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Review

A roadmap for high-resolution satellite soil moisture applications – confronting product characteristics with user requirements

Jian Peng [a,b,c,*], Clement Albergel [d,1], Anna Balenzano [e], Luca Brocca [f], Oliver Cartus [g], Michael H. Cosh [h], Wade T. Crow [h], Katarzyna Dabrowska-Zielinska [i], Simon Dadson [c,j], Malcolm W.J. Davidson [k], Patricia de Rosnay [l], Wouter Dorigo [m], Alexander Gruber [n], Stefan Hagemann [o], Martin Hirschi [p], Yann H. Kerr [q], Francesco Lovergine [e], Miguel D. Mahecha [b], Philip Marzahn [r], Francesco Mattia [e], Jan Pawel Musial [i], Swantje Preuschmann [s], Rolf H. Reichle [t], Giuseppe Satalino [e], Martyn Silgram [u,2], Peter M. van Bodegom [v], Niko E.C. Verhoest [w], Wolfgang Wagner [m], Jeffrey P. Walker [x], Urs Wegmüller [g], Alexander Loew [r,3]

[a] Department of Remote Sensing, Helmholtz Centre for Environmental Research–UFZ, Permoserstrasse 15, 04318 Leipzig, Germany
[b] Remote Sensing Centre for Earth System Research, Leipzig University, 04103 Leipzig, Germany
[c] School of Geography and the Environment, University of Oxford, OX1 3QY Oxford, UK
[d] CNRM, Université de Toulouse, Météo-France, CNRS, 31057 Toulouse, France
[e] Consiglio Nazionale delle Ricerche (CNR), Istituto per il Rilevamento Elettromagnetico dell'Ambiente, Bari, Italy
[f] Research Institute for Geo-Hydrological Protection, National Research Council, Perugia, Italy
[g] Gamma Remote Sensing Research and Consulting AG (GAMMA), Gümligen, Switzerland
[h] USDA-ARS Hydrology and Remote Sensing Laboratory, Beltsville, MD, USA
[i] Institute of Geodesy and Cartography (IGiK), Remote Sensing Centre, Warsaw, Poland
[j] Centre for Ecology and Hydrology, Maclean Building, Crowmarsh Gifford, Wallingford OX10 8BB, UK
[k] European Space Agency, Mission Science Division, 2200 AG Noordwijk, the Netherlands
[l] European Centre for Medium-Range Weather Forecasts (ECMWF), Reading RG2 9AX, UK
[m] Department of Geodesy and Geo-Information, TU Wien, Vienna, Austria
[n] Department of Earth and Environmental Sciences, KU Leuven, Heverlee, Belgium
[o] Institute of Coastal Research, Helmholtz-Zentrum Geesthacht, Geesthacht, Germany
[p] Institute for Atmospheric and Climate Science, ETH Zürich, Universitätsstrasse 16, 8092 Zürich, Switzerland
[q] CESBIO (UMR 5126 Université Toulouse 3, CNES, CNRS, INRAE, IRD), Toulouse, France
[r] Department of Geography, University of Munich (LMU), 80333 Munich, Germany
[s] Climate Service Center Germany (GERICS), Helmholtz-Zentrum Geesthacht, Hamburg, Germany
[t] Global Modeling and Assimilation Office, NASA/GSFC, Greenbelt, MD, USA
[u] ADAS UK Ltd., Woodthorne, Wergs Road, Wolverhampton WV6 8TQ, UK
[v] Institute of Environmental Sciences, Leiden University, 2333 CC Leiden, the Netherlands
[w] Laboratory of Hydrology and Water Management, Ghent University, Coupure links 653, Ghent 9000, Belgium
[x] Department of Civil Engineering, Monash University, Clayton, Victoria, Australia

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ABSTRACT

Soil moisture observations are of broad scientific interest and practical value for a wide range of applications. The scientific community has made significant progress in estimating soil moisture from satellite-based Earth observation data, particularly in operationalizing coarse-resolution (25-50 km) soil moisture products. This review summarizes existing applications of satellite-derived soil moisture products and identifies gaps between the characteristics of currently available soil moisture products and the application requirements from various

* Corresponding author at: Department of Remote Sensing, Helmholtz Centre for Environmental Research–UFZ, Permoserstrasse 15, 04318 Leipzig, Germany.
E-mail address: jian.peng@ufz.de (J. Peng).

[1] Now at European Space Agency Climate Office, ECSAT, Harwell Campus, Oxfordshire, Didcot OX11 0FD, UK.
[2] Deceased February 10, 2018.
[3] Deceased July 02, 2017.

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disciplines. We discuss the efforts devoted to the generation of high-resolution soil moisture products from satellite Synthetic Aperture Radar (SAR) data such as Sentinel-1 C-band backscatter observations and/or through downscaling of existing coarse-resolution microwave soil moisture products. Open issues and future opportunities of satellite-derived soil moisture are discussed, providing guidance for further development of operational soil moisture products and bridging the gap between the soil moisture user and supplier communities.

1. Introduction

Soil moisture is an essential component of the Earth system and plays an important role in the exchange of water, energy and biogeochemical fluxes between the atmosphere and the land surface (e.g., Ochsner et al., 2013; Robock et al., 2000; Seneviratne et al., 2010). Given its importance within the Earth system, soil moisture has been listed as one of the 50 Essential Climate Variables (ECVs) by the Global Climate Observing System (GCOS) in support of the work of the International Panel on Climate Change (IPCC) and the United Nations Framework Convention on Climate Change (UNFCCC) (GCOS-138, 2010). Furthermore, the importance of mapping soil moisture has been underlined by European Space Agency (ESA) Climate Change Initiative (CCI) (Dorigo et al., 2017), the International Soil Moisture Network (ISMN) (Dorigo et al., 2011), the European Organization for the Exploitation of Meteorological Satellites (EUMETSAT) Satellite Application Facility on Support to Operational Hydrology and Water Management (H-SAF), the National Environmental Satellite, Data, and Information Service (NESDIS) Operational Soil Moisture Products (SMOPS), the Soil Moisture and Ocean Salinity (SMOS) (Kerr et al., 2001) mission, and the Soil Moisture Active Passive (SMAP) mission (Entekhabi et al., 2010a).

Temporally and spatially continuous soil moisture datasets are commonly explored through hydrological and land surface models (Albergel et al., 2013; Albergel et al., 2017; Balsamo et al., 2018; Liang et al., 1996; Western et al., 2004). Such datasets are challenging to develop and validate using ground-based measurements alone (Brocca et al., 2017; Mohanty et al., 2017), owing to the high spatial and temporal variability of soil moisture (Crow et al., 2012; Famiglietti et al., 2008). The accuracy of these simulated soil moisture products depends on the quality and availability of meteorological observations, soil texture, soil hydraulic properties, and the physics of the models involved (Montzka et al., 2017; Reichle et al., 2011; Rodell et al., 2004; Walker et al., 2003). Existing in situ soil moisture monitoring networks and databases such as the TERENO (Zacharias et al., 2011), OzNet (Smith et al., 2012), COSMOS-UK (Evans et al., 2016), and ISMN have been instrumental for validating soil moisture derived from either model simulations or satellite retrievals.

Beyond in situ measurements and model simulations, remote sensing provides another path to estimating soil moisture (Kerr, 2007; Peng and Loew, 2017; Schmugge et al., 2002; Wagner et al., 2013; Wigneron et al., 2003), which can provide independent reference data for validating model simulations, while avoiding the spatial coverage limitations of ground-based measurements. Optical, thermal infrared, and microwave remote sensing observations have all been used to retrieve soil moisture (Babaeian et al., 2018; Peters et al., 2011; Petropoulos et al., 2015; Srivastava, 2017). However, due to its unavailability under cloudy conditions and its indirect physical linkage with soil moisture, optical and thermal remote sensing are less suited for accurate and seamless soil moisture retrieval (de Jeu et al., 2008; Dorigo et al., 2017). In contrast, the atmosphere is mostly transparent to low-frequency microwave radiation (e.g., Njoku and Entekhabi, 1996), and observations at Ku-, X-, C-, and L-band have been evaluated for their potential to retrieve soil moisture with various algorithms (Chan et al., 2018; Choker et al., 2017; Gruber et al., 2019; Kerr et al., 2001; Liu et al., 2012b; Naeimi et al., 2009; Owe et al., 2001). Microwave remote sensing includes both active and passive microwave sensors. The active sensors emit microwave energy towards the land surface and measure the reflected energy, while passive sensors detect energy naturally emitted from the land surface. Generally, passive radiometers are capable of providing frequent observations, albeit with coarse spatial resolution. Active microwave sensors such as synthetic aperture radar (SAR) can provide much higher spatial resolution but with more challenges in the retrieval of soil moisture, due to the combined effects of vegetation structure, surface roughness, and water content on the backscattering coefficients (Wagner et al., 2007). Comprehensive reviews on soil moisture retrieval from remote sensing measurements are available from, e.g., Wagner et al. (2007) and Karthikeyan et al. (2017).

Currently, there are several microwave-based soil moisture products available on the global scale. Operationally produced datasets include, but are not limited to, retrievals from the Advanced Scatterometer (ASCAT) (Bartalis et al., 2007) onboard the Metop satellites, the Advanced Microwave Scanning Radiometer2 (AMSR2) (Kim et al., 2015) onboard the Global Change Observation Mission-Water (GCOM-W), the Soil Moisture and Ocean Salinity (SMOS) mission (Kerr et al., 2010), and the Soil Moisture Active Passive (SMAP) mission (Entekhabi et al., 2010a). Apart from these soil moisture products, which are directly retrieved from single satellite platforms, merged long-term (40 years) soil moisture products have been produced within the ESA CCI by harmonizing and merging multiple microwave-based soil moisture products (Dorigo et al., 2017; Gruber et al., 2017; Gruber et al., 2019). This product, hereafter referred to as ESA CCI Soil Moisture (SM), aims to extend the typically short temporal coverage of single-sensor soil moisture products. These products are currently operationally produced and distributed every 10 days in the Copernicus Climate Change Service (C3S; https://climate.copernicus.eu/).

These recent global soil moisture datasets usually provide soil moisture information at coarse spatial resolution (around 25-50 km) (Brocca et al., 2017). A remaining challenge is the operational retrieval of high spatial resolution (0.1-1 km) soil moisture products with comparable spatial-temporal coverage and retrieval quality (Peng et al., 2017b; Sabaghy et al., 2018). Current and future satellite missions, such as the ESA Sentinel-1 European Radar Observatory, the Satélite Argentino de Observación COn Microondas (SAOCOM) mission, the NASA-ISRO Synthetic Aperture Radar (NISAR), the Radar Observing System for Europe L (ROSE-L), and the Tandem-L satellites, offer opportunities to generate high-resolution soil moisture products. Sentinel-1 is currently the most advanced SAR mission to support the systematic generation of a surface soil moisture product at high resolution and regional/continental scale. As an example, this has been demonstrated in the context of an ESA feasibility study (Mattia et al., 2019), where a Sentinel-1 surface soil moisture prototype for the Mediterranean was developed and implemented by the National Council of Research (CNR) of Italy and validated by (Balenzano, 2020). Another example is the Copernicus Global Land service that has recently started providing 1 km Sentinel-1 soil moisture retrievals in an operational fashion (Bauer-Marschallinger et al., 2019). While the relatively short historical Sentinel-1 record to date (the first Sentinel-1 mission was launched 2014) may not yet be sufficient for many applications such as climate and hydrological modelling, the European Commission and ESA are committed to continuing Sentinel-1 observations for the next few decades as part of the Copernicus programme.

Alternative approaches to high-resolution soil moisture mapping include the downscaling of coarse-resolution soil moisture products, using proxy observations such as optical and thermal infrared information, radar backscatter information, or prior knowledge of the soil moisture variability (e.g., Balenzano et al., 2011; Bauer-Marschallinger et al., 2018; Das et al., 2010; Merlin et al., 2012; Paloscia et al., 2013; Peng et al., 2016; Piles et al., 2011; Verhoest et al., 2015; Wu et al., 2014). After the failure of the SMAP L-band SAR sensor (7th July 2015), which was designed for downscaling of coarse resolution soil moisture estimates derived from the SMAP L-band radiometer, NASA merges SMAP L-band radiometer with Sentinel-1 C-band backscatter data to produce soil moisture maps at 3-km and 1-km resolutions (Das et al., 2019). In addition, the combined high-resolution ASCAT/Sentinel-1 (1 km) soil moisture product has also been published recently (Bauer-Marschallinger et al., 2019; Bauer-Marschallinger et al., 2018). Nonetheless, there is still a need to develop models and algorithms that combine multiple datasets (e.g., coarse and fine resolution observations from optical, thermal infrared and microwave sensors as well as in situ measurements) to generate long-term soil moisture datasets with high spatial and temporal resolution. Recent reviews by Peng et al. (2017b) and Sabaghy et al. (2018) have comprehensively summarized various downscaling approaches applied to improve the spatial resolution of existing soil moisture products.

Apart from spatial resolution limitations, a major constraint on satellite-based products is that the soil moisture information provided by microwave remote sensing is representative only for the upper few centimetres of the soil (Collow et al., 2012; Kerr, 2007), depending on the surface condition, vegetation density and microwave frequencies. From the user community, there is a growing interest in satellite-based root zone soil moisture estimates, which can be obtained via the assimilation of surface soil moisture into a land surface model (Albergel et al., 2017; Albergel et al., 2008; Reichle et al., 2008; Reichle et al., 2017b; Walker et al., 2001) or filtering techniques (Wagner et al., 1999).

One challenge for soil moisture retrieval algorithms is the difficulty in deriving reliable accuracy estimates. It is clear that any single accuracy metric is not sufficient for a comprehensive description of soil moisture data quality (Gruber et al., 2020). Users commonly require other metrics of data quality. For example, for many applications, the absolute soil moisture accuracy is not as relevant as the precise detection of the temporal changes between consecutive observations (Cosh et al., 2004; Crow et al., 2005; Entekhabi et al., 2010a; Koster et al., 2009; Loew et al., 2013; Mittelbach and Seneviratne, 2012).

Despite the many challenges and limitations encountered in microwave remote sensing of soil moisture, many satellite-derived soil moisture data products have been found to be beneficial for numerous applications such as applied hydrology (e.g., Jackson et al., 1996), precision agriculture (e.g., Ge et al., 2011), disaster prevention (e.g., Chaparro et al., 2016; Chaparro et al., 2017; Norbiato et al., 2008), Numerical Weather Prediction (NWP) (e.g., de Rosnay et al., 2013; Scipal et al., 2008), evaporation estimation (e.g., Martens et al., 2017; Miralles et al., 2011) and climate monitoring (e.g., Seneviratne et al., 2010). Therefore, they serve a wide range of the Global Earth Observation System of Systems (GEOSS) societal benefit areas (Akbar et al., 2018; Dong and Crow, 2019; Dorigo et al., 2017; Koster et al., 2018; McColl et al., 2017). The recently published high-resolution soil moisture products are expected to provide additional merit for a variety of applications.

In contrast to previous reviews that mainly focused on how to retrieve soil moisture (Karthikeyan et al., 2017; Wagner et al., 2007) and improve soil moisture spatial resolution (Peng et al., 2017b; Sabaghy et al., 2018), the aim of this paper is to summarize the gap between satellite products and various application requirements and to highlight the benefits/demands of high-resolution soil moisture estimates. Specifically, we discuss the usability and potential of high-resolution, satellite-derived soil moisture products for local applications and processes, with a special focus on user requirements for specific applications. Based on these applications, open issues and future opportunities for satellite-derived soil moisture products are identified, providing guidance for future development of operational, high-resolution, satellite-based soil moisture products, and for bridging the gap between the data producers and data users.

2. Applications of satellite-derived soil moisture datasets

Table 1 lists publicly available global satellite-based soil moisture products. All of them have been comprehensively validated (e.g., Albergel et al., 2012; Brocca et al., 2011; Chan et al., 2016; Colliander et al., 2017; Dorigo et al., 2015; Draper et al., 2009; Jackson et al., 2010; Peng et al., 2015b). The grid spacing shown in Table 1 refers to the spatial interval used to resample satellite observations. The grid spacing is not the actual satellite spatial resolution and is normally finer than actual spatial resolution. Fig. 1 provides an overview of the characteristic spatial and temporal resolutions of various land applications, ranging from applied hydrology to climate applications, in comparison to the characteristics of typical high- and low-resolution satellite soil moisture products. While it is difficult to generalize the requirements of the broad user communities listed in the figure, one can see that current operational soil moisture products can support the NWP/climate applications, as they are mainly representative of large-scale precipitation dynamics (Brocca et al., 2013). There are also various studies that have applied these products for regional-scale (i.e., 1,000 to 10,000 km^2) agriculture monitoring and stream-flow forecasting (Crow et al., 2018a; Ines et al., 2013; Mladenova et al., 2017). However, the coarse resolution of existing products places significant restrictions on these applications. For example, because individual production units cannot be resolved, existing agricultural applications are limited to passive regional monitoring and cannot be used for active decision support at the farm or ranch level. Therefore, accurate high-resolution soil moisture products will significantly benefit applications that require observations on local to regional scales at high temporal and spatial resolutions.

2.1. Numerical Weather Prediction

Soil moisture is of high interest for NWP and the value of assimilating soil moisture observations to provide an improved initialization of land surface conditions has been examined within a number of NWP forecasting systems (e.g., de Rosnay et al., 2014; de Rosnay et al., 2013). For example, the European Centre for Medium-Range Weather Forecasts (ECMWF) investigated the impacts of assimilating SMOS brightness temperature and SMOS near-real-time (NRT) soil moisture products for NWP (Muñoz-Sabater et al., 2019; Rodríguez-Fernández et al., 2016; Rodríguez-Fernández et al., 2017). De Rosnay et al. (2020) pointed out the relevance of the SMOS brightness temperature observations for long-term monitoring and suitability of L-band long-term data records for future reanalysis activities. Rodriguez-Fernandez et al. (2019) reported that the ECMWF forecasting skill has been improved after assimilating SMOS neural network soil moisture products. Fig. 2 shows the improved performance of 2 m air temperature forecasts after assimilating SMOS NRT soil moisture for the Northern Hemisphere extra tropics from July to December. The benefit of assimilating scatterometer-based soil moisture products to initialize the atmospheric forecasting model was also evaluated (e.g., Albergel et al., 2012; de Rosnay et al., 2014; Scipal et al., 2008). ECMWF currently assimilates the Metop ASCAT and the SMOS NRT soil moisture products for operational NWP. The UK Met Office is also assimilating ASCAT soil moisture products into their operational forecasting framework (Dharssi et al., 2011). Similarly, SMAP data has been assimilated into the Environment Canada's Regional Deterministic Prediction System (Bilodeau et al., 2016) to examine its impacts on NWP. In general, the integration of soil moisture in NWP models has been found to improve forecasts (Carrera et al., 2019; Mahfouf, 2010; Muñoz-Sabater et al., 2019). To date, global NWP models have been applied at a spatial resolution of about 10 km, while regional NWP models have already reached the 1-km resolution (Bauer et al., 2015; Boutle et al., 2016; Mass et al., 2002). Future generations of regional NWP models will operate at the sub-kilometre scale with cloud resolving schemes. This will require land surface observations at comparable spatial scales. High-resolution earth observation systems and

Table 1
Details of the publicly available satellite-derived global soil moisture products. Data links have been last accessed on March 17, 2020.

Institution	Temporal coverage	Temporal resolution	Grid spacing	Sensor	Data link	Reference
Vrije Universiteit Amsterdam	1978-1987	2-3 days	0.25 deg	SMMR	https://www.geo.vu.nl/~jeur/lprm/	Owe et al. (2001) and Holmes et al. (2009)
Vrije Universiteit Amsterdam	1987-1999	2-3 days	50 km	SSM/I	https://www.geo.vu.nl/~jeur/lprm/	Owe et al. (2008) and Holmes et al. (2009)
ESA	1991-2007	1-2 days	25/50 km	ERS AMI WS	https://earth.esa.int/web/sppa/activities/multi-sensors-timeseries/scirocco/	Wagner et al. (1999) and Crapolicchio et al., 2016
Vrije Universiteit Amsterdam	1998-2015	2-3 days	50 km	TRMM-TMI	https://www.geo.vu.nl/~jeur/lprm/	Owe et al. (2008) and Holmes et al. (2009)
Vrije Universiteit Amsterdam	2002-2011	1-3 days	25 km	AMSR-E	https://www.geo.vu.nl/~jeur/lprm/	Owe et al. (2008) and Holmes et al. (2009)
NASA	2002-now	Daily	25 km	AMSR-E, AMSR2	https://nsidc.org/data/au_land/versions/1	Kim et al. (2015)
CESBIO	2003-2011	Daily	15/25 km	SMOS, AMSR-E	https://www.catds.fr/Products/A	Rodríguez-Fernández et al. (2016)
EUMETSAT H-SAF	2007-now	1-2 days	12.5/25/50 km	ASCAT	http://hsaf.meteoam.it/	Bartalis et al. (2007) and Wagner et al. (2013)
CESBIO	2010-now	1-2 days	25 km	SMOS	https://www.catds.fr/Products/Available-products-from-CPDC	Rodríguez-Fernández et al. (2016) and Jacquette et al. (2010)
ESA	2010-now	1-2 days	15 km	SMOS	https://smos-diss.eo.esa.int/oads/access/	Rodríguez-Fernández et al. (2016) and Jacquette et al. (2010)
BEC	2010-now	Daily	15/25 km	SMOS	http://bec.icm.csic.es	González-Zamora et al. (2015)
NASA	2011-2015	7 days	1 deg	Aquarius	http://nsidc.org/data/aquarius/	Bindlish et al. (2015)
JAXA	2012-now	2-3 days	50 km	AMSR2	https://suzaku.eorc.jaxa.jp/GCOM_W/data/data_w_index.html	Kim et al. (2015)
NASA	2015-now	1-2 days	3/9/36 km	SMAP	https://nsidc.org/data/smap/smap-data.html	Entekhabi et al. (2010a)
NASA	2015-now	1-2 days	1/3 km	SMAP/ Sentinel-1	https://nsidc.org/data/smap/smap-data.html	Das et al. (2019)
ESA	1978-2019	Daily	0.25 deg	Merged Active+Passive Microwave Sensors (ESA CCI)	http://www.esa-soilmoisture-cci.org/	Dorigo et al. (2017); Gruber et al. (2019); Gruber et al. (2017)
NOAA	2012-now	6 hours	0.25 deg	Merged Active+Passive Microwave Sensors (SMOPS)	http://www.ospo.noaa.gov/Products/land/smops/	Liu et al. (2016)

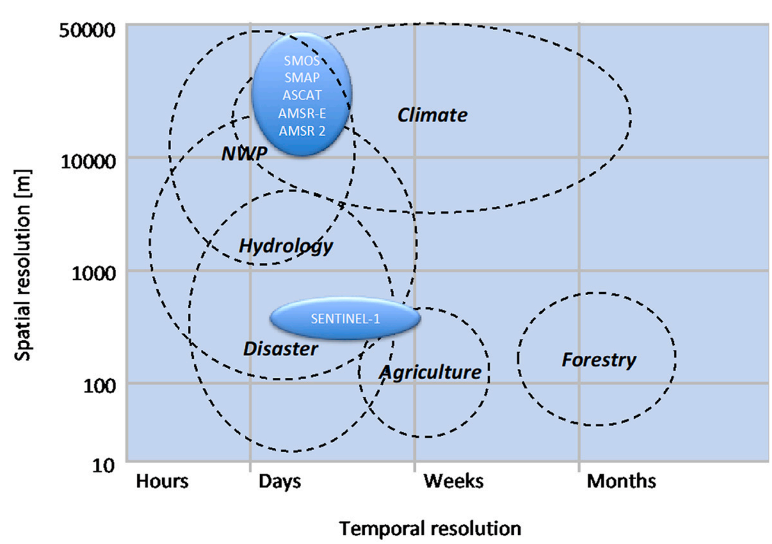

Fig. 1. Potential application areas for soil moisture products and their temporal and spatial resolution requirements in relation to selected soil moisture missions.

soil moisture downscaling schemes have great potential to provide high-resolution soil moisture information that meet this requirement.

2.2. Climate modelling and research

Climate research needs information on soil moisture to improve understanding of land-atmosphere processes (e.g., Loew et al., 2013; Seneviratne et al., 2013; Taylor et al., 2012; Van den Hurk et al., 2016). For example, based on AMSR-E and ASCAT soil moisture datasets, Taylor et al. (2012) found that afternoon precipitation occurred more frequently over dry soils across the entire globe (Fig. 3). Moreover, remote-sensing soil moisture products have also been used to study soil moisture-temperature and soil moisture-evapotranspiration coupling strengths (Lei et al., 2018), which are relevant metrics for the occurrence of hot extremes in transitional climate regimes (e.g., Dong and Crow, 2019; Hirschi et al., 2014). Likewise, the decline of global land

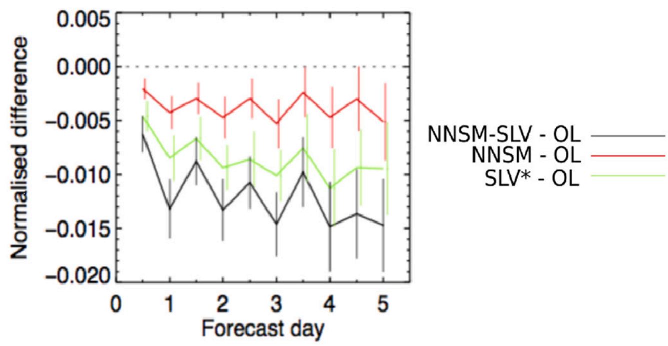

Fig. 2. Performance of 2 m air temperature (T2m) forecasts initialised from different offline soil moisture assimilation experiments for the Northern Hemisphere extra tropics from July to December 2012. The lines show T2m forecasts RMSE differences when different observations are used to analyse soil moisture and an "open loop" (OL) control without soil moisture data assimilation. ERA-Interim atmospheric analysis was used as forcing of the offline soil moisture analysis experiments. Negative values imply better forecast skill compared to a soil moisture OL initialisation. NNSM refers to an experiment that assimilates SMOS neural network soil moisture products, SLV is an experiment that assimilates 2 m air temperature and relative humidity measurements (with soil moisture as control variable), and NNSM-SLV is an experiment that assimilates both SMOS neural network soil moisture and SLV measurements (figure reprinted from Rodriguez-Fernandez et al. (2019)).

evapotranspiration in the early 2000s was caused by a decrease of soil moisture in the Southern Hemisphere (Jung et al., 2010) (Fig. 4), which was later shown to be driven by El Niño conditions (Miralles et al., 2014). Global models are currently run at spatial resolutions in the order of 50 kilometres, while the Coordinated Regional Downscaling Experiment (CORDEX) regional climate model (RCM) simulations are already run at around 10 km or finer (Iles et al., 2019). New generations of global climate models, such as the German ICON model (Crueger et al., 2018), allow for the simulation of regional nests at the 1-km scale and finer. Furthermore, it has been shown that the spatial heterogeneity of soil moisture can have a considerable impact on cloud and precipitation formation (Dong and Crow, 2018; Rieck et al., 2014; Schneider et al., 2014; Taylor et al., 2011). Dependent on the spatial soil moisture pattern, cloud formation might be enhanced or suppressed. High-resolution soil moisture products at kilometre scale will provide a more detailed picture of the fine scale heterogeneity which can enhance the ability to resolve boundary layer dynamics and large-scale eddy development.

2.3. Hydrology

The availability of spatially explicit soil moisture information has been beneficial to many fields in hydrology due to its important role in processes like runoff, flooding, rainfall, evaporation, infiltration, and ground water recharge (Dorigo et al., 2017; Scipal et al., 2005). Specifically, satellite-derived soil moisture products have been applied to a range of hydrological applications such as watershed management (e.g., Dahigamuwa et al., 2016; Heimhuber et al., 2017), runoff modelling/prediction (e.g., Alvarez-Garreton et al., 2015; Crow et al., 2017; Iacobellis et al., 2013; Lievens et al., 2016; Massari et al., 2015; Pauwels et al., 2002), landslide prediction (e.g., Brocca et al., 2012b; Ray and Jacobs, 2007; Ray et al., 2010; Zhuo et al., 2019), estimation of evapotranspiration (e.g., Lievens et al., 2017a; Loew et al., 2016; Martens et al., 2017), rainfall accumulation estimation (e.g., Brocca et al., 2013; Ciabatta et al., 2018; Román-Cascón et al., 2017), the quantification of groundwater storage (e.g., Asoka et al., 2017; Román-Cascón et al., 2017), the identification of soil moisture/runoff coupling biases in hydrological models and the estimation of the runoff ratio for subsequent rainfall (Crow et al., 2019; Crow et al., 2018a; Crow et al., 2017). Knowledge about the spatiotemporal dynamics of soil moisture is essential for understanding changes in the terrestrial water cycle. One example is the estimation of precipitation based on the ASCAT soil moisture product using the SM2RAIN (Soil Moisture to Rain) algorithm (Brocca et al., 2013). Based on a triple collocation analysis (Gruber et al., 2016), the SM2RAIN–ASCAT product was found to perform better than ground-based Global Precipitation Climatology Centre (GPCC) precipitation and the Global Precipitation Measurement Integrated Multi-satellitE Retrievals for Global Precipitation Measurement Early Run (GPM IMERG-ER) product over the Southern Hemisphere, central Asia, and the central western United States (Brocca et al., 2019) (Fig. 5).

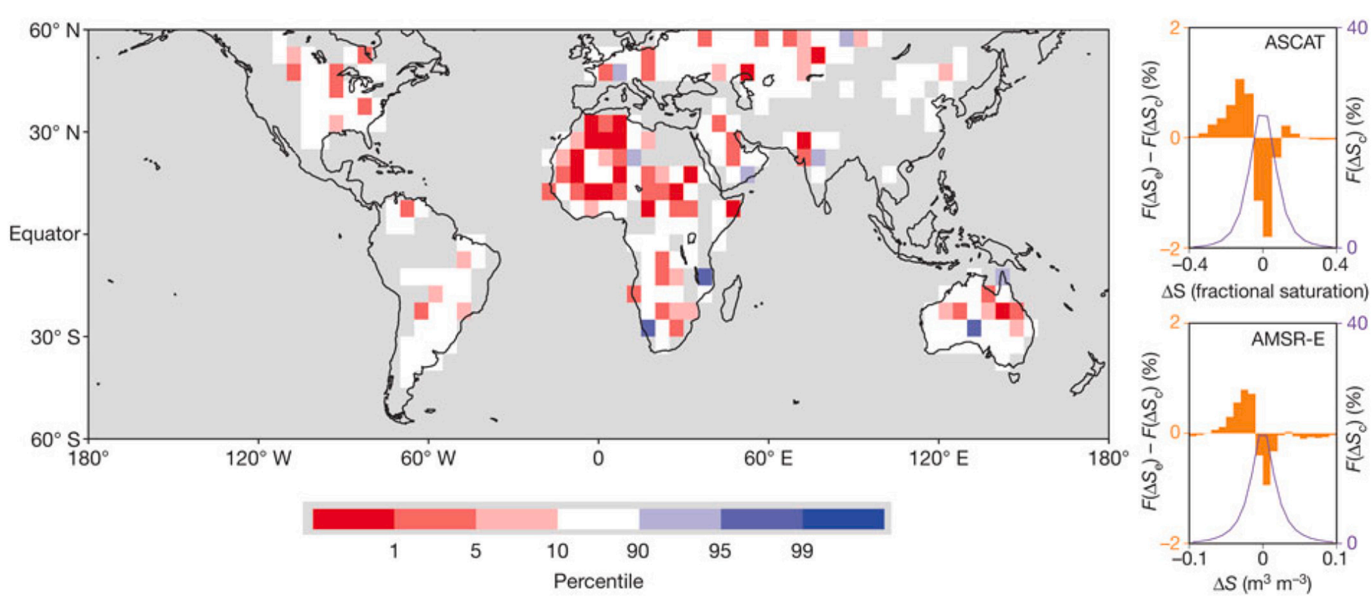

Fig. 3. Preference of afternoon precipitation over soil moisture anomalies. The low and high percentiles refer to where rainfall maxima occur over dry and wet soil more frequently than expected. The right panels present frequency histograms of soil moisture difference respectively calculated from AMSR-E and ASCAT. The $F(\Delta S_c)$ is based on a global control sample and is shown in a purple line, while $F(\Delta S_e) - F(\Delta S_c)$ (orange colour) denotes the frequency histogram difference between global event and global control samples. ASCAT and AMSR-E have different units, with fractional saturation for ASCAT and $m^3\ m^{-3}$ for AMSR-E (figure reprinted from Taylor et al., 2012).

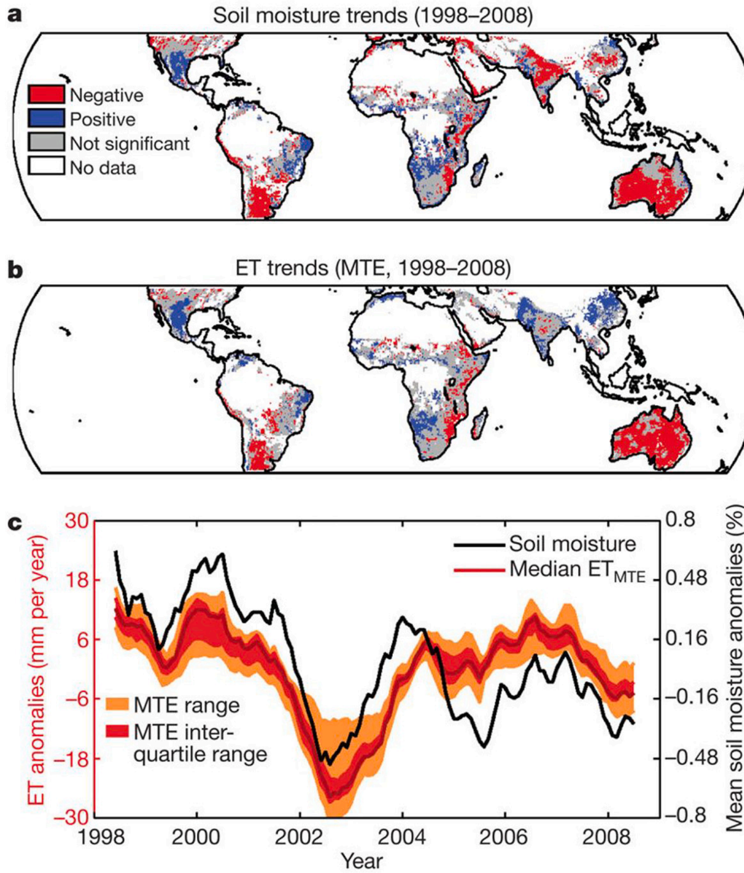

Fig. 4. Global trends of evapotranspiration and soil moisture: (a) soil moisture estimated from TRMM, (b) evapotranspiration, and (c) anomalies of mean evapotranspiration and soil moisture. Evapotranspiration was calculated based on FLUXNET, remote sensing and meteorological observations using a model tree ensemble (MTE) machine-learning method (figure reprinted from Jung et al., 2010).

Currently, soil moisture products can only be used for large river basins. However, in many cases, hydrological processes occur at spatial scales much smaller than the resolution of current satellite soil moisture observations. Hence, there is an increasing focus in hydrological modelling for the representation of fine-scale dynamics that cannot be resolved by existing satellite soil moisture observations. The availability of high-resolution soil moisture datasets at kilometre and sub-kilometre scale will therefore open a new perspective for hydrological modelling and improve the estimation of rainfall and evapotranspiration at these scales.

2.4. Hydrometeorological disasters

Hydrometeorological disasters are typically referred to as floods or droughts. In both cases, the soil moisture state plays a vital role in controlling the partitioning of surface water and energy fluxes (Koster et al., 2004). For flood forecasting applications, it is essential to know accurately the pre-rainstorm soil moisture conditions (in relation to the saturation level) and its spatial distribution within a watershed. Many studies have considered satellite-derived soil moisture to improve flood forecasting via data assimilation techniques (e.g., Komma et al., 2008; Li

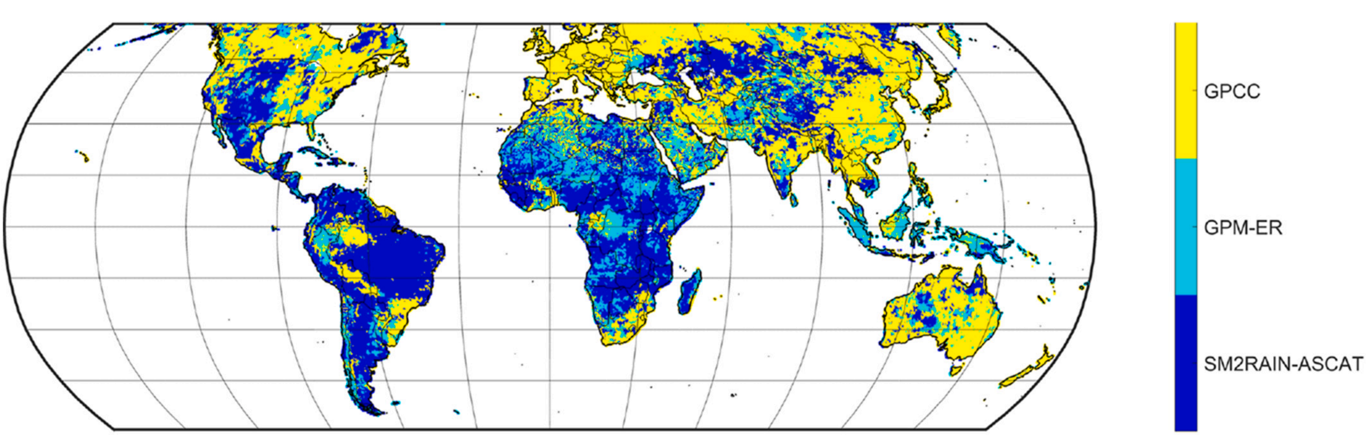

Fig. 5. Relatively best-performing precipitation product based on triple collocation analysis at global scale (figure reprinted from Brocca et al., 2019). The SM2RAIN product performs best over the Southern Hemisphere, central Asia, and the central western United States.

et al., 2018; Massari et al., 2018; Wanders et al., 2014). However, operational flood forecasting systems are still limited in their usage of existing satellite-derived soil moisture datasets because of: a) the lack of spatial detail, b) insufficient data continuity, c) limitations in data record lengths, and d) the lack of community acceptance. Long-term, high-resolution soil moisture records are needed to satisfy these requirements. It is thus important to motivate investment at operational flood forecasting centres to develop the appropriate infrastructure for assimilating high-resolution data.

Apart from flood forecasting, satellite-derived soil moisture can be used to analyze agricultural droughts caused by the prolonged absence of precipitation or increased evapotranspiration (Van Loon, 2015). For example, soil moisture datasets can be used to identify droughts (e.g., Anderson et al., 2012; Nicolai-Shaw et al., 2017; Peng et al., 2019), to develop drought indices (e.g., Carrão et al., 2016; Martínez-Fernández et al., 2016; Sadri et al., 2018), and to evaluate and improve process-based drought forecasting models (e.g., Bolten and Crow, 2012; McNally et al., 2017). Fig. 6 illustrates a comparison by Mishra et al. (2017) of a SMAP-based drought index with other well-known drought indices. Their study highlighted the good agreement between a SMAP-based drought index and the in situ Atmospheric Water Deficit (AWD) Index. On the regional scale, the drought responses are highly spatially variable due to differences in vegetation composition and cover. Thus, there is a strong demand for high-resolution soil moisture products.

2.5. Agriculture

Soil moisture is an important factor for agriculture. In particular, the availability of high-resolution soil moisture maps is essential for precision farming applications (at the scale of individual fields) and with the expectation to improve crop yield modelling (e.g., Dabrowska-Zielinska et al., 2007; Inoue et al., 2002; Verstraeten et al., 2010). So far, soil moisture products derived from satellites have been rarely used in farm- or field-scale agricultural decision support due to the coarse spatial resolution and the limited depth of the measurements (Brocca et al., 2018; Mulla, 2013). Nonetheless, satellite-derived soil moisture is expected to carry large potential if it can provide relevant information on appropriate temporal and spatial scales (as shown in Fig. 1). For instance, high-resolution soil moisture maps can help to identify and monitor irrigated areas, thereby providing valuable information for improving water management on local and regional scales (Merlin et al., 2013), particularly in areas facing scarce water resources (Brocca et al., 2018; Mulla, 2013; Zaussinger et al., 2019). Fig. 7 shows the variation of the new SMAP enhanced L3 9 km soil moisture product over both irrigated and non-irrigated sites (Lawston et al., 2017). It can be seen that the SMAP soil moisture product can identify well the onset of field irrigation (Malbeteau et al., 2018). Existing satellite-based soil moisture products can also be used to enhance yield forecasting, albeit at a relatively coarse spatial resolution (Mladenova et al., 2017).

Agricultural runoff is also a major pollutant affecting surface water bodies. Knowledge of the spatial soil moisture distribution can therefore help to minimize fertilizer usage and result in better surface and groundwater quality (Liu et al., 2012a). Another important aspect is soil erosion across agricultural fields, which impacts water quality of surface water bodies and may result in the loss of fertile agricultural land. Todisco et al. (2015) demonstrated that combining coarse-resolution ASCAT satellite soil moisture data with the Universal Soil Loss Equation-based (USLE) model improved soil erosion modelling capabilities in a region in central Italy compared to USLE model alone. The use of high-resolution soil moisture data is expected to open new perspectives in soil erosion modelling for agricultural fields because erosion processes happen on the farm and field scale.

2.6. Monitoring of wetlands and riparian zones

In the scope of wetland monitoring, soil moisture is one of the key variables used as an indicator of ecosystem change (Gabiri et al., 2018; Kasischke and Bourgeau-Chavez, 1997; Nghiem et al., 2017). The detection of global wetland area relies on satellite observations. Studies have shown that the coarse resolution of available data hampers the accurate mapping of wetland extent (e.g., Papa et al., 2006; Prigent et al., 2001), but also the estimation of biogeochemical cycling within wetlands (e.g., Melton et al., 2013). Soil moisture monitoring at high spatial resolution will allow detecting detrimental changes in wetlands and elongated riparian ecosystems (Dabrowska-Zielinska et al., 2018), which are not usually detectable at the coarse resolution of current soil moisture products. It should be noted that the retrieval of high-resolution soil moisture estimates from SAR observations is

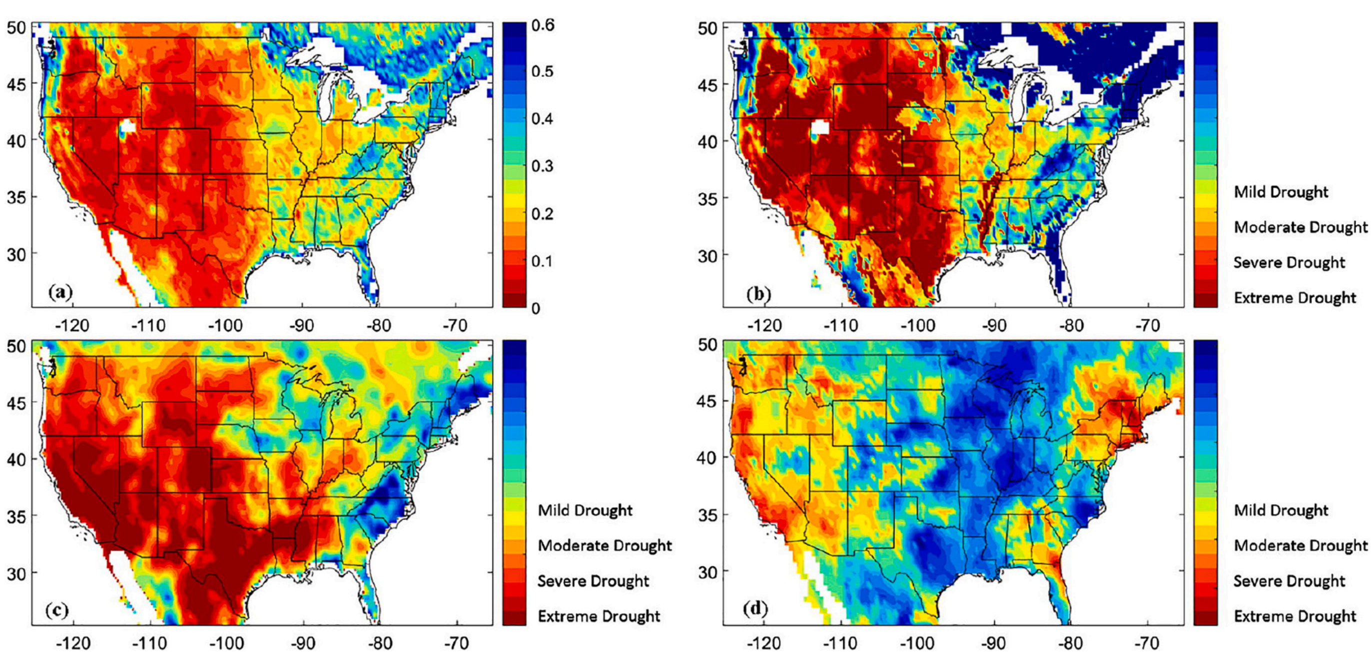

Fig. 6. Spatial maps of mean value on September, 2015 of: (a) SMAP L3 soil moisture, (b) Soil Water Deficit Index (SWDI) index based on SMAP, (c) Atmospheric Water Deficit (AWD) Index and (d) self-calibrating Palmer Drought Severity Index (sc-PDSI) (figure reprinted from Mishra et al., 2017).

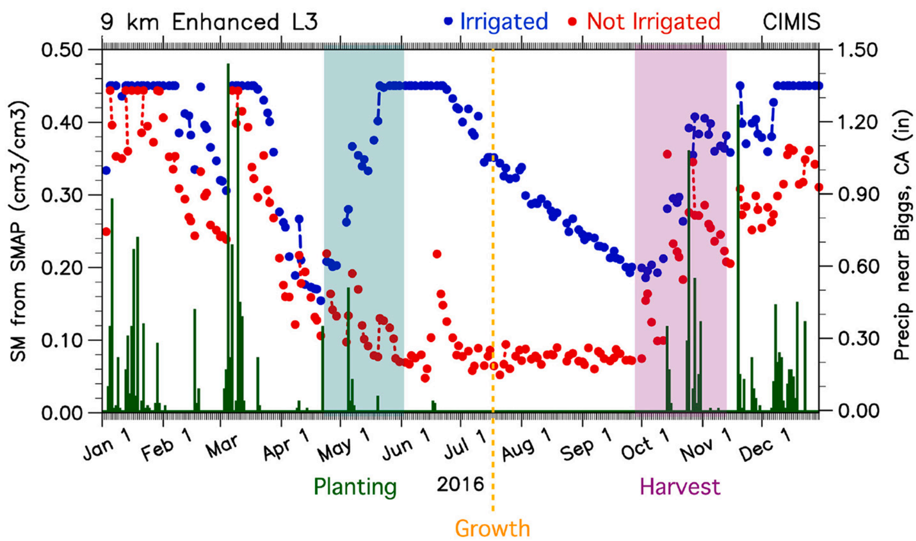

Fig. 7. Time series of SMAP soil moisture at an irrigated site (blue) and a non-irrigated site (red) in the northern California Central Valley (figure reprinted from Lawston et al., 2017).

challenging over wetlands due to the thick vegetation layer and possible presence of organic soil layers.

2.7. Other applications

Soil moisture also plays an important role in ecosystem research (Carvalhais et al., 2014; Nemani et al., 2003; Reichstein et al., 2013). Several studies have explored the response of ecosystems to soil moisture variations using satellite-based soil moisture products and vegetation indices (e.g., Dorigo et al., 2012; He et al., 2017; Murray-Tortarolo et al., 2016; Szczypta et al., 2014). The effect of water stress on gross primary production (GPP) estimation was quantified with SMOS-based high-resolution soil moisture by Sanchez-Ruiz et al. (2017). The relation between soil moisture and forest die-off episodes was investigated by Chaparro et al. (2017). In addition, various studies (e.g., Bartsch et al., 2009; Chaparro et al., 2016; Forkel et al., 2017; Forkel et al., 2012; Ichoku et al., 2016) examined the relationship of soil moisture with wildfire events, a major contributor to the uncertainty of terrestrial carbon cycle estimates (Friend et al., 2014). Soil moisture dynamics after a fire are also an indicator for the severity of a fire (dependent on the depth of the organic soil layer that has been destroyed) and indicate how fast a forest can recover (Chu and Guo, 2014; MacDonald and Huffman, 2004). High-resolution soil moisture observations together with vegetation datasets will further support the monitoring of wildfire probability and the development of appropriate fire models on regional scales. Soil moisture has also been used to monitor epidemic risk related to weather and environment conditions (Peters et al., 2014). Montosi et al. (2012) found that soil moisture plays an important role in malaria dynamics. There are many other applications that benefit from satellite-derived high spatial resolution soil moisture products such as desert locust preventive management (Escorihuela et al., 2018). With the advent of high spatial resolution soil moisture products additional applications will emerge.

3. User requirements review

User requirements on soil moisture products have been identified by international bodies and projects such as GCOS, EUMETSAT H SAF, ESA CCI SM, and dedicated satellite soil moisture missions such as SMOS and SMAP. Several workshops (e.g., the ECMWF/ESA workshop on using low frequency passive microwave measurements in research and operational applications, ECMWF, Reading, 4-6 December 2017, https://www.ecmwf.int/sites/default/files/medialibrary/2018-01/L-Band-WS-summary.pdf) have been held to discuss soil moisture applications and user requirements across disciplines. Table 2 summarizes the user requirements for soil moisture for selected fields of applications based on literature review and expert interviews. It should be noted that only a qualitative description of required accuracy is provided, as it is difficult to quantify the actual accuracy requirements for different applications. A target unbiased Root Mean Square Error (ubRMSE) of 0.04 m^3/m^3 has been defined for many soil moisture projects and satellite missions (e.g., Entekhabi et al., 2010a; Kerr et al., 2010). However, a single error metric is usually insufficient for representing the fitness-for-purpose of a particular application (Gruber et al., 2020). For example, under dry soil moisture condition, the ubRMSE of 0.04 m^3/m^3 may correspond to a relative error of 100%, while under wet conditions it would correspond to only 10% of the actual soil moisture variability (Entekhabi et al., 2010b). Therefore, more comprehensive error characterization methods are needed. Substantial recent progress in the calculation of potentially more informative metrics, in particular Signal-to-Noise Ratio (SNR) related measures, has been made using triple collocation analysis (Gruber et al., 2016; McColl et al., 2014).

A better understanding and description of soil moisture data quality requires close collaboration between data producers and the various user communities (Kerr and Escorihuela, 2019). In terms of spatial resolution, soil moisture products at high spatial resolution (i.e. ≤1 km) would benefit many applications, particularly on regional and local scales. For continental- or global-scale applications such as climate modelling and NWP, coarse spatial resolution soil moisture with long time coverage and high temporal resolution are currently successfully exploited. Based on a comprehensive analysis of the existing literature and expert interviews, we anticipate that a variety of applications, such as watershed runoff modelling, farm- and field-level agricultural management, and evapotranspiration/rainfall estimation, will benefit significantly from the complementarity of high- and low-resolution soil moisture observations (Table 3). Moreover, there is also a need for high temporal (sub-daily) resolution for model development applications. Furthermore, the products should preferably represent soil moisture within deeper soil layers, although the surface layer soil moisture is still valuable. To conclude, there is an urgent requirement by many user communities for soil moisture datasets at high temporal-spatial resolution, at multiple soil depths, with well-documented and consistent spatial-temporal error information.

Table 2
User requirements concerning satellite soil moisture products defined for selected applications. The summary is based on literature review and expert interviews.

Application	Usage	Accuracy	Soil moisture depth	Temporal resolution	Other
NWP	Assimilation of soil moisture or low-frequency microwave brightness temperature into NWP system	Accurate temporal dynamics	Surface and root zone	Daily or sub-daily	Reliable near real-time products
Climate	Evaluation of model performance and investigation of land-atmosphere interactions	Accurate temporal dynamics	Surface and root zone	Monthly or sub-monthly	Long-term soil moisture climatology
Hydrology	Hydrological modelling and estimation of water cycle components	Accurate absolute soil moisture	Surface and root zone	Sub-daily (e.g., hourly)	Reliable quality information
Agriculture	Precision agriculture and erosion modelling	Accurate absolute soil moisture	Root zone	Weekly and sub-weekly	Reliable quality information
Ecosystem	Ecosystem monitoring and ecological modelling	Accurate absolute soil moisture	Root zone	Weekly	Reliable quality information

Table 3
Applications that would benefit from soil moisture information on different spatial scales. The requirements level is indicated from high (+++) to low (+).

	Low spatial resolution (≥25km)	Medium spatial resolution (10km, 5km)	High spatial resolution (≤1km)
NWP	++	+++	++
Climate modelling	+++	+++	+
Watershed based runoff modelling	+	+++	++
Precipitation/ Evapotranspiration estimation	+++	+++	+++
Landslide prediction	+	++	+++
Flood forecasting	+	++	+++
Drought monitoring	+++	+++	+++
Precision agriculture		+	+++
Erosion modelling		+	+++

4. Open issues and future opportunities

In the following, open issues and future opportunities for satellite-derived soil moisture products are elaborated further, aiming to close the gap between application requirements and product characteristics. Moreover, recommendations are provided for next-generation operational satellite soil moisture datasets that will better meet user requirements and advance our collective scientific understanding.

4.1. High spatial and temporal resolutions

Although several kilometre-scale soil moisture products have been released recently, the major challenge in the retrieval of such high-resolution products from SAR data is how to accurately parameterize soil roughness and account for the impacts of observation angle (Verhoest et al., 2008; Zhu et al., 2019). Other challenges include retrieval uncertainty quantification and data continuity. In order to make use of the existing long-term coarse-resolution soil moisture products from e.g., ESA CCI SM, downscaling algorithms provide a means to improve the spatial resolution of soil moisture datasets. In addition to microwave observations, optical/thermal band observations have been used to either downscale microwave-based coarse-resolution soil moisture (e.g., Merlin et al., 2012; Peng et al., 2015a; Portal et al., 2018) or to directly estimate soil moisture (e.g., Babaeian et al., 2018; Rahimzadeh-Bajgiran et al., 2013; Wang et al., 2018). The advantages of optical/thermal band measurements include their very high spatial resolution (e.g., 10 meters from Sentinel-2) and sub-daily temporal resolution (e.g., geostationary satellites). A recent study by Sabaghy et al. (2020) has comprehensively evaluated existing downscaled soil moisture products from optical/thermal-, SAR-/radiometer-, and oversampling-based methods with both in situ and airborne soil moisture over the Yanco validation site in Australia. Downscaling approaches such as the optical and thermal-based Vegetation-Temperature Condition Index (VTCI) method presented in Peng et al. (2016) were found to perform well, but its results were also highly influenced by cloud cover. Moreover, using a data assimilation approach in a synergistic retrieval of soil moisture from optical and SAR data is also promising. For example, Marzahn et al. (2019) used a joint weak constrained data assimilation approach to retrieve soil moisture and other land surface variables with high accuracy. Therefore, it seems promising to generate long-term high -resolution soil moisture products through the synergistic use of microwave and optical/thermal measurements using data assimilation and machine learning methods (Ahmad et al., 2010; Draper et al., 2012; Kolassa et al., 2017; Lievens et al., 2017b).

While the generation of global soil moisture maps with sub-daily temporal resolution is not feasible with a single satellite platform (without a land data assimilation system), the combined use of microwave observations from multi-satellite constellations such as ASCAT onboard the Metop-A, B, and C platforms will probably lead to the generation of sub-daily microwave soil moisture products in the foreseeable future. Moreover, optical/thermal measurements from geostationary satellites with hourly temporal resolution might help to overcome this limitation through their integration with microwave observations (Hain et al., 2012; Piles et al., 2016; Zhao and Li, 2013). Future missions and instruments also provide new insights on monitoring soil moisture at high temporal and spatial resolution. One potential such mission, the ESA Geosynchronous-Continental Land Atmosphere Sensing System (G-CLASS/Hydroterra; (Hobbs et al., 2019), plans to launch SAR satellites in geosynchronous orbit (GEO). These SAR satellites are expected to monitor diurnal soil moisture dynamics on an hourly timescale. Another mission is the Copernicus Imaging Microwave Radiometer (CIMR), which is designed to provide sub-daily observations in Ku to L-band at the global scale (https://cimr.eu). Furthermore, CubeSat missions such as the Cyclone Global Navigation Satellite System (CYGNSS) are expected to play an important role in measuring soil moisture from space at high spatial and sub-daily temporal resolution (Al-Khaldi et al., 2019; Kim and Lakshmi, 2018).

4.2. Root zone soil moisture estimation

It is still challenging to estimate root zone soil moisture from satellite observations (Crow et al., 2018c), although several studies have implemented a soil water index based on an exponential filtering of surface soil moisture retrievals, which mimics the infiltration (Albergel et al., 2008; Wagner et al., 1999). Other efforts have been made to produce root-zone soil moisture through the assimilation of satellite-based surface soil moisture retrievals into land surface models (e.g., Balsamo et al., 2018; Das and Mohanty, 2006; De Lannoy and Reichle, 2016; Kumar et al., 2019; Kumar et al., 2009; Ridler et al., 2014; Walker et al., 2001). The ASCAT, SMOS, and SMAP soil moisture retrieval teams as well as the Global Land Evaporation Amsterdam Model team (Martens et al., 2017; Miralles et al., 2011) have released root zone soil moisture datasets (Brocca et al., 2012a; Mecklenburg et al., 2016; Reichle et al., 2017a; Reichle et al., 2017b; Reichle et al., 2019). These datasets can help to better understand the role of root-zone soil moisture in climate and hydrological predictions. However, the estimation of root-zone soil moisture at high spatial resolution still needs to be investigated. One option is to use P-band SAR that has a much deeper penetration depth than C- and L-band SAR. Several studies have already successfully used airborne P-band SAR data to retrieve root zone soil moisture (e.g., Crow et al., 2018c; Sadeghi et al., 2017). However, it is still challenging to build space-borne P-band SAR systems due to the increased antenna-length requirements and the effects of radio frequency interference. To overcome this limitation, the SigNals of Opportunity: P-band Investigation (SNoOPI) CubeSat mission will perform P-band reflectometry, which will be used to derive a root-zone soil moisture product covering the United States in the future (Azemati et al., 2019).

4.3. Validation and quality traceability

Validation of satellite-derived soil moisture and the provision of spatial-temporal error information are important for all applications. In general, the implementation of a thorough validation and monitoring framework for operational soil moisture products requires three main components: 1) reference data, 2) a validation guidance using appropriate metrics, and 3) validation and monitoring tools. The global in situ soil moisture networks together with the SMOS and SMAP satellite teams have made great efforts to provide extensive ground-based soil moisture measurements to the public. However, data quality, continuity, temporal legacy, gaps, and scaling errors of the reference data should be traceable, due to their fundamental role for the validation of satellite-based data. Traceable tools for the continuous monitoring and validation of satellite-derived data products are still in their infancy (Loew et al., 2017). The Quality Assurance for Essential Climate Variables (QA4ECV) framework was developed as the first initiative to demonstrate how reliable and traceable quality information can be provided for selected essential climate variables such as albedo, Leaf Area Index (LAI), and Fraction of Absorbed Photosynthetically Active Radiation (FAPAR) (Nightingale et al., 2018; Peng et al., 2017a). Following the same concept, the Quality Assurance for Soil Moisture (QA4SM) project (qa4sm.eodc.eu) was recently launched to provide an automated and, above all, transparent online validation tool for soil moisture. The tool follows standardized community good practice guidelines for the validation of satellite soil moisture products (Gruber et al., 2020). The validation tool produced by the QA4SM project and the community guidelines provided by Gruber et al. (2020) will serve as good practice recommendations for the validation of high spatial and temporal resolution soil moisture products in the future.

4.4. Mission continuity

Satellite mission continuity is crucial for the generation of consistent and long-term soil moisture datasets. A range of ESA, JAXA, and NASA sensors operating in C- and X-band have ensured the availability of soil moisture product since 1978. Thanks to efforts by ESA and JAXA, the continuation of these data products is largely ensured. In contrast, the ESA SMOS and NASA SMAP missions successfully provide L-band measurements and generate global soil moisture products. However, the continuity of these dedicated L-band soil moisture missions is not ensured. Based on lessons learned from SMOS and SMAP, it is therefore important to develop future L-band soil moisture missions to provide data continuity and high-resolution measurements. Currently, the above-mentioned CIMR mission plans include coarse-resolution L-band radiometer observations, and a potential SMOS follow-on mission, SMOS-HR (High-Resolution), is planned to deliver observations at 10 km (Rodríguez-Fernández et al., 2019). In addition, the European Commission and ESA have also committed the data continuity from Sentinel-1 SAR in next few decades through the Copernicus programme. As a complement to the Sentinel C-band SAR, the future ROSE-L mission will provide high resolution L-band SAR data.

5. Conclusions

Numerous operational soil moisture datasets, generated from satellite microwave remote sensing observations, have emerged over the last decade. Following the release of these soil moisture datasets, different science communities have made efforts to exploit the potential of these data by using them for a wide range of applications. Our review shows that there is a strong demand from various user communities for higher-resolution datasets at kilometre scale. The current and future satellite observations provide opportunities to develop high spatial resolution soil moisture products featuring moderate (e.g., daily) temporal resolution. Downscaling methods that integrate optical, thermal infrared and microwave observations based on data assimilation and machine learning provide an alternative to achieving high-resolution soil moisture products. However, challenges regarding high temporal resolution and the accuracy of the high-resolution products still need to be addressed. Integrating observations from multi-satellite constellations such as the Metop-A, B, and C platforms might lead to the generation of a twice-daily soil moisture product. In the future, the proposed Hydroterra geosynchronous radar satellite might provide hourly soil moisture data on a fine spatial scale - albeit with reduced area coverage. Moreover, CubeSats and small satellites have great potential for providing very high temporal-spatial resolution soil moisture. Quality assured long-term high-resolution soil moisture datasets will facilitate a wide range of applications of soil moisture products in the future.

Declaration of Competing Interest

None.

Acknowledgments

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