Advancing Sustainable Water Management in Southern Italy Through Integrated Hydrological Modeling and Earth Observation

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Abstract. In water-scarce regions, effective water resource management is crucial for performing sustainable agriculture. Scientists and decision-makers increasingly exploit the coupled use of hydrological and crop models to address resource conservation and productivity challenges. While emphasizing crop system performance and environmental impact assessment, equal attention is needed for ensuring sustainable crop production and effective water management.

In response to these needs, the Italian Space Agency (ASI), within the framework of the I4DP-SCIENCE programme, supports the collaborative THETIS project (EarTH Observation for the Early forecasT of Irrigation needS; Agreement n. 2023-52-HH.0).

THETIS aims at developing a spatial decision support system that integrates hydrologic and crop growth models with advanced Earth observation (EO) products, Artificial Intelligence, and a WEBGIS interface. Starting activities focus on processing tomatoes, which are highly water-demanding. A synergic data exchange between models is established to provide estimates of water needs before, at the beginning, and during the irrigation season with periodic updates.

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An essential component of the project entails producing estimated time series of root zone soil moisture, crucial for initializing the AquaCrop model and evaluating the water balance within the designated fields. To accomplish this task, in the THETIS project a joint use of the daily basin-scale hydrological model DREAM and the physically based Soil Moisture Analytical Relationship (SMAR) model forming a Soil Water Balance (SWB) module is proposed.

This paper provides a brief contextualization of the THETIS project focusing on the need for reliable estimations of soil moisture dynamics. To this end a review of the existing application of SMAR model is presented. It helped to draw remarks about the main challenges and perspectives of use of the model within a context where soil moisture may be strongly influenced by irrigation volumes and agricultural practices.

Keywords: Water needs · Soil moisture · Hydrological model · Satellite retrieval

1 Introduction

Root-zone soil moisture (RZSM) dynamics are pivotal in numerous research fields including numerical weather prediction, rainfall–runoff processes, agricultural applications, drought risk assessment, and eco-hydrological studies. In the past decade, many satellite missions have been dedicated for accurate spatiotemporal measurements/estimations of soil moisture, including Soil Moisture Ocean Salinity (SMOS) (Kerr et al., 2001), Soil Moisture Active Passive (SMAP) (Entekhabi et al., 2010) and Advanced Scatterometer (ASCAT) (Wagner et al., 2013). However, these satellite measurements are limited to the top few centimeters of the soil profile and many efforts have been made to extend satellite retrievals of surface soil moisture (SSM) data into the root zone (Li et al., 2023). Initial challenges involved identifying or creating models optimized for soil moisture data assimilation. The numerical weather prediction community, recognizing soil moisture's significance in land-atmosphere interactions, was the first to develop physically based Land Surface Models (LSMs) exploiting satellite soil moisture observations to accurately simulate profile soil moisture dynamics (De Santis, 2018). The European Centre for Medium Range Weather Forecasting (ECMWF) and the UK Met Office (UKMO) started operational assimilation of ASCAT SSM data, gaining improvement in soil moisture representation (de Rosnay et al., 2013; Dharssi et al., 2010).

Satellite SSM data assimilation efforts yielded root-zone soil moisture estimates. For instance, products like H14/SM-DAS-2 and H27/SM-DAS-3 were developed through the ECMWF Land Data Assimilation System (de Rosnay et al., 2013). Another reference product is the SMAP Level 4 Surface and Root-Zone Soil Moisture assimilating SMAP brightness temperature into the NASA Catchment land surface model using an Ensemble Kalman Filter (EnKF). The SMAP Level 4 product provides estimates of surface (0–5 cm) and root-zone (0–100 cm) soil moisture.

Various methods, such as the exponential filter (see, e.g., Wagner et al., 1999, Albergel et al., 2008; Brocca et al., 2012), regressions (see, e.g., Zhang et al., 2017), and artificial neural networks (Souissi et al., 2022) are employed to propagate SSM information to model depths of interest. The exponential filter typically leads to soil water index

estimates involving remotely-sensed surface measurements. The method is widespread for its simplicity as it involves using only one parameter, and has been extensively used to evaluate satellite-based RZSM estimates by comparison with in situ and modelled data (see, e.g., Paulik et al., 2014; Tobin et al. 2017).

The Copernicus Global Land Service provides a Soil Water Index (SWI) product from ASCAT SSM datasets (Paulik et al., 2014) and ASCAT-Sentinel-1 SSM (Bauer-Marschallinger et al., 2018) according to different exponential filter parameter values in order to represent soil moisture at various depths. SWI found application in a wide range of studies including drought and crop production forecastings (see, e.g. Qiu et al., 2014; González-Zamora et al., 2016).

Finally, physically based models such as SMAR (Manfreda et al., 2014) and SMAR-EnKF (Baldwin et al., 2017) show promise in predicting RZSM, being successfully applied to improve streamflow simulations (Patil & Ramsankaran, 2018).

In its original version, the SMAR model did not account for the high non-linearity of water loss function that may characterizes humid environments, making the model more suitable for arid zones and semi-arid basins, mainly characterized by flat areas and negligible baseflow (Baldwin et al., 2017). Faridani et al. (2017) and Rasche et al. (2024) have proposed modifications to the original version of SMAR. In particular, Faridani et al. (2017) included a non-linear soil water loss function explicitly describing deep percolation and evapotranspiration dynamics. Rasche et al. (2024) added three more parameters to the model along with the distinction between evapotranspiration and percolation terms. One of the main concerns for the application of SMAR consists of the calibration of its parameters, although they are somehow dependent on the physical soil properties and may be easily estimated based on the characteristics of the site under investigation (Manfreda et al., 2013).

This represent a key task for reliable RZSM estimates which are of concern for the collaborative THETIS project (EarTH Observation for the Early forecasT of Irrigation needS; Agreement n. 2023–52-HH.0). Based on the collaboration among different partner, the project aims at developing a spatial decision support system for the early assessment and forecasting of irrigation needs in the “Fortore” irrigation district located in the Apulian Tavoliere (Southern Italy). SMAR is expected to allow comparisons between soil moisture maps from Earth Observations (i.e., Sentinel-1 or other sensors) and the output of a basin-scale hydrological model, in order to provide reliable inputs of RZSM for AquaCrop.

As a part of the ongoing researches for supporting the project, this paper explores the main potential and challenges related to the use of the SMAR model for the research needs.

This paper is organized as follows: Sect. 2 provides a brief contextualization of the THETIS project and the research goals. Section 3 describes the area under investigation. Section 4 summarizes the main features of the SMAR model and presents an overview of studies which make use of SMAR for RZSM estimates. Finally, based on this review, a summary of the expected challenges to be addressed when applying the model in the context and for the needs of THETIS are reported in Sect. 5.

2 Research Context

In water-scarce regions, effective water resource management is crucial for performing sustainable agriculture. Scientists and decision-makers increasingly exploit the coupled use of hydrological and crop models to address resource conservation and productivity challenges. While emphasizing crop system performance and environmental impact assessment, equal attention is needed for ensuring sustainable crop production and effective water management.

In response to these needs, the Italian Space Agency (ASI), within the framework of the I4DP-SCIENCE programme, supports the collaborative THETIS project. The project involves the National Research Council – Institute for Electromagnetic Sensing of the Environment (CNR-IREA), the Council for Agricultural Research and Economics (CREA), the Polytechnic University of Bari, the University of Bari, and the Bonifica Capitanata Consortium (Foggia). THETIS focuses on the early assessment and forecasting of irrigation needs in the "Fortore" irrigation district located in the Apulian Tavoliere (Southern Italy).

The heart of THETIS lies in the development of a spatial decision support system that integrates hydrologic and crop growth models with advanced Earth observation (EO) products, Artificial Intelligence, and a WEBGIS interface. Starting activities focus on tomatoes which are highly water-demanding. A synergic data exchange between models is established to provide estimates of water needs before, at the beginning, and during the irrigation season with regular updates. Figure 1 illustrates the functional scheme of the preliminary THETIS architecture, identifying with different colors the input and output data, processing and models.

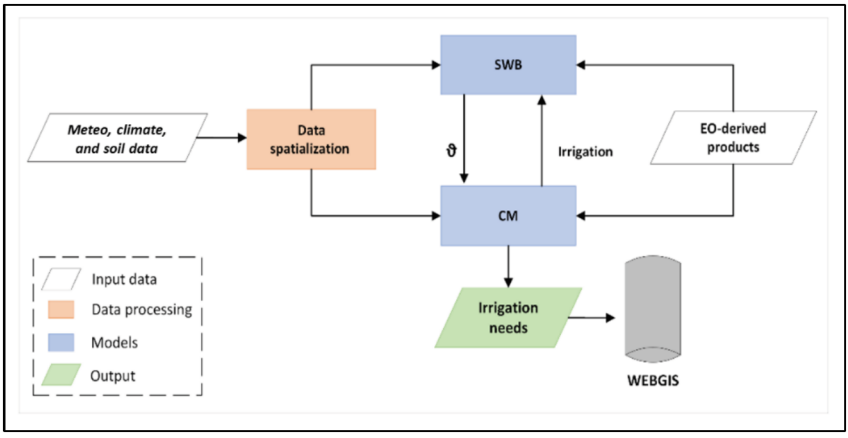

Fig. 1. Functional diagram on the integration of data and models in THETIS. ϑ: soil water content (depth of interest).

The scheme identifies the main relationships between the daily soil water balance (SWB) and crop (CM) models and highlights the role of data and information retrieved from Earth Observation (EO), including SSM maps, the leaf area index (LAI) and maps of

irrigated surfaces. Information such as LAI and irrigated areas, whose variability depends on the season and irrigation practices and may influence the predictive capabilities of the water balance model, can be directly or indirectly assimilated into the SWB module. Specifically, as a part of the SWB module, the SMAR model allows to relate the SSM maps from SAR data (i.e., Sentinel-1 or other sensors) and the output of the daily-hydrological model, within the irrigation district areas. This comparison could also serve as a local forcing for the semi-distributed hydrological model, based on the DREAM model (Manfreda et al., 2005), which operates over the whole watershed exploiting spatialized climatic data and transfers soil moisture information for the initialization of the crop model. The latter, in addition to high-resolution information related to vegetation indices and irrigated areas, will exploit observations related to EO-derived maps of tilled areas. CM periodically updates SWB with information regarding irrigated surfaces.

3 Pilot Case Study

The pilot case study is located within the plain of Tavoliere (Apulia Region, Southern Italy), which is the second largest plain in peninsular Italy after the Po Valley. It extends between the Daunian Mountains to the west, the promontory of Gargano and the Adriatic Sea to the east, the Fortore River to the north, and the Ofanto River to the south (Fig. 2a). The wide flat surfaces, predominantly cultivated with crops, extend up to the base of the Daunian Pre-Apennine. Specifically, the application area of the basin-scale hydrological model (based on the DREAM model) covers an area of approximately 2000 square kilometers, encompassing almost the entire basin of the Candelaro River (with its tributaries Triolo, Salsola, and Celone creeks), excluding the area near the mouth, in the Adriatic Sea (Fig. 2b). The plain and hilly areas are mainly used for the cultivation of wheat, durum wheat, and processing tomatoes, while pastures and forests prevail in the mountainous areas. Rainfall gauges, climate monitoring stations (at least thermometric) and hydrometric gauges are present within the basin and in the neighboring areas. They belong to two autonomous networks: Civil Protection Network (CP) and Land Reclamation Consortium (CBC, standing for "Consorzio di Bonifica della Capitanata"). The "Fortore" Irrigation District, which is crossed by many artificialized watercourses (Fig. 2c), represents the area of interest for the estimation of water consumptions by the AcquaCrop model, which needs to be initialized based on the soil moisture maps provided by the daily-SWB model.

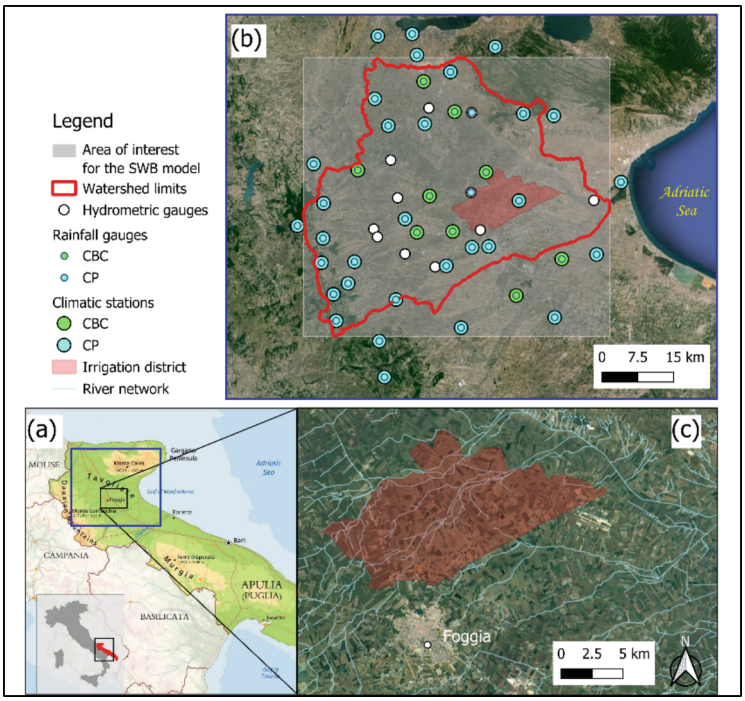

Fig. 2. Location of the areas of interest for the THETIS project (a). Area of application of the SWB model and active meteo-hydrological stations (b). Location of the "Fortore" Irrigation District (c).

4 SMAR Features and Use in the Literature

4.1 Description of the Model

The SMAR model (Manfreda et al., 2014) uses a physically based approach to estimate soil moisture in the reference soil thickness (i.e. the root zone) starting from SSM information. The model requires the estimation of some parameters, dependent on the physical characteristics of the soil as well as the availability of soil moisture satellite maps.

SMAR relies on the following hypotheses:

- Soil is schematized based on two layers of different depths (Fig. 3)
- Soil moisture movement from the upper to the lower layer according to Green & Ampt (1911);
- All water in the first layer above the field capacity moves into the lower layer within one day (Laio, 2006);
- Infinite permeability of the soil when the relative saturation reaches any value above the field capacity;
- Non-linearity of losses for high values of soil moisture is not accounted for.

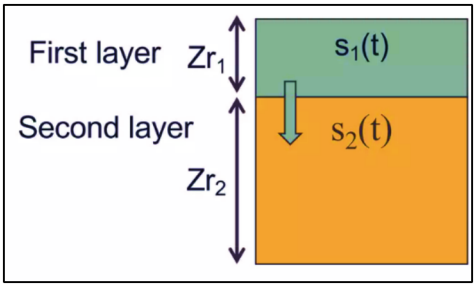

Fig. 3. Soil schematisation according to SMAR (adapted from Manfreda et al., 2014). s_1 and s_2 are the relative soil saturations of the first layer and the second layer, respectively.

Infiltration flux from layer 1 to layer 2 is modelled by Eq. 1

$$n_1 Z_{r1} y = n_1 Z_{r1} y[s_1(t), t] = n_1 Z_{r1} \begin{cases} s_1(t) - s_{c1}, s_1(t) \geq s_{c1} \\ 0, \quad s_1(t) < s_{c1} \end{cases} \tag{1}$$

where, n [-] is the soil porosity, Z_r [L] represents soil depth, V_2 [LT^{-1}] is the soil water loss coefficient accounting for both evapotranspiration and percolation, s_{c1} [-] is the relative soil saturation at the field capacity of the first layer.

By introducing $x_2 = \frac{s_2 - s_{w2}}{1 - s_{w2}}$ [-] as the "effective" relative soil saturation of the second soil layer and following the model hypotheses, a simplified soil water balance model is provided based on Eq. 2

$$(1 - s_{w2}) n_2 Z_{r2} \frac{dx_2(t)}{dt} = n_1 Z_{r1} y(t) - V_2 x_2(t) \tag{2}$$

The first product that appears in the second member of Eq. 2 represents infiltration, while the second describes losses.

By introducing the two normalized parameters a and b, defined as follows

$$a = \frac{V_2}{(1 - s_{w2}) n_2 Z_{r2}} \tag{3}$$

$$b = \frac{n_1 Z_{r1}}{(1 - s_{w2}) n_2 Z_{r2}} \tag{4}$$

after some analytical steps (see, Manfreda et al., 2014 for further details), Eq. 5 is derived allowing description of soil moisture in the root-zone, $s_2\ (t)$ at depth Zr_2 and at day t_j, based on the time series of surface soil relative saturation:

$$s_2(t_j) = s_{w2} + \left[s_2(t_{j-1}) - s_{w2}\right] e^{-a(t_j - t_{j-1})} + (1 - s_{w2}) b y(t_j) \left(t_j - t_{j-1}\right) \tag{5}$$

In the absence of reliable information for parameters estimation, a, b, s_{c1}, and s_{w2} (depending on physical properties of both the surface layer and the root zone layer) need to be calibrated, based on a comparison between daily field measurements of the relative saturation on the lower layer.

In the original version of the model a quite simple parameters calibration is proposed based on the minimization of the Root Mean Square Error (RMSE) between observed (field measurement) and simulated s_2.

It should be noted that SMAR may produce values higher than 1 and in consequence, these are automatically set equal to 1.

Following the calibration step, the SMAR model will be employed in THETIS to facilitate a comparison between the soil moisture maps calculated by the daily hydrological model and EO-derived SSM maps, when they are available.

4.2 Review of Applications

SMAR was originally applied in the arid and semi-arid environment of Africa (Benin, Mali, and Niger) and U.S. (New Mexico). The availability of climate and soil information about the study sites made possible the estimation of all model parameters. Moreover, consistent series of SSM and RZSM field measurements provided by the African Monsoon Multidisciplinary Analysis (AMMA) and the Soil Climate Analysis Network (SCAN) supported the comparison to the well-known exponential filter provided by Wagner et al. (1999) based on the T-parameter. This comparison helped to highlight the potential of SMAR for semi-arid environments. The application exploiting AMMA 25 × 25 Km^2 with calibrated parameters produced values very close to those estimated based on the physical information available for the sites confirming the physical consistency of the methodology. The dataset used in the original study has been used to support following applications of the model, with focus on (i) the use of satellite retrievals of SSM to support parameters calibration and (ii) improvement in the structure of the model to explicitly accounting for non-linearity of soil losses. In particular, Faridani et al. (2016) assessed the possibility to implement the TRMM/TMI (25 km resolution) dataset for parameters calibration. The Authors compared three different calibration strategies. The first one strategy exploited the time series of in situ SSM data and in situ observations of RZSM (i.e., point scale application). The second one used time series of satellite SSM data and in situ observations of RZSM (i.e., pixel scale application). The third one used a series of satellite SSM data and parameters values obtained from the point scale application. The Authors observed that in the transition from field to pixel of satellite data, parameters related only to soil texture are quite stable, while parameters linked to local soil properties, such as soil depth and water losses, show wider ranges of variation with respect to the input time series of SSM. Then, Faridani et al. (2017) suggested modification in the model structure to account for the non-linearity of soil losses explicitly accounting for percolation and evapotranspiration. An ensemble Kalman filter was used in Baldwin et al. (2017) to support SMAR by estimating a regional-scale satellite bias parameter using reference in situ data. The bias parameter is added to input AMSRE – 25 km SSM retrievals before their use in SMAR. The application concerned 43 sites located in the Eastern U.S. encompassing both wet and dry climates. SCAN/SNOTEL Soil Moisture Network (Schaefer et al., 2007) supported the calibration of three parameters over four, being the relative surface field capacity estimated through a Bayesian-MCMC method. The optimized SMAR-EnKF models RZSM with a lower degree of error with respect to previous SMAR calibration efforts. The new SMAR-EnKF found application in rainfall-runoff simulations over Krishna River basin, India. The study was conducted

by Patil & Ramsankaran (2018) who exploited SMOS L3 (0.25°) and ASCAT v. H113 (0.125°) products to overcome the absence of SSM field measurements. Model calibration was performed by using Particle Swarm Optimization (PSO) approach to match long-term subsurface soil moisture simulated through the Soil and Water Assessment Tool (SWAT) and using the Nash Sutcliffe Efficiency (NSE) in the objective function for optimisation. SMOS (25 km), AMSR2 (0.25°) and SMAP (36 km) products were used by Gheybi et al. (2019) for RZSM estimation in Iran. The INSAM (International Society for Agricultural Meteorology) supported parameters calibration over a period of about two years. Baldwin et al. (2019) extensively applied SMAR over 68 sites in the Eastern U.S., including a variety of climate conditions and exploiting information retrieved from series of 2 years with gaps less than 2 months of AMSRE (25 km), SMOS level 2, and SMAP level 3 (9 km), then validating results on the experimental Shale Hills catchment (U.S.). Both the SCAN/SNOTEL and the AMERIFLUX Monitoring Network (Baldocchi et al., 2024) supported calibration of the model parameters on regional scale, while the Shale Hills Automatic Sensors (Liu and Lin, 2015) and Shale Hills Manual TDR (Lin et al., 2006) supported site scale application. Zhuang et al. (2020) selected six satellite products for SSM retrievals, including AMSRE (25 km), SMOS (30 km), AMSR2 (25 km), SMAP (36 km), the European Space Agency Climate Change Initiative (ESA-CCI) Passive (25 km) and ESA-CCI Active (25 km). The study also assessed the potential use of blended ESA-CCI Soil Moisture (25 km) for SSM retrievals. The analysis concerned the application of the SMAR model over the Tibetan Plateau being available four in-situ measurement networks including arid, semi-arid and sub-humid environments. The analysis shed new light on the perspective of using blended products for SSM retrievals and confirmed poor model performances for humid environments compared to that of arid and semi-arid regions. Application of SMAR for the assessment of AMSR2 products and downscaled AMSR2 with MODIS parameters over the arid Rafsanjan Plain in Iran was found in Farokhi et al. (2021), who exploited the dataset provided by Ansari et al. (2015) to estimate three of the model parameters leaving only the loss term to be calibrated. Liu et al. (2023) proposed an application of SMAR on the Luan River in China, encompassing various climate zones. The Global Daily Surface Soil Moisture Dataset at 1-km resolution (2000–2020) provided by Zheng et al. (2023) was used for SSM retrievals. A selection of 34 stations of the field monitoring network described by Zhao et al. (2020), provided field measurement at different scales (large, 100 km; medium, 50 km; and small, 10 km). The Authors compared the RZSM series estimated by SMAR at different depths using covariates from different sources (China Soil Hydraulic Parameters dataset for SMAR-P1 configuration and literature references for SMAR-P2 configuration). Only SMAR-P1 successfully passed the significance test ($p < 0.05$) and finished the parameter regionalization process, highlighting the importance of the availability of local datasets for the description of soil properties. In a very recent study, Rasche et al. (2024) tested SMAR over the forested site of Serrahn (Germany) trying to extrapolate RZSM up to a depth of 450 cm. The analysis was supported by 1 year of 59 in-situ soil moisture measurements. The original SMAR could not capture the soil moisture dynamics well. Only with effective parameters in a non-physical range better model performances have been achieved. However, the inclusion of three more parameters in the model, specifically, the relative saturation at field capacity in the

second layer sc_2 (-), the cumulative root fraction to the maximum depth of the first and second layer R1 (-) and R2 (-) along with the explicit distinction between evapotranspiration and percolation terms leads to improve results. In general, a RMSE of 0.06 cm^3cm^{-3} was considered as a benchmark for performance assessment. Figure 4 shows applications of the original model and its modified versions worldwide.

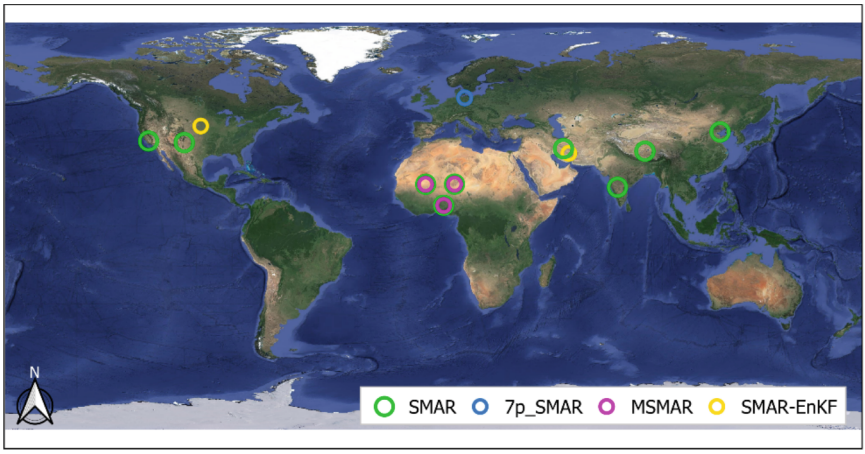

Fig. 4. Map of the applications of the model SMAR (original version and modifications) worldwide. "7p" stands for "seven parameters"

In summary, the SMAR model is a reliable tool for estimating root-zone soil moisture, especially in arid and semi-arid regions. While adaptable to satellite data, its accuracy decreases in humid environments. Past applications have shown the model's heavy reliance on local data for calibration and the frequent need for additional parameters or modifications to achieve optimal performance. Therefore, local climate or specific hydrological processes (like soil freezing or a water table) may significantly deviate from the model's simplified scheme, necessitating further parametrization or additional modules.

5 Conclusion and Research Directions

A reliable description of soil moisture dynamics is of paramount importance for applications concerning water management for sustainable agriculture. This represents one of the main goals of the THETIS project which aims at the early assessment and forecasting of irrigation needs in the "Fortore" irrigation district (Apulian Tavoliere, Southern Italy). Based on the review of works using SMAR, presented in Sect. 4, several challenges emerge that could be encountered in applying the model for the needs of THETIS and, more generally, in similar research context. They are mainly linked to the land use of the study area where soil moisture is strongly influenced by agricultural practices, water management and irrigation volumes. Such challenges can be summarized as follows:

- variability of soil properties: differences between soil properties among soil layers can significantly influence the parameters of the SMAR model. This introduces uncertainties when trying to estimate parameters based on coarse information;
- availability of local measurement on soil properties and climates: it seems to be essential for accurate calibration of the SMAR model. Studies using local data have demonstrated improved model performances compared to those using literature-based values;
- transition from local-scale to satellite-scale data: the use of satellite data for calibrating the model parameters may pose challenges in transitioning from local-scale to pixel-scale. This can lead to greater variability in parameters specifically related to local soil properties and processes;
- non-linearity of soil losses: structural modifications of the model to explicitly account for the non-linearity of soil losses might be necessary to improve the accuracy of the results, especially in contexts where irrigation and agricultural practices have a significant impact on soil moisture.

In conclusion, the application of SMAR in regions where agricultural practices and irrigation may have a significant impact on soil moisture dynamics, such as for the area of interest for the development of the THETIS spatial decision support system may present challenges related to the variability of soil properties, inhomogeneity in the resolution of input information, and the need to quantify irrigation contributions. Limitations may exist in the use of satellite-derived SSM data as reference observations for model input, mainly due to the inclusion of bias effect. However, potential benefits may be expected following the exploitation of high-resolution satellite retrievals about irrigated areas, detailed information on irrigation practices, and the available sparse measurements of surface and root zone soil moisture which remain essential for model calibration. Following calibration, as a part of model chain of the THETIS architecture, SMAR can be used jointly with the daily basin scale hydrological model, allowing for comparisons between satellite observations of soil moisture, soil moisture maps computed through basin-scale continuous simulations and crop-growth model outputs. This comparison is expected to ease and strengthen the coupled use of the hydrological and the crop-growth models in view of forecasting applications.

References

Albergel, C., et al.: From near-surface to root-zone soil moisture using an exponential filter: an assessment of the method based on in-situ observations and model simulations. Hydrol. Earth Syst. Sci. Discuss. **5**, 1603–1640 (2008). https://doi.org/10.5194/hessd-5-1603-2008

Ansari, H., Hassanpour, M.: Design and construction of REC-P55 for reading of soil moisture, temperature and salinity. Iran. J. Irrig. Drainage **9**(1), 32–43 (2015)

Baldwin, D., Manfreda, S., Keller, K., Smithwick, E.A.H.: Predicting root zone soil moisture with soil properties and satellite near-surface moisture data across the conterminous United States. J. Hydrol. **546**, 393–404 (2017)

Baldwin, D., Manfreda, S., Lin, H., Smithwick, E.A.: Estimating root zone soil moisture across the Eastern United States with passive microwave satellite data and a simple hydrologic model. Remote Sens. **11**(17), 2013 (2019)

Baldocchi, D., Novick, K., Keenan, T., Torn, M.: AmeriFlux: its impact on our understanding of the 'breathing of the biosphere', after 25 years. Agric. For. Meteorol. **348**, 109929 (2024)
Bauer-Marschallinger, B., et al.: Soil moisture from fusion of scatterometer and SAR: closing the scale gap with temporal filtering. Remote Sens. **10**(7), 1030 (2018)
Brocca, L., Moramarco, T., Melone, F., Wagner, W., Hasenauer, S., Hahn, S.: Assimilation of surface- and root-zone ASCAT soil moisture products into rainfall– runoff modeling. IEEE Trans. Geosci. Remote Sens. **50**(7), 2542–2555 (2012)
De Rosnay, P., Drusch, M., Vasiljevic, D., Balsamo, G., Albergel, C., Isaksen, L.: A simplified extended Kalman filter for the global operational soil moisture analysis at ECMWF. Q. J. R. Meteorol. Soc. **139**(674), 1199–1213 (2013)
De Santis, D.: Assimilation of satellite soil moisture in hydrological modeling: assessment of observations preprocessing and error characterization methods. PhD Thesis. University of Calabria (2018)
Dharssi, I., Bovis, K., Macpherson, B., Jones, C.: Assimilation of ASCAT surface soil wetness. Met Office, Exeter, UK Forecasting. Technical Report, vol. 548 (2010)
Entekhabi, D., et al.: The soil moisture active passive (SMAP) mission. Proc. IEEE **98**(5), 704–716 (2010)
Faridani, F., Farid, A., Ansari, H., Manfreda, S.: Estimation of the root-zone soil moisture using passive microwave remote sensing and SMAR model. J. Irrigation Drainage Eng. ASCE **143**(1), 04016070 (2016)
Faridani, F., Farid, A., Ansari, H., Manfreda, S.: A modified version of the SMAR model for estimating root-zone soil moisture from time-series of surface soil moisture. Water SA **43**(3), 492–498 (2017)
Farokhi, M., Faridani, F., Lasaponara, R., Ansari, H., Faridhosseini, A.: Enhanced estimation of root zone soil moisture at 1 km resolution using SMAR model and MODIS-based downscaled AMSR2 soil moisture data. Sensors **21**(15), 5211 (2021)
Gheybi, F., et al.: Soil moisture monitoring in Iran by implementing satellite data into the root-zone SMAR model. Hydrology **6**(2), 44 (2019)
González-Zamora, A., Sánchez, N., Martínez-Fernández, J., Wagner, W.: Root-zone plant available water estimation using the SMOS-derived soil water index. Adv. Water Resour. **96**, 339–353 (2016)
Green, W.H., Ampt, G.A.: Studies on soil Phyics. J. Agric. Sci. **4**(1), 1–24 (1911)
Kerr, Y.H., Waldteufel, P., Wigneron, J.P., Martinuzzi, J.M., Font, J., Berger, M.: Soil moisture retrieval from space: the Soil Moisture and Ocean Salinity (SMOS) mission. IEEE Trans. Geosci. Remote Sens. **39**, 1729–1735 (2001). https://doi.org/10.1109/36.942551
Laio, F.: A vertically extended stochastic model of soil moisture in the root zone. Water Resour. Res. **42**, W02406 (2006). https://doi.org/10.1029/2005WR004502
Li, M., Sun, H., Zhao, R.: A review of root zone soil moisture estimation methods based on remote sensing. Remote Sens. **15**(22), 5361 (2023)
Lin, H.S., Kogelmann, W., Walker, C., Bruns, M.A.: Soil moisture patterns in a forested catchment: a hydropedological perspective. Geoderma **131**(3–4), 345–368 (2006)
Liu, H., Lin, H.: Frequency and control of subsurface preferential flow: from Pedon to catchment scales. Soil Sci. Soc. Am. J. **79**(2), 362–377 (2015)
Manfreda, S., Brocca, L., Moramarco, T., Melone, F., Sheffield, J.: A physically based approach for the estimation of root-zone soil moisture from surface measurements. Hydrol. Earth Syst. Sci. **18**(3), 1199–1212 (2014)
Manfreda, S., Fiorentino, M., Iacobellis, V.: DREAM: a distributed model for runoff, evapotranspiration, and antecedent soil moisture simulation. Adv. Geosci. **2**, 31–39 (2005)
Manfreda, S., Fiorentino, M., Samela, C., Margiotta, M.R., Moramarco, T., Brocca, L.: A physically based approach for the estimation of root-zone soil moisture from surface measurements: application on the AMMA database. Hydrology Days 2013 (2013)

Patil, A., Ramsankaran, R.A.A.J.: Improved streamflow simulations by coupling soil moisture analytical relationship in EnKF based hydrological data assimilation framework. Adv. Water Resour. **121**, 173–188 (2018)

Paulik, C., Dorigo, W., Wagner, W., Kidd, R.: Validation of the ASCAT Soil Water Index using in-situ data from the international soil moisture network. Int. J. Appl. Earth Obs. Geoinf. **30**, 1–8 (2014)

Rasche, D., Blume, T., Güntner, A.: Depth-extrapolation of field-scale soil moisture time series derived with cosmic-ray neutron sensing using the SMAR model. EGUsphere **2024**, 1–49 (2024)

Qiu, J., Crow, W.T., Nearing, G.S., Mo, X., Liu, S.: The impact of vertical measurement depth on the information content of soil moisture times series data. Geophys. Res. Lett. **41**, 4997–5004 (2014)

Schaefer, G.L., Cosh, M.H., Jackson, T.J.: The USDA natural resources conservation service soil climate analysis network (SCAN). J. Atmos. Oceanic Tech. **24**(12), 2073–2077 (2007)

Souissi, R., et al.: Integrating process-related information into an artificial neural network for root-zone soil moisture prediction. Hydrol. Earth Syst. Sci. **26**(12), 3263–3297 (2022)

Tobin, K.J., Torres, R., Crow, W.T., Bennett, M.E.: Multi-decadal analysis of root-zone soil moisture applying the exponential filter across CONUS. Hydrol. Earth Syst. Sci. **21**, 4403–4417 (2017)

Wagner, W., et al.: The ASCAT soil moisture product: a review of its. Meteorologische Zeitschrift, **22**(1), 1–29 (2013). Wagner, W., Lemoine, G., Rott, H.: A method for estimating soil moisture from ERS scatterometer and soil data. Remote Sens. Environ. 70(2), 191– 207 (1999)

Zhang, N., Quiring, S., Ochsner, T., Ford, T.: Comparison of three methods for vertical extrapolation of soil moisture in Oklahoma. Vadose Zone J. **16**(10), 1–19 (2017). https://doi.org/10.2136/vzj2017.04.0085

Zhao, T., Shi, J., Lv, L.: Soil moisture experiment in the Luan River supporting new satellite mission opportunities. Remote Sens. Environ. **240**, 111680 (2020)

Zheng, C., Jia, L., Zhao, T.: A 21-year dataset (2000–2020) of gap-free global daily surface soil moisture at 1-km grid resolution. Sci. Data **10**, 139 (2023)

Zhuang, R., Zeng, Y., Manfreda, S., Su, Z.: Quantifying long-term land surface and root zone soil moisture over Tibetan Plateau. Remote Sens. **12**(3), 509 (2020)