass through the crop canopy. Indeed, SMOSAR encompasses a classification step (Masking block in Fig. 2) in which the agricultural areas where the algorithm cannot be applied (i.e. crops dominated by volume scattering) are masked. This step was not critical in this study as the landuse of the majority of the study area is winter wheat [Satalino et al., 2009], harvested in mid-June and thereafter changing the field status to bare soil, i.e. during the X-band acquisitions. After the classification step, the soil moisture retrieval is performed (Retrieval block in Fig. 2). The retrieval is based on the hypothesis that the backscatter ratio between two subsequent and temporally close SAR acquisitions can be approximated by the ratio between the correspondent alpha coefficients (alpha approximation [Balenzano et al., 2011]), which depend on the soil dielectric constants and the incidence angles only. For a time series of N SAR images, this leads to solve an underdetermined linear system of N-1 equations in N-alpha unknowns, subjected to linear constraints [Balenzano et al., 2011], i.e. the physical lower and upper bounds for the system unknowns. Once the alpha coefficient for each date is retrieved, the relative dielectric constant can be derived and then, the soil moisture content can be estimated by using an empirical dielectric constant model, such as [Hallikainen et al., 1985].

SMOSAR products have been validated over experimental sites using L-[Satalino et al., 2013], C- [Balenzano et al., 2012] and X- [Satalino et al., 2012] band SAR data, where it is shown that the accuracy of the retrieved \( m_\text{v} \) is approximately 5%-7% m\(^{-3}\)/m\(^{3}\). More details on the use of SMOSAR algorithm can be found in [Balenzano et al., 2013].

**Hydrological Model description and parameter estimation**

The DREAM model [Manfreda et al., 2005] is realized in a GIS-based approach, that explicitly takes into account the spatial heterogeneity of hydrological variables using distributed data contained in digital elevation models (DEMs), land use and soil texture maps. The DREAM model, using a Matlab code, carries out continuous hydrological simulation using the daily scale (D-DREAM) and the hourly scale (H-DREAM) [Fiorentino et al., 2006].

DREAM is developed to ensure a proper description of (i) the runoff production; (ii) the surface interception and storage effect; (iii) the chronologic sequence of state variables as soil moisture and base-flow discharge; (iv) the surface and subsurface routing.
The model includes two sub-models operating at distinct time scales with a grid-based representation of the river basin. The D-DREAM module is designed to reproduce daily runoff and soil dynamics, while H-DREAM is the module aimed to reproduce flood events at an hourly step.

DREAM simulations are based on the alternation of D-DREAM and H-DREAM runs, but the two modules may also be applied separately. The simulation process is activated by means of daily rainfall series inputs, which are required to run D-DREAM with the main purpose of providing the initial condition for flood-event hourly simulations. In principle, time series of synthetic streamflow, obtained by continuous simulation, can be used in order to reproduce the flood frequency distribution, the flow duration curves or for real-time forecasting.

A water balance equation provides, for any cell, the local soil water content, $S_t$ (mm/day), accounting for all the considered distributed vertical fluxes plus the local effect of lateral:

$$S_{t+\Delta t} = \min(S_t + P_t - RS_t - RG_t - ET_t, S_{\text{max}}) \quad [1]$$

where $t$ (day) is the time step, $P_t$ (mm/day) is net precipitation, $RS_t$ (mm/day) is subsurface lateral flow, $RG_t$ (mm/day) is groundwater recharge, $ET_t$ (mm/day) is actual evapotranspiration from bare and vegetated soil and $S_{\text{max}}$ (mm/day) is the soil water content at saturation. Net precipitation is given by precipitation minus canopy interception from canopy cover, evaluated as a simple bucket model with capacity $w_{sc}$ (mm) linearly proportional to LAI, as in Dickinson [1984].

Local runoff, $R_t$ (mm/day), occurs in any cell whenever soil water content reaches $S_{\text{max}}$.

$$R_t = \max(S_t + P_t - RS_t - RG_t - ET_t - S_{\text{max}}, 0) \quad [2]$$

The local subsurface lateral flow ($RS_t$) is evaluated depending on the soil water content at field capacity, $S_f$ (mm/day), the subsurface flow coefficient, $c$ (1/day), which is a lumped parameter representing the lateral hydraulic conductivity and the wetness index, $w$ (ln[m]), [Kirkby, 1975], which reflects the tendency of water to accumulate in cells with large upstream drainage area and relatively low local slope.

The crop reference evapotranspiration, $ET_c$ (mm/day), is evaluated using reference evapotranspiration, $ET_o$ (mm/day), and crop coefficients, $K_c$ (-):

$$ET_c = ET_o \cdot K_c \quad [3]$$

The actual evapotranspiration, $ET_t$, is represented by two distinct processes: bare-soil evaporation, $E_s$ (mm/day), and evapotranspiration from vegetated soil, $ET_{\text{veg}}$ (mm/day). The partitioning between two processes is given according to literature by the fractional vegetation cover, $M$ (-), which is estimated as a function of LAI.

In particular the evapotranspiration from vegetated soil, $ET_{\text{veg}}$, is evaluated as:
\[ ET_{\text{veg}} = M \left( \frac{S_t - S_{wp}}{0.75S_c - S_{wp}} \right) ET_c \quad [4] \]

where \( M \) is the fraction of soil covered by vegetation and \( S_{wp} \) (mm/day) is the soil water content at wilting point. According to Eagleson (1982) \( M \) is a function of LAI as in:

\[ M = 1 - e^{-\mu LAI} \quad [5] \]

where \( \mu \) (-) indicates the degree of decrease of light due to adsorption and scatter within a canopy.

Thus, using satellite imagery it is possible to evaluate the biomass present at the ground for proper simulation of certain processes such as the evapotranspiration, tapped by the vegetation and the snow melt. By means of the DREAM model it is possible to analyze the influence on the above mentioned model sub-processes depending on LAI [Gigante et al., 2009].

Groundwater recharge is obtained as percolation through the vadose zone and is assumed as a function of the hydraulic conductivity of soil, according to Eagleson [1978]:

\[ RG_t = k_s \left( \frac{S_t}{S_{\text{max}}} \right)^{\frac{2+3m}{m}} \quad [6] \]

where \( k_s \) (mm/day) is the saturated hydraulic conductivity and \( m \) (-) is the Brooks-Corey pore-size distribution index. The pore size distribution index is estimated using the equation proposed by Rawls and Brakensiek [1985].

This model is suitable for application in the field of drought prediction by means of long term continuous simulation at the daily scale (D-DREAM). The hourly model (H-DREAM), on the other hand, is used for flood prediction and can be used for long-medium term prediction and for the numerical assessment of the flood frequency distribution, as well as in real time flood prediction. In these cases the daily module D-DREAM is used for providing the initial conditions, in particular the antecedent soil moisture condition, for the hourly module that calculates the flow hydrograph and peak.

After Manfreda at al. [2005] the DREAM model has been object of further investigations mainly devoted to model testing and benchmarking by means of literature data and remote sensing data available for its parameterization (i.e. [Milella et al., 2011, 2012]). In particular, different methodologies for LAI retrieval have been used and tested on recent hydrological datasets (2007-2008) in order to characterise the hydrological response of river basins in Puglia and to assess the model performance improvements that can be achieved by exploiting the new remote sensing imageries and products.

In order to improve the evaluation of soil moisture content in particular on the top levels of soil (5 cm) the DREAM model was applied to Celone basin, with a grid cell size of 250 m x 250 m and, with respect to the original model, we eliminated the explicit evaluation of
surface depression storage and introduced the following changes.

- The crop coefficients were derived by satellite data applying a linear equation tested at Carapelle Basin [Milella et al., 2012]. The linear equation, reported in Figure 3, is based on the dependence between the literature monthly values of the wheat crop coefficients [Allen et al., 1998] and the Normalized Difference Vegetation Index, NDVI (-), values of MODIS images with a spatial resolution of 250 m (Earth Observing System Data and Information System, 2009); in particular this analysis was limited to areas covered by durum wheat considering 8 sample sites [Milella et al., 2012]. The monthly $K_c$ values were derived from the interpolation of the literature values of the crop coefficients $K_{c,ini}$ (for the initial stage), $K_{c,mid}$ (for the mid-season stage) and $K_{c,end}$ (for the end of the late season stage). The values obtained are reported in Figure 3, showing an excellent correlation ($R^2 = 0.94$) between monthly crop coefficients and NDVI. In this way, it is possible to produce distributed maps of $K_c$ that account for different crop stages that may occur in the basin because of difference in rainfall or temperature.

![Figure 3 - Linear relationship between monthly values of the wheat crop coefficients and the Normalized Difference Vegetation Index values from MODIS images with a spatial resolution of 250 m.](image)

- Introduction of the bare soil evaporation following the equation proposed by Bonan [1996] present in the GeoTOP model [Bertoldi et al., 2005]:

$$E_s = (1 - M) \, ET_e \, \frac{r_a}{r_a + r_s} \quad [7]$$

where $r_a$ (s/m) is the aerodynamic resistance and $r_s$ (s/m) is the surface resistance of the canopy. The air resistance is expressed as:

$$r_a = \frac{1}{\rho C_e u} \quad [8]$$
where \( \rho (\text{km/m}^3) \) is air density, \( C_E (-) \) is the bulk coefficient for latent heat transport and \( \bar{u} \) (m/s) is the mean wind velocity. The soil resistance is derived by the following equation:

\[
r_s = r_a \frac{1 - (S_i - S_r) / (S_{\text{max}} - S_r)}{(S_i - S_r) / (S_{\text{max}} - S_r)} \quad [9]
\]

where \( S_r \) (mm/day) is the residual water content which, in this study, was assumed equal to the water content at wilting point.

- Modelling of the groundwater residence times to produce baseflow \( Q_G \) (mm/day); which is evaluated by routing the total groundwater recharge (sum of all the local \( R_{G_i} \) values) by means of a two-parameters gamma distribution of residence time \( t_r \) (day) with probability density function:

\[
f(t_r) = t_r^{k_r-1} e^{-t_r/\eta} \eta^k \Gamma(k_b) \quad \text{for } t_r \geq 0 \text{ and } k_b, \eta > 0 \quad [10]
\]

with \( k_b (-) \) and \( \eta \) (day) lumped parameters of, respectively, shape and position of the gamma distribution and \( \Gamma(.) \) is the gamma function.

The mean residence time, \( \eta k_b \), of the groundwater component contributing to the streamflow hydrograph, (being the response of the groundwater storage interpreted as linear reservoir) was set equal to 14 days according to the observed baseflow recession constants.

In the model the discharge \( Q \) (m\(^3\)/s) is found, at any time step, as the areal integral of the local runoff \( R_t \) arising in all the basin cells, plus a base flow contribution, \( Q_G \).

- For the simulations at hourly scale, application of the Richards equation to derive top layer soil moisture maps. The Richards equation is expressed by:

\[
\frac{\partial \theta}{\partial t} = \frac{\partial}{\partial x}\left[K\left(\frac{\partial h}{\partial x} + \cos \omega\right)\right] - S \quad [11]
\]

where \( h \) (cm) is the water pressure head, \( \theta (-) \) is the volumetric water content, \( \tau \) (s) is time, \( x \) (cm) is the spatial coordinate, \( S \) (s\(^{-1}\)) is the sink term (which is related to potential transpiration and to the depth of the root zone), \( \omega \) (°) is the angle between flow direction and the vertical axis (\( \omega = 0^\circ \) for vertical flow) and \( K \) (cm/s) is the unsaturated hydraulic conductivity function.

The Richards routine is nested within the H-DREAM module, and runs, for each cell of the river basin, in a sub-module of 60 minutes with time step of 1 s. A numerical solution of the differential equation was implemented as in Simunek et al. [2009].

The unsaturated water content and the hydraulic conductivity were related to pressure head \( (h) \) using the equations of Van Genuchten [1980], depending on five parameters: the residual volumetric water content, \( \theta_r (-) \), the saturated volumetric water content \( \theta_s (-) \), the inverse of the bubbling pressure, \( \alpha \) (cm), the pore-size distribution index, \( m \) and the saturated hydraulic conductivity \( k_s \) (in cm/s):
\[ \theta(h) = \begin{cases} \theta_r + \frac{\theta_s - \theta_r}{1 + |\alpha h|^m}^a & h < 0 \\ \theta_s & h \geq 0 \end{cases} \]  

\[ K(h) = k_s S_e^{0.5} \left[ 1 - \left( 1 - S_e^{1/m} \right)^m \right]^2 \]

with \( a = 1 - 1/m \). \( S_e \) (-) is the effective saturation, given by [Brooks and Corey 1964]:

\[ S_e = \frac{\theta - \theta_r}{\theta_s - \theta_r} \]

Among all the methods present in literature to derive potential evapotranspiration, soil properties and leaf area index (LAI), we selected specific approaches on the basis of the results obtained by the application of the DREAM model to the Carapelle basin [Milella et al., 2011; Milella et al., 2012]. In particular we applied the equation of Penman-Monteith to derive potential evapotranspiration, the pedotransfer function of Saxton and Rawls [2006] to derive the soil water contents and the LAI maps available as products of MODIS [Earth Observing System Data and Information System, 2009] to derive vegetation cover. Detailed records of watershed physical information, land uses and climate data are required for the application of the model. Meteorological data recorded by the Regional Hydrographic Service were used for rainfall, temperature and wind speed (Fig. 1). The spatial distribution of rainfall was assessed using the Thiessen weighting procedure for daily application and the Inverse Distance Weighting (IDW) method for hourly applications. The spatial distribution of monthly and daily temperatures was assessed using the kriging with external drift (KED) interpolation method, using elevation as auxiliary variable. The monthly maps of wind speed were derived by the application of the IDW method. These maps of temperature and wind speed were used to derive the reference evapotranspiration applying the Penman-Monteith equation. The other climatic parameters presents in the Penman-Monteith equation were derived by temperature and wind speed as described in Allen et al. [1998]. The different techniques adopted for spatial interpolation of data where chosen according to best-fit results obtained by Milella [2010] and Milella et al. [2012]. Land use and vegetal coverage were obtained by the Corine land Cover (scale: 1:100’000). The topographic features were defined using the Digital elevation map (90 m x 90 m) of the Celone watershed from the SRTM (Shuttle Radar Topographic Mission) project carried out by the NASA (National Aeronautics and Space Administration) and the NGA (National Geospatial-Intelligence Agency). Monthly Leaf Area Index maps available as products of MODIS were used to derive vegetation cover [Eagleson, 1982]. The algorithm to derive LAI, based on relationships between the
Surface reflectances and the canopy/plant patterns, uses directly the information on the leaf canopy spectral properties and structural attributes and it exploits the spectral information content of surface reflectances at up to 7 spectral bands [Knyazikhin et al., 1999].

Soil parameters such as the textural classes, saturated hydraulic conductivity, soil depths and porosity were extracted from the ACLA2 project (scale 1: 100’000), a research program funded by the Puglia region aimed at agro-ecological characterization of the region on the basis of laboratory tests, observations field and photo interpretation of aerial photographs and satellite images [Caliandro et al., 2005]. On the basis of the USDA triangle the mean percentages by weight of sand, clay and silt were assigned to each textural class. The percentage of organic matter was derived from the project Octop of the European Soil Data Centre (ESDAC) (http://eusoils.jrc.ec.europa.eu).

The maps of soil water content at saturation, field capacity and wilting point were derived by the pedotransfer functions of Saxton and Rawls [2006]. The maps of the residual soil water content, bubbling pressure and pore-size distribution index were derived applying the pedotransfer functions of Rawls and Brakensiek [1985].

The minimum pressure head at the soil surface allowed under the prevailing soil conditions, \( h_a \) (cm), was calculated from the air humidity, \( H_r \) (-) as follows [Simunek et al., 2009]:

\[
h_a = -\frac{RT}{100 M^* g} \ln(H_r) \quad [15]
\]

where \( M^* \) (kg/mol) is the molecular weight of water, \( g \) (m/s^2) is the gravitational acceleration, \( R \) (J mol^{-1} K^{-1}) is the gas constant and \( T \) (K) is the temperature.

Relative air humidity was derived by minimum and maximum monthly temperatures maps using the equations described in Allen et al. [1998].

The DREAM calibration is made using different values of the subsurface flow coefficient \( c \), main parameter of calibration of the hydrological model at the daily time scale. This parameter is assumed as a basin constant and is calibrated considering a simulation efficiency measure related to the reliable prediction of water balance components. The value of \( c \) which provides the minimum Root Mean Square Error (RMSE) is chosen as the best fit for the model calibration.

**Results and discussion**

The DREAM predictions in terms of volumetric water content in the top 5 cm depth of soil were compared with SAR-derived \( m_v \) values. The simulation of the D-DREAM module begins on January 1 of the year 2007 and on January 1 of the year 2010 for the comparison in case of PALSAR and of CSK-derived soil moisture maps, respectively. During the simulation, the D-DREAM module switches to the H-DREAM module when the day of the acquisition is reached in order to increase the temporal scale at the date of the acquisition; in particular, when the DoY is characterized by a rainfall event, the hourly simulation starts at 1 a.m. of the day of the acquisition; if the considered day has rainfall equal to zero, the simulation begins at 6 a.m. of the same day (because we considered negligible evapotranspiration in the early hours of the day); finally if there is rainfall in the day before the data of the acquisition, the H-DREAM simulation starts at 1 a.m. of the day before. The
H-DREAM simulation ends at 9.30 a.m., time of the acquisition of PALSAR images and at 7 p.m. for the CSK images. At any time step of the H-DREAM simulation, the model switches to Richards sub-module which takes the initial soil moisture condition from the H-DREAM simulation; in particular for each cell, the soil moisture content at the end of the H-DREAM simulation is redistributed linearly in the entire soil profile investigated (equal to the depth of the radical apparatus) in the range between the residual soil moisture and the soil moisture corresponding to the saturation condition. The Richards module evaluates the volumetric water content ($\theta$) in the first 10 cm of the soil profile, solving the differential equations with spatial discretization of 1 cm in depth and temporal step of 1 s. At the end of any simulation, the Richards module provides, for each cell of the river basin, the mean value of the soil moisture content in the first 5 cm of the top soil ($\theta_5$). Figure 4 and Figure 6 report the maps of the superficial volumetric water content on the Celone at Ponte Foggia-S. Severo sub – basin obtained by DREAM model for all the selected days of the PALSAR and, as an example, for the CSK acquisitions in 2011, respectively; Figure 5 and Figure 7 report the comparison between the spatial average of the superficial volumetric water content over the study area obtained exploiting DREAM model (blue dots) and that extracted from PALSAR and CSK acquisitions (red dots); for the entire period of the acquisition the rainfall histogram is reported (red squares indicate the days of acquisitions). The red error bars take into account the accuracy of the SMOSAR soil moisture maps (i.e. 6% m$^3$/m$^3$ in average). Figure 5 and Figure 7 show that the discrepancy between the average DREAM and SMOSAR-derived soil moisture values is not significant with respect to the SMOSAR accuracy and inter-comparison between DREAM and SMOSAR model outputs is meaningful.

Table 1 reports some important model performance metrics evaluated in order to compare the simulated (hydrological) and retrieved values of the superficial volumetric water content (over the area of overlap between river basin and satellite images) for all the selected days of the PALSAR and CSK acquisitions. The Root Mean Square Error (RMSE) shows in both cases a fairly good agreement as well as the relative bias $\beta$ obtained as ratio of the mean values of simulated to retrieved data. The relative variability $\alpha$, which is the ratio between the standard deviations of simulated and retrieved data, shows a significant underestimation of soil moisture variability in time with respect to PALSAR acquisitions and an overestimation with respect to CSK. The linear correlation $r$ is more satisfactory for the PALSAR than for CSK acquisitions. This is not surprising considering that the range of soil moisture and the time span of the acquisitions covered by the PALSAR data were much larger than those provided from the CSK acquisitions. Such first results are quite encouraging for a combined use of SAR-retrieved information and hydrological simulations.

| Efficiency criteria | RMSE | $\beta$ | $\alpha$ | $r$  |
|---------------------|------|--------|--------|-----|
| Optimal value       | 0    | 1      | 1      | 1   |
| PALSAR              | 3.45 | 1.004  | 0.553  | 0.870 |
| CSK                 | 3.69 | 1.136  | 2.671  | 0.409 |
Figure 4 - Volumetric water content maps of soil top 5 cm on the Celone at Ponte Foggia-S. Severo sub-basin for all the PALSAR acquisition days.

Figure 5 - Comparison between the spatial average of soil moisture values (volumetric water content of soil top 5 cm) as a result of DREAM model (blue) and those obtained from PALSAR images (red). The error bars take into account the accuracy of the SMOSAR soil moisture maps (i.e. 6% m$^3$/m$^3$ in average).
In this work we focused on the possibility of exploiting remote sensing data for enhancing the hydrological model performances. In this framework, the estimate of $m_v$ derived from Earth observation data could allow a breakthrough advance of knowledge but requires strong efforts in implementing hydrological models able to reproduce the dynamic of soil moisture of the top layer (5 cm depth) of soil. This kind of variable shows in nature a strong variability in time and space being affected by a quick evolution of the soil moisture states strongly affected by highly space-time variable climate forcing, including evapotranspiration and

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**Conclusions**

In this work we focused on the possibility of exploiting remote sensing data for enhancing the hydrological model performances. In this framework, the estimate of $m_v$ derived from Earth observation data could allow a breakthrough advance of knowledge but requires strong efforts in implementing hydrological models able to reproduce the dynamic of soil moisture of the top layer (5 cm depth) of soil. This kind of variable shows in nature a strong variability in time and space being affected by a quick evolution of the soil moisture states strongly affected by highly space-time variable climate forcing, including evapotranspiration and
rainfall, and by several physical features such as the dynamic-hydraulic behaviour of soil. Structural unavailability of data necessary for this kind of investigation strongly affects the proposed research. For example, it is worth mentioning the gap in observations of rainfall (and more in general of climatic quantities including wind and temperature) which is still provided by point measurements. It is well known that in Italy the national program for the implementation of a network of meteorological ground based radar for the measure of precipitation has found interminable delays. Nevertheless, we tried to cope with this problem by introducing different methods for the interpolation of climatic data (including rainfall and temperature) as Thiessen method, inverse distance weighting and kriging with external drift. We also referred to an area (the Candelaro basin) where a detailed pedological database is available (ACLA2). We also managed to introduce a distributed implementation of the Richards equation, with time step of 1 s, in a large basin of about 91 km², in a reasonable run-time. In this implementation the peculiar property of the DREAM model, which evaluates the lateral flow with a water content redistribution weighted on the topographic index, was preserved and provided the basis for the nested implementation of the Richards equation which was used only for evaluating vertical flows in the top layer of soil. First results are very promising (see for example Fig. 5, Fig. 7 and Tab. 1), as they show a good agreement with both PALSAR and CSK predictions and also a good sensitivity to rainfall inputs. These results are useful not only for the calibration/validation of the hydrologic models with external data (see for example [Biondi et al., 2012]) but also offer promising perspectives for hydrological real time forecasting. Indeed, it is well known that, in this context, the so-called antecedent moisture condition plays a crucial role in the identification of thresholds useful for prediction of flood disasters. Moreover, the soil water content of the top layer particularly affects the runoff generation properties river basins. Thus, we strongly believe that further development and foremost applications of the proposed modelling structure, with the use of satellite data for model calibration/validation or assimilation, could provide strong enhancements in the performances of a feasible chain for real time flood prediction.

Acknowledgement
The research in this paper was supported by the Italian Space Agency (ASI) under contract n. I/051/09/0. COSMO-SkyMed data were provided by ©ASI in the framework of ©CSK AO 2161; PALSAR data were supplied in the framework of JAXA RA 13 & ESA ALOS ADEN AO 3597. The group of research would like to thank ASI for providing the COSMO-SkyMed images and the COSMO-SkyMed Order Desk for supporting the planning activity.

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