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

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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 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.

Keywords: Soil moisture; Remote sensing; Coarse resolution; High resolution; Hydrology; Meteorology; Geography; Agriculture; Ecosystem;

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.

85 2013; Wigneron et al. 2003), which can provide independent reference data for validating model

86 simulations, while avoiding the spatial coverage limitations of ground-based measurements.

87 Optical, thermal infrared, and microwave remote sensing observations have all been used to retrieve

88 soil moisture (Babaeian et al. 2018; Peters et al. 2011; Petropoulos et al. 2015; Srivastava 2017).

89 However, due to its unavailability under cloudy conditions and its indirect physical linkage with soil

90 moisture, optical and thermal remote sensing are less suited for accurate and seamless soil moisture

91 retrieval (de Jeu et al. 2008; Dorigo et al. 2017). In contrast, the atmosphere is mostly transparent to

92 low-frequency microwave radiation (e.g., Njoku and Entekhabi 1996), and observations at Ku-, X-,

93 C-, and L-band have been evaluated for their potential to retrieve soil moisture with various

94 algorithms (Chan et al. 2018; Choker et al. 2017; Gruber et al. 2019; Kerr et al. 2001; Liu et al.

95 2012b; Naeimi et al. 2009; Owe et al. 2001). Microwave remote sensing includes both active and

96 passive microwave sensors. The active sensors emit microwave energy towards the land surface and

97 measure the reflected energy, while passive sensors detect energy naturally emitted from the land

98 surface. Generally, passive radiometers are capable of providing frequent observations, albeit with

99 coarse spatial resolution. Active microwave sensors such as synthetic aperture radar (SAR) can

100 provide much higher spatial resolution but with more challenges in the retrieval of soil moisture,

101 due to the combined effects of vegetation structure, surface roughness, and water content on the

102 backscattering coefficients (Wagner et al. 2007). Comprehensive reviews on soil moisture retrieval

103 from remote sensing measurements are available from, e.g., Wagner et al. (2007) and Karthikeyan

104 et al. (2017).

105   Currently, there are several microwave-based soil moisture products available on the global

106 scale. Operationally produced datasets include, but are not limited to, retrievals from the Advanced

107 Scatterometer (ASCAT) (Bartalis et al. 2007) onboard the Metop satellites, the Advanced

108 Microwave Scanning Radiometer2 (AMSR2) (Kim et al. 2015) onboard the Global Change

109 Observation Mission-Water (GCOM-W), the Soil Moisture and Ocean Salinity (SMOS) mission

110 (Kerr et al. 2010), and the Soil Moisture Active Passive (SMAP) mission (Entekhabi et al. 2010a).

111 Apart from these soil moisture products, which are directly retrieved from single satellite platforms,

112 merged long-term (40 years) soil moisture products have been produced within the ESA CCI by

113 harmonizing and merging multiple microwave-based soil moisture products (Dorigo et al. 2017;

114Gruber et al. 2017; Gruber et al. 2019). This product, hereafter referred to as ESA CCI Soil

115Moisture (SM), aims to extend the typically short temporal coverage of single-sensor soil moisture

116products. These products are currently operationally produced and distributed every 10 days in the

117Copernicus Climate Change Service (C3S; https://climate.copernicus.eu/).

118 These recent global soil moisture datasets usually provide soil moisture information at coarse

119spatial resolution (around 25-50 km) (Brocca et al. 2017). A remaining challenge is the operational

120retrieval of high spatial resolution (0.1-1 km) soil moisture products with comparable spatial-

121temporal coverage and retrieval quality (Peng et al. 2017b; Sabaghy et al. 2018). Current and future

122satellite missions, such as the ESA Sentinel-1 European Radar Observatory, the Satélite Argentino

123de Observación COn Microondas (SAOCOM) mission, the NASA-ISRO Synthetic Aperture Radar

124(NISAR), the Radar Observing System for Europe L (ROSE-L), and the Tandem-L satellites, offer

125opportunities to generate high-resolution soil moisture products. Sentinel-1 is currently the most

126advanced SAR mission to support the systematic generation of a surface soil moisture product at

127high resolution and regional/continental scale. As an example, this has been demonstrated in the

128context of an ESA feasibility study (Mattia et al. 2019), where a Sentinel-1 surface soil moisture

129prototype for the Mediterranean was developed and implemented by the National Council of

130Research (CNR) of Italy and validated by (Balenzano 2020). Another example is the Copernicus

131Global Land service that has recently started providing 1 km Sentinel-1 soil moisture retrievals in

132an operational fashion (Bauer-Marschallinger et al. 2019). While the relatively short historical

133Sentinel-1 record to date (the first Sentinel-1 mission was launched 2014) may not yet be sufficient

134for many applications such as climate and hydrological modelling, the European Commission and

135ESA are committed to continuing Sentinel-1 observations for the next few decades as part of the

136Copernicus programme.

137 Alternative approaches to high-resolution soil moisture mapping include the downscaling of

138coarse-resolution soil moisture products, using proxy observations such as optical and thermal

139infrared information, radar backscatter information, or prior knowledge of the soil moisture

140variability (e.g., Balenzano et al. 2011; Bauer-Marschallinger et al. 2018; Das et al. 2010; Merlin et

141al. 2012; Paloscia et al. 2013; Peng et al. 2016; Piles et al. 2011; Verhoest et al. 2015; Wu et al.

1422014). After the failure of the SMAP L-band SAR sensor (7th July 2015), which was designed for

143downscaling of coarse resolution soil moisture estimates derived from the SMAP L-band
144radiometer, NASA merges SMAP L-band radiometer with Sentinel-1 C-band backscatter data to
145produce soil moisture maps at 3-km and 1-km resolutions (Das et al. 2019). In addition, the
146combined high-resolution ASCAT/Sentinel-1 (1 km) soil moisture product has also been published
147recently (Bauer-Marschallinger et al. 2019; Bauer-Marschallinger et al. 2018). Nonetheless, there is
148still a need to develop models and algorithms that combine multiple datasets (e.g., coarse and fine
149resolution observations from optical, thermal infrared and microwave sensors as well as in situ
150measurements) to generate long-term soil moisture datasets with high spatial and temporal
151resolution. Recent reviews by Peng et al. (2017b) and Sabaghy et al. (2018) have comprehensively
152summarized various downscaling approaches applied to improve the spatial resolution of existing
153soil moisture products.

154   Apart from spatial resolution limitations, a major constraint on satellite-based products is that
155the soil moisture information provided by microwave remote sensing is representative only for the
156upper few centimetres of the soil (Collow et al. 2012; Kerr 2007), depending on the surface
157condition, vegetation density and microwave frequencies. From the user community, there is a
158growing interest in satellite-based root zone soil moisture estimates, which can be obtained via the
159assimilation of surface soil moisture into a land surface model (Albergel et al. 2017; Albergel et al.
1602008; Reichle et al. 2008; Reichle et al. 2017b; Walker et al. 2001) or filtering techniques (Wagner
161et al. 1999).

162   One challenge for soil moisture retrieval algorithms is the difficulty in deriving reliable
163accuracy estimates. It is clear that any single accuracy metric is not sufficient for a comprehensive
164description of soil moisture data quality (Gruber et al. 2020). Users commonly require other metrics
165of data quality. For example, for many applications, the absolute soil moisture accuracy is not as
166relevant as the precise detection of the temporal changes between consecutive observations (Cosh et
167al. 2004; Crow et al. 2005; Entekhabi et al. 2010a; Koster et al. 2009; Loew et al. 2013; Mittelbach
168and Seneviratne 2012).

169   Despite the many challenges and limitations encountered in microwave remote sensing of soil
170moisture, many satellite-derived soil moisture data products have been found to be beneficial for
171numerous applications such as applied hydrology (e.g., Jackson et al. 1996), precision agriculture

172(e.g., Ge et al. 2011), disaster prevention (e.g., Chaparro et al. 2016; Chaparro et al. 2017; Norbiato

173et al. 2008), Numerical Weather Prediction (NWP) (e.g., de Rosnay et al. 2013; Scipal et al. 2008),

174evaporation estimation (e.g., Martens et al. 2017; Miralles et al. 2011) and climate monitoring (e.g.,

175Seneviratne et al. 2010). Therefore, they serve a wide range of the Global Earth Observation System

176of Systems (GEOSS) societal benefit areas (Akbar et al. 2018; Dong and Crow 2019; Dorigo et al.

1772017; Koster et al. 2018; McColl et al. 2017). The recently published high-resolution soil moisture

178products are expected to provide additional merit for a variety of applications.

179   In contrast to previous reviews that mainly focused on how to retrieve soil moisture

180(Karthikeyan et al. 2017; Wagner et al. 2007) and improve soil moisture spatial resolution (Peng et

181al. 2017b; Sabaghy et al. 2018), the aim of this paper is to summarize the gap between satellite

182products and various application requirements and to highlight the benefits/demands of high-

183resolution soil moisture estimates. Specifically, we discuss the usability and potential of high-

184resolution, satellite-derived soil moisture products for local applications and processes, with a

185special focus on user requirements for specific applications. Based on these applications, open

186issues and future opportunities for satellite-derived soil moisture products are identified, providing

187guidance for future development of operational, high-resolution, satellite-based soil moisture

188products, and for bridging the gap between the data producers and data users.

189**2. Applications of satellite-derived soil moisture datasets**

190Table 1 lists publicly available global satellite-based soil moisture products. All of them have been

191comprehensively validated (e.g., Albergel et al. 2012; Brocca et al. 2011; Chan et al. 2016;

192Colliander et al. 2017; Dorigo et al. 2015; Draper et al. 2009; Jackson et al. 2010; Peng et al.

1932015b). The grid spacing shown in Table 1 refers to the spatial interval used to resample satellite

194observations. The grid spacing is not the actual satellite spatial resolution and is normally finer than

195actual spatial resolution. Figure 1 provides an overview of the characteristic spatial and temporal

196resolutions of various land applications, ranging from applied hydrology to climate applications, in

197comparison to the characteristics of typical high- and low-resolution satellite soil moisture products.

198While it is difficult to generalize the requirements of the broad user communities listed in the figure,

199one can see that current operational soil moisture products can support the NWP/climate

200applications, as they are mainly representative of large-scale precipitation dynamics (Brocca et al.

2012013). There are also various studies that have applied these products for regional-scale (i.e., 1,000

202to 10,000 km^2) agriculture monitoring and stream-flow forecasting (Crow et al. 2018a; Ines et al.

2032013; Mladenova et al. 2017). However, the coarse resolution of existing products places significant

204restrictions on these applications. For example, because individual production units cannot be

205resolved, existing agricultural applications are limited to passive regional monitoring and cannot be

206used for active decision support at the farm or ranch level. Therefore, accurate high-resolution soil

207moisture products will significantly benefit applications that require observations on local to

208regional scales at high temporal and spatial resolutions.

209

210Table 1: Details of the publicly available satellite-derived global soil moisture products. Data links have been
211last accessed on March 17, 2020.

212

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. (
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://	Rodríguez-

|					www.catds.fr/ Products/ Available- products-from- CPDC	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.j p/GCOM_W/data/ data_w_index.htm l	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+Passiv e 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+Passiv e Microwave Sensors (SMOPS)	http:// www.ospo.noaa.g ov/Products/land/ smops/	Liu et al. (2016)

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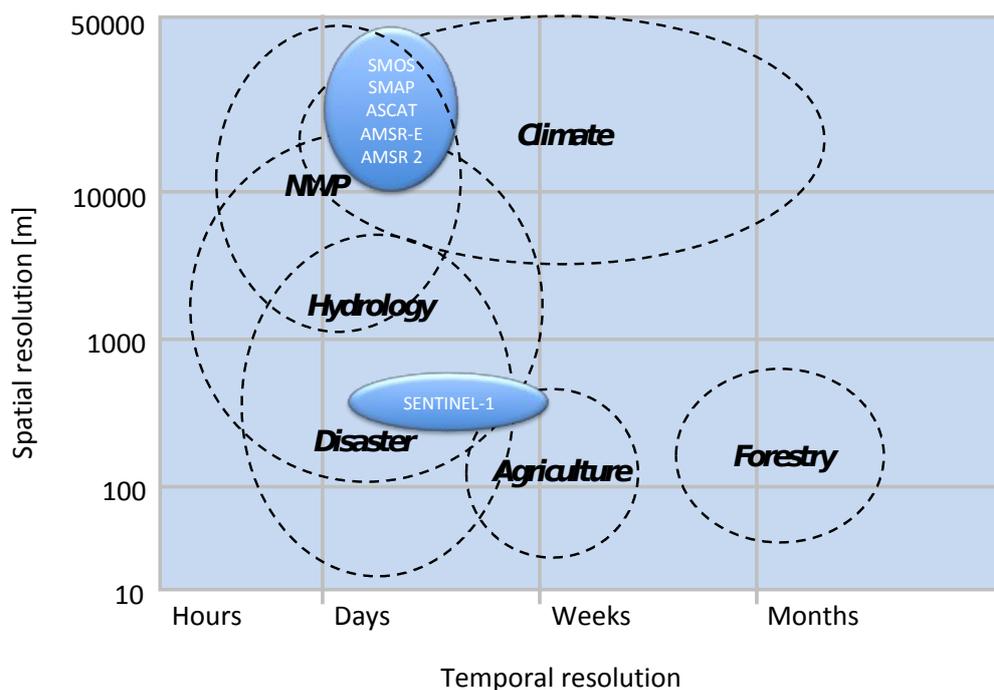
217 Figure 1: Potential application areas for soil moisture products and their temporal and spatial resolution
218 requirements in relation to selected soil moisture missions (Adapted from Loew (2004)).

219 2.1 Numerical Weather Prediction

220 Soil moisture is of high interest for NWP and the value of assimilating soil moisture observations to

221 provide an improved initialization of land surface conditions has been examined within a number of

222 NWP forecasting systems (e.g., de Rosnay et al. 2014; de Rosnay et al. 2013). For example, the

223 European Centre for Medium-Range Weather Forecasts (ECMWF) investigated the impacts of

224 assimilating SMOS brightness temperature and SMOS near-real-time (NRT) soil moisture products

225 for NWP (Muñoz-Sabater et al. 2019; Rodríguez-Fernández et al. 2016; Rodríguez-Fernández et al.

226 2017). De Rosnay et al. (2020) pointed out the relevance of the SMOS brightness temperature

227 observations for long-term monitoring and suitability of L-band long-term data records for future

228 reanalysis activities. Rodriguez-Fernandez et al. (2019) reported that the ECMWF forecasting skill

229 has been improved after assimilating SMOS neural network soil moisture products. Figure 2 shows

230 the improved performance of 2 m air temperature forecasts after assimilating SMOS NRT soil

231 moisture for the Northern Hemisphere extra tropics from July to December. The benefit of

232 assimilating scatterometer-based soil moisture products to initialize the atmospheric forecasting

233 model was also evaluated (e.g., Albergel et al. 2012; de Rosnay et al. 2014; Scipal et al. 2008).

234ECMWF currently assimilates the Metop ASCAT and the SMOS NRT soil moisture products for

235operational NWP. The UK Met Office is also assimilating ASCAT soil moisture products into their

236operational forecasting framework (Dharssi et al. 2011). Similarly, SMAP data has been assimilated

237into the Environment Canada's Regional Deterministic Prediction System (Bilodeau et al. 2016) to

238examine its impacts on NWP. In general, the integration of soil moisture in NWP models has been

239found to improve forecasts (Carrera et al. 2019; Mahfouf 2010; Muñoz-Sabater et al. 2019). To

240date, global NWP models have been applied at a spatial resolution of about 10 km, while regional

241NWP models have already reached the 1-km resolution (Bauer et al. 2015; Boutle et al. 2016; Mass

242et al. 2002). Future generations of regional NWP models will operate at the sub-kilometre scale

243with cloud resolving schemes. This will require land surface observations at comparable spatial

244scales. High-resolution earth observation systems and soil moisture downscaling schemes have

245great potential to provide high-resolution soil moisture information that meet this requirement.
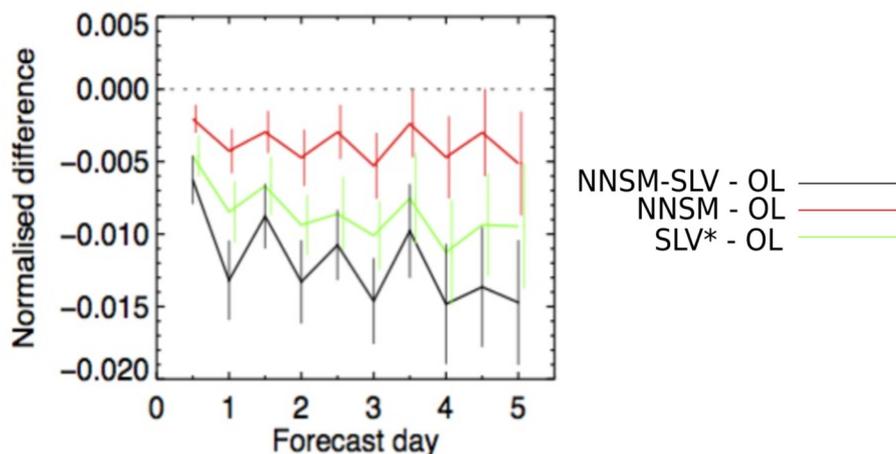

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247Figure 2: Performance of 2 m air temperature (T2m) forecasts initialised from different offline soil moisture
248assimilation experiments for the Northern Hemisphere extra tropics from July to December 2012. The lines
249show T2m forecasts RMSE differences when different observations are used to analyse soil moisture and an
250"open loop" (OL) control without soil moisture data assimilation. ERA-Interim atmospheric analysis was used
251as forcing of the offline soil moisture analysis experiments. Negative values imply better forecast skill
252compared to a soil moisture OL initialisation. NNSM refers to an experiment that assimilates SMOS neural
253network soil moisture products, SLV is an experiment that assimilates 2 m air temperature and relative
254humidity measurements (with soil moisture as control variable), and NNSM-SLV is an experiment that
255assimilates both SMOS neural network soil moisture and SLV measurements (figure reprinted from
256Rodriguez-Fernandez et al. (2019)).

257

2582.2 Climate modelling and research

259Climate research needs information on soil moisture to improve understanding of land-atmosphere
260processes (e.g., Loew et al. 2013; Seneviratne et al. 2013; Taylor et al. 2012; Van den Hurk et al.
2612016). For example, based on AMSR-E and ASCAT soil moisture datasets, Taylor et al. (2012)
262found that afternoon precipitation occurred more frequently over dry soils across the entire globe
263(Figure 3). Moreover, remote-sensing soil moisture products have also been used to study soil
264moisture-temperature and soil moisture-evapotranspiration coupling strengths (Lei et al. 2018),
265which are relevant metrics for the occurrence of hot extremes in transitional climate regimes (e.g.,
266Dong and Crow 2019; Hirschi et al. 2014). Likewise, the decline of global land evapotranspiration
267in the early 2000s was caused by a decrease of soil moisture in the Southern Hemisphere (Jung et al.
2682010) (Figure 4), which was later shown to be driven by El Niño conditions (Miralles et al. 2014).
269Global models are currently run at spatial resolutions in the order of 50 kilometres, while the
270Coordinated Regional Downscaling Experiment (CORDEX) regional climate model (RCM)
271simulations are already run at around 10 km or finer (Iles et al. 2019). New generations of global
272climate models, such as the German ICON model (Crueger et al. 2018), allow for the simulation of
273regional nests at the 1-km scale and finer. Furthermore, it has been shown that the spatial
274heterogeneity of soil moisture can have a considerable impact on cloud and precipitation formation
275(Dong and Crow 2018; Rieck et al. 2014; Schneider et al. 2014; Taylor et al. 2011). Dependent on
276the spatial soil moisture pattern, cloud formation might be enhanced or suppressed. High-resolution
277soil moisture products at kilometre scale will provide a more detailed picture of the fine scale
278heterogeneity which can enhance the ability to resolve boundary layer dynamics and large-scale
279eddy development.

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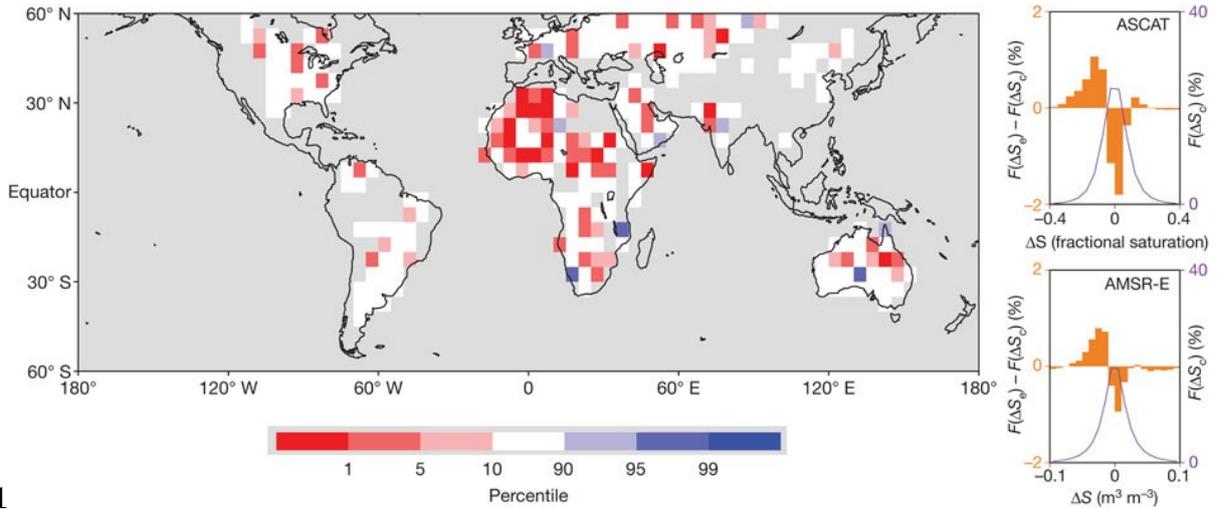
Figure 3: Preference of afternoon precipitation over soil moisture anomalies. The low and high percentiles refer to where rainfall maxima occur over dry and wet soil more frequently than expected. The right panels present frequency histograms of soil moisture difference respectively calculated from AMSR-E 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).
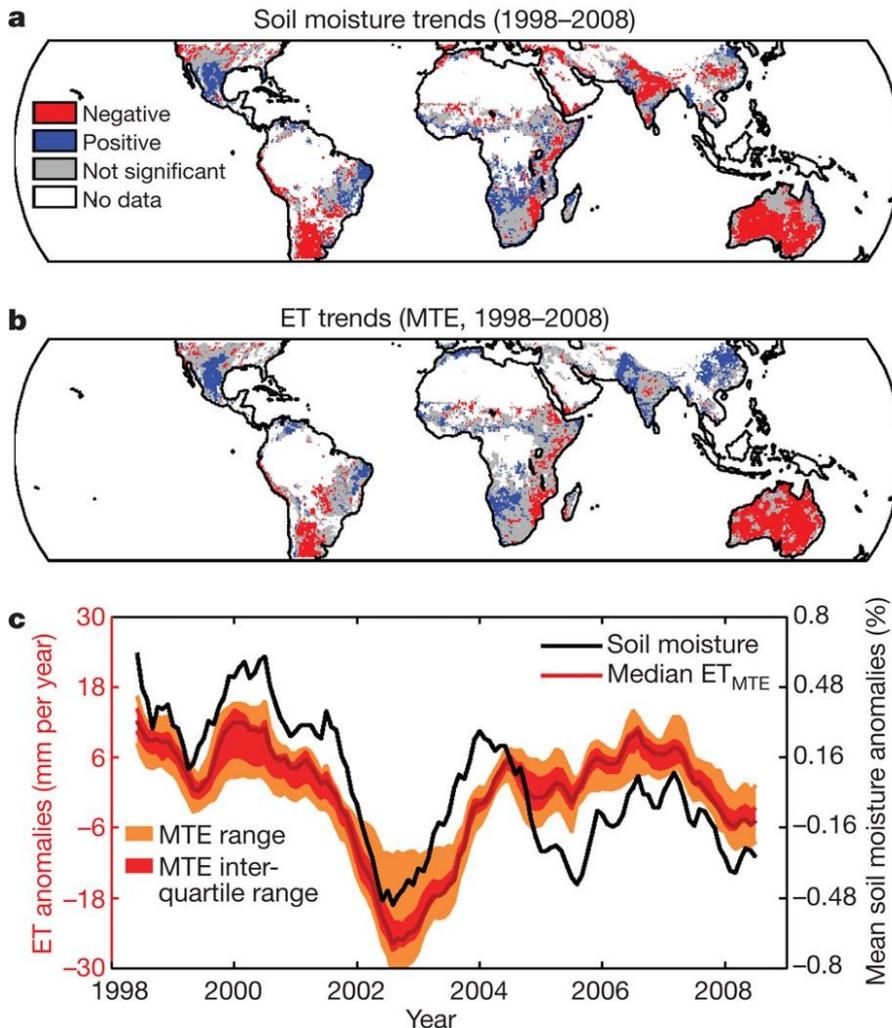

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290Figure 4: Global trends of evapotranspiration and soil moisture: (a) soil moisture estimated from TRMM, (b) 291evapotranspiration, and (c) anomalies of mean evapotranspiration and soil moisture. Evapotranspiration was 292calculated based on FLUXNET, remote sensing and meteorological observations using a model tree ensemble 293(MTE) machine-learning method (figure reprinted from Jung et al. 2010).

2942.3 Hydrology

295The availability of spatially explicit soil moisture information has been beneficial to many fields in

296hydrology due to its important role in processes like runoff, flooding, rainfall, evaporation,

297infiltration, and ground water recharge (Dorigo et al. 2017; Scipal et al. 2005). Specifically,

298satellite-derived soil moisture products have been applied to a range of hydrological applications

299such as watershed management (e.g., Dahigamuwa et al. 2016; Heimhuber et al. 2017), runoff

300modelling/prediction (e.g., Alvarez-Garreton et al. 2015; Crow et al. 2017; Iacobellis et al. 2013;

301Lievens et al. 2016; Massari et al. 2015; Pauwels et al. 2002), landslide prediction (e.g., Brocca et

302al. 2012b; Ray and Jacobs 2007; Ray et al. 2010; Zhuo et al. 2019), estimation of evapotranspiration

303(e.g., Lievens et al. 2017a; Loew et al. 2016; Martens et al. 2017), rainfall accumulation estimation

304(e.g., Brocca et al. 2013; Ciabatta et al. 2018; Román-Cascón et al. 2017), the quantification of

305groundwater storage (e.g., Asoka et al. 2017; Román-Cascón et al. 2017), the identification of soil

306moisture/runoff coupling biases in hydrological models and the estimation of the runoff ratio for

307subsequent rainfall (Crow et al. 2019; Crow et al. 2018a; Crow et al. 2017). Knowledge about the

308spatiotemporal dynamics of soil moisture is essential for understanding changes in the terrestrial

309water cycle. One example is the estimation of precipitation based on the ASCAT soil moisture

310product using the SM2RAIN (Soil Moisture to Rain) algorithm (Brocca et al. 2013). Based on a

311triple collocation analysis (Gruber et al. 2016), the SM2RAIN–ASCAT product was found to

312perform better than ground-based Global Precipitation Climatology Centre (GPCC) precipitation

313and the Global Precipitation Measurement Integrated Multi-satellitE Retrievals for Global

314Precipitation Measurement Early Run (GPM IMERG-ER) product over the Southern Hemisphere,

315central Asia, and the central western United States (Brocca et al. 2019) (Figure 5). Currently, soil

316moisture products can only be used for large river basins. However, in many cases, hydrological

317processes occur at spatial scales much smaller than the resolution of current satellite soil moisture

318observations. Hence, there is an increasing focus in hydrological modelling for the representation of

319fine-scale dynamics that cannot be resolved by existing satellite soil moisture observations. The

320availability of high-resolution soil moisture datasets at kilometre and sub-kilometre scale will

321therefore open a new perspective for hydrological modelling and improve the estimation of rainfall

322and evapotranspiration at these scales.
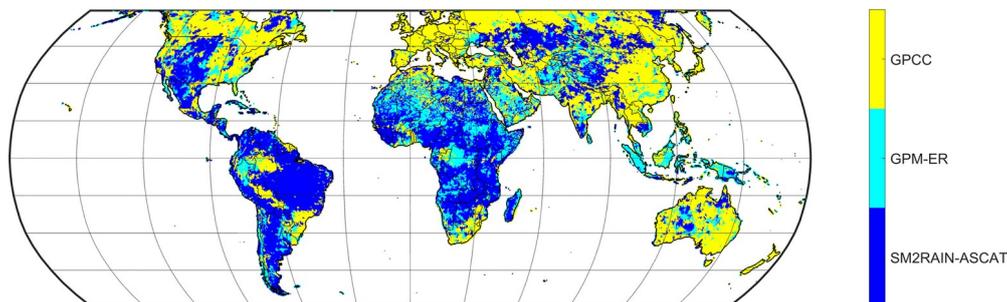
323

324Figure 5: Relatively best-performing precipitation product based on triple collocation analysis at global scale
325(figure reprinted from Brocca et al. 2019). The SM2RAIN product performs best over the Southern
326Hemisphere, central Asia, and the central western United States.

3272.4 Hydrometeorological disasters

328Hydrometeorological disasters are typically referred to as floods or droughts. In both cases, the soil

329moisture state plays a vital role in controlling the partitioning of surface water and energy fluxes

330(Koster et al. 2004). For flood forecasting applications, it is essential to know accurately the pre-

331rainstorm soil moisture conditions (in relation to the saturation level) and its spatial distribution

332within a watershed. Many studies have considered satellite-derived soil moisture to improve flood

333forecasting via data assimilation techniques (e.g., Komma et al. 2008; Li et al. 2018; Massari et al.

3342018; Wanders et al. 2014). However, operational flood forecasting systems are still limited in their

335usage of existing satellite-derived soil moisture datasets because of: a) the lack of spatial detail, b)

336insufficient data continuity, c) limitations in data record lengths, and d) the lack of community

337acceptance. Long-term, high-resolution soil moisture records are needed to satisfy these

338requirements. It is thus important to motivate investment at operational flood forecasting centres to

339develop the appropriate infrastructure for assimilating high-resolution data.

340   Apart from flood forecasting, satellite-derived soil moisture can be used to analyze agricultural

341droughts caused by the prolonged absence of precipitation or increased evapotranspiration (Van

342Loon 2015). For example, soil moisture datasets can be used to identify droughts (e.g., Anderson et

343al. 2012; Nicolai-Shaw et al. 2017; Peng et al. 2019), to develop drought indices (e.g., Carrão et al.

3442016; Martínez-Fernández et al. 2016; Sadri et al. 2018), and to evaluate and improve process-based

345drought forecasting models (e.g., Bolten and Crow 2012; McNally et al. 2017). Figure 6 illustrates a

346comparison by Mishra et al. (2017) of a SMAP-based drought index with other well-known drought

347indices. Their study highlighted the good agreement between a SMAP-based drought index and the

348in situ Atmospheric Water Deficit (AWD) Index. On the regional scale, the drought responses are

349highly spatially variable due to differences in vegetation composition and cover. Thus, there is a

350strong demand for high-resolution soil moisture products.

351
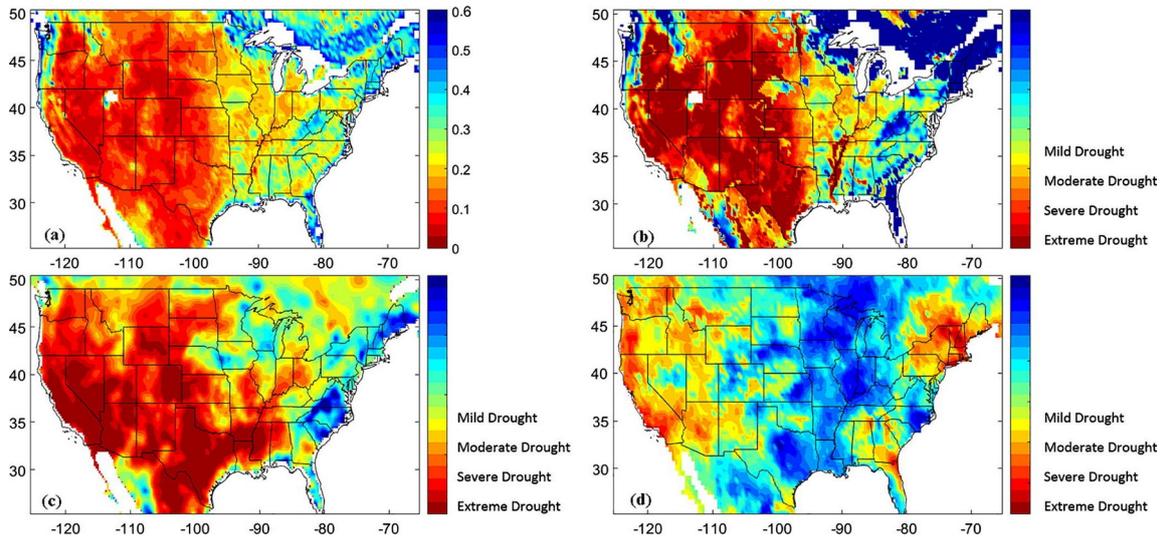
353Figure 6: Spatial maps of mean value on September, 2015 of: (a) SMAP L3 soil moisture, (b) Soil Water
354Deficit Index (SWDI) index based on SMAP, (c) Atmospheric Water Deficit (AWD) Index and (d) self-
355calibrating Palmer Drought Severity Index (sc-PDSI) (figure reprinted from Mishra et al. 2017).

3562.5 Agriculture

357Soil moisture is an important factor for agriculture. In particular, the availability of high-resolution

358soil moisture maps is essential for precision farming applications (at the scale of individual fields)

359and with the expectation to improve crop yield modelling (e.g., Dabrowska-Zielinska et al. 2007;

360Inoue et al. 2002; Verstraeten et al. 2010). So far, soil moisture products derived from satellites

361have been rarely used in farm- or field-scale agricultural decision support due to the coarse spatial

362resolution and the limited depth of the measurements (Brocca et al. 2018; Mulla 2013).

363Nonetheless, satellite-derived soil moisture is expected to carry large potential if it can provide

364relevant information on appropriate temporal and spatial scales (as shown in Figure 1). For instance,

365high-resolution soil moisture maps can help to identify and monitor irrigated areas, thereby

366providing valuable information for improving water management on local and regional scales

367(Merlin et al. 2013), particularly in areas facing scarce water resources (Brocca et al. 2018; Mulla

3682013; Zaussinger et al. 2019). Figure 7 shows the variation of the new SMAP enhanced L3 9 km

369soil moisture product over both irrigated and non-irrigated sites (Lawston et al. 2017). It can be seen

370that the SMAP soil moisture product can identify well the onset of field irrigation (Malbeteau et al.

3712018). Existing satellite-based soil moisture products can also be used to enhance yield forecasting,

372albeit at a relatively coarse spatial resolution (Mladenova et al. 2017).

373   Agricultural runoff is also a major pollutant affecting surface water bodies. Knowledge of the

374spatial soil moisture distribution can therefore help to minimize fertilizer usage and result in better

375surface and groundwater quality (Liu et al. 2012a). Another important aspect is soil erosion across

376agricultural fields, which impacts water quality of surface water bodies and may result in the loss of

377fertile agricultural land. Todisco et al. (2015) demonstrated that combining coarse-resolution

378ASCAT satellite soil moisture data with the Universal Soil Loss Equation-based (USLE) model

379improved soil erosion modelling capabilities in a region in central Italy compared to USLE model

380alone. The use of high-resolution soil moisture data is expected to open new perspectives in soil

381erosion modelling for agricultural fields because erosion processes happen on the farm and field

382scale.

383
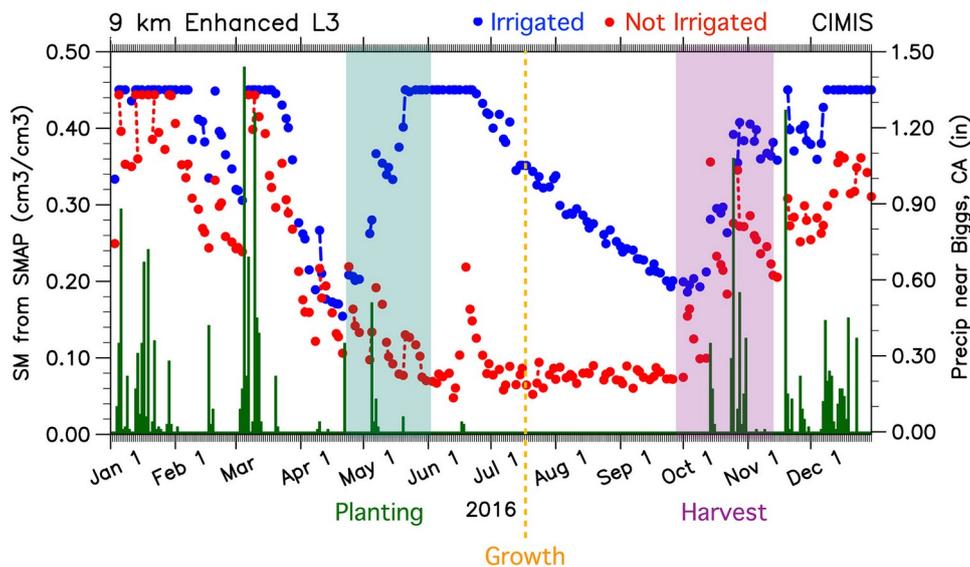
385Figure 7: Time series of SMAP soil moisture at an irrigated site (blue) and a non-irrigated site (red) in the
386northern California Central Valley (figure reprinted from Lawston et al. 2017).

3872.6 Monitoring of wetlands and riparian zones

388In the scope of wetland monitoring, soil moisture is one of the key variables used as an indicator of

389ecosystem change (Gabiri et al. 2018; Kasischke and Bourgeau-Chavez 1997; Nghiem et al. 2017).

390The detection of global wetland area relies on satellite observations. Studies have shown that the

391coarse resolution of available data hampers the accurate mapping of wetland extent (e.g., Papa et al.

392 2006; Prigent et al. 2001), but also the estimation of biogeochemical cycling within wetlands (e.g.,
393 Melton et al. 2013). Soil moisture monitoring at high spatial resolution will allow detecting
394 detrimental changes in wetlands and elongated riparian ecosystems (Dabrowska-Zielinska et al.
395 2018), which are not usually detectable at the coarse resolution of current soil moisture products. It
396 should be noted that the retrieval of high-resolution soil moisture estimates from SAR observations
397 is challenging over wetlands due to the thick vegetation layer and possible presence of organic soil
398 layers.

399 2.7 Other applications

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

420**3. User requirements review**

421User requirements on soil moisture products have been identified by international bodies and
422projects such as GCOS, EUMETSAT H SAF, ESA CCI SM, and dedicated satellite soil moisture
423missions such as SMOS and SMAP. Several workshops (e.g., the ECMWF/ESA workshop on using
424low frequency passive microwave measurements in research and operational applications, ECMWF,
425Reading, 4-6 December 2017, https://www.ecmwf.int/sites/default/files/medialibrary/2018-01/L-
426Band-WS-summary.pdf) have been held to discuss soil moisture applications and user requirements
427across disciplines. Table 2 summarizes the user requirements for soil moisture for selected fields of
428applications based on literature review and expert interviews. It should be noted that only a
429qualitative description of required accuracy is provided, as it is difficult to quantify the actual
430accuracy requirements for different applications. A target unbiased Root Mean Square Error
431(ubRMSE) of 0.04 m^3/m^3 has been defined for many soil moisture projects and satellite missions
432(e.g., Entekhabi et al. 2010a; Kerr et al. 2010). However, a single error metric is usually insufficient
433for representing the fitness-for-purpose of a particular application (Gruber et al. 2020). For
434example, under dry soil moisture condition, the ubRMSE of 0.04 m^3/m^3 may correspond to a relative
435error of 100%, while under wet conditions it would correspond to only 10% of the actual soil
436moisture variability (Entekhabi et al. 2010b). Therefore, more comprehensive error characterization
437methods are needed. Substantial recent progress in the calculation of potentially more informative
438metrics, in particular Signal-to-Noise Ratio (SNR) related measures, has been made using triple
439collocation analysis (Gruber et al. 2016; McColl et al. 2014).

440 A better understanding and description of soil moisture data quality requires close
441collaboration between data producers and the various user communities (Kerr and Escorihuela
4422019). In terms of spatial resolution, soil moisture products at high spatial resolution (i.e. ≤1 km)
443would benefit many applications, particularly on regional and local scales. For continental- or
444global-scale applications such as climate modelling and NWP, coarse spatial resolution soil
445moisture with long time coverage and high temporal resolution are currently successfully exploited.
446Based on a comprehensive analysis of the existing literature and expert interviews, we anticipate
447that a variety of applications, such as watershed runoff modelling, farm- and field-level agricultural
448management, and evapotranspiration/rainfall estimation, will benefit significantly from the

449complementarity of high- and low-resolution soil moisture observations (Table 3). Moreover, there

450is also a need for high temporal (sub-daily) resolution for model development applications.

451Furthermore, the products should preferably represent soil moisture within deeper soil layers,

452although the surface layer soil moisture is still valuable. To conclude, there is an urgent requirement

453by many user communities for soil moisture datasets at high temporal-spatial resolution, at multiple

454soil depths, with well-documented and consistent spatial-temporal error information.

455

456 Table 2: User requirements concerning satellite soil moisture products defined for selected applications.
457 The summary is based on literature review and expert interviews.
458

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

459

460 Table 3: Applications that would benefit from soil moisture information on different spatial scales. The
461 requirements level is indicated from high (+++) to low (+).
462

	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		+	+++

463

464 4. Open issues and future opportunities

465In the following, open issues and future opportunities for satellite-derived soil moisture products are 466elaborated further, aiming to close the gap between application requirements and product 467characteristics. Moreover, recommendations are provided for next-generation operational satellite 468soil moisture datasets that will better meet user requirements and advance our collective scientific 469understanding.

4704.1 High spatial and temporal resolutions

471Although several kilometre-scale soil moisture products have been released recently, the major 472challenge in the retrieval of such high-resolution products from SAR data is how to accurately 473parameterize soil roughness and account for the impacts of observation angle (Verhoest et al. 2008; 474Zhu et al. 2019). Other challenges include retrieval uncertainty quantification and data continuity. 475In order to make use of the existing long-term coarse-resolution soil moisture products from e.g., 476ESA CCI SM, downscaling algorithms provide a means to improve the spatial resolution of soil 477moisture datasets. In addition to microwave observations, optical/thermal band observations have 478been used to either downscale microwave-based coarse-resolution soil moisture (e.g., Merlin et al. 4792012; Peng et al. 2015a; Portal et al. 2018) or to directly estimate soil moisture (e.g., Babaeian et al. 4802018; Rahimzadeh-Bajgiran et al. 2013; Wang et al. 2018). The advantages of optical/thermal band 481measurements include their very high spatial resolution (e.g., 10 meters from Sentinel-2) and sub-482daily temporal resolution (e.g., geostationary satellites). A recent study by Sabaghy et al. (2020) has

483comprehensively evaluated existing downscaled soil moisture products from optical/thermal-,
484SAR-/radiometer-, and oversampling-based methods with both in situ and airborne soil moisture
485over the Yanco validation site in Australia. Downscaling approaches such as the optical and
486thermal-based Vegetation-Temperature Condition Index (VTCI) method presented in Peng et al.
487(2016) were found to perform well, but its results were also highly influenced by cloud cover.
488Moreover, using a data assimilation approach in a synergistic retrieval of soil moisture from optical
489and SAR data is also promising. For example, Marzahn et al. (2019) used a joint weak constrained
490data assimilation approach to retrieve soil moisture and other land surface variables with high
491accuracy. Therefore, it seems promising to generate long-term high -resolution soil moisture
492products through the synergistic use of microwave and optical/thermal measurements using data
493assimilation and machine learning methods (Ahmad et al. 2010; Draper et al. 2012; Kolassa et al.
4942017; Lievens et al. 2017b).

495   While the generation of global soil moisture maps with sub-daily temporal resolution is not
496feasible with a single satellite platform (without a land data assimilation system), the combined use
497of microwave observations from multi-satellite constellations such as ASCAT onboard the Metop-
498A, B, and C platforms will probably lead to the generation of sub-daily microwave soil moisture
499products in the foreseeable future. Moreover, optical/thermal measurements from geostationary
500satellites with hourly temporal resolution might help to overcome this limitation through their
501integration with microwave observations (Hain et al. 2012; Piles et al. 2016; Zhao and Li 2013).
502Future missions and instruments also provide new insights on monitoring soil moisture at high
503temporal and spatial resolution. One potential such mission, the ESA Geosynchronous-Continental
504Land Atmosphere Sensing System (G-CLASS/Hydroterra; (Hobbs et al. 2019), plans to launch
505SAR satellites in geosynchronous orbit (GEO). These SAR satellites are expected to monitor
506diurnal soil moisture dynamics on an hourly timescale. Another mission is the Copernicus Imaging
507Microwave Radiometer (CIMR), which is designed to provide sub-daily observations in Ku to L-
508band at the global scale (https://cimr.eu). Furthermore, CubeSat missions such as the Cyclone
509Global Navigation Satellite System (CYGNSS) are expected to play an important role in measuring
510soil moisture from space at high spatial and sub-daily temporal resolution (Al-Khaldi et al. 2019;
511Kim and Lakshmi 2018).

512 **4.2 Root zone soil moisture estimation**

513 It is still challenging to estimate root zone soil moisture from satellite observations (Crow et al.
514 2018c), although several studies have implemented a soil water index based on an exponential
515 filtering of surface soil moisture retrievals, which mimics the infiltration (Albergel et al. 2008;
516 Wagner et al. 1999). Other efforts have been made to produce root-zone soil moisture through the
517 assimilation of satellite-based surface soil moisture retrievals into land surface models (e.g.,
518 Balsamo et al. 2018; Das and Mohanty 2006; De Lannoy and Reichle 2016; Kumar et al. 2019;
519 Kumar et al. 2009; Ridler et al. 2014; Walker et al. 2001). The ASCAT, SMOS, and SMAP soil
520 moisture retrieval teams as well as the Global Land Evaporation Amsterdam Model team (Martens
521 et al. 2017; Miralles et al. 2011) have released root zone soil moisture datasets (Brocca et al. 2012a;
522 Mecklenburg et al. 2016; Reichle et al. 2017a; Reichle et al. 2017b; Reichle et al. 2019). These
523 datasets can help to better understand the role of root-zone soil moisture in climate and hydrological
524 predictions. However, the estimation of root-zone soil moisture at high spatial resolution still needs
525 to be investigated. One option is to use P-band SAR that has a much deeper penetration depth than
526 C- and L-band SAR. Several studies have already successfully used airborne P-band SAR data to
527 retrieve root zone soil moisture (e.g., Crow et al. 2018c; Sadeghi et al. 2017). However, it is still
528 challenging to build space-borne P-band SAR systems due to the increased antenna-length
529 requirements and the effects of radio frequency interference. To overcome this limitation, the
530 SigNals of Opportunity: P-band Investigation (SNoOPI) CubeSat mission will perform P-band
531 reflectometry, which will be used to derive a root-zone soil moisture product covering the United
532 States in the future (Azemati et al. 2019).

533 **4.3 Validation and quality traceability**

534 Validation of satellite-derived soil moisture and the provision of spatial-temporal error information
535 are important for all applications. In general, the implementation of a thorough validation and
536 monitoring framework for operational soil moisture products requires three main components: 1)
537 reference data, 2) a validation guidance using appropriate metrics, and 3) validation and monitoring
538 tools. The global in situ soil moisture networks together with the SMOS and SMAP satellite teams
539 have made great efforts to provide extensive ground-based soil moisture measurements to the

540public. However, data quality, continuity, temporal legacy, gaps, and scaling errors of the reference

541data should be traceable, due to their fundamental role for the validation of satellite-based data.

542Traceable tools for the continuous monitoring and validation of satellite-derived data products are

543still in their infancy (Loew et al. 2017). The Quality Assurance for Essential Climate Variables

544(QA4ECV) framework was developed as the first initiative to demonstrate how reliable and

545traceable quality information can be provided for selected essential climate variables such as

546albedo, Leaf Area Index (LAI), and Fraction of Absorbed Photosynthetically Active Radiation

547(FAPAR) (Nightingale et al. 2018; Peng et al. 2017a). Following the same concept, the Quality

548Assurance for Soil Moisture (QA4SM) project (qa4sm.eodc.eu) was recently launched to provide an

549automated and, above all, transparent online validation tool for soil moisture. The tool follows

550standardized community good practice guidelines for the validation of satellite soil moisture

551products (Gruber et al. 2020). The validation tool produced by the QA4SM project and the

552community guidelines provided by Gruber et al. (2020) will serve as good practice

553recommendations for the validation of high spatial and temporal resolution soil moisture products in

554the future.

5554.4 Mission continuity

556Satellite mission continuity is crucial for the generation of consistent and long-term soil moisture

557datasets. A range of ESA, JAXA, and NASA sensors operating in C- and X-band have ensured the

558availability of soil moisture product since 1978. Thanks to efforts by ESA and JAXA, the

559continuation of these data products is largely ensured. In contrast, the ESA SMOS and NASA

560SMAP missions successfully provide L-band measurements and generate global soil moisture

561products. However, the continuity of these dedicated L-band soil moisture missions is not ensured.

562Based on lessons learned from SMOS and SMAP, it is therefore important to develop future L-band

563soil moisture missions to provide data continuity and high-resolution measurements. Currently, the

564above-mentioned CIMR mission plans include coarse-resolution L-band radiometer observations,

565and a potential SMOS follow-on mission, SMOS-HR (High-Resolution), is planned to deliver

566observations at 10 km (Rodríguez-Fernández et al. 2019). In addition, the European Commission

567and ESA have also committed the data continuity from Sentinel-1 SAR in next few decades through

568the Copernicus programme. As a complement to the Sentinel C-band SAR, the future ROSE-L

569mission will provide high resolution L-band SAR data.

570**5. Conclusions**

571Numerous operational soil moisture datasets, generated from satellite microwave remote sensing

572observations, have emerged over the last decade. Following the release of these soil moisture

573datasets, different science communities have made efforts to exploit the potential of these data by

574using them for a wide range of applications. Our review shows that there is a strong demand from

575various user communities for higher-resolution datasets at kilometre scale. The current and future

576satellite observations provide opportunities to develop high spatial resolution soil moisture products

577featuring moderate (e.g., daily) temporal resolution. Downscaling methods that integrate optical,

578thermal infrared and microwave observations based on data assimilation and machine learning

579provide an alternative to achieving high-resolution soil moisture products. However, challenges

580regarding high temporal resolution and the accuracy of the high-resolution products still need to be

581addressed. Integrating observations from multi-satellite constellations such as the Metop-A, B, and

582C platforms might lead to the generation of a twice-daily soil moisture product. In the future, the

583proposed Hydroterra geosynchronous radar satellite might provide hourly soil moisture data on a

584fine spatial scale - albeit with reduced area coverage. Moreover, CubeSats and small satellites have

585great potential for providing very high temporal-spatial resolution soil moisture. Quality assured

586long-term high-resolution soil moisture datasets will facilitate a wide range of applications of soil

587moisture products in the future.

588

600

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