



HAL
open science

Assessment and inter-comparison of recently developed/reprocessed microwave satellite soil moisture products using ISMN ground-based measurements

A. Al-Yaari, J.-P. Wigneron, W. Dorigo, A. Colliander, T. Pellarin, S. Hahn, Arnaud Mialon, Philippe Richaume, R. Fernandez-Moran, L. Fan, et al.

► To cite this version:

A. Al-Yaari, J.-P. Wigneron, W. Dorigo, A. Colliander, T. Pellarin, et al.. Assessment and inter-comparison of recently developed/reprocessed microwave satellite soil moisture products using ISMN ground-based measurements. *Remote Sensing of Environment*, 2019, 224, pp.289-303. 10.1016/j.rse.2019.02.008 . hal-02402614

HAL Id: hal-02402614

<https://hal.science/hal-02402614v1>

Submitted on 22 Oct 2021

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution - NonCommercial 4.0 International License

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27

Assessment and inter-comparison of recently developed/reprocessed microwave satellite soil moisture products using ISMN ground-based measurements

A. Al-Yaari^a, J.-P. Wigneron^a, W. Dorigo^b, A. Colliander^c, T. Pellarin^d, S. Hahn^b, A. Mialon^e, P. Richaume^e, R. Fernandez-Moran^f, L. Fan^{a,g}, Y. H. Kerr^e, G. De Lannoy^h

^aINRA, UMR1391 ISPA, Villenave d’Ornon, France, amen.al-yaari@inra.fr,

^bDepartment of Geodesy and Geoinformation, Vienna University of Technology, Vienna, Austria

^cJet Propulsion Laboratory, California Institute of Technology, Pasadena CA91109, USA

^dUniv. Grenoble Alpes, CNRS, IRD, Grenoble INP, IGE, F-38000 Grenoble, France

^e Université de Toulouse, CNES, CNRS, INRA, IRD, UPS, UMR 5126, Toulouse France

^fUniversity of Valencia, IPL (Image Processing Laboratory), Spain

^gCollaborative Innovation Center on Forecast and Evaluation of Meteorological Disaster, School of Geographical Sciences, Nanjing University of Information Science and Technology, Nanjing 210044, China

^hKULeuven, Department of Earth and Environmental Sciences, Belgium

Abstract

28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58

Soil moisture (SM) is a key state variable in understanding the climate system through its control on the land surface energy, water budget partitioning, and the carbon cycle. Monitoring SM at regional scale has become possible thanks to microwave remote sensing. In the past two decades, several satellites were launched carrying on board either radiometer (passive) or radar (active) or both sensors in different frequency bands with various spatial and temporal resolutions. Soil moisture algorithms are in rapid development and their improvements/revisions are ongoing. The latest SM retrieval products and versions of products that have been recently released are not yet, to our knowledge, comprehensively evaluated and inter-compared over different ecoregions and climate conditions. The aim of this paper is to comprehensively evaluate the most recent microwave-based SM retrieval products available from NASA's (National Aeronautics and Space Administration) SMAP (Soil Moisture Active Passive) satellite, ESA's led mission (European Space Agency) SMOS (Soil Moisture and Ocean Salinity) satellite, ASCAT (Advanced Scatterometer) sensor on board the meteorological operational (Metop) platforms Metop-A and Metop-B, and the ESA Climate Change Initiative (CCI) blended long-term SM time series. More specifically, in this study we compared SMAPL3 V4, SMOSL3 V300, SMOSL2 V650, ASCAT H111, and CCI V04.2 and the new SMOS-IC (V105) SM product. This evaluation was achieved using four statistical scores: Pearson correlation (considering both original observations and anomalies), RMSE, unbiased RMSE, and Bias between remotely-sensed SM retrievals and ground-based measurements from more than 1000 stations from 17 monitoring networks, spread over the globe, disseminated through the International Soil Moisture Network (ISMN). The analysis reveals that the performance of the remotely-sensed SM retrievals generally varies depending on ecoregions, land cover types, climate conditions, and between the monitoring networks. It also reveals that temporal sampling of the data, the frequency of data in time and the spatial coverage, affect the performance metrics. Overall, the performance of SMAP and SMOS-IC products compared slightly better with respect to the ISMN *in situ* observations than the other remotely-sensed products.

59 **1. Introduction**

60

61 Surface soil moisture (i.e. the water content in the first few centimeters of the soil;
62 referred to as SM in the following) is a key state variable in better understanding the climate
63 system through controlling land surface energy, water budget partitioning (Chen et al., 2016;
64 Koster et al., 2004; Miralles et al., 2014a; Miralles et al., 2014b; Pitman, 2003; Seneviratne et
65 al., 2010; Seneviratne et al., 2013), and its important role in the carbon cycle (Jung et al.,
66 2017). Monitoring SM at the regional scale has become possible thanks to active and passive
67 microwave remote sensing. In the past two decades, several satellites were launched carrying
68 either a radiometer (passive) or radar (active) or both, using frequency bands with various
69 spatial and temporal resolutions. These satellites (or sensors) include, but are not limited to,
70 SMAP (Soil Moisture Active Passive) launched by the National Aeronautics and Space
71 Administration (NASA) in 2015 (Entekhabi et al., 2010), SMOS (Soil Moisture and Ocean
72 Salinity) launched by the European space agency (ESA) in 2009 (Kerr et al., 2001), and ASCAT
73 (Advanced Scatterometer) (Wagner et al., 2013) on board the meteorological operational (Metop)
74 platforms Metop-A, Metop-B, and Metop-C. Since then, SM was retrieved from either
75 brightness temperature (passive) or backscatter coefficient (active) observations relying
76 mainly on radiative transfer model inversion (passive; Mo et al., 1982), change detection (active;
77 Wagner et al., 1999), or neural network algorithms (Kolassa et al., 2018; Rodríguez-Fernández et al., 2016).
78 These remotely sensed SM products are provided separately or blended (such as the one
79 produced by the ESA project: Climate Change Initiative (CCI) SM long time series (Dorigo et
80 al., 2017; Liu et al., 2012)).

81 Performance evaluation of these remotely-sensed SM retrievals is important to help
82 improving satellite products and evaluating their interest for possible applications in climate,
83 hydrology, and natural hazards (flood, drought, etc.). Numerous validation/evaluation studies
84 of satellite-based SM retrievals have been conducted during the last decade (e.g., Al-Yaari et al.,

85 2014a; Al-Yaari et al., 2014b; Al-Yaari et al., 2015; Al-Yaari et al., 2017; Albergel et al., 2009; Albergel et al., 2012; Brocca
86 et al., 2011; Colliander et al., 2017; Dorigo et al., 2015; Draper et al., 2009; Kerr et al., 2016; Pierdicca et al., 2013; Sahoo et
87 al., 2008; Su et al., 2013) using different approaches (e.g., sparse and dense networks, core
88 validation sites, field campaigns, inter-comparisons among satellites, model simulations,
89 etc.). However, SM retrieval algorithms are in rapid development and their
90 improvements/revisions are ongoing adopting new concepts or conducting new calibrations;
91 thus improving parameterizations and optimizing parameters in the algorithms (Wigneron et
92 al., 2017). Therefore, new SM products and new versions of SM products have been released
93 that are not, to our knowledge, comprehensively evaluated and inter-compared yet. One such
94 new product is the SMOS-IC SM product, which was recently developed by INRA (Institut
95 National de la Recherche Agronomique) in collaboration with CESBIO (Centre d'Etudes
96 Spatiales de la BIOSphere) (Fernandez-Moran et al., 2017b). To our knowledge, the last SMOS-IC
97 version has only been evaluated against modelled SM data from ECMWF (Fernandez-Moran et al.,
98 2017b), although a previous version was already tested using several *in situ* datasets from
99 ISMN (International Soil Moisture Network) for the period 2011-2013 (Fernandez-Moran et al.,
100 2017a). The objective of this study is to evaluate the SMOS-IC SM product along with the
101 most recent versions, available at the time of writing, of five other satellite-based SM
102 products, namely: NASA SMAP Level 3 (V4), ESA SMOS Level 3 (V300) and Level 2
103 (V650), ASCAT (H111), and the CCI long-term record SM (V04.2). This was achieved using
104 ground-based surface SM measurements from the ISMN (Dorigo et al., 2011; Dorigo et al., 2013). For
105 the passive sensors, we limited this study to L-band SM retrievals which are more optimal for
106 monitoring SM. Other key SM observations (AMSR-E/AMSR2) were merged in the CCI
107 product. This paper is organized as follows. The datasets and scores used are briefly
108 described in Section 2. Results and discussion are presented in Sections 3 and 4,
109 respectively. Finally, concluding remarks are given in Section 5.

110 **2. Materials and Methods**

111 **2.1 Datasets**

112

113 Table 1 presents an overview of the SM products used in this study. More details are given in
 114 the following subsections.

115

116 Table 1. Overview of all soil moisture data sets under investigation.

	Passive		Active	Combined (CCI)
Sensor	SMOS	SMAP	ASCAT	SMMR SSM/I TMI AMSRE AMSR2 Windsat ERS ASCAT SMOS
Satellite	SMOS	SMAP	Metop-A & Metop-B	Various
Time period	Jan 2010–present	Mar 2015–present	Jan 2007–present	Jan 1978– Dec 2016
Band frequency	1.4 GHz	1.4 GHz	5.3 GHz	1.4– 19.3 GHz
Spatial sampling	15 km DGG - 25 km EASEv2	36 km EASEv2	12.5 km	0.25°
Sensor resolution	27-55 km	43 km	25-34 km	various
Spatial coverage	Global	Global	Global	Global
Acquisition time	Descending: 06:00 pm Ascending: 06:00 am	Descending: 06:00 am Ascending: 06:00 pm	Descending: 09:30 am Ascending 9:30 pm	-
Product version	SMOSL2 V650 SMOSL3 V300 SMOS-IC V105	SMAPL3 V4	H111	CCI V04.2
Unit	m ³ /m ³	m ³ /m ³	Degree of saturation (%)	m ³ /m ³

117

118

119 **2.1.1 SMOS**

120

121 The SMOS satellite, developed by the ESA with contributions from CNES (Centre
 122 National d'Etudes Spatiales) and CDTI (Centro para el Desarrollo Tecnológico Industrial), is
 123 the first polar orbiting L-Band (1.4 GHz) radiometer, with a spatial resolution of (~ 43 km)
 124 and 3-day revisit. The SMOS satellite mission has been providing fully polarized brightness
 125 temperature (TB, level 1) observations since 2010 and over a range of incidence angles (~ 0-

126 60°) (Kerr et al., 2010). These SMOS TB observations are used to retrieve SM and vegetation
127 optical depth (VOD) using a forward emission model, namely, the L-band Microwave
128 Emission of the Biosphere (L-MEB) model (Wigneron et al., 2007). The retrieval approach is
129 simply based on iterative estimation of SM and VOD values providing the lowest difference
130 between modelled and observed TB data by minimizing a cost function (sum of the squared
131 weighted differences between modelled and observed TB) (Wigneron et al., 2000).

132 Currently, there are three main physically-based SMOS SM retrieval products
133 available (SMOS-IC, SMOS Level 2 (L2), and SMOS Level 3 (L3)), for which all: (i) use the
134 L-MEB radiative transfer model (ii) provide SM as volumetric water content (m^3/m^3) with
135 global coverage of 3 days; (iv) provide data at both ascending (06:00 am) and descending
136 (06:00 pm) orbits; (vi) adopt the NETCDF format for the products; and (vii) use the
137 European Centre for Medium-Range Weather Forecasts (ECMWF) soil temperature products.
138 However, the products differ by the projection and grid used as well as with the temporal
139 aggregation for L3 products sampling, as detailed below. It should be noted that SMOS
140 provides also root zone SM at 0-1 m as Level 4.

141 *2.1.1.1 SMOS-IC*

142 In this study, we used the SMOS-IC V105 SM product. The SMOS-IC SM product is
143 based on a relatively simple approach that considers homogeneous pixels (unlike SMOSL3
144 and SMOSL2 where the details of the SMOS footprint at a resolution of 4 km x 4 km are
145 taken into account), to avoid possible uncertainties and errors associated with the datasets
146 used to characterize the heterogeneity of the pixel in the SMOSL2 and SMOSL3 algorithms.
147 The SMOS-IC inversion algorithm aims at a minimal use of auxiliary data through the
148 optimal use of the multi-angular TB observations. Therefore, SMOS-IC (unlike SMOSL2 and
149 SMOSL3) does not use ECMWF SM or the Moderate Resolution Imaging Spectroradiometer
150 (MODIS) LAI (Leaf Area Index) products as first guesses and in the simulation of TB over

151 heterogeneous pixels including forested areas. In SMOS-IC, the effective vegetation
152 scattering albedo (ω) parameter was optimized using the ISMN in-situ observations (Fernandez-
153 Moran et al., 2017a) and the roughness parameters were derived from the global map of Parrens et
154 al. (2016). The "optimization" process of ω led to a very simple result: $\omega \sim 0.1$ over low
155 vegetation and bare soils, while $\omega \sim 0.06$ over forested areas. Also, SMOS-IC does not take
156 into account the corrections associated with the characterization of the antenna patterns as a
157 function of viewing angle and azimuth. To filter out observations/retrievals strongly impacted
158 by RFI (the probability of instantaneous radio frequency interferences) effects, SMOS-IC SM
159 retrievals were excluded when the Root Mean Square Error (RMSE) between SMOSL3 TB
160 and simulated TB > 10 K in the present study. SMOS-IC is currently delivered as a scientific
161 product in the Equal-Area Scalable Earth (EASE) grid version 2 at 25 km resolution and
162 publicly available at CATDS (Centre Aval de Traitement des Données SMOS):
163 <https://www.catds.fr/Products/Available-products-from-CEC-SM/SMOS-IC>. Note that
164 although SMOS-IC was recently released, it corresponds to the initial SMOS 2-Parameter
165 retrieval approach, relying on the relatively low temporal variation of VOD, and fully
166 described in Wigneron et al. (2000). Also note that SMOS-IC is currently in its first version
167 and is thus prone to evolve and progress as it is still undergoing refinements and
168 improvements.

169 **2.1.1.2 SMOSL2**

170 In this study, we used the SMOSL2 SM product in version V650. There are some
171 changes in this version relative to the previous ones (e.g., V620) such as updating some
172 processing parameters (e.g., Chi^2 rescaling), configuration (that can be used for additional
173 quality control checks), and auxiliary files. The most important one is replacing the
174 ECOCLIMAP (218 ecosystems) database (Masson et al., 2003) with the International Geosphere
175 Biosphere Programme (IGBP; 17 land cover classes) land cover map (Friedl et al., 2010), which is

176 also used by the SMAP Level 2 algorithm. This change influences the distribution of the
177 forested areas (FO) and the nominal vegetated soil and therefore leads to different SM values
178 from previous versions.

179 SMOSL2 (and SMOSL3) algorithm considers pixel heterogeneity and inversion is
180 done on the dominant fraction: low vegetation, bare soil or forest and water surfaces. On the
181 non-dominant fraction, auxiliary information (e.g., ECMWF SM and MODIS LAI_{Fmax}, the
182 maximum yearly value of LAI) is used to simulate TB and to better constrain the model
183 inversion. However, these auxiliary data contain errors that can propagate in the inversion
184 algorithm, which may lead to noise and bias in the SM retrievals. In the latest SMOSL2
185 version, ECMWF SM is used to simulate TB over heterogeneous pixels including forested
186 areas after re-scaling. This was done by using cumulative distribution function (CDF)
187 matching, to better match to the histogram of the SMOS SM retrieved values.

188 SMOSL2 SM is provided in swath mode in the Icosahedral Equal Area (ISEA) 4H9
189 Discrete Global Grid (DGG) at 15 km resolution and can be freely obtained from the ESA
190 website portal <https://earth.esa.int/web/guest/missions/esa-operational-eo-missions/smos>.
191 Readers are referred to Kerr et al. (2012) for more details. SMOSL2 SM retrievals were filtered
192 excluding the following: Chi² index (i.e. retrieval fit quality index between the observed
193 SMOS TBs and the simulated TBs) > 3 and RFI > 20%; where RFI was calculated as
194 follows:

$$195 \quad RFI = \frac{NRFI_x + NRFI_y}{MAVA0} \quad (1)$$

196 where:

197 NRFI_x: is the number of TB flagged for RFI in the X-direction.

198 NRFI_y: is the number of TB flagged for RFI in the Y-direction.

199 MAVAO: is the total number of TB observations at this point.

200

201 **2.1.1.3 SMOSL3**

202 The SMOSL3 SM algorithm is based on the same complex approach (i.e. accounting
203 for heterogeneity) used in the SMOSL2 but enhanced through a multi-orbit algorithm that
204 uses retrievals from several revisits over a seven day window (Al Bitar et al., 2017; Jacquette et al.,
205 2013). In addition, the objective of SMOSL3 is to provide enhanced products that are easier to
206 process by the scientific community, given as daily, aggregated in 3-days (moving window
207 mean), 10-days (median, minimum and maximum values), and monthly (mean) global maps.
208 Here we used the daily SMOSL3 version 300, which can be freely obtained from the CATDS
209 website portal in the EASE grid v2 (25 km), which is much easier to process than the grid
210 used in the SMOSL2 processor. SMOSL3 SM retrievals were excluded when RFI > 20%.
211 Readers are referred to Al-Bitar et al. (2017) for more details about SMOSL3.

212 It should be noted here that the soil roughness and effective vegetation scattering
213 albedo parameters used in SMOSL2 and SMOSL3 are still pre-launch values and thus
214 different from those currently used in the SMOS-IC algorithm (note that tests made using the
215 SMOS-IC parameters in SMOSL2 did lead in improvements in the L2 SM retrievals). Also
216 note that SMOSL3 is based upon an older version of L2 and that a bug was identified in the
217 current SMOSL3 algorithm (V300) and will be corrected in the next version.

218 **2.1.2 SMAP**

219 SMAP is a NASA satellite mission that was launched in 2015 to monitor global SM
220 and landscape freeze/thaw state (Entekhabi et al., 2010). The SMAP satellite carries a
221 radiometer (operational; 1.41 GHz) and radar (stopped working after about three months of
222 operation; 1.26 GHz) operating in the L-band frequency. The spatial resolution of radar and
223 radiometer is ~ 3 km and ~40 km, respectively, with a 1000-km swath width and a constant
224 40-degree incidence angle. The SMAP mission provides surface (~ 5 cm) SM (Chan et al., 2016)
225 and root zone SM (1 m; Reichle et al., 2017); and also other geophysical variables such as
226 landscape freeze/thaw (Derksen et al., 2017) and net ecosystem exchange of carbon (NEE) (Jones et

227 al., 2017). Like SMOS, different levels of SM products are delivered as half-orbit products
228 (swath based product; SMAPL2), daily gridded composites (SMAPL3), and model-
229 assimilated products i.e. SMAPL4. In this study, we used the 36-km EASEv2 gridded
230 L3SMP. V4 SM product (only when the retrieval quality is recommended i.e. unfrozen soils
231 and a vegetation water content $< 5 \text{ kg/m}^2$). This version (herein referred to as SMAP) was
232 preceded by a beta quality version (released in 2015) and Version 3 validated SM data
233 (released in 2016) (O' Neill et al., 2017).

234

235 **2.1.3 ASCAT**

236

237 The Advanced Scatterometer (ASCAT) is a real aperture radar carried on-board
238 Metop-A satellite that was launched in October 2006, followed by Metop-B satellite launched
239 in September 2012 (PUM, 2016). Both satellites share the same sun-synchronous near-polar
240 orbit and are half an orbital period apart from each other (~50 min.). The mean local solar
241 time of the descending node is 9:30 a.m. and 9:30 p.m. for the ascending node. ASCAT
242 operates in the C-band frequency (VV polarization) and measures the Normalized Radar
243 Cross Section (NRCS), also known as backscatter coefficient. The two main ASCAT level 1b
244 backscatter products are provided at a spatial resolution of 25-34 km and 50 km. The Vienna
245 University of Technology (TU Wien) semi-empirical change detection algorithm exploits the
246 multi-angle backscatter measurements from ASCAT in order to obtain surface SM expressed
247 in degree of saturation (Wagner et al., 1999).

248 In this study, we used Metop ASCAT Surface SM Climate Data Record (CDR) time
249 series obtained from the Satellite Application Facility on Support to Operational Hydrology
250 and Water Management (H SAF), namely, H111 - Metop ASCAT SSM CDR2016: Metop
251 ASCAT SM CDR2016 time series with 12.5 km spatial sampling. Soil moisture values were
252 only kept when the confidence flag [frozen or snow cover probability $> 50\%$ and using the
253 Surface State Flag (SSF) information] = 0 (Paulik et al., 2014). The relative surface SM given

254 in degree of saturation was converted into absolute SM (expressed in m^3/m^3) using porosity
255 information (provided with the ASCAT datasets) computed from the Harmonized World Soil
256 Database (HWSD; (FAO et al., 2012)) using the formulas of Saxton and Rawls. (2006). It should
257 be noted that, root zone SM index is produced based on ASCAT SM assimilation in the
258 ECMWF Land Data Assimilation System, namely the H-SAF SM-DAS-2 product. The
259 reader is referred to the Product User Manual (PUM) for more details (PUM, 2016) about
260 ASCAT SM.

261

262 **2.1.4 ESA CCI Soil Moisture**

263 The ESA CCI combined SM product is produced by merging both passive and active
264 SM products (Liu et al., 2012) and available over 11/1978 – 12/ 2016 on global scale. These
265 include scatterometer-based SM data (ERS ½, Metop A/B ASCAT) and radiometer-based
266 SM data (SMMR, SSM/I, TMI, AMSR-E, WindSat, AMSR2, and SMOS). The merging
267 between active and passive SM products is done based on a weighted average method with
268 the weights being proportional to Signal to Noise Ratio (SNR; estimated using triple
269 collocation analysis) of each product (Dorigo et al., 2017; Gruber et al., 2017). It should be noted that
270 all these different datasets are scaled to a common model SM climatology, provided by the
271 Global Land Data Assimilation System (GLDAS) Noah Land Surface Model (Rodell et al., 2004)
272 using a CDF matching technique. Therefore, this study will show the Bias values but will not
273 discuss them as they reflect the GLDAS model.

274 Regions of frozen soils or snow covered soils were already masked in the product
275 obtained from the level 2 quality flags and no data are provided over rainforest regions
276 (Dorigo et al., 2017). More details about the theoretical and algorithmic base of this product
277 and detailed analysis about the uncertainties of the SM datasets can be found in (Dorigo et al.,
278 2017; Gruber et al., 2017; Liu et al., 2012). The reader is also referred to <http://www.esa-soilmoisture->

279 cci.org for more information about the daily CCI volumetric (m^3/m^3) SM product, which is
280 provided in a NETCDF format with a spatial resolution of $0.25^\circ \times 0.25^\circ$ (WGS 84); and can
281 be freely downloaded after registration on the CCI SM Website.

282 283 **2.1.5 ISMN *in situ* data**

284
285 The International Soil Moisture Network (ISMN) was initiated in 2009 in order to
286 support the calibration/validation (cal/val) activities of remotely-sensed SM retrievals (Dorigo
287 et al., 2011; Dorigo et al., 2013). More specifically, it was supported by ESA in the framework of the
288 SMOS mission to help in the cal/val activities. Once *in situ* SM observations are collected
289 from international networks, they are quality controlled and harmonized to be distributed
290 through the ISMN website portal: <https://ismn.geo.tuwien.ac.at/>. Currently, the ISMN
291 database hosts ground-based SM measurements from about ~ 58 networks located all over
292 the world. Some of these datasets (e.g., SCAN, the US Climate Reference Network) are
293 provided in near-real time. The *in situ* SM networks used in this study during the 2010-2017
294 period are listed in Table S1 and displayed in Fig. S1, covering a variety of climate and
295 vegetation conditions (see supplementary materials) but not all ecosystems are equally well
296 represented. In this study, only SM observations flagged as “Good” were considered in the
297 evaluations (Dorigo et al., 2013). In addition, OZNET and AMMA networks datasets were
298 obtained from <http://www.oznet.org.au/mdbdata/mdbdata.html> and T. Pellarin (personal
299 communication), respectively. Some networks have their stations distributed over an area that
300 is smaller than the typical footprint of the space borne instruments considered in this study.
301 This results in samples that are not independent in the comparisons, but this was not
302 considered as a problem because the effect is largely the same for each product.

303

304

305 2.2 Methodology

306

307 The satellite SM products were evaluated against ground-based measurements
308 following two approaches i) using all available SM retrievals for each product within the
309 period 2010-2017; ii) using common dates (i.e. days where all satellite-based SM
310 observations are available) between the different datasets, either with or without including
311 SMAP. Approach (i) is used assuming that the final users of SM products may use these
312 products separately, and hence limiting the evaluation to common dates may not correspond
313 to the actual accuracy which will be obtained by the end user. SMAP is available for a shorter
314 period compared to the other products, and was therefore either included or excluded in
315 approach (ii) to evaluate the influence of time series length and data sampling in the
316 evaluation. All products used in this study were provided in “a daily time step”, therefor, in
317 all these cases the instantaneous overpass times, for each day, were matched with
318 instantaneous *in situ* measurements within a time window of 1 hour. Dates with no match
319 with *in situ* observations were not considered in the analyses. In addition, stations with a
320 number of data pairs lower than one month (~31) were excluded from the analyses (e.g.,
321 Kolassa et al., 2018). Finally, stations where all remotely-sensed SM products obtained
322 Pearson correlation values (R) lower than 0.5 were screened out.

323 Four scores, widely used by the SM community, were used here to evaluate the
324 remotely-sensed SM products: Pearson correlation coefficient (R; Eq. 2) to evaluate the
325 ability of satellite-based retrievals on capturing SM seasonal variations of *in situ*
326 measurements, Bias (Eq. 3) to measure the dryness or wetness of the satellite-based retrievals
327 compared to *in situ* observations, RMSE (Root mean square error; Eq. 4), and the unbiased
328 RMSE (ubRMSE; Eq. 5) given as follows:

329

$$R = \sqrt{1 - \frac{(\overline{SM_{RS}} - \overline{SM_{REF}})^2}{(\overline{SM_{RS}} - \overline{SM_{REF}})^2}} \quad (2)$$

$$\text{Bias} = \overline{SM_{RS}} - \overline{SM_{REF}} \quad (3)$$

$$\text{RMSE} = \sqrt{\overline{(SM_{RS} - SM_{REF})^2}} \quad (4)$$

$$\text{ubRMSE} = \sqrt{\text{RMSE}^2 - \text{Bias}^2} \quad (5)$$

334

335 where SM_{RS} is the satellite-based SM, SM_{REF} is the ISMN *in situ* SM used as a reference, and
 336 the temporal mean of the entire time series is indicated by an overbar.

337 The ground-based measurements are based on *in situ* observations at single location.
 338 Therefore, the *in situ* data have a spatial support that differs largely from the gridded SM
 339 retrieval products, which themselves are derived from elliptical footprints. The problem is all
 340 the more complex for SMOS, as (i) SMOS retrievals are based on multi-angular observations,
 341 and (ii) the available range of the SMOS observations over a given pixel changes from one
 342 date to the other (with a sub-cycle of about 16 days). Consequently, all metrics will be prone
 343 to representativeness error (Gruber et al., *in review*). These errors have been earlier analyzed, for
 344 example, by Crow et al. (2012) and Famiglietti et al. (2008). These studies showed that the
 345 representativeness errors significantly affect the reliability of the metrics in the absolute
 346 sense. However, the analysis presented here is comparative in nature and while the
 347 representativeness errors also degrade the ability of the comparisons to detect differences
 348 between the products, the results carry information on relative merits of the products.
 349 Alternative approaches that may mitigate this problem for sparse networks include
 350 deployment of triple collocation technique (for example, (Chen et al., 2017a)), but this is outside
 351 of the scope of this study. Moreover, the sampling depth can be different among satellites and
 352 among *in situ* sensors thus leading to mismatch in soil depth, which can potentially affect the

353 evaluation. OZNET network, for instance, measures SM within the 0-5 cm topsoil layer,
354 while most of the other networks measure SM at 5 cm.

355 Furthermore, the SM seasonal cycle was removed by computing R using anomalies
356 (R_{anom}). This is to evaluate the ability of satellite-based SM retrievals on capturing the day to
357 day variability (short variations) of *in situ* SM observations, which is more important than
358 absolute values for many applications (e.g. data assimilation) and which also reduces part of
359 the representativeness issue mentioned above. The anomaly was computed using the
360 following formula (e.g., Parrens et al., 2012; Rodríguez-Fernández et al., 2016):

361

$$362 \quad SM_{anom} = \frac{SM_i - \overline{SM(w)}}{SD(SM(w))} \quad (6)$$

363

364 where SM_i is the SM value at day (i) and $\overline{SM(w)}$ and $SD(SM(w))$ are the mean and
365 standard deviation over a sliding window (w) of 35 days (Albergel et al., 2012; Brocca et al., 2011),
366 respectively. Note that the seasonalities are not averaged across years into a climatology.

367 SM time series were extracted from the original grids (e.g., 36 km for SMAP, 25 km
368 for SMOSL3, etc.) from those pixels that correspond to each station separately (based on its
369 latitude and longitude). This being said, it is likely that some stations from a dense network
370 (e.g., OZNET) may correspond to the same passive (SMAP, SMOS, and CCI) pixel but for
371 several active (ASCAT) pixels. Then, the metrics between satellite data and the *in situ*
372 observations were computed separately for each station. Finally, the median of each metric
373 for all stations within a continent was calculated. In addition, the median of each metric for
374 all stations within a land cover type (derived from MODIS (Friedl et al., 2010)), LAI category, or
375 Köppen-Geiger climate zone (Rubel et al., 2017), displayed in Fig. S1 (in the supplementary),
376 was also computed and presented in the following section. Correlation coefficients (R) are

377 not additive measures and thus cannot be simply averaged; therefore, the median was instead
378 computed. The spatial standard deviation is added to the median skill metrics.

379 **3. Results**

380

381 **3.1 Using all available observations**

382

383 The four scores (R, Bias, RMSE, and ubRMSE) were computed between remotely-
384 sensed SM retrievals (if available) and 17 ISMN *in situ* observation networks listed in Table
385 S1 in the supplementary. As mentioned before, all observations available within the 2010-
386 2017 period were considered. This being said, the period used to compute the scores for each
387 product can be different.

388 Fig. 1 shows the overall performance (R, R_{anom} , Bias, RMSE, and ubRMSE scores) of
389 each product stratified by continent. For stations located in Africa, ASCAT had overall
390 slightly higher correlation values but also higher Bias, RMSE, and ubRMSE values than all
391 other SM products. Nonetheless, there are small differences in terms of R between the
392 remotely-sensed SM products (R ranging from ~0.75 to ~0.80). Therefore, temporal SM
393 variations from *in situ* stations over sites in this continent are well reproduced by the
394 remotely-sensed SM products. However, R_{anom} dropped for all the remotely-sensed SM
395 products with higher and similar performances by SMAP and SMOS-IC. Over this region, all
396 products were wetter than the *in situ* observations (consistent with Al-Bitar et al. (2017) for
397 SMOS V300 and Rodríguez-Fernández et al. (2016) for ESA CCI V2.02 SM).

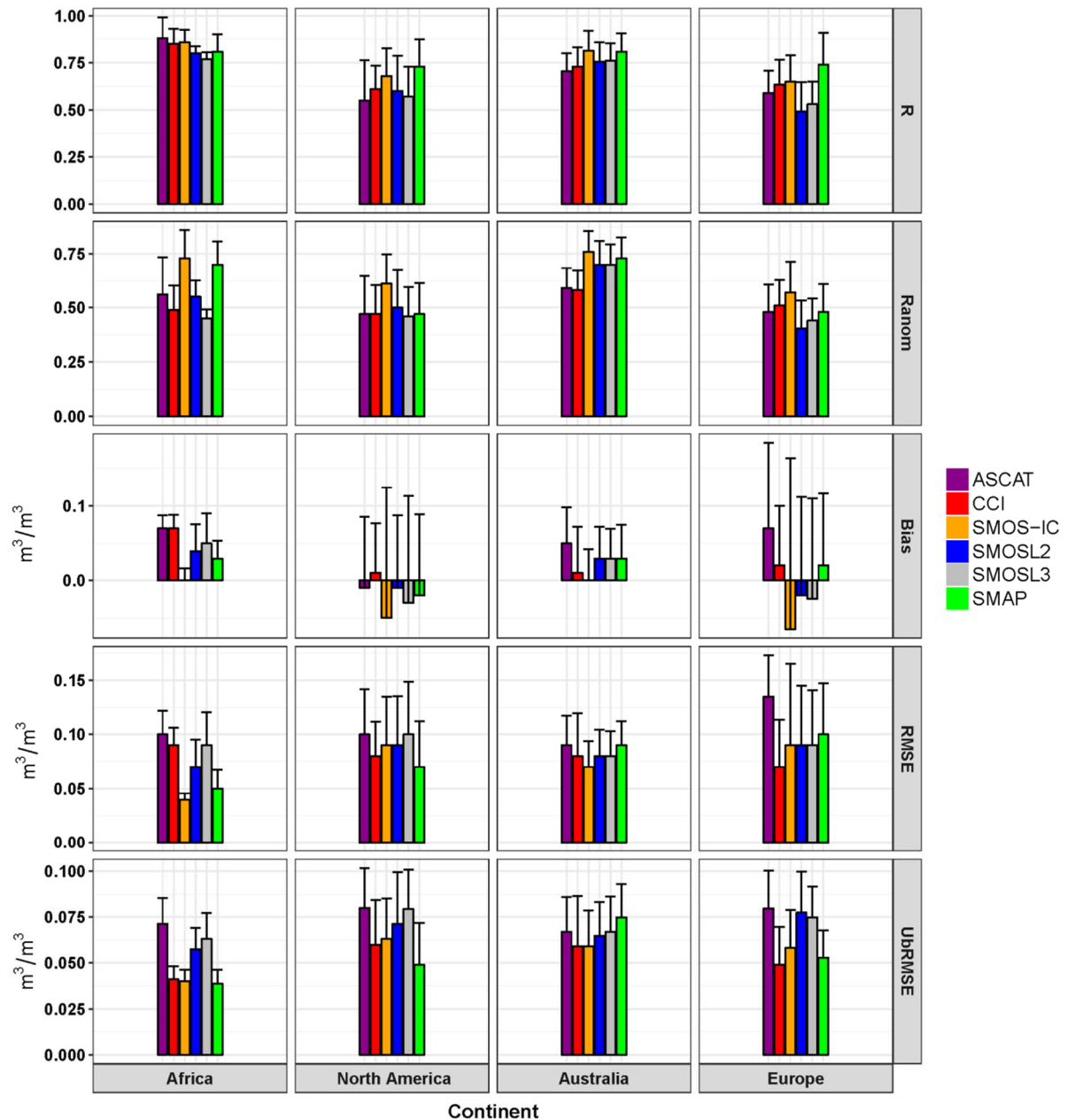
398 For the U.S. networks (e.g., SCAN, SNOTEL, SOILSCAPE, USCRN, etc.), SMAP
399 had the highest correlation (followed by SMOS-IC), lowest ubRMSE and RMSE values
400 (followed by CCI). In terms of R_{anom} , SMOS-IC had the highest value, whereas the other five

401 products had similar performances. All data sets were drier than the ISMN observations with
402 the highest Bias values obtained by SMOS-IC.

403 For the Australian network (OZNET), while SMOS-IC and CCI had the lowest
404 ubRMSE (followed by SMOSL2 SM) and RMSE values, SMAP and SMOS-IC had the
405 highest correlation (original and anomalies) values along with SMOSL2 and SMOSL3. All
406 products were wetter than the *in situ* observations. The results over the OZNET network are
407 consistent with Colliander et al. (2017) who also showed, for instance, that SMAP is wet
408 (although the study was based only on data of the Yanco site and used SMAPL2 V2).

409 In case of the European networks (e.g., REMEDHUS, SMOSMANIA, BIEBRZA_S-
410 1, RSMN, HOBE, etc.), ESA CCI SM had the lowest overall ubRMSE (followed by SMAP)
411 and RMSE values, while SMAP and SMOS-IC showed the highest values in terms of
412 correlations. SMOS-IC, again, had the highest R_{anom} values. There is a strong variability in
413 terms of Bias for the different products: from an underestimation by all SMOS products to an
414 overestimation by SMAP, ASCAT and the ESA CCI SM.

415 Generally, the best performance of all remotely-sensed SM products was found over
416 Australian and African stations, while the worst and diverse results were found over the U.S.
417 and Europe. Remarkably, a systematic overestimation or underestimation of the ISMN *in situ*
418 observations has been observed by remotely-sensed SM products over stations located over
419 Africa (and Australia) and America, respectively. Generally, for areas without or with very
420 few RFI (Australia and Africa) SMOS had positive biases but when there are many (Europe)
421 it is always negative (Bircher et al., 2012). It should be noted that some areas are much better
422 represented than others (US vs Africa for instance) in terms of number of points and that for
423 Africa only one ecosystem is considered when it ranges from temperate to arid via tropical.



424

425 *Figure 1 Median evaluation metric (R , R_{anom} , Bias, RMSE, and ubRMSE) for the entire period 2010-*
 426 *2017, across all sites for all products (without data cross masking) compared to ISMN in situ SM,*
 427 *stratified by continent: America ($n=448$ stations), Australia ($n=46$ stations), Europe ($n=128$ stations),*
 428 *and Africa ($n=13$ stations). Error bars represent the standard deviation (SD; variability) of the*
 429 *station metrics (median+SD) and do not represent anything on the temporal sampling frequency.*

430 3.2 Using only temporally collocated data

431

432 3.2.1 For the SMAP period (Jan 2015-Dec 2016)

433 Here, we limited the analyses to only common dates by doing a temporal collocation
 434 between the different satellite-based SM retrievals (Fig. 2). Due to the short period of SMAP,

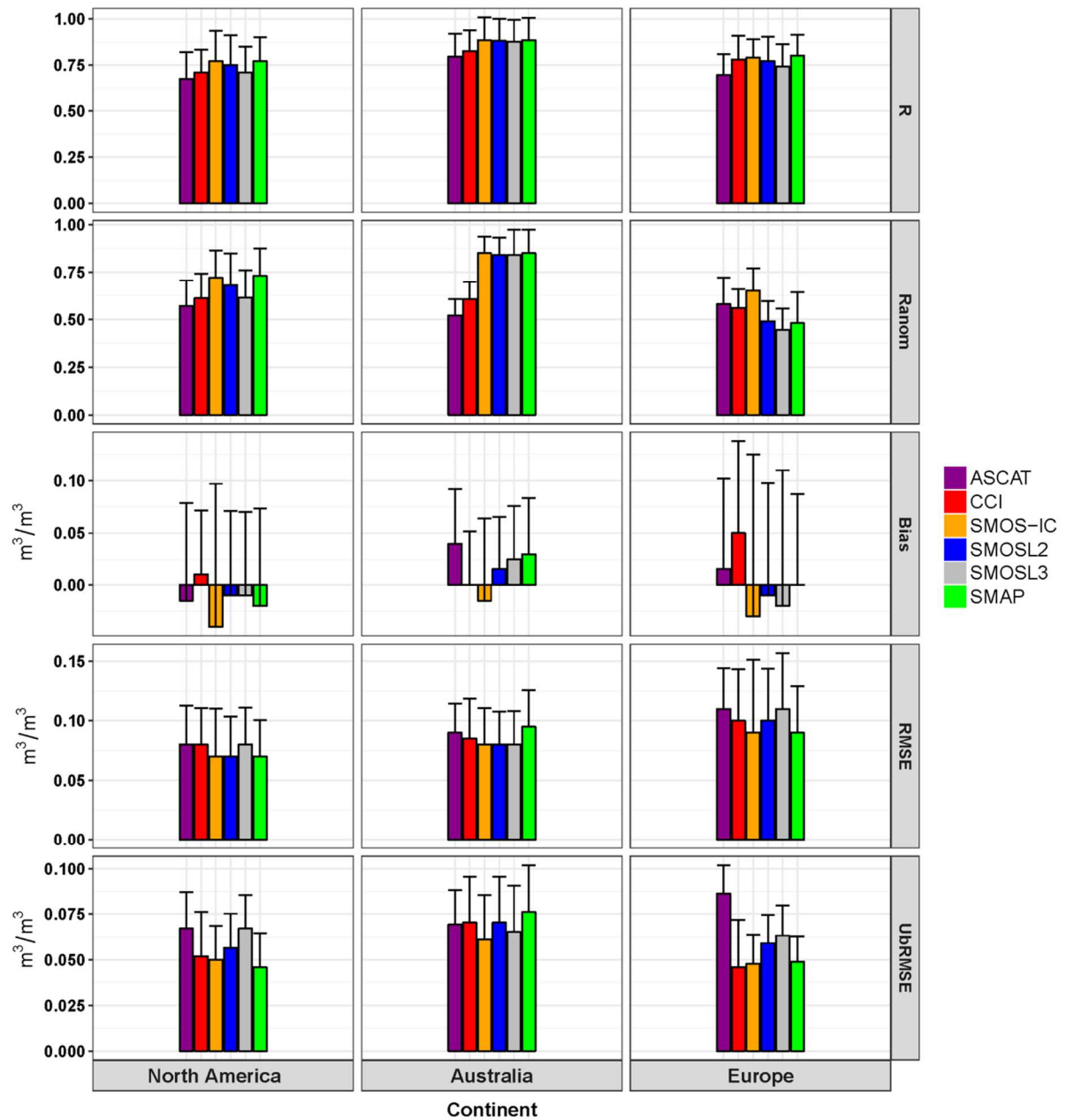
435 only 9 networks out of 17 were retained: OZNET, PBO_H2o, REMEDHUS, RSMN, SCAN,
436 SMOSMANIA, SNOTEL, SOILSCAPE, and USCRN. As expected, the rank of the product
437 performances in Fig. 2 is different to the one shown in Fig. 1 (without temporal collocation).

438 Over the U.S. networks (North America), SMOS-IC, SMOSL2, and SMAP (ASCAT)
439 had the highest (lowest) correlations (both original and anomalies). There is almost similar
440 performance in terms of R and RMSE values between SMOSL2, SMOS-IC and SMAP but
441 lowest (highest) ubRMSE was obtained by SMAP (SMOSL3 and ASCAT). All products
442 (except for ESA CCI SM, whose bias is the model bias of GLDAS Noah) are drier than the *in*
443 *situ* observations; with, again, marked underestimation by SMOS-IC as already seen in Fig.
444 1. Lower R_{anom} values were obtained by all products but the performance rank of the products
445 was unchanged.

446 Over the Australian network (OZNET), all SMOS versions and SMAP had almost
447 similar performance in capturing the temporal dynamics (both annual cycle and day to day
448 variations) of the ISMN *in situ* observations and better compared to *in situ* observations than
449 ESA CCI SM and ASCAT SM products. SMOS-IC and SMOSL3 (SMAP) had the lowest
450 (highest) ubRMSE values. All SMOS products had similar RMSE values and lower than the
451 other products. All remotely-sensed SM products were wetter than the *in situ* measurements
452 (with the exception of SMOS-IC).

453

454



455

456 *Figure 2 Same as Figure 1, but now only including common data points for each product within the*
 457 *2015-2016 period, and hence using a reduced number of stations (n) over America (n=174 stations),*
 458 *Australia (n=30 stations), and Europe (n=27 stations).*

459

460

461

462

463

464 In case of Europe, there is generally no big difference in terms of correlations
465 between the products but strong differences can be noted in terms of UBRMSE and Bias.
466 SMOS-IC and ASCAT had the highest R_{anom} values against the ISMN observations.
467 Similarly to what was already found in Fig. 1, while all SMOS SM products were drier than
468 the *in situ* measurements, ESA CCI SM and ASCAT were wetter than the *in situ*
469 measurements.

470

471 **3.2.2 For the period without SMAP (Jan 2010-Dec 2016)**

472 Excluding SMAP, only SMOS, ESA CCI, and ASCAT SM products were considered.
473 Here, fourteen *in situ* SM networks were retained: AMMA, ARM, BIEBRZA_S-1, DAHRA,
474 HOBE, OZNET, PBO_H2O, REMEDHUS, RSMN, SCAN, SMOSMANIA, SNOTEL,
475 SOILSCAPE, and USCRN. As done in Figs. 1 and 2, Fig. 3 shows the overall performance of
476 the remote-sensing SM products stratified per continent.

477 In the case of sites located over Africa, there are generally strong correlations between
478 satellite-based SM products and the *in situ* observations with similar performances in terms
479 of correlations (R) - with the exception of SMOSL3- and lowest ubRMSE values were
480 obtained by SMOS-IC and ESA CCI SM products. As over America and Europe, no change
481 in terms of Bias from Fig. 1 was found. It should be noted that SMOSL2 outperformed
482 SMOSL3 in most scores, which is in line with the findings of Al Bitar et al. (2017), using
483 SMOSL2 V620 and SMOSL3 V300.

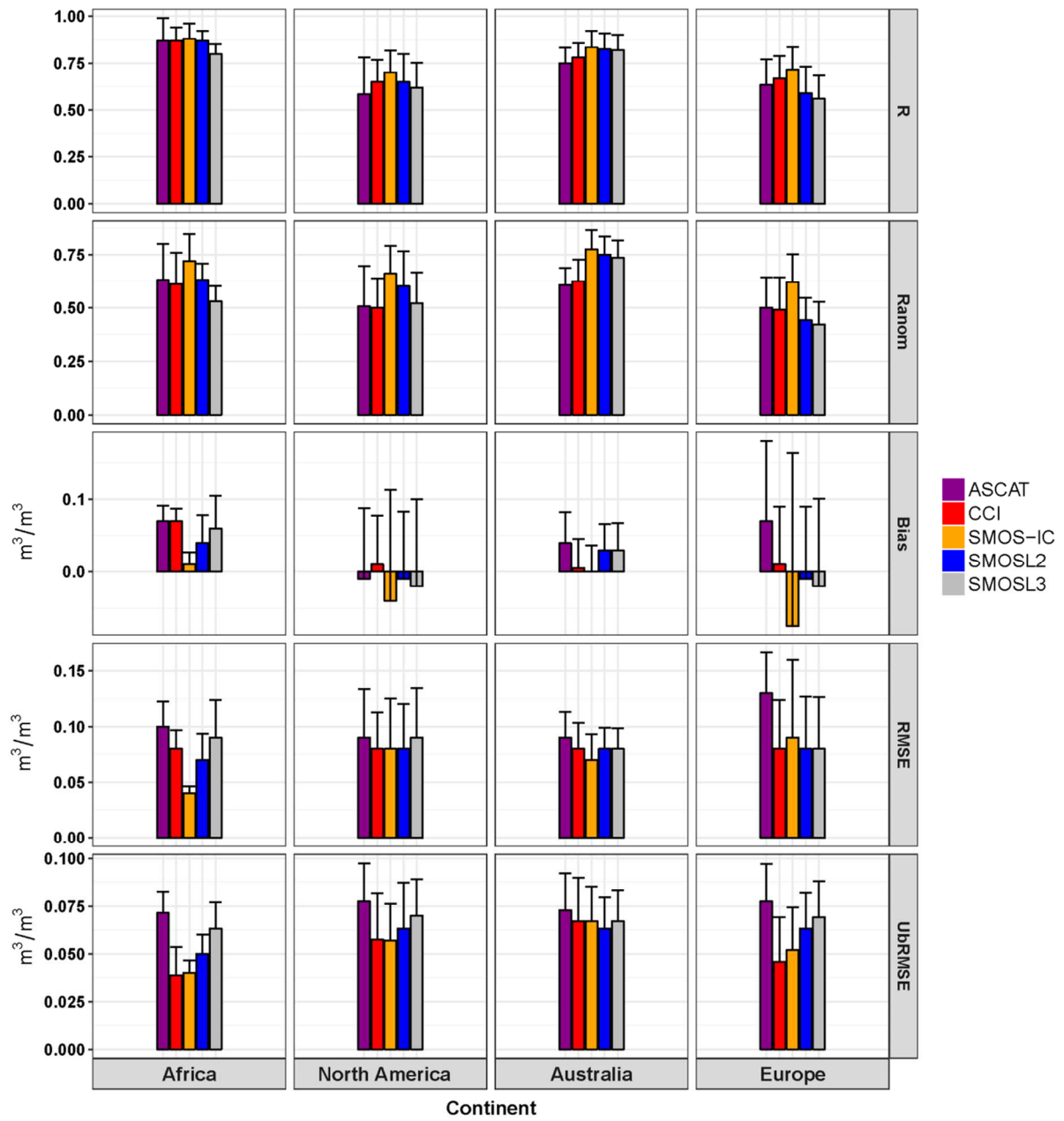
484 For the U.S. networks, SMOS-IC (followed by SMOSL2 and ESA CCI) presented
485 slightly higher correlation values. SMOS-IC and SMOSL2 presented higher R_{anom} and the
486 other three products performed similarly. As found in Fig. 1, all data were drier than the *in*
487 *situ* observations except ESA CCI SM which is wetter, with again marked underestimation by

488 SMOS-IC. Similar and lower RMSE values were obtained by ESA CCI, SMOSL2, and
489 SMOS-IC. Similar and lower ubRMSE values were obtained by ESA CCI and SMOS-IC.

490 Over the Australian network, the highest correlation values (R and R_{anom}) were
491 obtained by SMOS-IC, SMOSL2, and SMOSL3. The lowest ubRMSE value was obtained by
492 SMOSL2. In general, over Australia, the SMOS SM products perform better than the ESA
493 CCI SM and ASCAT (in line with the findings of Holgate et al. (2016)) products but there are
494 small (or no) differences between the SMOS products and the ESA CCI SM products in
495 terms of RMSE and ubRMSE values with SMOSL2 product being the best for UbrRMSE and
496 SMOS-IC for RMSE. No change in terms of sign of Bias from Fig. 1 (although the
497 magnitudes are different).

498 In the case of sites located over Europe, SMOS-IC (followed by ESA CCI SM and
499 ASCAT), again performed slightly better in terms of correlations (R and R_{anom}) than the other
500 products but the lowest ubRMSE values were obtained by ESA CCI SM. Lowest RMSE
501 values were obtained by ESA CCI, SMOSL3, and SMOSL2. No change in terms of sign of
502 Bias can be noted in comparison to Fig. 1.

503
504



506

507 *Figure 3 Same as Figure 2, but now excluding SMAP and extending the evaluation period to common*
 508 *data points in 2010-2017, over America (n=393 stations), Australia (n=28 stations), Europe (n=94*
 509 *stations), and Africa (n=13 stations).*

510

511

512

513

514

515 **3.3 Impact of vegetation and climate**

516

517 For the ISMN networks used in this study, climate and land cover can be quite
518 heterogeneous in some continents (e.g. America, Europe) and relatively homogeneous in
519 others (e.g. Australia, Africa). So in this section we analyze more in depth the impact of
520 vegetation and climate on the performances of the satellite-based SM products.

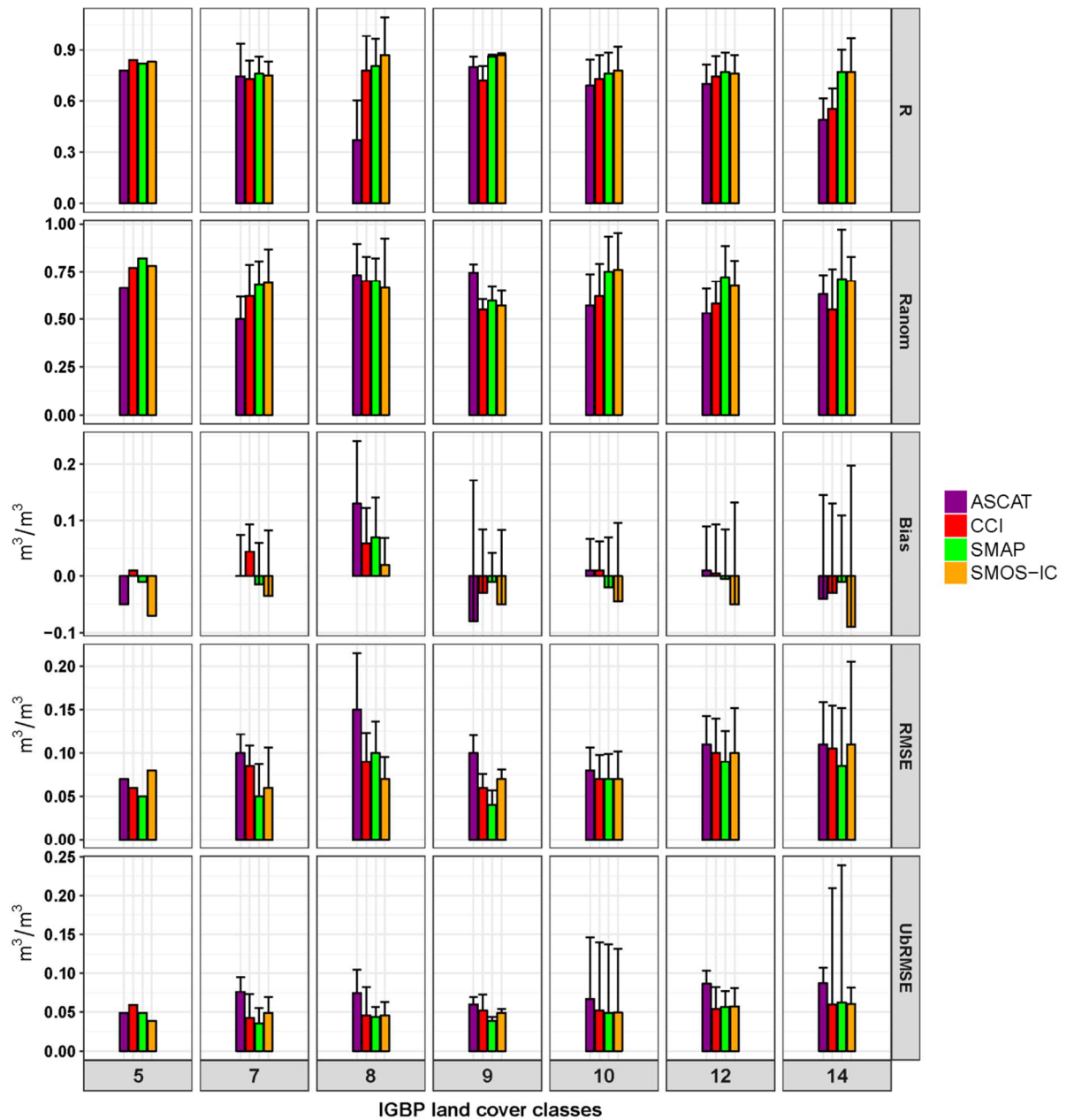
521 **3.3.1 Vegetation**

522 There is consensus among the SM community that vegetation density affects the
523 remotely-sensed SM quality (Jackson et al., 1982; Wigneron et al., 2017). Earlier studies
524 (e.g., Al-Yaari et al., 2014a; Al-Yaari et al., 2014b) found that the performance of the
525 satellite-based SM products varies depending on the vegetation density and land cover type.
526 This section is devoted to re-evaluate the impact of vegetation on the performance of SM
527 products using new SM versions/products. Given the fact that all SMOS products (i.e.
528 SMOS-IC, SMOSL3, and SMOSL2) use SMOS TB observations and ECMWF soil
529 temperature data, they are not totally independent. Also, there is slightly better performance
530 of SMOS-IC over the other SMOS products. Therefore, to simplify the inter-comparison, this
531 section is limited to the SMOS-IC version and other none-SMOS products. The evaluation
532 scores (for all stations) i.e. R , R_{anom} , Bias, RMSE, and ubRMSE are stratified based on the
533 IGBP land cover type (see Fig. S1 in the supplementary). Results, based only on common
534 dates within the period 2015-2016 (2 years), are displayed in Fig. 4.

535

536

537



538

539 *Figure 4 Median metrics (R , R_{anom} , Bias, RMSE, and ubRMSE) of all sites stratified by IGBP land*
 540 *cover type (see Fig. S1) for SMOS-IC, ASCAT, CCI, and SMAP: Mixed forest (5; $n=1$ station), Open*
 541 *shrublands (7; $n=10$ stations), Woody savannas (8; $n=8$ stations), Savannas (9; $n=27$ stations),*
 542 *Grasslands (10; $n=132$ stations), Croplands (12; $n=67$ stations), Cropland/Natural vegetation*
 543 *mosaic (14; $n=22$ stations). n denotes the number of stations per land cover type. Error bars*
 544 *represent the standard deviation (SD; variability) of stations (median+SD). Only data points at*
 545 *common dates within the period 2015-2017 are included.*

546

547

548

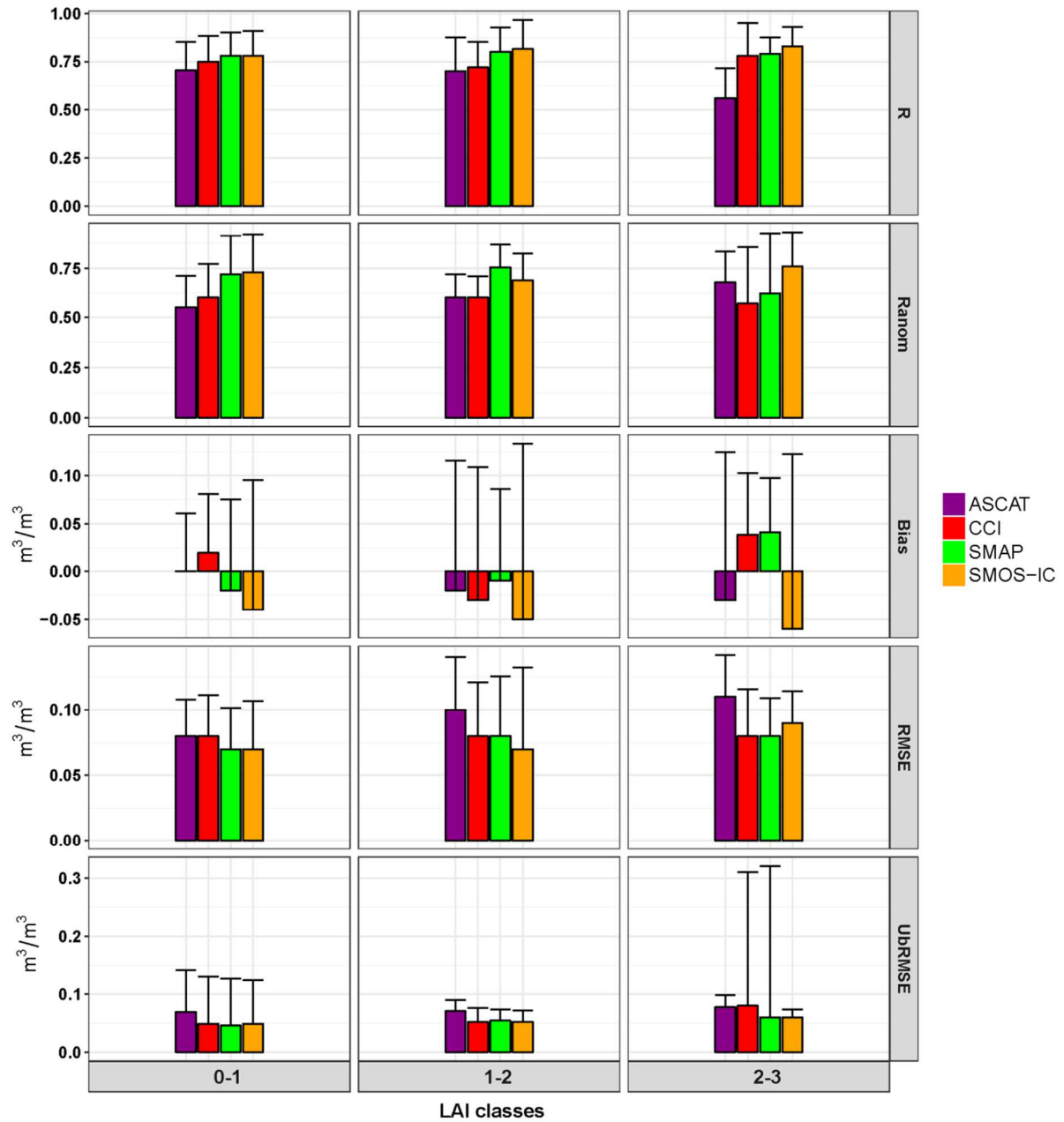
549 In terms of correlation (R), similar performances between the four products (SMOS-
550 IC, ESA CCI SM, ASCAT, and SMAP) were found over “Open shrublands”, “Croplands”,
551 and “Mixed forest”. A notable difference between ASCAT (lower performance) and the other
552 three products was found over “Woody savannas”. SMOS-IC and SMAP had best
553 correlations with the ISMN observations over “Cropland/Natural vegetation mosaic”. SMAP
554 and SMOS-IC had the highest anomaly correlations over “Grasslands” and “Croplands”.
555 ASCAT was correlating better to *in situ* measurements anomalies over “Savannas”. All the
556 four products agree in terms of sign of the bias value: while all underestimated the ISMN
557 observations over “Cropland/Natural vegetation mosaic” and “Savannas”, they all
558 overestimated the ISMN observations over “Woody savannas”. However, there is no
559 agreement between products in terms of sign of the bias over all other land cover types. In
560 terms of RMSE and ubRMSE, while ASCAT had generally the highest values, the other three
561 SM products performed similarly over most of the land cover types.

562 A different insight on the impact of vegetation on the performance of satellite-based
563 SM retrievals with respect to the ISMN *in situ* observations can be seen in Fig. 5. Fig. 5
564 displays the median of all the statistics considered in this study stratified based on MODIS
565 LAI categories: 0-1, 1-2, and 2-3 m^2/m^2 (see Fig. S1 for the MODIS LAI map). Evidently,
566 because the prior data masking to locations with less than 5 kg/m^2 VWC, only limited data
567 are available for evaluation in densely vegetated areas. It can be noticed from this figure that
568 there is an increase in ubRMSE for all remotely-sensed SM products with increasing
569 vegetation density. For SMAP and ESA CCI there is a high variability of their performances
570 among stations as indicated by the high standard deviation over the LAI 2-3 category. In
571 terms of R, similar performances among products can be noticed over the category 0-1 but
572 better performance was obtained by SMOS-IC going from 0-1 to 2-3 categories, whereas
573 ASCAT retrievals degraded for denser vegetation. The best R_{anom} values were obtained by

574 SMOS-IC (followed by ASCAT) and SMAP (followed by SMOS-IC) over the 2-3 and 1-2
575 categories, respectively. SMOS-IC and SMAP performed similarly in terms of R_{anom} over the
576 0-1 category. In terms of ubRMSE, none is superior over all LAI categories. For instance,
577 while SMAP, SMOS-IC, ESA CCI SM products had similar ubRMSE values over regions
578 with LAI values ranging between 0 and 2 m^2/m^2 , SMOS-IC and SMAP had lowest values
579 over the LAI 2-3 category. The four products only agree in terms of sign of bias (dry) over
580 LAI 1-2 category and higher Bias values were obtained by SMOS-IC.

581
582
583
584
585
586
587
588
589
590
591
592
593
594
595
596
597
598
599

600
601
602



603

604 *Figure 5 Same as Figure 4, but now grouped by LAI values in 3 classes: 0-1, 1-2, 2-3 m²/m². Number*
 605 *of stations per category: 0-1 (n=160 stations), 1-2 (n=99 stations), 2-3 (n= 9 stations).*

606

607

608

609

610 3.3.2 Climate

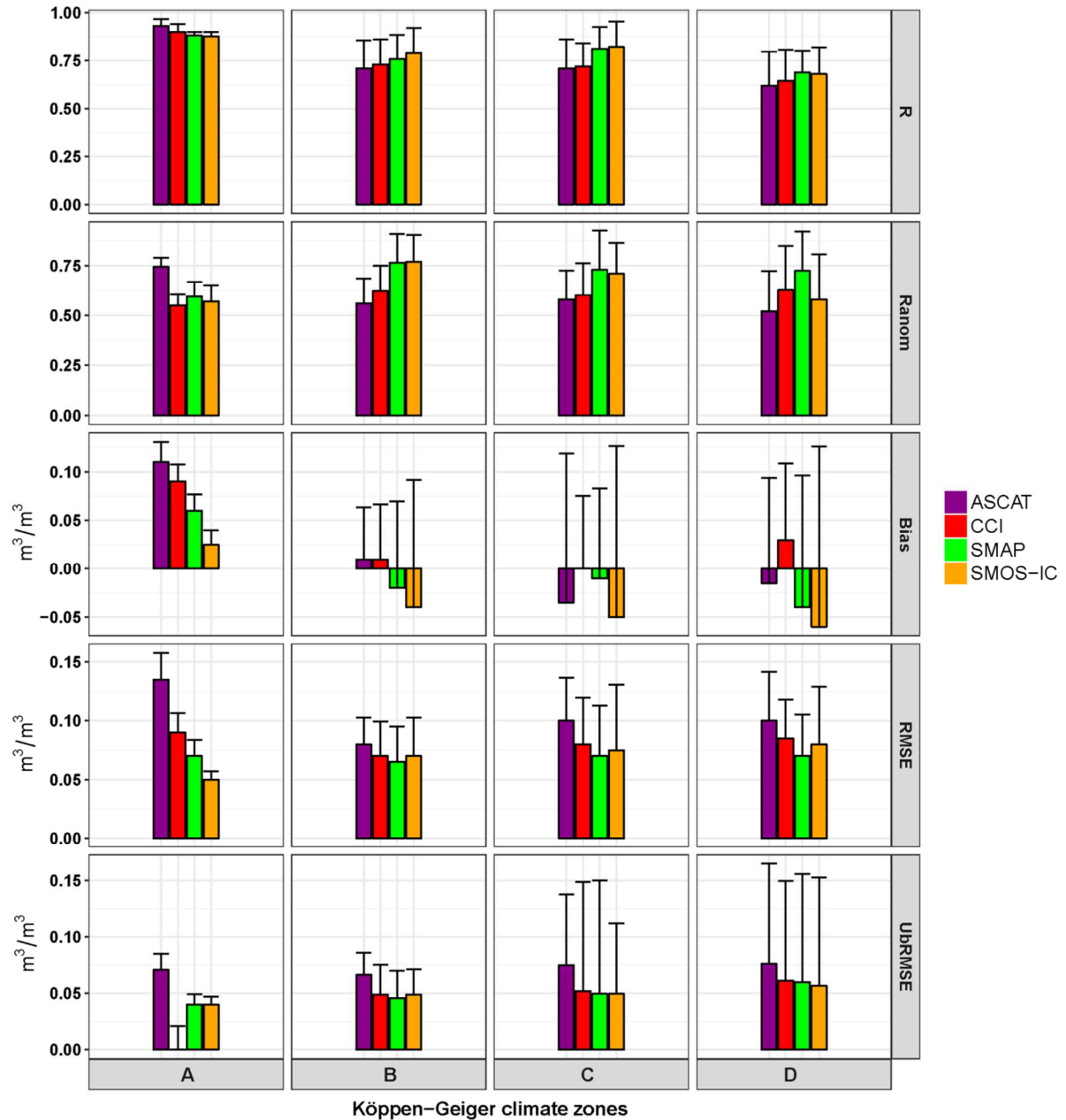
611

612 Climate is another factor that can impact the performance of the remotely-sensed SM
613 products. In this study, we assessed the relationship between satellite performance metrics
614 and the Köppen-Geiger climate classification (Kottek et al., 2006). Fig. 6 displays the median of
615 all the statistics considered in this study as a function of Köppen-Geiger main climates (see
616 Fig. S1 for the Köppen-Geiger map): “Equatorial (Savanna) climates: (A)”, “Arid and semi-
617 arid climates (B)”, “Warm temperate climates (C)”, and “Cold climates (D)”. It can be
618 noticed from this figure that there is a high variability in the performance of the satellite-
619 based products over regions classified as “B”, “C”, and “D” in terms of Bias. All remotely-
620 sensed SM products have comparable performances (with small differences) in terms of
621 correlations over “A”, “B”, and “D” climates in terms of R. The lowest correlations and
622 highest RMSE and ubRMSE values for all products were obtained over “cold climates”
623 climate. SMAP and SMOS-IC correlated better to the ISMN observations over “warm
624 temperate climates” climates than ESA CCI and ASCAT. ASCAT had higher RMSE and
625 ubRMSE over all the main climates and lower R_{anom} over “B”, “C”, and “D”. However,
626 ASCAT had higher correlations (both original and anomalies) over “Equatorial (Savana)
627 climates”. The correlations values computed based on anomalies were lower than the original
628 ones particularly over “Equatorial (Savana) climates” and the performance is more spread
629 over the stations. SMAP had a higher R_{anom} over “cold climates” but comparable with
630 SMOS-IC over “Arid and semi-arid climates” and “warm temperate climates” and with
631 SMOS-IC and CCI over “Equatorial (Savana) climates”. In terms of anomalies, the rank of
632 the products did not change over “Arid and semi-arid climates”. With the exception of CCI,
633 remotely-sensed SM products had underestimated *in situ* observations over “warm temperate
634 climates” and “cold climates” and overestimated the ISMN SM observations over “Equatorial
635 (Savana) climates”. With the exception of ASCAT, all products had comparable ubRMSE

636 values over “B”, “C”, and “D” regions. Moreover, “Arid and semi-arid climates” region
 637 exhibits high variability in terms of performance scores.

638

639



640

641 *Figure 6 Same as Figure 4, but now grouped by Köppen-Geiger main climates (see Fig. S1). A:*
 642 *Equatorial (Savanna; n= 8 stations), B: Arid and semiarid (n=90 stations), C: Warm temperate*
 643 *climates (n=132 stations), D: Cold climates (n=42 stations). Source of the climate classifications:*
 644 *(Kottek et al., 2006).*

645

646 **4. Discussion**

647 Based on the evaluation results shown above in Figs. 1-3, it was found that comparing
648 remotely-sensed SM product to the ISMN in-situ measurements individually (i.e. taking all
649 available observations) or limiting observations to the availability of the other remotely-
650 sensed SM products can impact the evaluation scores and the ranking of the various SM
651 retrieval products, due to differences in spatial and temporal sampling. On the one hand,
652 considering all observations, SMAP and SMOS-IC gave the best performance in terms of
653 correlations (Fig. 1), while on the other hand, they had similar performance to SMOSL2 and
654 SMOSL3 when considering only common dates over the Australia network (Fig. 2). Another
655 example concerns stations situated over Africa, where ASCAT provided the highest
656 correlation value (though the differences were small) when considering all observations (Fig.
657 1) but when considering only observations collocated with the other products, a similar
658 performance with CCI, SMOSL2, and SMOS-IC (Fig. 3) was obtained.

659 In some cases, the performances were unchanged when cross masking data. This may
660 be coincidence, or it may indicate that the masked data are indeed a representative subsample
661 of all data. For instance, in terms of ubRMSE, ESA CCI SM was the best in all cases over
662 Europe. SMOS-IC was the best for ubRMSE and this position was unchanged whether all
663 observations were considered (Fig. 1) or considering only common dates (Figs. 2 and 3) over
664 the Australian network. All remotely-sensed SM products were consistently wetter than the
665 ISMN SM products over the African and Australian networks in all cases considered in this
666 study i.e. using all observations or only common dates. Similarly, the small bias in dryness
667 (wetness) of ASCAT, SMAP, and SMOS (ESA CCI SM) with respect to the ISMN
668 observations over stations located in the U.S. persisted, regardless of the data masking. The
669 dryness of SMAP is in line with previous studies conducted by Chen et al. (2017b), over the
670 Tibetan Plateau. The presence of bias is a common problem of the remotely-sensed SM

671 products analyzed in this study. Other than the representativeness errors between the point-
672 scale in situ measurements and coarse-resolution space borne products, the absolute value of
673 Bias is affected by (Al Bitar et al., 2017; Draper et al., 2009; Escorihuela et al., 2010; Jackson et al., 2012):
674 different sensing depths (and thus observed volume), the use of auxiliary variables from
675 models (e.g., soil temperature), uncertainties due to the *in situ* sensor errors, scaling and
676 conversion of units (mainly for ESA CCI SM and ASCAT), and spatial heterogeneity.

677 Overall, the ubRMSE is larger than the target uncertainty of $0.04 \text{ m}^3/\text{m}^3$ when doing
678 an evaluation against sparse networks, which suffer largely from representativeness error. It
679 is worth noting that the ubRMSE values (particularly for SMAP) found in this study are in
680 line with those found by El Hajj et al. (2018), but larger than those found by Colliander et al.
681 (2017) and Chan et al. (2016). These later studies used core validation sites, which have
682 significantly smaller representation errors through upscaling of the dense SM networks; here
683 we considered the median value of the scores of individual stations within continents, land
684 cover types, or climate zones. Furthermore, it was shown that ASCAT generally had the
685 highest ubRMSE values compared to other products over most of the networks and lower
686 correlations over arid environments. This could be explained by volume scattering in dry
687 sands and the fact that the ASCAT product is given as a degree of saturation unit, which was
688 converted to the volumetric units (i.e. m^3/m^3) using soil porosity information (Wagner et al.,
689 2013). Soil porosity datasets are often not very accurate (Brocca et al., 2011), and they may
690 significantly affect the Bias and ubRMSE scores obtained by ASCAT. In addition, it should
691 be noted that the Bias values obtained for ESA CCI are imposed by the GLDAS Noah model,
692 as already mentioned above.

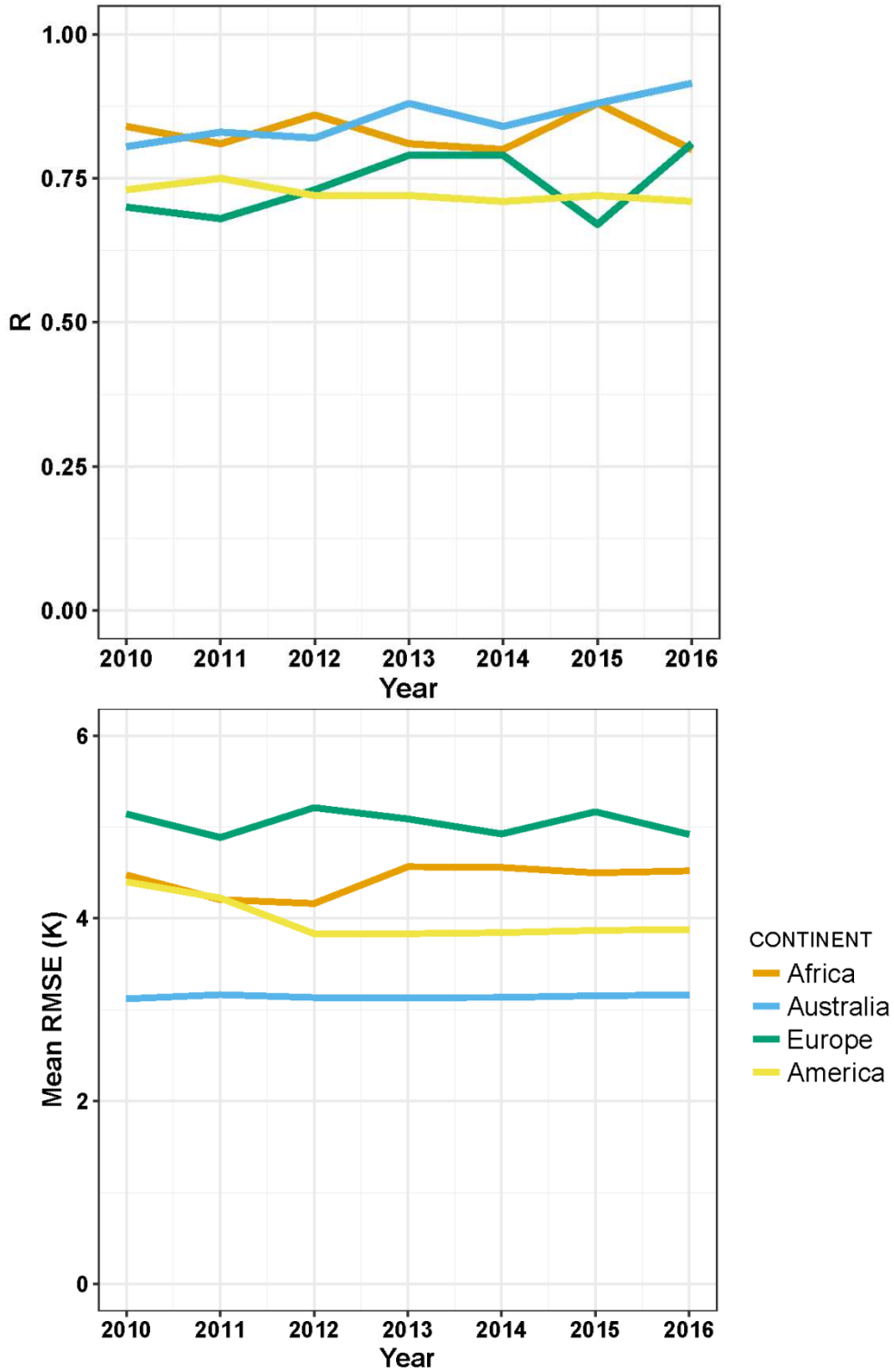
693 The increase in R values when only common data points are used is most likely
694 because less stations are included, which each now has a more complete time series, allowing
695 to sample more of the long-term variability. When excluding SMAP from the analyses (Fig.

696 3), SMOS-IC generally (followed by SMOSL2 and ESA CCI in most cases) ranked first in
697 terms of correlations (both original SM values and anomalies) for most of the ISMN stations
698 considered in this study. However, the differences in R values are rather very small. The
699 slightly better performance of SMOS-IC is probably due to the improvements introduced into
700 the algorithm (e.g., limiting the use of auxiliary information, new calibration, etc.). However,
701 SMOS-IC showed higher Bias values comparing to other products which is expected as Bias
702 was considered as the least important metric in the SMOS-IC SM algorithm calibration
703 processes (Fernandez-Moran et al., 2017a).

704 While the best performances of all remotely-sensed SM products in terms of
705 correlation was found over the Australian and African networks (due to common low
706 vegetation density over these networks), the worst and more diverse results were found over
707 the European networks (particularly SMOS). However, in most cases and particularly for
708 stations located over Africa, anomaly correlations were lower than for the original
709 correlations, which means that the correlations of those stations were controlled by the annual
710 cycle (pronounced dry and wet seasons). In the case of Europe, the SMOS observations are
711 affected by RFIs plus snow freezing not always well taken into account (partial coverage,
712 human impacts) that could partially explain the lower performances of SMOSL2 and
713 SMOSL3 over this continent.

714 As RFIs signals play a key role in the accuracy of the SM products retrieved from the
715 passive microwave systems, we further analyzed the impact of this factor in Fig. 7 for the
716 SMOS sensor, (times series of observations were too short for the SMAP data which are not
717 included in this analysis). More specifically, the time variation in the quality of the SMOS
718 SM product since 2010 was investigated over the four continents: America, Australia, Africa,
719 and Europe. The correlation values shown in Fig. 7 (upper panel) were calculated for each
720 year separately between the SMOS-IC and ISMN data and then only the median of all sites

721 per continent and year was retained. In Fig. 7 (upper panel), it can be seen that the
722 performance of SMOS-IC over America is stable with no substantial differences between
723 years. Over Australia and Europe (except for 2015), there is a small tendency of increasing
724 correlations from 2010 onwards. Over Africa, there is no obvious trend as the performance of
725 SMOS-IC changes from one year to the other. In order to investigate the effect of RFI on the
726 SMOS-IC results in Fig. 7 (upper panel), the temporal mean of the RMSE of the fit between
727 measured and simulated TB (which can be considered as a proxy of RFI impacts on the TB
728 observations) was computed per year and spatially averaged for the same corresponding
729 entire continents; displayed in Fig. 7 (lower panel). While a substantial decrease in RFI can
730 be noticed over America, RFI over Australia keeps stable through the seven years. Over
731 Africa and Europe, RFI signals effects changed from one year to the other with no general
732 trends. Interestingly, the notable decrease in the performance of SMOS-IC over 2013-2014
733 over Africa and 2015 over Europe correspond to higher RFI levels than in the preceding and
734 following years. So, these figures tend to confirm that the RFI effects may be a key factor to
735 explain time variations in the performance of SMOS-IC over these continents. The lowest
736 RFI signals among continents were found over Australia, which was reflected in the best
737 performance of SMOS-IC in all years in terms of correlations over the continents. The results
738 showed that the performance of SMOS datasets is still highly affected by RFI signals, even if
739 the ESA already put a lot of effort in closing down many RFI sources (Oliva et al., 2016). However,
740 this cannot be generalized as for instance over Europe, the TB RMSE decrease in 2011
741 (lower RFI conditions) matches with an R-decrease in SM.



742

743 *Figure 7 Correlation between SMOS-IC SM and the ISMN in situ SM observations (upper panel) and*

744 *RMSE of the fit between measured and simulated TB (bottom panel) during the 2010-2016 period*

745 *over Africa, Europe, America, and Australia. Correlations were calculated per year separately for all*

746 *stations located in the same continent and then the median of all stations was computed.*

747 Other general disturbing factors that impact the performance of the remote sensing
748 SM products over Europe include climate, dense vegetation, or mountains. The regions of
749 SM networks over the African and Australia networks are relatively homogenous with less
750 spatial variability in SM, which led to higher skills of remote sensing retrievals (e.g., Dorigo
751 et al., 2012). In terms of correlations and ubRMSE: while lowest performances (with more
752 variability) of most the remotely-sent SM products were obtained for “cold climates”, which
753 is expected due to the effects of snow and frozen conditions that are not well filtered or the
754 landscape (vegetation, soil) is very different from the other areas where much of the
755 algorithm development has occurred. Highest performances were obtained over “tropical
756 savanna climates”, which is, as mentioned above, mainly controlled by the annual cycle. This
757 indicates that climate and the time series length is a significant factor when comparing
758 satellite-based SM products.

759 The better performance, particularly in terms of temporal dynamics, of SMAP and
760 SMOS-IC over active (ASCAT) products, using only common dates, over regions where LAI
761 range between 2 and 3 m^2/m^2 is probably due to the fact that SMAP and SMOS (and ESA
762 CCI which contains SMOS) operate at L-band which is optimal for SM monitoring: L-band
763 observations have higher penetration capabilities through dense vegetation and lower
764 sensitivity to atmospheric effects such as heavy rainfall events than higher frequencies (C-
765 and X- bands). However, over these regions, ASCAT showed similar R_{anom} as SMAP. Over
766 some land cover types/regions, the ESA CCI SM product was performing similarly to SMOS-
767 IC and SMAP, which is probably due to the fact that it contains SMOS L-band observations.
768 The small difference in correlation values (both R and R_{anom}) between SMOS-IC (higher) and
769 SMAP (lower) over regions where LAI values range between 2 and 3 could be due to the
770 capability of SMOS satellite to measure TB at multi-angular incidence angles and thus better
771 decouple between the soil and vegetation effects. Conversely, the better performance, mainly

772 in terms of ubRMSE of SMAP over the SMOS products is generally due to the improved
773 technology used in SMAP (SMAP has a much better RFI filtering).

774 **4 Conclusion**

775

776 In this study, the assessment and inter-comparison of six recently
777 developed/reprocessed satellite SM products (i.e. SMOS-IC, SMOSL2, SMOSL3, SMAP,
778 ASCAT, and ESA CCI SM) against the ISMN ground-based measurements across different
779 climate and vegetation conditions were conducted. This was accomplished using the Pearson
780 correlation coefficient (R), anomalies (R_{anom}), Bias, RMSE, and ubRMSE metrics. Several
781 conclusions can be drawn from the evaluation presented above:

782 (i) The performance of the six datasets in terms of correlations (temporal dynamics)
783 was rather similar over contrasted biomes and climate conditions, but with a
784 slightly higher skill of both SMAP and SMOS-IC products especially when the
785 data were temporally collocated;

786 (ii) The performances of SM products related to systematic and random errors (i.e.
787 Bias and ubRMSE) varied strongly between products and locations, but with a
788 slightly higher skill of ESA CCI SM, SMOS-IC, and SMAP products. More
789 specifically, similar performances in terms of dryness or wetness with respect to
790 *in situ* observations were obtained over Australia and America, with the exception
791 of ESA CCI SM, regardless of the period or temporal collocation. The six
792 products did not agree in the sign of the Bias over Europe in all of the analyses
793 presented above. Bias strongly depends on the reference data sets and/or model
794 parameters used to determine the absolute SM conditions such as porosity data for
795 ASCAT or GLDAS Noah model for the ESA CCI SM products. Further research

796 on teasing out and quantifying systematic errors in satellite-based SM retrievals
797 should be recommended for the future;

798 (iii) When excluding SMAP from the analyses, SMOS-IC was correlating best to the
799 ISMN *in situ* observations and both ESA CCI SM and SMOS-IC presented the
800 lowest ubRMSE values;

801 (iv) The performance of SMOS-IC, in particular, seems highly impacted by RFI
802 (which is not the case for SMAP or to lesser extent) as indicated by the decrease
803 in correlations values for higher continent-averaged RFI values. RFIs may also to
804 some extent influence the ESA CCI product which integrates both SMOS and
805 AMSR-E/2;

806 (v) While the best performance (i.e. a better range of correlation values) of all
807 remotely-sensed products was found for stations located in Australia and Africa
808 (semi-arid environments), the worst and more diverse performances were found
809 over Europe (particularly SMOS) and cold climates; and

810 (vi) A complementarity between ASCAT, SMOS, ESA CCI SM, and SMAP satellite-
811 based SM products was demonstrated in this study given the none superiority of
812 any of them and the different performances of each product over different land
813 cover classes and climate conditions across the globe.

814 One should be very careful when trying to select the most skillful product, as the
815 performance of each product varies based on the period of evaluation, the evaluation
816 protocol, the data quality control, the number of data points and the study region. These
817 factors could favor one of the products over the others, as it was demonstrated in this study,
818 which makes it a challenge to draw firm conclusions. The SM community is actively working
819 on establishing common guidelines (Gruber et al., in review) for evaluating satellite-based SM

820 products, which should help future studies in the ranking of various SM products for various
821 applications.

822 **Acknowledgements**

823 This work was jointly supported by CNES (Centre National d'Etudes Spatiales) through
824 the TOSCA (Terre Océan Surfaces Continentales et Atmosphère) program and the
825 European Space Agency (ESA).

826 .

827 **References**

- 828 Al-Yaari, A., Wigneron, J.P., Ducharne, A., Kerr, Y., de Rosnay, P., de Jeu, R., Govind, A., Al Bitar, A.,
829 Albergel, C., Muñoz-Sabater, J., Richaume, P. & Mialon, A. (2014a). Global-scale evaluation
830 of two satellite-based passive microwave soil moisture datasets (SMOS and AMSR-E) with
831 respect to Land Data Assimilation System estimates. *Remote Sensing of Environment*, *149*,
832 181-195
- 833 Al-Yaari, A., Wigneron, J.P., Ducharne, A., Kerr, Y.H., Wagner, W., De Lannoy, G., Reichle, R., Al Bitar,
834 A., Dorigo, W., Richaume, P. & Mialon, A. (2014b). Global-scale comparison of passive
835 (SMOS) and active (ASCAT) satellite based microwave soil moisture retrievals with soil
836 moisture simulations (MERRA-Land). *Remote Sensing of Environment*, *152*, 614-626
- 837 Al-Yaari, A., Wigneron, J.P., Ducharne, A., Kerr, Y., Fernandez-Moran, R., Parrens, M., Bi-tar, A.A.,
838 Mialon, A. & Richaume, P. (2015). Evaluation of the most recent reprocessed SMOS soil
839 moisture products: Comparison between SMOS level 3 V246 and V272. In, *2015 IEEE*
840 *International Geoscience and Remote Sensing Symposium (IGARSS)* (pp. 2493-2496)
- 841 Al-Yaari, A., Wigneron, J.P., Kerr, Y., Rodriguez-Fernandez, N., O'Neill, P.E., Jackson, T.J., De Lannoy,
842 G.J.M., Al Bitar, A., Mialon, A., Richaume, P., Walker, J.P., Mahmoodi, A. & Yueh, S. (2017).
843 Evaluating soil moisture retrievals from ESA's SMOS and NASA's SMAP brightness
844 temperature datasets. *Remote Sensing of Environment*, *193*, 257-273
- 845 Al Bitar, A., Mialon, A., Kerr, Y.H., Cabot, F., Richaume, P., Jacqueline, E., Quesney, A., Mahmoodi, A.,
846 Tarot, S., Parrens, M., Al-Yaari, A., Pellarin, T., Rodriguez-Fernandez, N. & Wigneron, J.P.
847 (2017). The global SMOS Level 3 daily soil moisture and brightness temperature maps. *Earth*
848 *Syst. Sci. Data*, *9*, 293-315
- 849 Albergel, C., Rüdiger, C., Carrer, D., Calvet, J.-C., Fritz, N., Naeimi, V., Bartalis, Z. & Hasenauer, S.
850 (2009). An evaluation of ASCAT surface soil moisture products with in-situ observations in
851 Southwestern France. *Hydrology and Earth System Sciences*, *13*
- 852 Albergel, C., de Rosnay, P., Gruhier, C., Munoz-Sabater, J., Hasenauer, S., Isaksen, L., Kerr, Y. &
853 Wagner, W. (2012). Evaluation of remotely sensed and modelled soil moisture products
854 using global ground-based in situ observations. *Remote Sensing of Environment*, *118*, 215-
855 226
- 856 Bircher, S., Balling, J.E., Skou, N. & Kerr, Y.H. (2012). Validation of SMOS Brightness Temperatures
857 During the HOBE Airborne Campaign, Western Denmark. *IEEE Transactions on Geoscience*
858 *and Remote Sensing*, *50*, 1468-1482
- 859 Brocca, L., Hasenauer, S., Lacava, T., Melone, F., Moramarco, T., Wagner, W., Dorigo, W., Matgen, P.,
860 Martínez-Fernández, J., Llorens, P., Latron, J., Martin, C. & Bittelli, M. (2011). Soil moisture

861 estimation through ASCAT and AMSR-E sensors: An intercomparison and validation study
862 across Europe. *Remote Sensing of Environment*, 115, 3390-3408

863 Chan, S., Rajat Bindlish, Peggy O'Neill, Eni Njoku, Tom Jackson, Andreas Colliander, Fan Chen, Mariko
864 Burgin, Scott Dunbar, Jeffrey Piepmeier, Simon Yueh, Dara Entekhabi, Michael H. Cosh, Todd
865 Caldwell, Jeffrey Walker, Xiaoling Wu, Aaron Berg, Tracy Rowlandson, Anna Pacheco,
866 Heather McNairn, Marc Thibeault, José Martínez-Fernández, Ángel González-Zamora, Mark
867 Seyfried, David Bosch, Patrick Starks, David Goodrich, John Prueger, Michael Palecki, Eric E.
868 Small, Marek Zreda, Jean-Christophe Calvet, Wade T. Crow & Kerr, Y. (2016). Assessment of
869 the SMAP Passive Soil Moisture Product. *IEEE Transactions on Geoscience and Remote
870 Sensing*, 54, 4994 - 5007

871 Chen, F., Crow, W.T., Colliander, A., Cosh, M.H., Jackson, T.J., Bindlish, R., Reichle, R.H., Chan, S.K.,
872 Bosch, D.D., Starks, P.J., Goodrich, D.C. & Seyfried, M.S. (2017a). Application of Triple
873 Collocation in Ground-Based Validation of Soil Moisture Active/Passive (SMAP) Level 2 Data
874 Products. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*,
875 10, 489-502

876 Chen, T., McVicar, R.T., Wang, G., Chen, X., de Jeu, A.R., Liu, Y.Y., Shen, H., Zhang, F. & Dolman, J.A.
877 (2016). Advantages of Using Microwave Satellite Soil Moisture over Gridded Precipitation
878 Products and Land Surface Model Output in Assessing Regional Vegetation Water Availability
879 and Growth Dynamics for a Lateral Inflow Receiving Landscape. *Remote Sensing*, 8

880 Chen, Y., Yang, K., Qin, J., Cui, Q., Lu, H., La, Z., Han, M. & Tang, W. (2017b). Evaluation of SMAP,
881 SMOS, and AMSR2 soil moisture retrievals against observations from two networks on the
882 Tibetan Plateau. *Journal of Geophysical Research: Atmospheres*, 122, 5780-5792

883 Colliander, A., Jackson, T.J., Bindlish, R., Chan, S., Das, N., Kim, S.B., Cosh, M.H., Dunbar, R.S., Dang,
884 L., Pashaian, L., Asanuma, J., Aida, K., Berg, A., Rowlandson, T., Bosch, D., Caldwell, T., Caylor,
885 K., Goodrich, D., al Jassar, H., Lopez-Baeza, E., Martínez-Fernández, J., González-Zamora, A.,
886 Livingston, S., McNairn, H., Pacheco, A., Moghaddam, M., Montzka, C., Notarnicola, C.,
887 Niedrist, G., Pellarin, T., Prueger, J., Pulliainen, J., Rautiainen, K., Ramos, J., Seyfried, M.,
888 Starks, P., Su, Z., Zeng, Y., van der Velde, R., Thibeault, M., Dorigo, W., Vreugdenhil, M.,
889 Walker, J.P., Wu, X., Monerris, A., O'Neill, P.E., Entekhabi, D., Njoku, E.G. & Yueh, S. (2017).
890 Validation of SMAP surface soil moisture products with core validation sites. *Remote Sensing
891 of Environment*, 191, 215-231

892 Crow, W.T., Berg, A.A., Cosh, M.H., Loew, A., Mohanty, B.P., Panciera, R., Rosnay, P., Ryu, D. &
893 Walker, J.P. (2012). Upscaling sparse ground-based soil moisture observations for the
894 validation of coarse-resolution satellite soil moisture products. *Reviews of Geophysics*, 50

895 Derksen, C., Xu, X., Scott Dunbar, R., Colliander, A., Kim, Y., Kimball, J.S., Black, T.A., Euskirchen, E.,
896 Langlois, A., Loranty, M.M., Marsh, P., Rautiainen, K., Roy, A., Royer, A. & Stephens, J. (2017).
897 Retrieving landscape freeze/thaw state from Soil Moisture Active Passive (SMAP) radar and
898 radiometer measurements. *Remote Sensing of Environment*, 194, 48-62

899 Dorigo, W., de Jeu, R., Chung, D., Parinussa, R., Liu, Y., Wagner, W. & Fernández-Prieto, D. (2012).
900 Evaluating global trends (1988–2010) in harmonized multi-satellite surface soil moisture.
901 *Geophysical Research Letters*, 39, L18405

902 Dorigo, W., Wagner, W., Albergel, C., Albrecht, F., Balsamo, G., Brocca, L., Chung, D., Ertl, M., Forkel,
903 M., Gruber, A., Haas, E., Hamer, P.D., Hirschi, M., Ikonen, J., de Jeu, R., Kidd, R., Lahoz, W.,
904 Liu, Y.Y., Miralles, D., Mistelbauer, T., Nicolai-Shaw, N., Parinussa, R., Pratola, C., Reimer, C.,
905 van der Schalie, R., Seneviratne, S.I., Smolander, T. & Lecomte, P. (2017). ESA CCI Soil
906 Moisture for improved Earth system understanding: State-of-the art and future directions.
907 *Remote Sensing of Environment*, 203, 185-215

908 Dorigo, W.A., Wagner, W., Hohensinn, R., Hahn, S., Paulik, C., Xaver, A., Gruber, A., Drusch, M.,
909 Mecklenburg, S., van Oevelen, P., Robock, A. & Jackson, T. (2011). The International Soil
910 Moisture Network: a data hosting facility for global in situ soil moisture measurements.
911 *Hydrol. Earth Syst. Sci.*, 15, 1675-1698

912 Dorigo, W.A., Xaver, A., Vreugdenhil, M., Gruber, A., Hegyiová, A., Sanchis-Dufau, A.D., Zamojski, D.,
913 Cordes, C., Wagner, W. & Drusch, M. (2013). Global Automated Quality Control of In Situ Soil
914 Moisture Data from the International Soil Moisture Network. *Vadose Zone Journal*, 12

915 Dorigo, W.A., Gruber, A., De Jeu, R.A.M., Wagner, W., Stacke, T., Loew, A., Albergel, C., Brocca, L.,
916 Chung, D., Parinussa, R.M. & Kidd, R. (2015). Evaluation of the ESA CCI soil moisture product
917 using ground-based observations. *Remote Sensing of Environment*, 162, 380-395

918 Draper, C.S., Walker, J.P., Steinle, P.J., de Jeu, R.A.M. & Holmes, T.R.H. (2009). An evaluation of
919 AMSR-E derived soil moisture over Australia. *Remote Sensing of Environment*, 113, 703-710

920 Entekhabi, D., Njoku, E.G., O'Neill, P.E., Kellogg, K.H., Crow, W.T., Edelstein, W.N., Entin, J.K.,
921 Goodman, S.D., Jackson, T.J., Johnson, J., Kimball, J., Piepmeier, J.R., Koster, R.D., Martin, N.,
922 McDonald, K.C., Moghaddam, M., Moran, S., Reichle, R., Shi, J.C., Spencer, M.W., Thurman,
923 S.W., Leung, T. & Van Zyl, J. (2010). The Soil Moisture Active Passive (SMAP) Mission.
924 *Proceedings of the IEEE*, 98, 704-716

925 Escorihuela, M.J., Chanzy, A., Wigneron, J.P. & Kerr, Y.H. (2010). Effective soil moisture sampling
926 depth of L-band radiometry: A case study. *Remote Sensing of Environment*, 114, 995-1001

927 Famiglietti, J.S., Ryu, D., Berg, A.A., Rodell, M. & Jackson, T.J. (2008). Field observations of soil
928 moisture variability across scales. *Water Resources Research*, 44

929 FAO, IIASA, ISRIC, ISS-CAS & JRC (2012). Harmonized World Soil Database (version 1.2). FAO and
930 IIASA, Feb 2012. URL [http://web.archive.iiasa.ac.at/Research/LUC/External-World-soil-](http://web.archive.iiasa.ac.at/Research/LUC/External-World-soil-database/HWSD_Documentation.pdf)
931 [database/HWSD_Documentation.pdf](http://web.archive.iiasa.ac.at/Research/LUC/External-World-soil-database/HWSD_Documentation.pdf). [Accessed on 20 Nov 2018]

932 Fernandez-Moran, R., Wigneron, J.P., De Lannoy, G., Lopez-Baeza, E., Parrens, M., Mialon, A.,
933 Mahmoodi, A., Al-Yaari, A., Bircher, S., Al Bitar, A., Richaume, P. & Kerr, Y. (2017a). A new
934 calibration of the effective scattering albedo and soil roughness parameters in the SMOS SM
935 retrieval algorithm. *International Journal of Applied Earth Observation and Geoinformation*,
936 62, 27-38

937 Fernandez-Moran, R., Al-Yaari, A., Mialon, A., Mahmoodi, A., Al Bitar, A., De Lannoy, G., Rodriguez-
938 Fernandez, N., Lopez-Baeza, E., Kerr, Y. & Wigneron, J.-P. (2017b). SMOS-IC: An Alternative
939 SMOS Soil Moisture and Vegetation Optical Depth Product. *Remote Sensing*, 9

940 Friedl, M.A., Sulla-Menashe, D., Tan, B., Schneider, A., Ramankutty, N., Sibley, A. & Huang, X. (2010).
941 MODIS Collection 5 global land cover: Algorithm refinements and characterization of new
942 datasets. *Remote Sensing of Environment*, 114, 168-182

943 Gruber, A., Dorigo, W.A., Crow, W. & Wagner, W. (2017). Triple Collocation-Based Merging of
944 Satellite Soil Moisture Retrievals. *IEEE Transactions on Geoscience and Remote Sensing*, 55,
945 6780-6792

946 Gruber, A., Clement Albergel., Brian Barrett., Luca Brocca., Andreas Colliander., Michael Cosh, Wade
947 Crow, Richard de Jeu, Wouter Dorigo, Seyed Hamed Alemohammad, Martin Hirschi, A.K.,
948 William Lahoz, Alexander Loew, Kaighin McColl, Nadine Nicolai-Shaw, Robert Parinussa,
949 Chiara Pratola, Sonia Seneviratne, Chun-Hsu Su, Robin van der Schalie, Wolfgang Wagner. &
950 Zwieback, S. (in review). Validation practices for satellite soil moisture products - What are
951 (the) errors? *Remote Sens. Environ*

952 Holgate, C.M., De Jeu, R.A.M., van Dijk, A.I.J.M., Liu, Y.Y., Renzullo, L.J., Vinodkumar, Dharssi, I.,
953 Parinussa, R.M., Van Der Schalie, R., Gevaert, A., Walker, J., McJannet, D., Cleverly, J.,
954 Haverd, V., Trudinger, C.M. & Briggs, P.R. (2016). Comparison of remotely sensed and
955 modelled soil moisture data sets across Australia. *Remote Sensing of Environment*, 186, 479-
956 500

957 Jackson, T.J., Schmugge, T.J. & Wang, J.R. (1982). Passive microwave sensing of soil moisture under
958 vegetation canopies. *Water Resources Research*, 18, 1137-1142

959 Jackson, T.J., Bindlish, R., Cosh, M.H., Tianjie, Z., Starks, P.J., Bosch, D.D., Seyfried, M., Moran, M.S.,
960 Goodrich, D.C., Kerr, Y.H. & Leroux, D. (2012). Validation of Soil Moisture and Ocean Salinity
961 (SMOS) Soil Moisture Over Watershed Networks in the U.S. *Geoscience and Remote Sensing*,
962 *IEEE Transactions on*, 50, 1530-1543

963 Jacquette, E., Al Bitar, A., Cabot, F., Mialon, A., Richaume, P., Quesney, A. & Berthon, L. (2013).
964 CATDS SMOS L3 soil moisture retrieval processor Algorithm Theoretical Baseline Document
965 (ATBD). available at [http://www.cesbio.ups-tlse.fr/SMOS_blog/wp-](http://www.cesbio.ups-tlse.fr/SMOS_blog/wp-content/uploads/2013/08/ATBD_L3_rev2_draft.pdf)
966 [content/uploads/2013/08/ATBD_L3_rev2_draft.pdf](http://www.cesbio.ups-tlse.fr/SMOS_blog/wp-content/uploads/2013/08/ATBD_L3_rev2_draft.pdf) . Last access at:01/04/2015

967 Jones, L.A., Kimball, J.S., Reichle, R.H., Madani, N., Glassy, J., Ardizzone, J.V., Colliander, A., Cleverly,
968 J., Desai, A.R., Eamus, D., Euskirchen, E.S., Hutley, L., Macfarlane, C. & Scott, R.L. (2017). The
969 SMAP Level 4 Carbon Product for Monitoring Ecosystem Land–Atmosphere
970 CO₂ Exchange. *IEEE Transactions on Geoscience and Remote Sensing*, *55*, 6517-
971 6532

972 Jung, M., Reichstein, M., Schwalm, C.R., Huntingford, C., Sitch, S., Ahlström, A., Arneth, A., Camps-
973 Valls, G., Ciais, P., Friedlingstein, P., Gans, F., Ichii, K., Jain, A.K., Kato, E., Papale, D., Poulter,
974 B., Raduly, B., Rödenbeck, C., Tramontana, G., Viovy, N., Wang, Y.-P., Weber, U., Zaehle, S. &
975 Zeng, N. (2017). Compensatory water effects link yearly global land CO₂ sink changes to
976 temperature. *Nature*, *541*, 516

977 Kerr, Y.H., Waldteufel, P., Wigneron, J.P., Martinuzzi, J., Font, J. & Berger, M. (2001). Soil moisture
978 retrieval from space: the Soil Moisture and Ocean Salinity (SMOS) mission. *IEEE Transactions*
979 *on Geoscience and Remote Sensing*, *39*, 1729-1735

980 Kerr, Y.H., Waldteufel, P., Wigneron, J.P., Delwart, S., Cabot, F., Boutin, J., Escorihuela, M.J., Font, J.,
981 Reul, N., Gruhier, C., Juglea, S.E., Drinkwater, M.R., Hahne, A., Martin-Neira, M. &
982 Mecklenburg, S. (2010). The SMOS Mission: New Tool for Monitoring Key Elements of the
983 Global Water Cycle. *Proceedings of the IEEE*, *98*, 666-687

984 Kerr, Y.H., Waldteufel, P., Richaume, P., Wigneron, J.P., Ferrazzoli, P., Mahmoodi, A., Al Bitar, A.,
985 Cabot, F., Gruhier, C., Juglea, S.E., Leroux, D., Mialon, A. & Delwart, S. (2012). The SMOS Soil
986 Moisture Retrieval Algorithm. *IEEE Transactions on Geoscience and Remote Sensing*, *50*,
987 1384-1403

988 Kerr, Y.H., Al-Yaari, A., Rodriguez-Fernandez, N., Parrens, M., Molero, B., Leroux, D., Bircher, S.,
989 Mahmoodi, A., Mialon, A., Richaume, P., Delwart, S., Al Bitar, A., Pellarin, T., Bindlish, R.,
990 Jackson, T.J., Rüdiger, C., Waldteufel, P., Mecklenburg, S. & Wigneron, J.P. (2016). Overview
991 of SMOS performance in terms of global soil moisture monitoring after six years in
992 operation. *Remote Sensing of Environment*, *180*, 40-63

993 Kolassa, J., Reichle, R.H., Liu, Q., Alemohammad, S.H., Gentine, P., Aida, K., Asanuma, J., Bircher, S.,
994 Caldwell, T., Colliander, A., Cosh, M., Holifield Collins, C., Jackson, T.J., Martínez-Fernández,
995 J., McNairn, H., Pacheco, A., Thibeault, M. & Walker, J.P. (2018). Estimating surface soil
996 moisture from SMAP observations using a Neural Network technique. *Remote Sensing of*
997 *Environment*, *204*, 43-59

998 Koster, R.D., Dirmeyer, P.A., Guo, Z., Bonan, G., Chan, E., Cox, P., Gordon, C.T., Kanae, S., Kowalczyk,
999 E., Lawrence, D., Liu, P., Lu, C.-H., Malyshev, S., McAvaney, B., Mitchell, K., Mocko, D., Oki, T.,
1000 Oleson, K., Pitman, A., Sud, Y.C., Taylor, C.M., Verseghy, D., Vasic, R., Xue, Y. & Yamada, T.
1001 (2004). Regions of Strong Coupling Between Soil Moisture and Precipitation. *Science*, *305*,
1002 1138-1140

1003 Kottke, M., Grieser, J., Beck, C., Rudolf, B. & Rubel, F. (2006). World Map of the Köppen-Geiger
1004 climate classification updated. *Meteorologische Zeitschrift*, *15*, 259-263

1005 Liu, Y.Y., Dorigo, W.A., Parinussa, R.M., de Jeu, R.A.M., Wagner, W., McCabe, M.F., Evans, J.P. & van
1006 Dijk, A.I.J.M. (2012). Trend-preserving blending of passive and active microwave soil
1007 moisture retrievals. *Remote Sensing of Environment*, *123*, 280-297

1008 Masson, V., Champeaux, J.-L., Chauvin, F., Meriguet, C. & Lacaze, R. (2003). A Global Database of
1009 Land Surface Parameters at 1-km Resolution in Meteorological and Climate Models. *Journal*
1010 *of Climate*, *16*, 1261-1282

1011 Miralles, D.G., van den Berg, M.J., Gash, J.H., Parinussa, R.M., de Jeu, R.A.M., Beck, H.E., Holmes,
1012 T.R.H., Jiménez, C., Verhoest, N.E.C., Dorigo, W.A., Teuling, A.J. & Johannes Dolman, A.

1013 (2014a). El Niño–La Niña cycle and recent trends in continental evaporation. *Nature Clim.*
1014 *Change*, 4, 122-126

1015 Miralles, D.G., Teuling, A.J., van Heerwaarden, C.C. & Vila-Guerau de Arellano, J. (2014b). Mega-
1016 heatwave temperatures due to combined soil desiccation and atmospheric heat
1017 accumulation. *Nature Geosci*, 7, 345-349

1018 Mo, T., Choudhury, B.J., Schmugge, T.J., Wang, J.R. & Jackson, T.J. (1982). A model for microwave
1019 emission from vegetation-covered fields. *Journal of Geophysical Research: Oceans*, 87,
1020 11229-11237

1021 O' Neill, P., Chan, S., Bindlish, R., Jackson, T., Colliander, A., Dunbar, S., Chen, F., Piepmeier, J., Yueh,
1022 S., Entekhabi, D., Cosh, M., Caldwell, T., Walker, J., Wu, X., Berg, A., Rowlandson, T., Pacheco,
1023 A., McNairn, H., Thibeault, M., Martínez-Fernández, J., Á, G.-Z., Lopez-Baeza, E., Udall, F.,
1024 Seyfried, M., Bosch, D., Starks, P., Holifield, C., Prueger, J., Su, Z., Velde, R.v.d., Asanuma, J.,
1025 Palecki, M., Small, E., Zreda, M., Calvet, J.C., Crow, W. & Kerr, Y. (2017). Assessment of
1026 version 4 of the SMAP passive soil moisture standard product. In, *2017 IEEE International*
1027 *Geoscience and Remote Sensing Symposium (IGARSS)* (pp. 3941-3944)

1028 Oliva, R., Daganzo, E., Richaume, P., Kerr, Y., Cabot, F., Soldo, Y., Anterrieu, E., Reul, N., Gutierrez, A.,
1029 Barbosa, J. & Lopes, G. (2016). Status of Radio Frequency Interference (RFI) in the 1400–
1030 1427 MHz passive band based on six years of SMOS mission. *Remote Sensing of*
1031 *Environment*, 180, 64-75

1032 Parrens, M., Zakharova, E., Lafont, S., Calvet, J.C., Kerr, Y., Wagner, W. & Wigneron, J.P. (2012).
1033 Comparing soil moisture retrievals from SMOS and ASCAT over France. *Hydrology and Earth*
1034 *System Sciences*, 16, 423-440

1035 Parrens, M., Wigneron, J.-P., Richaume, P., Mialon, A., Al Bitar, A., Fernandez-Moran, R., Al-Yaari, A.
1036 & Kerr, Y.H. (2016). Global-scale surface roughness effects at L-band as estimated from
1037 SMOS observations. *Remote Sensing of Environment*, 181, 122-136

1038 Paulik, C., Dorigo, W., Wagner, W. & Kidd, R. (2014). Validation of the ASCAT Soil Water Index using
1039 in situ data from the International Soil Moisture Network. *International Journal of Applied*
1040 *Earth Observation and Geoinformation*, 30, 1-8

1041 Pierdicca, N., Luca, P., Fabio, F., Raffaele, C. & Marco, T. (2013). Analysis of two years of ASCAT- and
1042 SMOS-derived soil moisture estimates over Europe and North Africa. *EUROPEAN JOURNAL*
1043 *OF REMOTE SENSING*, 46, 759-773

1044 Pitman, A.J. (2003). The evolution of, and revolution in, land surface schemes designed for climate
1045 models. *International Journal of Climatology* 23, 479–510

1046 PUM (2016). Product User Manual (PUM) Soil Moisture Data Records, Metop ASCAT Soil Moisture
1047 Time Series. Doc. No: SAF/HSAF/CDOP2/PUM, v0.4, 2016.
1048 http://hsaf.meteoam.it/documents/PUM/SSM_ASCAT_DR_PUM_v0.4.pdf

1049 Reichle, R.H., De Lannoy, G.J.M., Liu, Q., Ardizzone, J.V., Colliander, A., Conaty, A., Crow, W., Jackson,
1050 T.J., Jones, L.A., Kimball, J.S., Koster, R.D., Mahanama, S.P., Smith, E.B., Berg, A., Bircher, S.,
1051 Bosch, D., Caldwell, T.G., Cosh, M., González-Zamora, Á., Holifield Collins, C.D., Jensen, K.H.,
1052 Livingston, S., Lopez-Baeza, E., Martínez-Fernández, J., McNairn, H., Moghaddam, M.,
1053 Pacheco, A., Pellarin, T., Prueger, J., Rowlandson, T., Seyfried, M., Starks, P., Su, Z., Thibeault,
1054 M., van der Velde, R., Walker, J., Wu, X. & Zeng, Y. (2017). Assessment of the SMAP Level-4
1055 Surface and Root-Zone Soil Moisture Product Using In Situ Measurements. *Journal of*
1056 *Hydrometeorology*, 18, 2621-2645

1057 Rodell, M., Houser, P.R., Jambor, U., Gottschalck, J., Mitchell, K., Meng, C.J., Arsenault, K., Cosgrove,
1058 B., Radakovich, J., Bosilovich, M., Entin, J.K., Walker, J.P., Lohmann, D. & Toll, D. (2004). The
1059 Global Land Data Assimilation System. *Bulletin of the American Meteorological Society*, 85,
1060 381-394

1061 Rodríguez-Fernández, J.N., Kerr, H.Y., van der Schalie, R., Al-Yaari, A., Wigneron, J.-P., de Jeu, R.,
1062 Richaume, P., Dutra, E., Mialon, A. & Drusch, M. (2016). Long Term Global Surface Soil

1063 Moisture Fields Using an SMOS-Trained Neural Network Applied to AMSR-E Data. *Remote*
1064 *Sensing, 8*

1065 Rubel, F., Brugger, K., Haslinger, K. & Auer, I. (2017). The climate of the European Alps: Shift of very
1066 high resolution Köppen-Geiger climate zones 1800–2100. *Meteorologische Zeitschrift, 26*,
1067 115-125

1068 Sahoo, A.K., Houser, P.R., Ferguson, C., Wood, E.F., Dirmeyer, P.A. & Kafatos, M. (2008). Evaluation
1069 of AMSR-E soil moisture results using the in-situ data over the Little River Experimental
1070 Watershed, Georgia. *Remote Sensing of Environment, 112*, 3142-3152

1071 Saxton, K.E. & Rawls, W.J. (2006). Soil Water Characteristic Estimates by Texture and Organic Matter
1072 for Hydrologic Solutions. *Soil Science Society of America Journal, 70*, 1569-1578

1073 Seneviratne, S.I., Corti, T., Davin, E.L., Hirschi, M., Jaeger, E.B., Lehner, I., Orlowsky, B. & Teuling, A.J.
1074 (2010). Investigating soil moisture–climate interactions in a changing climate: A review.
1075 *Earth-Science Reviews, 99*, 125-161

1076 Seneviratne, S.I., Wilhelm, M., Stanelle, T., van den Hurk, B., Hagemann, S., Berg, A., Cheruy, F.,
1077 Higgins, M.E., Meier, A., Brovkin, V., Claussen, M., Ducharne, A., Dufresne, J.-L., Findell, K.L.,
1078 Ghattas, J., Lawrence, D.M., Malyshev, S., Rummukainen, M. & Smith, B. (2013). Impact of
1079 soil moisture-climate feedbacks on CMIP5 projections: First results from the GLACE-CMIP5
1080 experiment. *Geophysical Research Letters, 40*, 5212-5217

1081 Su, C.-H., Ryu, D., Young, R.I., Western, A.W. & Wagner, W. (2013). Inter-comparison of microwave
1082 satellite soil moisture retrievals over the Murrumbidgee Basin, southeast Australia. *Remote*
1083 *Sensing of Environment, 134*, 1-11

1084 Wagner, W., Lemoine, G. & Rott, H. (1999). A Method for Estimating Soil Moisture from ERS
1085 Scatterometer and Soil Data. *Remote Sensing of Environment, 70*, 191-207

1086 Wagner, W., Hahn, S., Kidd, R., Melzer, T., Bartalis, Z., Hasenauer, S., Figa-Saldaña, J., de Rosnay, P.,
1087 Jann, A., Schneider, S., Komma, J., Kubu, G., Brugger, K., Aubrecht, C., Züger, J., Gangkofner,
1088 U., Kienberger, S., Brocca, L., Wang, Y., Blöschl, G., Eitzinger, J. & Steinnocher, K. (2013). The
1089 ASCAT Soil Moisture Product: A Review of its Specifications, Validation Results, and Emerging
1090 Applications. *Meteorologische Zeitschrift, 22*, 5-33

1091 Wigneron, J.P., Waldteufel, P., Chanzy, A., Calvet, J.C. & Kerr, Y. (2000). Two-Dimensional Microwave
1092 Interferometer Retrieval Capabilities over Land Surfaces (SMOS Mission). *Remote Sensing of*
1093 *Environment, 73*, 270-282

1094 Wigneron, J.P., Kerr, Y., Waldteufel, P., Saleh, K., Escorihuela, M.J., Richaume, P., Ferrazzoli, P., de
1095 Rosnay, P., Gurney, R., Calvet, J.C., Grant, J.P., Guglielmetti, M., Hornbuckle, B., Mätzler, C.,
1096 Pellarin, T. & Schwank, M. (2007). L-band Microwave Emission of the Biosphere (L-MEB)
1097 Model: Description and calibration against experimental data sets over crop fields. *Remote*
1098 *Sensing of Environment, 107*, 639-655

1099 Wigneron, J.P., Jackson, T.J., O'Neill, P., De Lannoy, G., de Rosnay, P., Walker, J.P., Ferrazzoli, P.,
1100 Mironov, V., Bircher, S., Grant, J.P., Kurum, M., Schwank, M., Munoz-Sabater, J., Das, N.,
1101 Royer, A., Al-Yaari, A., Al Bitar, A., Fernandez-Moran, R., Lawrence, H., Mialon, A., Parrens,
1102 M., Richaume, P., Delwart, S. & Kerr, Y. (2017). Modelling the passive microwave signature
1103 from land surfaces: A review of recent results and application to the L-band SMOS & SMAP
1104 soil moisture retrieval algorithms. *Remote Sensing of Environment, 192*, 238-262
1105
1106