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# Soil Moisture for Hydrological Applications: Open Questions and New Opportunities

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**Abstract:** Soil moisture is widely recognized as a key parameter in the mass and energy balance between the land surface and the atmosphere and, hence, the potential societal benefits of an accurate estimation of soil moisture are immense. Recently, scientific community is making great effort for addressing the estimation of soil moisture over large areas through in situ sensors, remote sensing and modelling approaches. The different techniques used for addressing the monitoring of soil moisture for hydrological applications are briefly reviewed here. Moreover, some examples in which in situ and satellite soil moisture data are successfully employed for improving hydrological monitoring and predictions (e.g., floods, landslides, precipitation and irrigation) are presented. Finally, the emerging applications, the open issues and the future opportunities given by the increased availability of soil moisture measurements are outlined.

**Keywords:** soil moisture; hydrology; in situ measurements; remote sensing; floods; landslides; precipitation; irrigation

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## 1. Introduction

The importance of soil moisture in the hydrological cycle has been stressed in a number of papers [1–4] and scientific projects (European Space Agency Climate Change Initiative Soil Moisture, ESACCISM [5], Soil Moisture Active and Passive mission, SMAP [6], International Soil Moisture Network, ISMN [7], and Cosmic-ray Soil Moisture Observing System, COSMOS [8]). Soil moisture governs the partitioning of the mass and energy fluxes between the land and the atmosphere, thus playing a key role in the assessment of the different components of the water and energy balance. Soil moisture is an important variable for flood and landslide modelling and prediction [9–12], for drought assessment and forecasting [13–15], and for numerical weather prediction [16–19], to cite a few. Soil moisture is also the water source for plants and, hence, its knowledge is required for irrigation management and agricultural studies [20]. The scientific community has well recognized the very important role of soil moisture in Earth Science applications and in the last 40 years new approaches and techniques for monitoring, modelling and using soil moisture data have been developed.

In this review, an overview of the potential of soil moisture observations for improving hydrological applications is presented. Firstly, we briefly describe the main techniques employed for soil moisture estimation at different spatial scales. Secondly, the understanding that we gained in the assessment of soil moisture spatial-temporal variability is illustrated. Thirdly, we provide a list of the hydrological applications that have benefited (and will benefit) from the use of soil moisture observations. Finally, the open questions and the novel opportunities that would be important to address in future investigations are described.

We underline that this paper reflects the opinion and the experience of the authors on this research topic and we mainly focus on the applications and the research questions that we investigated in the past. This paper should not be considered as a review paper. Indeed, several recent reviews already investigated different hydrological aspects related to soil moisture, e.g., the estimation of soil moisture through remote sensing [3,21,22], the different techniques for in situ soil moisture monitoring at different scales [23,24], the use of satellite soil moisture data in hydrological and climatic applications [25,26], and the assessment and modelling of soil moisture spatial-temporal variability [2,27,28]. Therefore, we believe there is no need of an additional review on soil moisture. Differently, the manuscript is conceived to be a comprehensive summary of our research activity on soil moisture and our view for future opportunities to be analysed. We wanted to identify the main knowledge gaps that need to be filled in future investigations for improving the monitoring, and the use, of soil moisture observations in hydrological (and others) applications.

## 2. How Do We Estimate Soil Moisture?

Notwithstanding soil moisture is largely recognized as a fundamental physical variable, e.g., soil moisture is included at the 2nd place among the Essential Climate Variable by the Global Climate Observing System (GCOS), its monitoring over large areas is still an open research activity [23,29]. Indeed, differently from precipitation, in situ monitoring networks for soil moisture are much less developed and only in few countries (e.g., United States) a good coverage of in situ stations is present (see Figure 1). This should be attributed to the very recent availability, with respect to precipitation, of ground sensors measuring soil moisture, and partly to the lower knowledge of the large benefits that we can obtain from soil moisture observations. Currently, three different approaches are used for providing soil moisture estimates: (1) in situ observations; (2) remote sensing; and (3) modelled data. In the following, we describe the main features of each approach in order to underline their pros and cons. Overall, it is widely accepted that the integration of in situ, satellite and modelled data is the best approach to exploit the potential of soil moisture in hydrological applications [25,30].

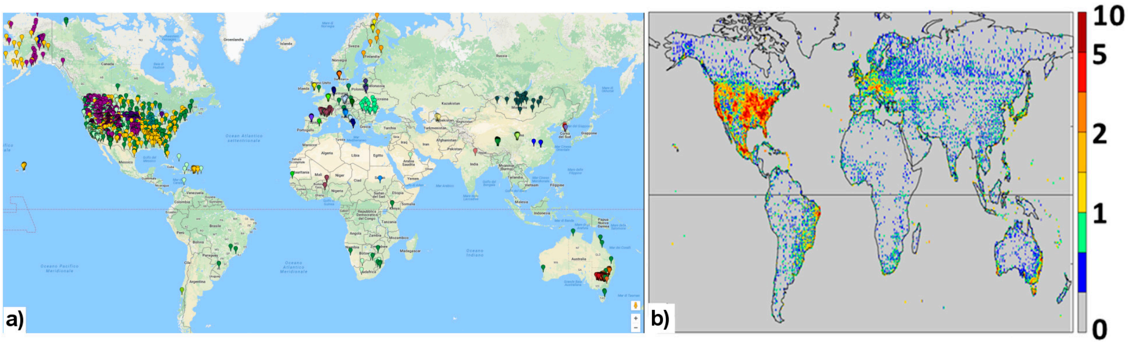


**Figure 1.** (**a**) Global distribution of soil moisture stations available at the International Soil Moisture Network from January 2000 ([7]); different colours refer to different networks; (**b**) Density of rain gauges underlying the Climate Prediction Center Unified Gauge-Based Analysis of Global Daily Precipitation (number of gauges/0.5°). Even though the two maps are not directly comparable, it is evident that the number of soil moisture stations is much lower than precipitation gauges, and, except in USA and Europe, soil moisture data are nearly absent.

### 2.1. In Situ Measurements

The first approaches for monitoring soil moisture through in situ observations are based on gravimetric, tensiometric and nuclear techniques [24]. Although invasive and time consuming, the gravimetric technique is still the reference method to which the other techniques and new methods are calibrated and tested. In the 1980s, Topp et al. [31] proposed the Time Domain Reflectometry

(TDR) technique. TDR was found to provide accurate measurements for a wide range of soils and settings thus becoming the new standard approach for measuring soil moisture and replacing the gravimetric approach (TDR is less time consuming and invasive). More recently, the emergence of low-cost capacitance sensors, based on Frequency Domain Reflectometry (FDR) technique, as well as impedance, time domain transmission sensors, etc., strongly promoted the usage of soil moisture sensors in environmental research [32]. Currently, FDR is likely the most used approach for in situ monitoring of soil moisture thanks to its lower cost with respect to TDR, even though at the expense of lower accuracy. Moreover, recent advances for the calibration and testing of electromagnetic sensors were proposed by Bogena et al. [33], thus further improving the accuracy and reliability of soil moisture sensors.

However, all the approaches listed above provide only point measurements that are representative of a small volume of soil [34]. The emergence of wireless sensor networks made it possible to cover larger areas with low-budget soil moisture sensors [35], but still this technology is only used for scientific studies. In the last decade, novel technologies were developed for providing soil moisture measurements over larger areas [29]. Currently, cosmic ray neutron sensors, Global Positioning System (GPS), and geophysical measurements (e.g., electrical resistivity and electromagnetic induction) are the most promising techniques [33,36–38]. Indeed, they are able to provide measurements with a support scale much larger than few cubic centimetres as point scale measurements. Cosmic ray and GPS techniques are well developed and some networks are already established in various countries (COSMOS [8], COSMOS-UK [39], and Plate Boundary Observatory to study the water cycle: PBO H2O [40]). However, these techniques are very recent, e.g., COSMOS network in UK was set up starting from 2016, and their use as established technique still requires further research and technical investigations.

Point in situ measurements of soil moisture (e.g., gravimetric, TDR, and FDR) are surely the most accurate techniques; however, they suffer from low spatial representativeness. The new techniques (e.g., cosmic ray and GPS) partly address this issue. Specifically, several papers demonstrated that the accuracy of the cosmic ray is similar to that point sensors, even under unfavourable conditions (e.g., [41–43]). Moreover, the maintenance of in situ soil moisture networks requires significant economic and human resources (even though lower than climatic stations) and, frequently, it is a non-trivial task to make a network operational for several (e.g., >5) years [34]. On this basis, it is evident that the development of established techniques providing measurements at 0.1–1 km spatial scale is vital [29].

### *2.2. Remote Sensing*

Remote sensing is definitely the most appropriate technique to obtain large scale soil moisture measurements. Different methods were developed in the last 40 years for the retrieval of soil moisture from microwave, optical and thermal satellite sensors. Several review papers on this topic were published recently [21,22,44] that well describe the algorithms developed for the retrieval of soil moisture from the different bands of the electromagnetic spectrum. In this paper, we focus only on active and passive microwave-based products as they are the most used methods, also providing operational soil moisture products [45]; the reader is referred to Rahimzadeh-Bajgiran and Berg [44] for a review on recent advances in thermal and optical remote sensing for soil moisture estimation. Specifically, it is important to distinguish among active microwave sensors, i.e., between Synthetic Aperture Radars (SARs) and scatterometers. The former (SAR) can provide high spatial resolution (<1 km) but coarse temporal resolution (i.e., >10 days). The latter (scatterometer) provides coarse spatial resolution (~20 km) and high temporal coverage (~daily). Passive microwave radiometers are characterized by nearly the same spatial-temporal resolution of scatterometers. We note that the temporal coverage of satellite data can be significantly improved by using multiple sensors or even a constellation of sensors [46,47]. Another important aspect is the specific band in the microwave range of the electromagnetic spectrum. Usually, X-, C- and L-band are used for estimating soil moisture with the latter theoretically more suitable [48]. However, other aspects such as the radiometric accuracy and the radio frequency interferences can significantly affect the final quality of soil moisture retrievals, even more than the microwave band [45].

At the time of writing (January 2017), four quasi-operational, i.e., available either in near real time (NRT) or few days after sensing, coarse resolution satellite surface soil moisture products are available: (1) the Soil Moisture Active and Passive (SMAP) mission (L-band radiometer) starting from April 2015 with ~36 km/2-day spatial/temporal resolution [49]; (2) the Advanced Microwave Scanning Radiometer 2 (AMSR2) onboard the Global Change Observation Mission for Water, GCOM-W, satellite (C- and X-band radiometers) starting from July 2012 with ~25 km/1-day spatial/temporal resolution [50]; (3) the Soil Moisture and Ocean Salinity (SMOS) mission product (L-band radiometer) starting from January 2010 with ~50 km/2-day spatial/temporal resolution [51]; and (4) the Advanced SCATterometer (ASCAT) onboard Metop-A and Metop-B satellites (C-band scatterometer) starting from January 2007 with ~25 km/1-day spatial/temporal resolution [45]. Recently, higher resolution (~1 km) soil moisture products are becoming available based on the disaggregation of coarse resolution products [52–54] and, in the near future, from Sentinel-1 satellites (e.g., [55]). However, thus far a high-resolution soil moisture product from SAR sensors has never been made available.

The most striking benefit of remote sensing observations is related to their spatial-temporal coverage, and the relatively lower costs for large scale applications. The accuracy of satellite soil moisture products is surely lower than in situ observations, even though the recent products listed above have achieved a high level of reliability and maturity, as demonstrated in several validation studies comparing satellite data with in situ observations and land surface/hydrological modelling ([56–59] to cite a few). Moreover, the number of applications already using these products is an indirect assessment of their good quality level, as it was demonstrated their utility for improving and supporting hydrological and climatic predictions (see below and [26,60,61]). The three major limitations of satellite soil moisture products are: (1) the very shallow soil layer (2–7 cm) that is sensed from satellites; (2) the coarse spatial resolution (~20 km) of the currently available products; and (3) the very low quality under certain surface conditions (dense vegetation, frozen soils, snow, mountainous terrain). While these limitations may prevent their use in several hydrological applications [25], some approaches were already developed to overcome these issues, i.e., spatial downscaling techniques (e.g., [53]) and simplified methods for root-zone soil moisture estimation from surface measurements (e.g., [62,63]).

### *2.3. Hydrological and Land Surface Modelling*

Hydrological and land surface models are largely used for estimating soil moisture at different spatial and temporal scales (e.g., [64]). Basically, both hydrological and land surface models use the same set of equations for simulating the water and energy balance, and hence soil moisture [65]. Indeed, different models use different structures for simulating each of the components (e.g., Richard's equation or variable infiltration curve for infiltration), but the main governing balance equations are the same. The models differ with respect to the spatial (horizontal and vertical) and temporal discretization, to the simulated physical processes and to the corresponding parameterization. More frequently, hydrological models are discretized at basin level and land surface model considers regular grids, but it is not always the case. Potentially, through modelling we are able to obtain soil moisture estimates at the desired temporal and spatial resolution (e.g., sub-hourly and 100 m, [66]).

The accuracy of modelled soil moisture data is strongly dependent on the employed model. However, besides to the model accuracy, the quality of meteorological observations used as input data also plays a very important role. Even a perfect model will fail if the quality, or the density, of meteorological inputs is low. Similarly, also the spatial and temporal discretization depends on the resolution of meteorological forcings, as well as of static information such as land use and soil texture maps [67]. Sometimes, high resolution modelled data (e.g., 500 m) are obtained by using as inputs coarse scale meteorological forcings (e.g., precipitation data at 10–100 km resolution). In these cases, the effective resolution of modelled data should be the one of the meteorological inputs (i.e., 10–100 km and not 500 m). A common issue faced by modeller is related to the parameterization of complex modelling structure and of the model parameter values. For instance, the parameterization of soil hydraulic parameters is a very difficult task, even in well gauged or experimental sites [68], and mainly over large areas [69]. Additionally, many key hydrologic processes are extremely difficult to parameterize (e.g., irrigation, dam operation, snow melting, and interception), especially in challenging regions (deserts, pluvial forests, and high altitudes). Therefore, modelled soil moisture data surely represents an important dataset that, however, needs to be used with caution [70,71].

## 3. How Does the Soil Moisture Vary in Space and Time?

In the last 40 years, a large number of studies were dedicated to the understanding of the spatial and temporal variability of soil moisture from the local to the regional and global scale (e.g., [2,72–75]). Indeed, after the development of the first measurement techniques, several researchers carried out detailed field campaigns in different geomorphological and climatic settings to assess soil moisture variability [24]. Different methods were applied including statistical [2,75] and geostatistical approaches [76], temporal stability analysis [73,77], and regression and wavelet techniques [78]. In this section, we provide a short overview of the major results obtained in the different studies trying to summarize the status of the knowledge we gained about the soil moisture spatial-temporal variability.

A large body of scientific literature analysed the statistical properties of soil moisture datasets obtained by field campaigns. The values of the first two statistical moments of absolute soil moisture data (in volumetric units, $m^3/m^3$), i.e., mean and variance, as well as their mutual relationship, were largely investigated (e.g., [79]). In most cases, a convex upward relationship is obtained between mean and variance thus concluding that soil moisture variability peaks for intermediates wetness conditions (e.g., [2,75,80,81]). Recently, Mittelbach and Seneviratne [82] proposed a new framework to decompose the soil moisture variability of the temporal mean and temporal anomalies. Interestingly, they obtained that the variability of soil moisture anomalies is larger for wet and dry conditions, with the minimum occurring at intermediate wetness conditions (see also [83,84]). Therefore, the behaviour of absolute and anomaly soil moisture values is not consistent and additional investigations are required.

A fundamental concept was introduced by [73], i.e., the soil moisture temporal stability. Vachaud et al. [73] found that the spatial patterns of soil moisture are stable over time and they named it as "temporal stability" (see [77] for a recent review). In other words, while the mean soil moisture for a given area might be changing over time, the spatial location of wetter and drier areas does not change. Figure 2 shows an example of soil moisture spatial patterns obtained by portable soil moisture measurements in the Colorso experimental plot in central Italy [2]. As can be seen, the different maps show the same pattern with wetter areas in the centre and southern part of the plot, and drier values in the northern part. The patterns are also quite consistent with the topography [2]. The simple concept of temporal stability has tremendous implications in hydrological and climate applications. It means that the monitoring of soil moisture with in situ observations over large areas (>100–200 $km^2$) can be carried out with a limited number of stations [75,77,83,85], with evident economic and time savings. Similarly, a limited number of stations can be used for the validation of coarse scale satellite soil moisture products, as indirectly demonstrated by the high correlations that are frequently obtained between coarse scale (~20 km) and point scale (~5 cm) measurements (e.g., [57–59]). Vice versa, coarse scale measurements, as obtained by remote sensing, can be used for regional or local studies (e.g., [11,86]). In summary, the temporal stability concept allows to mitigate the spatial discrepancies between point measurements and the scale needed in the applications.

A series of publications investigated the factors influencing soil moisture variability, both in time [87] and in space [88]. In time, soil moisture is mainly driven by precipitation and evapotranspiration, and its temporal variability is also a function of soil characteristics, vegetation, topography and groundwater [87,89]. Several modelling studies obtained very good performances in simulating point- (grid-) scale soil moisture temporal evolution [65,67,90], thus showing that a good knowledge has been gained about the factors influencing point scale soil moisture temporal variability. Figure 3 shows a comparison between observed and modelled data at two sites in central Italy using the Soil Water Balance Model [67]. The agreement with observations highlights the good model performances, and similar results were obtained at several sites in Europe (e.g., [57,91]). In space, the same meteorological factors, i.e., precipitation and evapotranspiration, have a clear impact on soil moisture patterns at large scales (>500–1000 km$^2$). At smaller scales, static factors such as land cover, topography and soil texture/structure affects soil moisture spatial variability (see Figure 1 in [75]). Several authors compared soil moisture spatial patterns with these static factors (e.g., [2,92]) obtaining moderate to low predictive capability, largely varying across sites and climates. Therefore, our knowledge about the factors influencing spatial variability of soil moisture is still limited. This important point is evident if we compare the capability of hydrological models in reproducing soil moisture spatial variability with respect to temporal variability. Frequently, the magnitude of variability is severely underestimated [90,93,94], and at regional scale soil moisture spatial patterns from modelling and satellite observations are found to be not consistent [95]. In this context, some recent modelling studies are demonstrating the value of soil moisture data for a more in-depth validation of distributed hydrological models [96,97].

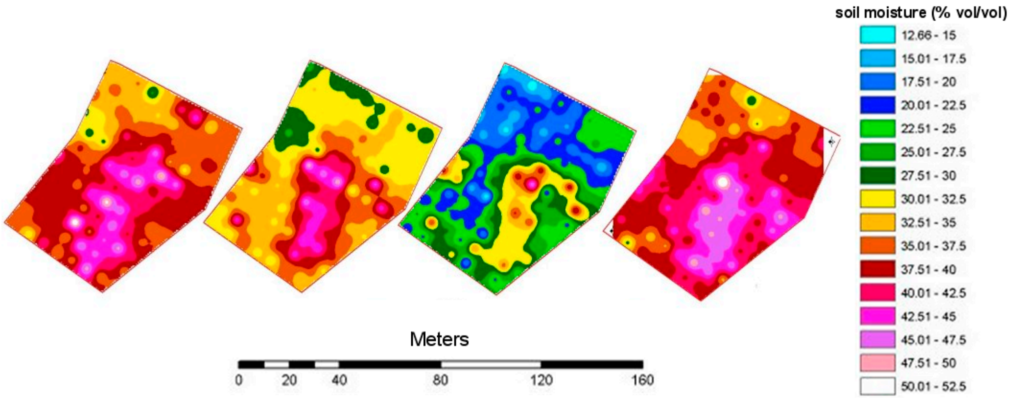


**Figure 2.** Spatial soil moisture maps (% vol/vol) obtained for the Colorso experimental plot in Italy at fuor different dates (from left to right): 21 April 2005, 28 April 2005, 5 May 2005, and 2 December 2005 (data from [2]). Even though the mean soil moisture conditions are changing over time, the spatial pattern of wetter and drier areas remains the same.

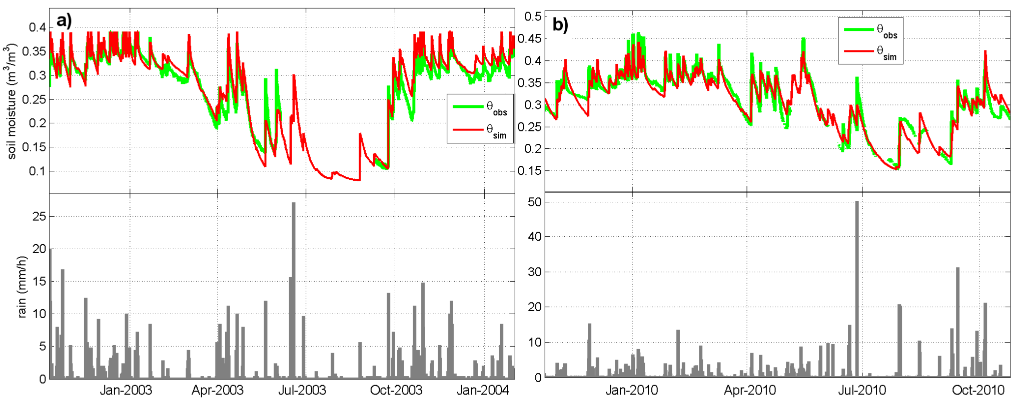


**Figure 3.** Modelled, $\theta_{sim}$, through the Soil Water Balance Model [67], versus observed, $\theta_{obs}$, soil moisture for: Colorso (**a**); and Ingegneria (**b**) sites in central Italy. The agreement between observed and modelled data reveals the good capability we achieved in simulating point scale soil moisture temporal evolution.

## 4. Which Hydrological Applications Are Benefiting (and Will Benefit) from Soil Moisture Data?

As evidenced in Section 2, several in situ, satellite and modelled soil moisture datasets are currently available, with large spatial and temporal coverage, and with appropriate spatial and temporal resolutions for hydrological, climatic and agricultural applications. Drought monitoring, runoff modelling and flood forecasting, numerical weather prediction, land surface and climate models assessment, wildfire risk assessment, agricultural monitoring and crop yield forecast [25,26,60,61] are among the most important applications benefiting from in situ and satellite soil moisture observations.

In this section, we mainly focus on a single hydrological application that was the object of our previous and on-going studies, i.e., runoff modelling and flood forecasting. Moreover, we list a number of "emerging" applications in which soil moisture data are being used in the last couple of years: (1) landslides and erosion prediction; (2) epidemic risk monitoring; (3) rainfall estimation; and (4) irrigation detection and assessment.

The purpose of this section is to briefly describe the main outcomes of previous studies on the selected applications in order to highlight the open issues to be addressed.

### *4.1. Runoff Modelling*

Soil moisture is the key variable for the partitioning of rainfall into infiltration and runoff, thus playing a fundamental role in runoff modelling and flood forecasting [9,10]. On the one hand, several studies employed in situ soil moisture observations for enhancing: (1) the estimation of initial conditions in flood modelling [98,99]; (2) the calibration of hydrological models [100,101]; and (3) flood simulation through data assimilation approaches [86,102,103]. Overall, these studies demonstrated the value of in situ soil moisture observations for improving flood simulation even though a comprehensive assessment was not possible due to the very limited spatial and temporal coverage of in situ observations. On the other hand, due the recent availability of satellite soil moisture products, the number of studies considering satellite soil moisture observations in this topic is significantly increasing in the last five years. For instance, under the Climate Change Initiative (CCI)—Soil Moisture of the European Space Agency (ESA), a global-scale and long-term soil moisture product is currently available from 1979 to 2015 (i.e., 36 years [46]), and next year it is foreseen that it will be available in near real-time [104]. The global-scale ASCAT soil moisture product is already available in near real-time (130 min after satellite pass) through the Satellite Application Facility on support to Operational Hydrology and Water Management (H SAF) project of EUMETSAT (European Organization for the Exploitation of Meteorological Satellites) since 2007. These new products have large potential to be employed for long-term and real-time flood forecasting. Similarly to in situ observations, satellite data have been used for model initialization [105–109], for hydrological model calibration [110,111], and in a data assimilation framework [9,86,112–115]. By way of example, Figure 4 shows the results of the assimilation of the ESA CCI soil moisture product [46] in MISDc (Modello Idrologico Semi-Distribuito in continuo) rainfall-runoff model [116] for the Niccone basin in central Italy in the period 1995–2010. For the latest period 2007–2010, in which the temporal density of satellite observations is higher, the assimilation provides a significant increase in the model performance with a Nash-Sutcliffe efficiency value from 0.79 to 0.88 when the ESA CCI soil moisture product is assimilated. The improvement in discharge simulation is more evident for larger flood events.

However, the analysis of the scientific literature on this topic reveals that the actual added-value in using satellite soil moisture for runoff modelling is still unclear [86,113]. Some authors obtained moderate to significant improvement through the assimilation of satellite data soil moisture in hydrological modelling (e.g., [9,112,117]) while other studies obtained a deterioration of the performances (e.g., [118]). These contrasting results have to be attributed to the inherent uncertainties and issues involved in the use of satellite (and in situ) soil moisture data in hydrological modelling. By considering the example of data assimilation, Massari et al. [113] clarified well that several choices should be made (i.e., the "cooking techniques") in a data assimilation study and they might have a significant impact on final results, with even the same relevance of the considered hydrological model, observation to be assimilated, and assimilation approach (i.e., the "ingredients"). These choices include the assessment of the magnitude and the structure of the errors in the hydrological model and in the observations, and the selection of the rescaling (e.g., linear and non-linear bias correction, triple collocation, [119]) and/or filtering (e.g., the Soil Water Index method [62]) techniques. Moreover, several inherent issues are related to the spatial mismatch between observations, i.e., point scale for in situ data and coarse scale (plus shallow soil depth) for satellite data, and modelled data, to the structure of hydrological models [103,112], and to the error characterization of (satellite) observations. For that, a strong effort is required from the hydrologic and remote sensing communities to overcome these issues. On the one hand, hydrologists should modify hydrological models that usually consider a single soil layer and are spatially lumped (basin scale). Both in situ and satellite data requires a model tailored to their use. It would mean including a shallow soil layer close to the surface and a distributed spatial discretization for fully exploiting the potential of satellite soil moisture observations [112,120]. On the other hand, remote sensing scientists should improve the characterization of the errors associated to the soil moisture products, increase their spatial and temporal resolution, their temporal coverage and temporal consistency. Indeed, long-term soil moisture datasets (e.g., >10–15 years) are needed not only in the climate community but also from hydrologists to assess the impact of using such datasets through robust analyses.

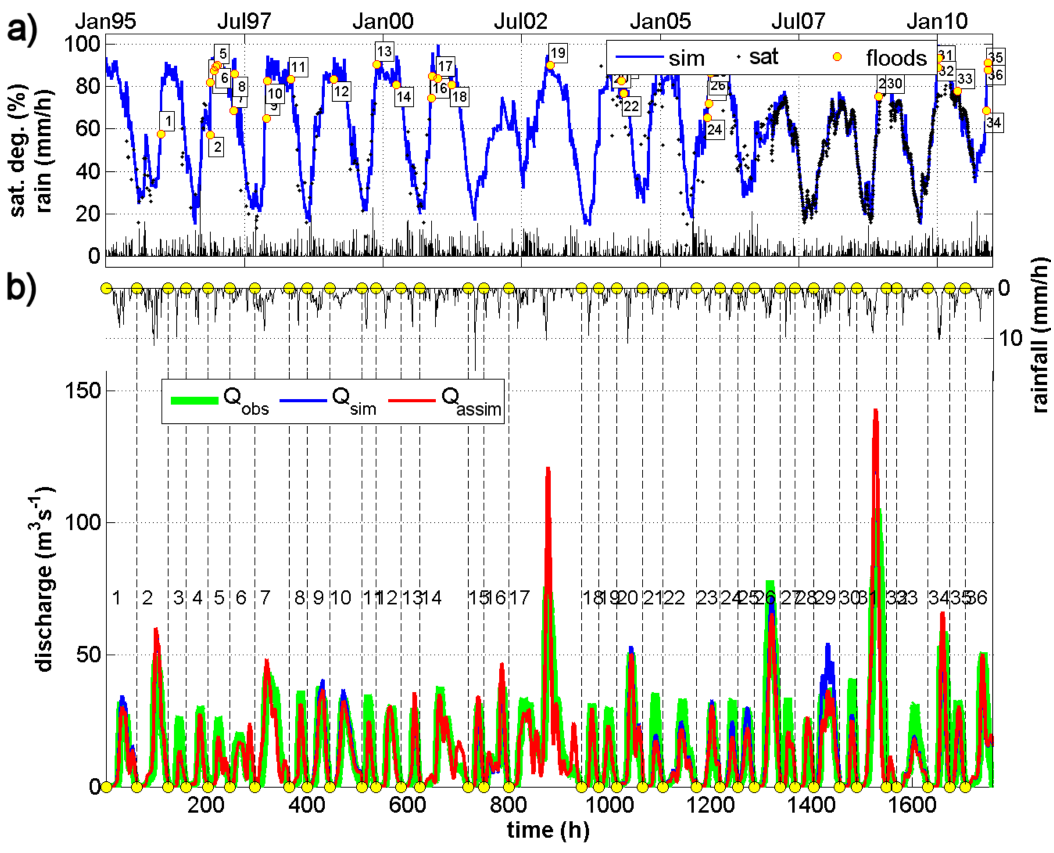


**Figure 4.** MISDc model results without and with the assimilation of ESA CCI soil moisture product in the Niccone river basin (central Italy). (**a**) Root zone soil moisture simulated by the model, sim, and obtained by ESA CCI soil moisture product, sat, for the period 1995–2010. The filled circles, floods, represent the initial conditions of the selected flood events simulated by MISDc model and identified by the numbers in the lower panel; (**b**) Observed, $Q_{obs}$, versus simulated, $Q_{sim}$, and simulated with assimilation, $Q_{assim}$, discharge for the sequence of the flood events occurred in the study period. The corresponding hourly rainfall is also shown in both panels (note that time axis is different in the upper and lower panel).

## 4.2. Emerging Applications

Soil moisture observations play an important role for the mitigation of many natural hazards other than floods, i.e., for landslide and erosion prediction [121,122]. Several studies used in situ observations for studying the linkage between soil moisture conditions and landslide occurrence [12,123]. For instance, Hawke and McConchie [124] analysed this relationship in a small area of New Zealand affected by landslide and obtained that the slope failure occurred when maximum soil moisture conditions were observed. Based on these studies, the use of soil moisture stations for monitoring slope stability conditions is becoming a standard (e.g., [125], United States Geological Survey website [126]). Differently from in situ observations, satellite soil moisture data were rarely employed in this context and only three studies were published [11,127,128]. Brocca et al. [11] demonstrated that the ASCAT soil moisture product is able to improve the performances of a statistical regression model aimed at predicting the temporal evolution of landslide movement for a small landslide in central Italy. Similarly, in the context of erosion prediction, Todisco et al. [122] recently suggested that ASCAT soil moisture data might be used for predicting event soil losses at plot scale in central Italy. The very small number of studies employing satellite soil moisture data for these applications is related firstly to the spatial mismatch between the targeted areas, typically a hillslopes or a small catchment, and the spatial resolution of satellite products, and secondly, to the difficulties in the exploitation of these technologies from the hydrological community [129,130]. Based on the studies mentioned above, we think that satellite soil moisture products have a high potential for improving the prediction of landslide and erosion processes, therefore these aspects deserve further investigations [26].

Soil moisture information might be helpful for the assessment and the monitoring of the epidemic risk. In the scientific literature, meteorological observations have been widely employed for determining spatial and temporal occurrence of epidemic risk (e.g., [131]), while only recently soil moisture data from modelling and observations have been considered in this respect [45,132,133]. For instance, Montosi et al. [132] developed an ecohydrological model for identifying the factors influencing malaria dynamics and highlighted the important role played by soil moisture. By using published data of malaria incidence rates in Mpumalanga and Botswana regions (Africa), we performed a simple correlation analysis between European Remote Sensing Scatterometer (ESCAT) and ASCAT satellite soil moisture products and malaria incidence rates (Figure 5). Although mainly driven by the seasonal cycle, a moderate agreement is observed between the monthly time series in the two regions, thus highlighting the potential of using satellite soil moisture data in this application that is extremely important in developing countries.

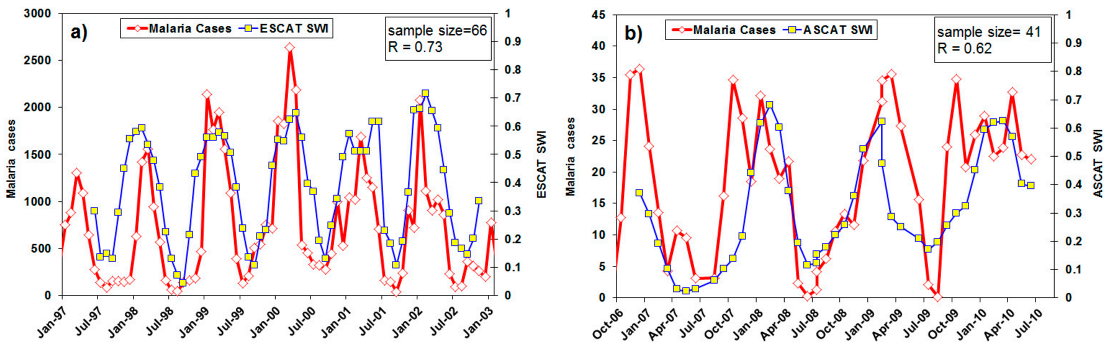


**Figure 5.** Comparison between malaria cases and soil moisture time series obtained by ESCAT Soil Water Index: SWI, in Mpumalanga (**a**); and ASCAT SWI in Botswana (**b**). The data on malaria cases are obtained by: Montosi et al. [132] (**a**); and by Chirebvu et al. [131] (**b**). R is the Pearson's correlation coefficient.

Pellarin et al. [134] and Crow et al. [135] made the first studies using satellite soil moisture observations for correcting satellite precipitation estimates. Thanks to the strong relationship between the temporal evolution of rainfall and soil moisture, the latter can be employed for improving the quality of satellite precipitation products that are affected by several issues (e.g., [136]). More recently, the number of publications on this topic is remarkably increasing likely due to the work by Brocca et al. [137,138] who developed a "bottom-up" approach, called SM2RAIN, for directly estimating precipitation rates from soil moisture observations only. The method has been applied on a local scale with in situ observations [137,139] and on a regional/global scale with satellite data [138,140,141]. Moreover, the "bottom-up" approach was integrated with state-of-the-art rainfall products (i.e., "top-down" approach) for obtaining a superior rainfall product by Brocca et al. [141] and Ciabatta et al. [142] in Australia and Italy. Finally, the precipitation product corrected through soil moisture data were used in several recent studies for improving flood prediction [98,143,144]. This new application is receiving more and more attention in the recent time, as also confirmed by a number of research projects funded by ESA, EUMETSAT, and NASA on this topic. Therefore, we believe that its further development and widespread application is highly beneficial for contributing to efforts in global precipitation estimation [140].

Soil moisture observations can be highly important for the detection and the quantification of irrigation, and specifically satellite datasets thanks to their large scale coverage [145,146]. For instance, Singh et al. [147] used Advanced Microwave Scanning Radiometer-Earth Observing System (AMSR-E) soil moisture data for discerning the shifting over time in the irrigation practices in north western India while Qiu et al. [146] highlighted that the ESA CCI SM product can be used to detect irrigated areas in eastern China by comparing trends in satellite precipitation and soil moisture. For instance, by using the SM2RAIN method described above, the quantification of irrigation from soil moisture data can be also performed. Figure 6 shows an example in Nebraska in which soil moisture data from ASCAT satellite and European Re Analysis -Interim (ERA-Interim) reanalysis were considered. The higher values of satellite soil moisture data compared to ERA-Interim reanalysis during summer are clearly visible in the Figure 6a (highlighted by grey areas). As ERA-Interim reanalysis does not incorporate irrigation data, the higher values obtained through satellite observations identify the occurrence and the amount of irrigation (Figure 6b,c). As the amount of water used for irrigation is largely unknown on a global scale, the capability of satellite soil moisture data to estimate irrigation might have a tremendous impact in future applications. We note, however, that dedicated studies still need to be carried out to demonstrate the feasibility of this application.

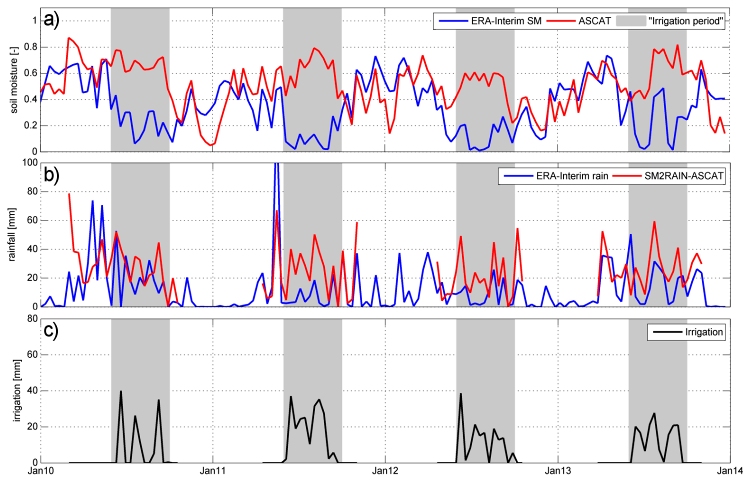


**Figure 6.** Soil moisture and rainfall time series for a pixel in Nebraska (Longitude, Latitude = −98 E, 40 N). (**a**) Temporal evolution of ASCAT and ERA-Interim soil moisture, SM, data (10-day moving average). Grey areas represent the months during which irrigation takes place; (**b**) Temporal evolution of ERA-Interim and SM2RAIN-ASCAT rainfall (10-day accumulations); (**c**) Temporal evolution of irrigation obtained as the difference between SM2RAIN-ASCAT and ERA-Interim rainfall (10-day accumulations).

## 5. Soil Moisture for Hydrological Applications: A Scientific Roadmap

In the previous three sections, we provided a short overview on the techniques used for soil moisture monitoring, on the spatial-temporal variability of soil moisture and on (some of) the hydrological applications in which soil moisture data are beneficial. Specifically, we highlighted the main limitations and research issues to be addressed together with the new hydrological applications that, in our opinion, should be investigated in the near future. We want to underline here that some of the open issues we raised might be considered as not doable, at least from the theoretical viewpoint. Theoretically, coarse resolution satellite soil moisture observations, or point scale in situ observations, cannot be used for catchment-scale applications; but several studies demonstrated the opposite in contrast with expectations (e.g., [9,11,86,113,122]). Similarly, it was not expected that soil moisture data could be used for rainfall estimation (as shown in [138]) or that C-band scatterometer data (i.e., ASCAT) could provide an accurate and usable satellite soil moisture product as it was shown in [26] and [45]. Research activities in the recent years demonstrated that our a priori, or theoretical, knowledge might fail when we started using actual observations. We believe that, as scientists, we have to experimentally demonstrate our hypothesis, and it was the rationale behind our past and on-going research activities. Bearing that in mind, we have defined three open issues to be addressed in the near future and the corresponding research opportunities that come from the attempt to answer to these scientific questions.

### *5.1. High Spatial-Temporal Resolution Soil Moisture Measurements*

Currently, we are able to estimate accurately soil moisture at the point scale through in situ sensors. Moreover, less accurate measurements can be obtained at coarse scale (~20 km) using satellite sensors. Daily and sub-daily temporal resolutions can be obtained through these techniques. However, soil moisture measurements at high spatial (i.e., <5 km) and temporal (sub-daily) resolution are not available at the time of writing (January 2017). To get this target, we must improve, test and integrate the new ground-based monitoring techniques such as GPS, cosmic ray and geophysical methods with more accurate point measurements techniques (e.g., TDR). At the same time, satellite sensors are rapidly increasing their capabilities in terms of spatial and temporal resolution, and accuracy. By way of example, in the near future (2020), the launch of next generation scatterometer sensors by EUMETSAT [148] will provide 5 km/daily soil moisture data by using a well-established technology and a soil moisture retrieval algorithm largely tested with ASCAT data. Moreover, Sentinel-1 is expected to deliver soon high spatial resolution (1 km) soil moisture measurements every 6 days [55] and new technologies such as cubesat and nano-satellites, if well designed, have the potential to provide high spatial-temporal resolution at low costs [130]. Finally, spatial downscaling/upscaling approaches can be used to integrate the different techniques, as well as observations with modelling. Data assimilation and merging methods can be also considered to optimally integrate in situ, satellite and modelled data.

On this basis, an exciting future is foreseen in a couple of years from now in which high resolution soil moisture datasets are expected to be developed. The availability of these datasets to the hydrological (and climate) communities and users, also in an operational context (e.g., data availability in real-time) will open a number of new and unexplored research opportunities.

### *5.2. Soil Moisture Modelling in Space*

As highlighted in Section 3, modelling soil moisture in space is an important issue that is largely unexplored. Currently, this issue is magnified by: (1) the unavailability (only for small regions and limited time periods) of spatially detailed soil moisture datasets; (2) the difficulties in obtaining static (e.g., soil type) and dynamic (e.g., precipitation) inputs at high spatial resolution for modelling; and (3) the larger interest of hydrological and climate communities to simulate soil moisture in time with respect to in space. In our opinion, we should improve our capability in modelling soil moisture both in time and in space.

Several research questions, and corresponding opportunities, should be addressed to achieve this target. Firstly, the spatial comparison between satellite and modelled data would reveal the similarities and the differences between the derived patterns. Mainly looking at the differences, we would gain knowledge on where (and when) satellite and modelled datasets need improvements. Secondly, a stronger link between studies that analysed soil moisture spatial variability and studies performing satellite datasets validation and/or using these datasets in hydrological and climatic applications should be carried out. For instance, lower (higher) performances in the comparison between in situ and satellite datasets can be expected when the spatial variance is higher (lower). Similarly, the error characterization of satellite-based soil moisture measurements (with coarse resolution) should be related to soil moisture spatial variability. We believe that detailed investigations on these two points would provide new important insights and, consequently, new research chance.

### *5.3. Comprehensive Assessment of the Value of Soil Moisture Data*

The robust assessment of the effective value of in situ and satellite soil moisture data in hydrological applications is still missing. Theoretically, we are fully aware of the fundamental role of soil moisture but, with actual observations, contrasting results have been obtained. Open questions are: (1) What is the required accuracy of soil moisture data to be of benefit in hydrological applications? (2) What is the needed spatial and temporal resolution? Do we need higher spatial or temporal resolution? (3) What is the added-value of soil moisture data with respect to other physical quantities (e.g., river discharge, precipitation)? The answers to these questions are not trivial as, they are application-, model- and scale-dependent, and require dedicated studies encompassing a wide range of climates, models, etc. In this context, we strongly support the investigation of soil moisture data assimilation into flood modelling for different basins, climates, hydrological models and datasets (e.g., from different satellite sensors). For instance, we still need to assess if it is preferable to assimilate in situ or satellite soil moisture data (or alternatively, soil moisture or river discharge data). Moreover, another interesting research topic is related to the estimation of hydraulic soil properties using data assimilation of soil moisture (e.g., [149]). As mentioned above, the benefit in assimilating soil moisture data should also be related to soil moisture spatial-temporal variability studies.

Besides a comprehensive assessment in flood applications, we foster the use of soil moisture data in emerging applications. Indeed, we obtained that in situ and satellite soil moisture data can be extremely useful for landslides and erosion prediction, for malaria risk monitoring and for rainfall and irrigation assessment. Each of these new applications deserves further investigations in order to test the effective usability of soil moisture data on these topics. If successful, these new research activities can potentially open a number of new scientific and practical opportunities. For instance, the quantitative irrigation assessment from soil moisture data would be highly important for food security and management on a global scale, which is becoming more and more challenging under climate changing scenarios.

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