Towards improved spatio-temporal resolution soil moisture retrievals from the synergy of SMOS and MSG SEVIRI spaceborne observations

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Abstract

Earth Observation (EO) technology is today at a maturity level that allows deriving operational estimates of Surface Soil Moisture (SSM) from a variety of sensors; yet, such products are provided at present at a coarse spatial and/or temporal resolution, which restricts their use in local or regional scale studies and practical applications. Herein, a methodology to derive SSM estimates from space at previously unattained spatio-temporal resolutions is proposed. The method is based on a variant of the “triangle” inversion technique leveraging on the strengths and synergies of SMOS (Soil Moisture and Ocean Salinity mission) microwave observations and geostationary optical/infrared data. The SSM retrieval technique allows for: i) enhancing the spatial resolution of SMOS SSM product estimates to 3 km spatial resolution, and, ii) providing a temporal average daytime SM product from the instantaneous fine-scale SSM estimates acquired every 15 minutes; the latter is allowing higher coverage in presence of clouds and representativeness (up to 96 estimates per day) in comparison to the instantaneous estimate at the time of satellite overpass.

The proposed technique has been implemented to SMOS and MSG (Meteosat Second Generation) SEVIRI (Spinning Enhanced Visible and Infrared Imager) observations acquired over the Iberian Peninsula and Southern France during year 2011. SSM instantaneous estimates at the time of SMOS overpass and daytime-averaged SSM estimates have been obtained and evaluated separately against collocated in-situ measurements acquired from a total of 40 stations belonging to the REMEDHUS, VAS and SMOSMANIA permanent soil moisture measurement networks. Statistical agreement between compared datasets has

29 been evaluated both at individual stations and considering the network average on the basis of several
30 statistical terms computed including correlation, bias, root-mean-squared errors and slope and
31 intercept of linear regression. Results showed that the proposed method not only preserves the quality
32 of SMOS SSM at finer spatial scales, but also allows achieving higher temporal coverage and
33 representativeness in daytime averages. The synergy of SMOS and SEVIRI provides a pathway to
34 enhance water cycle EO capabilities taking full advantage of the new observational records of SSM and
35 operational geostationary information.

36

37 **Keywords:** *soil moisture, SMOS, MSG SEVIRI, synergy, downscaling, temporal resolution, spatial resolution*

38

39 1. INTRODUCTION

40 Accurate monitoring of Earth's terrestrial water and energy cycles is today critically important to many
41 hydrological applications such as global food production, assessment of water resources sustainability,
42 flood, drought, and climate change prediction [Wood et al., 2011]. In this regard, global information on
43 the spatio-temporal variation of parameters such as surface soil moisture (SSM) is of key significance.
44 SSM is a key state variable of the hydrological cycle that governs most physical processes dominant in
45 the Earth system and exerts a strong control not only on the water cycle but also in ecosystem
46 functioning [Riveros-Iregui et al., 2012; Shen et al., 2014]. It controls the partitioning of available energy
47 at the ground surface into sensible and latent heat exchange through evaporation and transpiration
48 processes and on the allocation of precipitation into runoff, subsurface flow and infiltration
49 [Petropoulos et al., 2014; GOSIC 2015]. Changes in soil moisture may also have a very serious impact on
50 agricultural productivity, forestry, and ecosystem health. Monitoring SSM is therefore critical in both
51 managing natural resources and in improving our understanding of land surface physical processes and
52 Earth system interactions. Thus, justifiably, being able to provide accurate information on the spatio-
53 temporal variability of SSM is of paramount importance [North et al., 2015].

54 In the last few decades, Earth Observation (EO) technology has played an increasingly important role in
55 determining SSM. There have been many efforts to obtain an accurate understanding of soil moisture
56 distribution at different spatial and temporal scales, utilising information from different types of
57 spaceborne sensors [Zhao and Li, 2013, see also recent review by Petropoulos et al., 2015]. There are at
58 present three globally distributed operational products for the retrieval of SSM from space, which all
59 exploit EO data acquired from microwave instruments. The European Space Agency's (ESA) Soil
60 Moisture and Ocean Salinity (SMOS) mission is the first passive L-band microwave space mission
61 dedicated to globally measure the Earth's SSM. Since the end of 2009, it provides ~ 35 km SSM estimates
62 every 3 days with a target accuracy of $0.04 \text{ m}^3 \text{ m}^{-3}$. The spatial resolution of SMOS is adequate for many
63 global applications, but restricts the use of the data in regional studies over land, where a resolution of
64 1–10 km is needed [Piles et al., 2011]. Soil moisture information is also being retrieved from active

65 microwave sensors, specifically from ESA's Advanced Scatterometer (ASCAT), which was launched in
66 2006 aboard MetOp-A satellite [Oschner et al., 2013]. ASCAT is a C-band active radar operating at 5.255
67 GHz which produces SSM estimates with a spatial resolution of 50 km and 25 km (resampled to 25 km
68 and 12.5 km grids in the swath geometry), and a temporal resolution of 3 days [Wagner et al., 2013].
69 However, C-band observations are not optimal for soil moisture retrieval as they are sensitive to a
70 shallower soil layer than L-band observations and are more significantly affected by vegetation
71 attenuation [Panciera et al., 2014]. The recently launched Soil Moisture Active Passive (SMAP) satellite
72 utilises combined passive (radiometer) and active (radar) microwave instruments at L-band to provide
73 measurements of near-surface soil moisture (0–5 cm depth) and land freeze/thaw condition over a
74 1000 km swath with a global revisit of 2–3 days. The dual sensor SMAP profits from the specific
75 advantages of each microwave instrument, allowing for a higher spatio-temporal resolution SSM dataset
76 in comparison to either individual passive (typically coarse resolution) or active (typically low temporal
77 resolution) sensors. However, operations of active-passive products ceased abruptly with the failure of
78 the SMAP radar after about ten weeks of operations.

79 Despite the breadth of EO sensors currently in orbit and the promising accuracies reported by different
80 techniques measuring SSM from space, the primary challenges in using existing operational SSM data
81 remain. Perhaps the key challenge is that the spatial and/or temporal support volumes do not
82 sufficiently represent the spatio-temporal dynamics/variations and uncertainties of SSM at small scales
83 [Oschner et al., 2013; Barrett and Petropoulos, 2013]. Many hydrological applications require
84 information on soil moisture at sub-daily temporal resolutions, where this time-dependent data is
85 needed to initialise and update forecast, storm water management, flood or hydrological models.
86 Therefore, there is a requirement for the development of EO synergistic approaches that allow
87 providing SSM information at the requisite spatio-temporal scale for the monitoring of hydrological
88 processes and applications [Petropoulos et al., 2015].

89 Many studies have recently focused on exploring the complementarity and interchangeability between
90 different EO data and modelling approaches aiming at offering a potential solution to decompose (or

91 disaggregate) passive microwave SSM estimates to higher spatial or temporal resolutions, particularly
92 based on the synergy with visible, infrared and thermal information [Merlin et al., 2010; Piles et al.
93 2011;2014; Sánchez-Ruiz et al., 2014]. In this respect, these methods exploit the relationships that exist
94 between optically-derived estimates of surface temperature (LST), vegetation index (VI), and
95 microwave-based soil moisture. One of the key advantages of this group of approaches is that they
96 potentially overcome the limitations (or combines the advantages) of the use of optical or microwave
97 data alone for soil moisture retrieval [Petropoulos et al., 2015]. Whereas optical measurements are
98 available at high spatial and temporal resolutions, the optical signal is significantly affected by soil
99 physical properties, has limited ability to penetrate vegetation and is highly attenuated by the Earth's
100 atmosphere. Microwave observations, in turn, allow for direct estimation of soil moisture under all-
101 weather conditions but needs parameterisation of vegetation properties and is available at low spatial
102 and temporal coverage resolution. In this regard, optical-microwave synergistic approaches provide an
103 optimal blend of spatial resolution and accuracy for soil moisture retrieval. Furthermore, these
104 approaches have shown they can potentially provide an easier transformation between instantaneous
105 and daytime averaged fluxes, highlighting the potential application of these methods for the operational
106 estimation of SSM, which has been underlined by a number of investigators [Fontanelli et al., 2012;
107 Petropoulos and Carlson, 2010; Piles et al., 2014]. Indeed, a variant of the LST/VI method has already
108 been subject of research investigations aiming at developing operational estimates of SSM from the
109 National Polar-orbiting Operational Environmental Satellite System (NPOESS) and its use has already
110 been demonstrated using 1 km AVHRR and 25 km SSM/I data (Chauhan et al., 2003). Another variant
111 has been used to improve the spatial resolution of SMOS-derived SSM estimates using MODIS data [Piles
112 et al., 2011; 2014].

113 The SMOS downscaling algorithm first presented in Piles et al. [2011] utilises a combination of SMOS
114 brightness temperatures with higher resolution VIS/IR data from MODIS via an extension of the
115 “triangle” technique to obtain operational estimates of SSM at 1 km spatial resolution that are at present
116 available for the Iberian Peninsula [Piles et al, 2014]. These maps have routinely been used in forest fire
117 prevention services since 2012 [Piles et al., 2013, Chaparro et al., 2015a], and have been shown to be

118 useful in a variety of other applications, such as Gross Primary Productivity estimation [Sánchez-Ruiz et
119 al., 2015], and forest die-off prediction models [Chaparro et al., 2015b]. This synergistic concept has also
120 been applied to downscale SMOS/MODIS to 500 m using a SWIR-based VI [Sánchez-Ruiz et al., 2014],
121 and to retrieve very high spatial resolution soil moisture from hyperspectral optical, thermal and
122 microwave L-band airborne observations [Sánchez et al., 2014]. Although this technique is able to
123 provide SSM estimates at 1 km spatial resolution, its temporal resolution depends on the presence of
124 clouds, which mask MODIS observations, and is therefore limited in its temporal capability. Polar-
125 orbiting satellites, such as NASA's Terra/Aqua, provide a limited number of MODIS images of a given
126 site on a daily basis (up to a maximum of 4 per day). Geostationary meteorological satellites, in turn,
127 provide data every 15', greatly increasing the possibilities of having clear-sky conditions at a given site
128 on a daily basis [Zhang et al., 2014].

129 In the present study, a methodology for deriving SSM maps from EO data at previously unattained
130 spatio-temporal resolutions is proposed. The approach is based on the synergistic use of EO data from
131 the MIRAS-SMOS and SEVIRI-MSG instruments and it allows to: (1) enhance the spatial resolution of the
132 SMOS SSM estimates to 3 km spatial resolution, and, (2) provide a temporal extrapolation of the
133 instantaneous fine-scale downscaled SSM estimates acquired every 15 minutes from SMOS between 6
134 a.m. to 6 p.m. to a "daytime SSM" estimate. The proposed algorithm has been applied to SMOS/SEVIRI
135 observations acquired over the Iberian Peninsula and Southern France covering a complete calendar
136 year (2011). Validation of the derived SSM maps has been undertaken against collocated *in-situ*
137 measurements from REMEDHUS (Spain), Vas (Spain) and SMOSMANIA (France) permanent soil
138 moisture measurement networks, utilising ground measurements acquired from a total of 40 stations.
139 Those were selected carefully to represent a variety of climatic, topographic and environmental
140 conditions and allow for the inclusion of contrasting conditions.

141

142 **2. DATASETS (IN-SITU, SATELLITE, ANCILLARY) DESCRIPTION & PRE-PROCESSING**

143 *2.1 ISMN soil moisture: REMEDHUS, SMOSMANIA and VAS*

144 *In-situ* soil moisture was obtained from REMEDHUS, SMOSMANIA and VAS *in-situ* monitoring networks
145 through the International Soil Moisture Network (ISMN, Dorigo et al., 2011). The locations of the *in situ*
146 networks used for this study are presented in Fig. 1.

147

148 <Insert Figure 1 here>

149

150 REMEDHUS is composed of 23 automated soil moisture monitoring stations located in an area of 1300
151 km² in a semi-arid sector of the Duero basin in Spain (Figure 1) (41.1° to 41.5° N, and 5.1° to 5.7° W).
152 Each station within the network is equipped with capacitance probes (Hydra Probes of Stevens Water
153 Monitoring System, Inc.) installed horizontally at a depth of 5 cm, integrating measurements over a
154 depth of 0-5 cm with a reported accuracy of 0.003 m³ m⁻³. This dataset provides a continuous
155 measurement of soil moisture each hour. The homogeneity of the area makes it ideal for the validation
156 of all kinds of soil moisture products as shown in the use of this network in a number of validation
157 exercises. Data from the REMEDHUS network have also been used previously to study the spatial and
158 temporal dynamics of soil moisture [Martínez-Fernandez and Ceballos, 2003] and for satellite product
159 validation [Ceballos et al., 2005; Liu et al., 2011; Parinussa et al., 2011]. The land use is mainly
160 agricultural, consisting primarily of rainfed cereals grown in winter and spring (78%), irrigated crops in
161 summer (5%), and perennial vineyards (3%) and forest-pasture areas (13%). This area is nearly flat
162 (less than 12% slope) and ranges from 700 to 900 m. a. s. l. The regional climate is continental semi-arid
163 Mediterranean with an average annual precipitation of 385 mm and a mean temperature of 12°C
164 [Sánchez et al., 2012]. More details on the equipment installed at the stations can be found in Sanchez et
165 al. [2012]. For the time period included in this study (i.e. year 2011), data from 19 REMEDHUS stations
166 were available (out of the 23).

167 SMOSMANIA is a long-term data acquisition network based on the existing automatic weather station
168 network of Meteo-France (RADOME - Réseau d'Acquisition de Données d'Observations Météorologiques
169 Etendu). Twenty one existing stations of RADOME in southwestern France were chosen for inclusion in
170 the SMOSMANIA project. The network consists of a 400 km transect based on 21 automatic weather

stations (the average distance between two neighbouring stations is approximately 40 km) forming a Mediterranean-Atlantic gradient equipped with 4 capacitance probes (ThetaProbe ML2X of Delta-T Devices) at each site measuring soil moisture at four different depths (5, 10, 20, and 30 cm). Stations have obtained data since January 2007 with a 12 minute time step. The vegetation cover at those sites consists of natural fallow, harvested once or twice a year, where the area is relatively flat (except for 3 sites with an altitude above 500 ma.s.l.) [Calvet et al., 2007; Albergel et al., 2008]. Data from the top soil 5 cm over the year 2011 were used in this study. Measurements taken by this network have been extensively used for validating various satellite-based soil moisture products [Albergel et al., 2009, 2010; Li et al., 2010; Brocca et al., 2011; Liu et al., 2011; Parinussa et al., 2011]. Data from a total of 19 SMOSMANIA stations were used herein.

The Valencia Anchor Station (VAS) network is comprised of 3 stations established in 2001 by The University of Valencia as a robust automatic meteorological station located towards the North-West part of the Utiel-Requena Plateau in the Valencia region, close to the town of Caudete de las Fuentes (39°3 N, 1°1W) at about 80 km from the city of Valencia [López-Baeza et al., 2003]. The network represents a reasonably homogeneous and mostly flat area of about 50×50 km². The main land cover type is vineyards, about 56%, followed by trees, shrubs, forest, industrial and urban. Beside the vineyard growing season, the area remains mostly under bare soil conditions. The climate oscillates between semi-arid and dry-sub-humid with annual mean temperatures variations from 12 °C to 14.2°C and annual precipitation variations between 396 mm to 451 mm [Juglea et al., 2010]. Two VAS stations soil moisture measurements acquired with capacitance probes (Hydra Probes and Theta Probes ML2X) from the top soil 5 cm over the year 2011 were used in this study.

As already noted above, the half-hourly SSM observations acquired at the surface layer (0-5 cm) for the year 2011 were obtained for the above (40 in total) ISMN sites. For each day, the *in situ* soil moisture at SMOS morning overpass time (6 a.m.) was extracted. Subsequently, the *in situ* half-hourly observations registered from 6 a.m. to 6 p.m. were averaged to match SMOS/SEVIRI daytime average soil moisture estimates. It should be noted that if any hourly granules for the period between 6 a.m. to 6 p.m. were missing or contained an error value, these days were excluded from any further analysis.

198

199 2.2 SMOS L3 soil moisture

200 The ESA SMOS mission was launched on 2 November 2009 as the second Earth Explorer Opportunity
201 mission to be developed as part of ESA's Living Planet Programme. This polar orbiting satellite operates
202 in a sun-synchronous orbit at a mean altitude of 758 km and an inclination of 98.44°, with a spatial
203 resolution of 40-50 km operating through a dusk-down orbit with a 3 day revisit at the equator [Kerr et
204 al., 2010]. The Microwave Imaging Radiometer with Aperture Synthesis (MIRAS) is the main instrument
205 onboard the SMOS platform which records emitted energy from the Earth's surface in the microwave L-
206 band (1.4 GHz) with the aim of providing soil moisture estimates at accuracies better than 0.04 m³ m⁻³.
207 The SMOS BEC L3 daily global soil moisture product v.1 from the Barcelona Expert Center (BEC) was
208 used in this study. It is available in netCDF format through the CP34-BEC web service ([http://cp34-
209 bec.cmima.csic.es/](http://cp34-bec.cmima.csic.es/)), and is obtained through quality filtering and binning the ESA's SMUDP2 product
210 (v5.51) to a regular grid; the original L2 estimates with negative soil moisture values and/or DQX values
211 greater than 0.07 are discarded, and a weighted average is applied to bin the data to a 25 km EASE-ML
212 regular grid [see further details in González-Zamora et al, 2015]. This SMOS product includes
213 geophysical parameters, a theoretical estimate of their accuracy, and a set of product flags and
214 descriptors. A comprehensive evaluation of this product using two complementary small-scale and
215 large-scale *in-situ* networks and a surface water balance model was performed in González-Zamora et al.
216 [2015]. Results showed that SMOS BEC L3 soil moisture estimates were consistent with SMOS L2 and *in-*
217 *situ* measurements in the time series comparisons, with Pearson's correlation coefficients (R) and an
218 Agreement Index (AI) higher than 0.8 for the total average and the land-use averages and higher than
219 0.85 for the soil-texture averages.

220

221 2.3 SEVIRI LST, FVC

222 SEVIRI is a geostationary orbit optical imaging radiometer which serves as the main payload on-board
223 the MSG satellite. This is a co-funded space mission between the European Space Agency (ESA) and

224 EUMETSAT. SEVIRI has 12 spectral channels, consisting of three Visible and Near-InfraRed (VNIR)
225 channels (centered at 0.6, 0.8 and 1.6 μm), eight InfraRed (IR) channels (centred at 3.9, 6.2, 7.3, 8.7, 9.7,
226 10.8, 12.0 and 13.4 μm) and one visible broadband channel (at 0.5–0.9 μm) called the High Resolution
227 Visible channel (HRV). The satellite provides image data at 3 km spatial resolution at the sub-satellite
228 point (nadir) for standard channels, and at 1 km for the HRV channel, providing permanent visible and
229 infrared imaging of the Earth's disc, over 4 specific geographical regions (Europe, Africa - North_Africa
230 and South_Africa- and South America), with a baseline repeat cycle of 15 minutes [Aminou 2002;
231 Sobrino and Romaguera, 2004]. A series of operational products from SEVIRI are provided by
232 EUMETSAT such as Land Surface Temperature (LST) and Fractional Vegetation Cover (FVC). Those are
233 distributed by the Land Surface Analysis Satellite Applications Facility (LSA SAF;
234 <http://landsaf.meteo.pt/>).

235 The retrieval of SEVIRI LST is based on clear-sky measurements from the MSG system in the thermal
236 infrared window (IR 10.8 and 12.0 μm MSG/SEVIRI channels) and has been generated on an operational
237 basis since February 2005 for the European region and since July 2005 for the whole Meteosat disk. The
238 main algorithm for LST estimation is based on a Generalized Split Window (GSW) that uses the
239 difference between two adjacent window channels to correct the atmospheric absorption [Caselles et
240 al., 1997]. Theoretically, LST values can be determined 96 times per day from MSG but in practice fewer
241 observations are available due to cloud cover. For this study, the SEVIRI LST product was downloaded
242 for the Euro region of the Meteosat disk for the year 2011. For each time-slot and geographical region,
243 the LST field and respective Quality Control (QC) data was acquired in Hierarchical Data Format (HDF5)
244 and HDF5 file attributes [LSA-SAF 2015].

245 The SEVIRI FVC product is generated daily at the full spatial resolution of the MSG/SEVIRI instrument (3
246 km). The product is computed using as input the three short-wave channels (VIS 0.6 μm , NIR 0.8 μm ,
247 SWIR 1.6 μm) and a parametric BRDF (Bi-directional Reflectance Distribution Function) model [Roujean
248 et al. 1992]. In the product, fractional vegetation cover amount is expressed as percentage (%), ranging
249 from 0 to 100%, corrected from uncertainty derived of the view/sun angles and also the anisotropy

250 effects of surface reflectance in the SEVIRI image. The FVC product includes routine quality check and
251 error estimates. Herein, the SEVIRI FVC product was downloaded for the Euro region of the Meteosat
252 disk for the year 2011. For each day and geographical region, the FVC product, its error estimate and the
253 processing flag were acquired in Hierarchical Data Format (HDF5) file attributes [LSA-SAF 2015].

254 All the acquired SEVIRI datasets were reprojected from Normalized Geostationary Projection (NGP) to a
255 regular latitude/longitude grid and tailored from the full disk image to the study region (34°-45°N,
256 11°W-5°E). Subsequently, each image was subsetting to cover only the countries on which the
257 experimental sites were located. All these steps were implemented using Matlab routines available.

258

259 **3. SPATIO-TEMPORAL DOWNSCALING**

260 *3.1 Physical Properties of the LST/VI Scatterplot Domain in respect to SSM*

261 The LST/VI methods, including the “triangle” inversion modelling technique, have their basis in the
262 relationships obtained between SSM, a satellite-derived Vegetation Index (VI), such as the FVC, and LST,
263 when plotted in a two-dimensional scatterplot. Provided that cloudy and water pixels have been masked
264 out and that there is a full variability of FVC cover in the acquired satellite data, in such a scatterplot, a
265 triangular/trapezoidal-shape has been shown to emerge. This is the result of the low sensitivity of LST
266 to variations of SSM over vegetated areas, but its increased sensitivity (and thus greater spatial
267 variation) over areas of bare soil. In this triangular/trapezoidal space, the dry (warm) and wet (cold)
268 edges provide important boundary conditions for the contextual LST-VI (or FVC) relationship. The
269 theoretical “dry edge” is the triangular space boundary representing maximum soil water-limiting
270 conditions for the plant canopy, characterised by maximum water stress derived from limiting
271 conditions of soil moisture or evapotranspiration. In contrast, the “wet edge” is the LST-VI space
272 boundary for pixels representative of maximum soil wetness conditions or surfaces with limited or no
273 water stress. Based on these specific boundary conditions, SSM can be derived for any given satellite

274 pixel and a range of techniques have been proposed to do so exploiting a wide range of appropriate EO
275 data [see review by Petropoulos et al., 2009].

276 3.2 Algorithm for SSM estimation at high spatio-temporal resolution using SMOS and SEVIRI data

277 In this study, the potential use of the SEVIRI LST/VI sensitivity to estimate soil moisture variations
278 within a coarse-scale SMOS pixel is evaluated. To do so, an algorithm for soil moisture estimation at MSG
279 high spatio-temporal resolution (3 km, 15 minutes), exploiting the synergies between SMOS and SEVIRI
280 observations has been developed. It builds upon the algorithm used for the operational SMOS/MODIS 1
281 km soil moisture product available at BEC. Details concerning the implementation of this technique are
282 available in Piles et al. [2014]. The proposed technique consists of a semi-empirical model that links
283 SMOS- and SEVIRI-derived information from a specific day and scene to SSM as follows:

$$284 \quad \quad \quad \Sigma \quad \quad \quad \Sigma$$

285 (1)

286
287 where LST is SEVIRI normalized LST, FVC is SEVIRI Fractional Vegetation Cover, and $T_{BH\theta_i}$ and $T_{BV\theta_i}$ are
288 normalized horizontal and vertically polarized brightness temperatures, respectively, at incidence
289 angles θ_i of 32.5°, 42.5° and 52.5°. Normalization of land surface and brightness temperatures is
290 performed between the minimum and maximum values registered within the study area per
291 overpass/acquisition.

292 Parameters in the model are represented in the two spatial scales under consideration (i.e. SMOS 25 km
293 and SEVIRI 3 km): LST and FVC are aggregated to 25 km and $T_{BH\theta_i}$ and $T_{BV\theta_i}$ are resampled at 3 km. The
294 model is first applied at low resolution for all image pixels using SMOS L3 as soil moisture reference at
295 coarse-scale to determine the coefficients. Subsequently, the model is applied at high resolution using
296 the obtained coefficients to estimate the fine-scale SMOS-derived soil moisture.

297 SMOS/SEVIRI instantaneous SSM estimates can be temporally averaged to achieve higher coverage (in
298 case the presence of clouds masks SEVIRI data) and representativeness (up to 48 estimates per pixel
299 can be obtained for SMOS ascending and SEVIRI daytime, with a total of 96 per day). Also, an estimate of

the daytime average SSM value is considered of more practical use in many applications in comparison to the instantaneous estimate [Barrett and Petropoulos, 2013]. Different combinations of available SMOS and MODIS images were composited into a temporally averaged downscaled soil moisture estimate in a previous study, as a first step towards increasing the spatio-temporal coverage in SSM data [Merlin et al., 2012]. It is hypothesized the availability of high frequency SEVIRI observations will allow for improved coverage and robust daily mean soil moisture estimates, with respect to the use of polar orbiting satellites. Also, the high temporal frequency of the estimates paves the way for the development of gap-filling approaches for complete coverage [Dumedah et al., 2014; Turlapaty et al., 2012; Wang et al., 2012]. In this regard, both the instantaneous and the temporally-averaged SSM estimates could prove useful depending on the application. Hence, in this study SMOS ascending (6 a.m.) and SEVIRI daytime (6 a.m. to 6 p.m.) observations from year 2011 are used to generate a data set of SSM instantaneous estimates at the time of SMOS overpass (hereafter L4 instant) and a data set of SSM average values from 6 a.m. to 6 p.m. (hereafter L4 daytime). The performance of the two retrievals is evaluated separately from comparison with *in-situ* data. Also, the number of observations per pixel used to obtain the daytime averages is registered to evaluate the minimum number of SEVIRI snapshots required to obtain a representative daytime estimate.

316

317 4. STATISTICAL ANALYSIS

Three time-series of SSM derived from the EO data were compared to *in-situ* data from the 40 ISMN stations: 1) SMOS L3 SSM at 6 a.m. and 25 km spatial resolution, 2) SMOS/SEVIRI SSM at 6 a.m. at 3 km spatial resolution (L4 instant), and 3) SMOS/SEVIRI SSM average from 6 a.m. to 6 p.m. observations at 3 km spatial resolution (L4 daytime).

The spatial resolution enhancement is evaluated with SMOS L3 and SMOS/SEVIRI L4 instant data sets (Section 5.1). The agreement of the two data sets against the collocated *in-situ* data was evaluated based on direct point-by-point comparisons of date-pixel pairs available for both L3 and L4 instant data sets at every *in situ* station (n=40). Selecting *in situ*, L3 and L4 instant series based only on spatial and

temporally concurrent data (i.e., same sample size for all image products) ensures a fair comparison between datasets. In addition, a dedicated analysis to evaluate the efficiency, precision, and accuracy of the downscaling approach has been performed.

The spatio-temporal resolution enhancement is evaluated with the L4 daytime product (Section 5.2); for every *in situ* station, all averaged measurements acquired from 6 a.m. to 6 p.m. are compared with their corresponding L4 daytime, i.e. the average of the available SMOS/SEVIRI instantaneous SSM estimates from 6 a.m. to 6 p.m. An additional analysis was performed using the L4 daytime data set to evaluate the minimum number of SEVIRI observations per pixel (i.e. cloud-free snapshots) required to ensure the representativeness of the daytime estimate. The accuracy of L4 daytime SSM series was analysed separately at every *in situ* station for days with different percentage coverage: 0-24%, 25-49%, 50-74% and 75-100%.

An analysis of the three SSM time series at the network scale (Section 5.3) is also performed to ensure that the agreement of the fine-scale soil moisture is not due to a representative issue (i.e. an *in situ* probe being more representative of the 1 km surrounding it, than of the 25 km surrounding it). When network averages are used, all the 3 km and 25 km pixels over *in situ* stations are averaged.

Eight statistical performance assessment metrics were used to evaluate the agreement between satellite and *in situ* measurements (Table 1). These included the Root Mean Square Difference (RMSD), the unbiased or centered RMSD (cRMSD), the Pearson's Correlation Coefficient (R), the bias (*in-situ* minus estimated), the scatter or standard deviation, (Entekhabi et al., 2010). The p-value at 95% and 99% confidence level was used to determine the series with non-significant correlation. These statistical metrics have also been widely used in similar validation experiments carried out previously (e.g. Falge et al. 2005; Giertz et al., 2006; Marshall et al., 2013). In addition, the slope *a* and intercept *b* of a robust regression are computed using iterative re-weighted least squares (Street et al., 1988), which is less influenced by the outliers than the ordinary least squares fit. Three dedicated metrics (G_EFFI, G_PREC, G_ACCU) to evaluate the performance of the downscaling algorithm have also been computed (Merlin et al., 2015). G_EFFI characterizes the efficiency of the disaggregation method; if the downscaling

352 approach is efficient, the slope between satellite retrievals and *in situ* soil moisture should increase and
353 be closer to one in the disaggregation case, relative to the non-disaggregation case ($G_EFFI > 0$). The
354 precision of a downscaling algorithm can be seen as the degree to which repeated application under
355 unchanged conditions shows the same downscaled value; the gain in precision can be estimated as the
356 gain in R ($G_PREC > 0$). Finally, the gain in accuracy in the downscaling algorithm can be seen as the
357 improvement in the bias obtained with *in situ* data ($G_ACCU > 0$).

358 *<Insert Table 1 here>*

359 **5. RESULTS**

360 Two sample L4 instant and L4 daytime SSM maps are shown for a dry day (July 31st 2011) and a wet day
361 (December 27th 2011) over the central part of the Duero basin, including the REMEDHUS network
362 (Figure 2). For the dry period (Figure 2, top), the L4 maps clearly show higher soil moisture content
363 near the main rivers. This pattern reflects the irrigated plots close to the rivers (see also Figure 1).
364 These areas are typically well watered during the summer, when the growing cycle of the irrigated plots
365 (corn, sugarbeet) takes place. Also, the wettest areas in this period are found in the south, coinciding
366 with the forested areas of the Sistema Central range (see the location map in Figure 1). This effect is
367 reinforced in the wet period (Figure 2, bottom), where this wet pattern is extended and amplified.
368 Significant differences can be seen between the two products during the wet period. The higher soil
369 moisture content obtained in L4 daytime most probably integrates rain events in the area during the
370 time lapse between 6 a.m. to 6 p.m., which are not captured by the L4 instant. This hypothesis was
371 supported as well by the records of precipitation at this day from two rain gauge stations of the Spanish
372 Meteorological Agency located in the southern area of the map, which registered 0.2 mm at 11 a.m. The
373 spatial and temporal patterns of SSM are consistent for the two products, but a slightly higher dynamic
374 range can be detected in the L4 instant (Figure 2 a). These qualitative differences are quantified in the
375 statistical analysis hereafter.

376 *<Insert Fig. 2 here>*

377

378 5.1 Spatial resolution enhancement: SMOS/SEVIRI SSM instantaneous measurements

379 The comparison of SMOS L3, SMOS/SEVIRI L4 instant and collocated *in-situ* measurements at 6 a.m.
380 from three representative stations of low water content (07-REMEDHUS), high water content
381 (Narbonne-SMOSMANIA), and intermediate water content (Melbex1-VAS) for year 2011 are shown in
382 Fig. 3. The evolution of soil moisture trends reveals that both coarse and fine scale SSM estimates agree
383 well with *in situ* measurements and generally follow the dry-downs and wetting-up events. The scatter
384 plots of L3 and L4 instant vs. *in situ* SSM (Figure 3, right), in turn, show that there is a good
385 correspondence between satellite and ground-based SSM estimates, with SMOS L3 providing to some
386 extent a better agreement in terms of slope in Melbex1 and Narbonne (closer to the 1:1 line) and the L4
387 instant showing an improved correlation in 07. This underlines and quantifies what has already been
388 shown with the temporal plots: the L4 instant product preserves the quality of the SMOS L3 product
389 whilst improving its spatial representation through integration of SEVIRI LST/FVC information.

390 <Insert Fig. 3 here>

391 The detailed statistical results from comparison with the 40 ISMN stations are displayed in Tables 2 and
392 3 for SMOS L3 AND SMOS/SEVIRI L4 instant, respectively. Comparing the two tables, it can be observed
393 that L3 and L4 instant have a similar performance in terms of root mean squared errors (RMSD and
394 cRMSD), with small differences leading to half of the stations showing slightly smaller errors for L3
395 (mostly in SMOSMANIA) and the other half for L4 instant (mostly in REMEDHUS and VAS). The bias of
396 L3 is mostly positive (dry bias), suggesting an underestimation of the remotely sensed product in
397 comparison to the in-situ (reference dataset). Notably, 13 out of 19 stations in REMEDHUS, 16 out of 19
398 in SMOSMANIA and the two VAS stations show a dry bias. This SMOS L3 dry bias is consistent with
399 recent and on-going calibration studies on SMOS coarse-resolution data at a variety of sites, which
400 indicates a general underestimation of SMOS retrievals with respect to 0-5 cm soil moisture
401 measurement [Al Bitar et al., 2012; Gherboudj et al, 2012; González-Zamora 2015]. The dry bias in the
402 L3 product was generally stressed in SMOSMANIA (the network with the highest soil moisture content)

403 but, when the series were unbiased (cRMSD), the performance of the L3 product was similar in the
404 three networks.

405 The improvement of slope, correlation and bias of the L4 instant product with respect to the SMOS L3 is
406 quantified through the G_EFFI, G_PREC and G_ACC metrics (in Table 3). These gains indicate what
407 stations result in an improvement of the associated statistics after the downscaling (positive gain sign,
408 indicated in bold in Table 3), and to what extent (the larger the gain value, the higher the degree of
409 improvement). A positive gain means that the downscaling improves the spatial representativeness of
410 SSM data at the validation scale, relative to the low-resolution data (Merlin et al., 2015). Taking these
411 metrics as a reference, 20 out of 40 stations present an improvement in efficiency (slope), 26 show an
412 improvement in precision (R) and 19 reflect an improvement in accuracy (bias). Considering these
413 three metrics, more than 80 % of the stations (precisely 33 out of 40 stations) present improved
414 statistics at the fine-scale.

415 The improvement of the temporal correlation and slope of linear regression of the L4 with respect to L3
416 should be particularly highlighted. Also, some stations in REMEDHUS and SMOSMANIA had an
417 unreasonable bias (bigger than $0.15 \text{ m}^3 \text{ m}^{-3}$) in the two products, probably related with irrigation supply
418 at these particular plots (Sánchez et al., 2012; Liu et al, 2014).

419 *<Insert Tables 2, 3 here>*

420 To assess the downscaling performance separately from the SMOS/SEVIRI synergy at high (3 km) and
421 low (25 km) resolution, a comparison between 25 km resolution aggregated L4 SMOS/SEVIRI soil
422 moisture and the original 25 km resolution L3 SMOS soil moisture was made through G_EFFI, G_ACCU
423 and G_PREC (Table 4). First, it is noticeable that the L4 aggregated product behaves similarly to the high
424 resolution L4 in terms of R (better than L3) and root-mean-squared errors (similar to L3). Second, the
425 gain analysis shows comparable results to the L4 high resolution (Table 3), i.e., 18 out of 40 stations
426 improved the efficiency, 25 showed an improvement in precision and 21 reflect an improvement in
427 accuracy. This indicates that the proposed downscaling scheme not only provides a better

428 representativeness of the resulting product owing its better resolution, but also allows for a
429 qualitatively improvement due to the inclusion of SEVIRI data.

430 <Insert Table 4 here>

431 5.2 Spatio-temporal downscaling: SMOS/SEVIRI SSM daytime composites

432 The comparison of instantaneous L4 daytime and collocated *in situ* measurements from three
433 representative stations of low water content (07-REMEDIHUS), high water content (Narbonne-
434 SMOSMANIA), and intermediate water content (Melbex1-VAS) are shown in Fig. 4. From the time-
435 evolution plots, it can be seen that L4 daytime follows the range and temporal dynamics of the *in situ*
436 daytime measurements at station 07, and shows a general underestimation at Narbonne, in line with
437 results for L3 and L4 instant on Fig. 3. The slope obtained for the L4 daytime estimates (Fig. 4, right) are
438 closer to the 1:1 line than with the L4 instant (Fig. 3, right).

439 <Insert Fig. 4 here>

440 The statistical results from comparison with the 40 ISMN stations are displayed in Table 5 for
441 SMOS/SEVIRI L4 daytime. Note that the daytime average is computed with *in situ* data using all
442 measurements acquired from 6 a.m. to 6 p.m. but with the satellite data only with the cloud-free
443 snapshots during this time lapse. Hence, this analysis is focused on assessing how representative a
444 daytime composite is of the mean soil moisture conditions.

445 Comparing the two L4 estimates (Tables 3 and 5), it is clear that L4 instant showed better correlations
446 than L4 daytime in most of the stations. Regarding the errors and bias statistics, a smaller cRMSD is
447 obtained for the L4 instant ($0.022 \text{ m}^3 \text{ m}^{-3} < \text{cRMSD} < 0.121 \text{ m}^3 \text{ m}^{-3}$) than for L4 daytime ($0.044 \text{ m}^3 \text{ m}^{-3} <$
448 $\text{cRMSD} < 0.146 \text{ m}^3 \text{ m}^{-3}$). As expected, the accuracy of the instantaneous product is higher than that of the
449 time-integrated, since the representativeness of L4 daytime highly depends on the cloud-free snapshots
450 that can contribute to the daytime average.

451 <Insert Table 5 here>

452 The number of SSM instantaneous estimates per 3 km pixel used to obtain the L4 daytime product was
453 registered as ancillary information with the retrievals. This information has been used to evaluate the
454 minimum number of observations required to obtain a representative daytime estimate. To do so, the
455 L4 daytime product was divided into four thresholds dependent on the percentage of SEVIRI snapshots
456 with data: 0-24%, 25-49%, 50-74%, 75-100%. Subsequently, R and cRMSD statistics were computed for
457 each station and threshold. Results for the 9 stations that have significant correlation at a 95% in the
458 four-percentage coverage considered are shown in Fig. 6. As a general trend, it is seen that higher R are
459 obtained for coverages greater than 25% and lower cRMSD are obtained for coverages greater than
460 50%. These results suggest that the high temporal resolution of SEVIRI not only allows increasing the
461 possibility of cloud-free conditions for a given region, but also provides more accurate temporally-
462 averaged SSM estimates. The 0-24% coverage was significant in 14 out of the 40 ISMN stations, whereas
463 the other percentages were significant in 26-30 stations. As perhaps would be expected, the stations
464 with at least a 25% daytime SEVIRI coverage provide a representative averaged SSM estimate in a
465 higher number of locations.

466 *<Insert Fig. 5 here>*

467 These results suggest that the information on sub-hourly scale variability in LST from SEVIRI (LST being
468 the only parameter in Eq. 1 that varies from 6 a.m. to 6 p.m.) has an important impact on the estimated
469 SSM. Indeed, the correlation between SEVIRI land surface temperature and soil moisture is expected to
470 vary at the hourly scale during the day (Pablos et al., 2014). Further work would be directed towards
471 the validation of the methodology at the time step of SEVIRI and to the analysis of the SSM- LST
472 relationship dependence on season and time of the day.

473 **5.3 Overview of SSM time series at the network scale**

474 The comparison of network averages is summarised in Fig. 6 and Table 6. Scatter plots are shown for
475 instantaneous (left column) and daytime (right column) remotely sensed vs. *in situ* measurements.
476 These scatter plots follow the same pattern that that of the individual stations, i.e., a slight
477 underestimation of the observed soil moisture and a good fit between series, slightly worse for the L4

daytime estimations. Again, since SMOSMANIA is the wettest area, its slope is around 0.5, and its bias and cRMSD is the highest of the three networks (Table 6). Results for network averages are consistent with results at individual stations, with L4 instant providing improved R and cRMSD over REMEDHUS and VAS networks. Statistical results for REMEDHUS (first row) and VAS (third row) are comparable to the ones shown in Fig. 3 and 4 for stations O7 and Melbex 1, respectively. This can be explained by the fact that these two networks cover an area of approximately one SMOS pixel and can be considered relatively homogeneous. The SMOSMANIA network covers a wider area of ~40 SMOS pixels, and results shown for Narbonne station in Figs. 4 and 5 differ to the ones obtained for the network average in Fig. 6. In particular, cRMSD are higher and the slopes of the linear regression are lower for the network average than for the individual stations. This fact can also explain the better fit of REMEDHUS and VAS than SMOSMANIA for all products.

< Insert Fig. 6 here >

It is important to note that different sensors in each network (ThetaProbe ML2X from Delta-T Devices in SMOSMANIA and VAS vs. Hydraprobes from Stevens Inc. for REMEDHUS and VAS) may lead to a certain bias in the comparisons presented. Even though both have the same principle measurement (capacitance probes), and that site-specific calibration curves were developed using *in situ* gravimetric soil samples in each network, their comparative accuracy and performance in different field scenarios may need to be investigated when used altogether (Albergel et al. 2012). This could particularly explain the lower performance of both L4 and L3 over SMOSMANIA stations, together with topographic and possible irrigation effects.

The better agreement of SMOS/SEVIRI L4 than SMOS L3 to *in situ* shown in sections 5.1 and 5.2 might be due to high resolution SSM estimates being more representative of a SSM point measurement than coarse resolution estimates. Indeed, the representativeness of the *in situ* measurements appears to have a clear impact in the validation, especially over highly heterogeneous sites. Nonetheless, as has been shown in this section, the results obtained at individual stations are also confirmed using network averages. These results support that the proposed synergistic approach not only improves the spatial

504 representation of the soil moisture data down to 3 km, but also allows for obtaining representative soil
505 moisture averages at the spatial scales of ~40 km (VAS and REMEDHUS) and ~1000 km (SMOSMANIA).

506

507 **6. DISCUSSION AND CONCLUSIONS**

508 This study has explored the potential for obtaining high spatio-temporal soil moisture mapping from the
509 combination of SMOS and SEVIRI remotely sensed observations. A synergistic technique has been
510 presented that allows estimating instantaneous soil moisture every 15' at 3 km spatial resolution from
511 spaceborne data. The instantaneous SMOS/SEVIRI SSM estimates are of special interest for hydrological
512 modelling and applications where information on SSM at high spatio-temporal resolution may be used
513 to initialise and update forecasts, storm water management, flood or hydrological models. Also,
514 evidently, they have the potential to be temporally averaged if the purpose is to achieve higher coverage
515 (in case the presence of clouds masks SEVIRI data) and representativeness (up to 48 estimates per pixel
516 can be obtained for SMOS ascending and SEVIRI daytime). In this study, the instantaneous SSM
517 estimates acquired at the time of SMOS morning overpass (6 a.m., L4 instant) and the SSM daytime
518 average (computed with observations available from 6 a.m. to 6 p.m., L4 daytime) have been validated
519 using a year of SMOS and SEVIRI observations over the Iberian Peninsula and Northern France. A
520 comprehensive validation has been undertaken using collocated *in situ* measurements from three
521 permanent soil moisture networks: REMEDHUS, VAS and SMOSMANIA acquired over a full year (2011).
522 The performances of the downscaling approach and the disaggregated soil moisture maps were
523 evaluated separately using a series of statistical metrics.

524 Results from statistical analysis at individual stations showed that combining SMOS/SEVIRI into L4
525 instant SSM estimates preserves the quality of the SMOS L3 product whilst improving its spatial
526 representation. The two products have a similar performance in terms of root-mean squared errors. L3
527 generally underestimated the ground-based measurements of soil moisture (Table 2), as previously
528 observed with the L2-derived L3 products (González-Zamora et al. 2015) and L2 itself (Sánchez et al.,
529 2012; dall'Amico et al., 2012). This dry bias is also present in the L4 product, and generally stressed in

530 SMOSMANIA (the network with the highest soil moisture content). When the series were unbiased
531 (cRMSD), the performance of L3 and L4 were similar in the three networks. The same trends were
532 obtained when the statistical analysis were performed independently for each product with all the dates
533 available (not shown).

534 Specific performance metrics were used to assess the gain in efficiency, precision and accuracy after the
535 downscaling at high (3km) and low (25 km aggregated) resolutions (Merlin et al., 2015). Results for L4
536 instant show that 20 out of 40 stations present an improvement in efficiency (slope), 26 present an
537 improvement in precision (R) and 19 present an improvement in accuracy (bias). The results obtained
538 for L4 instant aggregated are comparable (18 stations with improved efficiency, 25 with improved R
539 and 21 with improved bias). Hence, taking these metrics as reference, the downscaling has improved
540 the spatial representativeness of SSM data from 25 to 3 km in more than 80% of the stations. These
541 results suggest that the synergistic SMOS/SEVIRI retrieval approach proposed herein provides a
542 pathway for an improved SSM characterization, in comparison to using SMOS data alone.

543 This work explored as well the feasibility of soil moisture spatio-temporal downscaling. To do so, SSM
544 was estimated at the temporal resolution of the MSG geostationary platform (15') and used to compose
545 a daytime average with increased coverage in case of clouds. Results from comparison with individual
546 stations showed that L4 daytime provides a representative estimate of *in-situ* measurements (Fig. 6,
547 Table 5), with coverage higher than 25% leading to higher R and coverage higher than 50% lead to
548 lower cRMSD (Fig. 6). As expected, L4 instant provides more accurate SSM estimates than L4 daytime
549 when a minimum coverage is not imposed. Still, the higher performance of L4 instant versus L4 daytime
550 can also be influenced by the fact that at 6 a.m. the weather conditions are very stable (lack of neither
551 insolation nor evaporation/evapotranspiration). Indeed, the correlation between *in-situ* soil moisture at
552 6 a.m. and the daily average *in-situ* in the studied networks is very high (R=0.96 for both REMEDHUS
553 and VAS and R=0.91 for SMOSMANIA). Hence, in no-rain conditions the L4 instant product at 6 a.m. is
554 representative of average daily conditions. Further research should be directed towards the analysis of

555 the SSM-LST relationship dependence on time of the day and its impact in the disaggregated SSM
556 estimates.

557 Results from Fig. 3 and Table 3 showed that L4 instant obtained from SMOS/SEVIRI is comparable to the
558 SSM estimates obtained from SMOS/MODIS (Piles et al, 2014; Sánchez-Ruiz et al., 2014). Hence, by
559 combining SMOS with a geostationary satellite it was shown that instantaneous SSM estimates of similar
560 quality than when using a polar satellite can be provided. One of the main advantages of using SEVIRI
561 VIS/IR information to enhance passive microwave data versus the use of polar orbiting satellites (e.g.
562 MODIS) is the increase of the number of potential observations. More importantly, it was shown that an
563 averaged SSM value with higher coverage can be obtained and that the SSM evolution every 15' can be
564 potentially estimated. Further research may be directed towards exploring the SSM instantaneous
565 measurements obtained at the sub-daily scale with the aim of providing robust composites and also at
566 studying the added value of the high frequency observations in highly dynamic SSM contexts such as an
567 irrigated field or intense rain events.

568 The inter-comparison of the three remotely sensed SSM series (L3, L4 instant and L4 daytime) at the
569 network scale was also presented in this study (Fig. 6, Table 6). The results obtained at individual
570 stations for each product are confirmed using network averages, supporting that the synergistic
571 retrievals allows for synoptic soil moisture retrievals at different spatial scales (3, 40 and 1000 km).
572 Regarding the comparison of L3 and L4 instant, result for network averages over REMEDHUS and VAS
573 are consistent to those obtained for individual stations, with L4 instant providing higher R and
574 comparable cRMSD. In contrast, results for SMOSMANIA reveal a lower R and higher bias and mean
575 squared errors for L4 in regards to L3. This result suggests that the spatial variability of soil moisture
576 fields across SMOSMANIA is perhaps not captured by simple linear spatial average of point-based
577 measurements (Crow et al., 2002). It is important to note that whereas REMEDHUS and VAS stations are
578 distributed within the area of a SMOS pixel, SMOSMANIA provides sparse ground-based measurements
579 covering an area of approximately 40 SMOS pixels. This different network topology may also explain the

580 degraded accuracy of the estimates obtained in SMOSMANIA in all the statistical analyses with respect
581 to REMEDHUS and VAS.

582 The analysis of the daily spatial correlation between SMOS-derived and *in-situ* SSM estimates to show
583 spatial coherency of remotely sensed maps is debatable due to both the mismatch of point vs. footprint
584 scales and the difficulty of having a sufficient number of estimates at a temporal snapshot to obtain
585 significant results (González-Zamora et al, 2015). A land surface model may be useful to bridge this gap
586 and further analyze the spatial variability of remotely sensed SSM estimates. An in-depth comparison of
587 the SSM spatial structures that are resolved by SMOS and by a land surface model was presented in
588 (Polcher et al, 2015). Results showed a good temporal correlation between modeled and remotely
589 sensed SSM but a poor match of spatial co-variances, probably due to disagreements found in the
590 effective inertia of the soil moisture reservoir (SMOS observing a shallower and faster soil moisture
591 reservoir than the model). In this regard, the proposed method could provide an interesting data set of
592 remotely sensed SSM estimates at high spatial resolution but also at the sub-daily scale to offer more
593 insight in the comparisons of remotely sensed, *in-situ*, and modeled SSM. A continuous effort in this
594 direction is needed to support the use of remote sensing SSM in data assimilation schemes for improved
595 weather forecasts and climate predictions (Seneviratne et al., 2010).

596 Variability in atmospheric conditions and land surface characteristics impacts the variability in soil
597 moisture at different spatial scales. Previous experimental studies have reported two separate scales of
598 variation of soil moisture, one smaller scale, dominated by land surface variations, and a second larger
599 scale, influenced by meteorological processes (Entin et al., 2000, Brocca et al., 2007, Lakhankar et al.,
600 2010). In this regard, the proposed model captures the spatial variability in land surface conditions at
601 the higher spatial resolution of the SEVIRI data (i.e. Ts, FVC), and the influence of atmospheric
602 conditions, determined by precipitation and evaporation patterns at the SMOS larger scale (i.e.
603 brightness temperatures). The downscaling technique can therefore be potentially implemented at any
604 area size covered under the field of view of the required input satellite data. However, the impact of
605 non-linear interactions between the canopy, the soil and the atmospheric circulation, caused by

606 changing atmospheric or landscape conditions and not captured by the proposed semi-empirical model
607 may certainly place a limit to the extension of the area used to apply the methodology. Further
608 investigation into the relationships of optical and microwave observations and derived parameters at
609 different spatial scales could help resolving this question.

610 Our study contributes towards on-going efforts aimed at developing a global operational SSM product
611 applicable at the spatio-temporal resolution required in a wide spectrum of application and research
612 studies. The method proposed herein offers a very promising potential to allow for the first time
613 monitoring of the Earth's SSM at previously unattained spatial and temporal resolutions, and
614 consequently transform the way we utilize EO data to obtain a better understanding of Earth's water
615 and energy cycles. The latter is today one of the key research priorities to be addressed by the global
616 scientific community. Likewise, the EO-based SSM products developed and presented in this study open
617 potentially a new pathway for the development of applications using EO data at previously unattained
618 spatio-temporal resolutions, greatly increasing the scientific and societal return of the economic
619 investment in space missions.

620

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628

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Table 1. Statistical measures computed to evaluate the agreement between satellite and *in situ* soil moisture measurements and the performance of the downscaling approach. $E[\cdot]$ is the expectation operator, σ_{sat} is the standard deviation of satellite measurements θ_{sat} , $\sigma_{in-situ}$ is the standard deviation of in situ measurements $\theta_{in-situ}$, a is the slope of the linear regression between satellite and in situ soil moisture. Subscripts L3 and L4 indicate statistics associated to SMOS L3 and SMOS/SEVIRI L4 products.

Name	Description	Mathematical Definition
bias/ B	Mean bias	$bias = E[\theta_{sat}] - E[\theta_{in-situ}]$
R	Linear time series correlation	$R = \frac{E[(\theta_{sat} - E[\theta_{sat}])(\theta_{in-situ} - E[\theta_{in-situ}])]}{\sigma_{sat}\sigma_{in-situ}}$
RMSD	Root Mean Square Difference	$RMSD = \sqrt{E[(\theta_{sat} - \theta_{in-situ})^2]} = \sqrt{\sigma_{sat}^2 + \sigma_{in-situ}^2 - 2 \cdot r \cdot \sigma_{sat} \cdot \sigma_{in-situ} + B^2}$
cRMSD	Unbiased or Centred RMSD	$cRMSD = \sqrt{\sigma_{sat}^2 + \sigma_{in-situ}^2 - 2 \cdot r \cdot \sigma_{sat} \cdot \sigma_{in-situ}}$
G_{EFFI}	Dissagregation efficiency gain	$G_{EFFI} = \frac{ 1 - a_{L3} - 1 - a_{L4} }{ 1 - a_{L3} + 1 - a_{L4} }$
G_{PREC}	Dissagregation precision gain	$G_{PREC} = \frac{ 1 - R_{L3} - 1 - R_{L4} }{ 1 - R_{L3} + 1 - R_{L4} }$
G_{ACCU}	Dissagregation accuracy gain	$G_{ACCU} = \frac{ B_{L3} - B_{L4} }{ B_{L3} + B_{L4} }$

Table 2. Summary of the statistical metrics (R, RMSD, cRMSD, bias, slope a and intercept b of the linear regression, and number of observations N) for the individual comparisons between the SMOS L3 against concurrent *in situ* observations at each network. Stations with not-significant correlation at 0.05/0.01 confidence level are indicated by */** respectively.

REMEDHUS	R	RMSD	cRMSD	bias	a	b	N
E10	0.80	0.075	0.040	-0.063	2.249	0.042	48
F6	0.26	0.085	0.063	0.058	0.492	-0.013	59
H7	0.56	0.065	0.051	-0.041	3.531	-0.037	56
H9	0.66	0.238	0.135	0.196	0.178	0.008	63
H13	0.73	0.056	0.039	0.040	0.590	-0.002	64
I6	0.78	0.072	0.044	-0.056	3.817	0.019	80
J3	0.74	0.067	0.041	-0.052	2.278	0.031	78
J12	0.76	0.194	0.041	0.190	0.567	-0.085	64
K4	0.78	0.057	0.040	-0.040	2.351	0.002	80
K9	0.25	0.069	0.052	0.045	0.272	0.028	60
K10	0.59	0.055	0.041	-0.037	1.301	0.025	63
K13	0.65	0.135	0.050	0.125	0.459	-0.027	66
L3	0.58	0.044	0.043	0.012	1.080	-0.021	80
L7	0.78	0.106	0.047	0.095	0.500	-0.019	67
M5	0.49	0.057	0.051	0.025	0.843	-0.006	26
M9	0.77	0.105	0.036	0.099	0.491	-0.026	60
M13	0.46	0.175	0.111	0.136	0.156	0.035	47
N9	0.61	0.093	0.046	0.081	0.430	-0.007	65
O7	0.80	0.032	0.030	0.010	0.764	0.005	62
SMOSMANIA							
Barnas *	0.35	0.133	0.046	0.125	0.356	0.004	8
Berzeme **	0.85	0.109	0.032	0.104	1.112	-0.126	12
Condom	0.57	0.184	0.043	0.179	0.556	-0.052	47
Creond	0.66	0.046	0.038	0.025	0.758	0.003	43
Lahas	0.45	0.144	0.084	0.118	0.300	0.065	53
Lezignan	0.81	0.080	0.037	-0.071	1.286	0.049	46
Mazan *	0.24	0.234	0.094	0.214	0.113	0.049	6
Mejannes	0.67	0.107	0.073	0.078	0.335	0.041	43
Montaut	0.75	0.181	0.064	0.169	0.344	0.009	43
Mouthoumet	0.66	0.078	0.054	0.056	0.855	-0.039	51
Narbonne	0.58	0.065	0.065	-0.002	0.760	0.045	59
Peyrusse	0.55	0.122	0.052	0.110	0.483	0.015	57
Pezenas	0.80	0.079	0.075	-0.024	1.265	-0.024	60
Prades	0.60	0.080	0.066	0.046	0.885	-0.031	34
Sabres	-0.47	0.083	0.055	0.063	-0.266	0.086	3
SaintFelix	0.41	0.116	0.055	0.102	0.797	-0.045	19
Savenes	0.68	0.058	0.047	0.034	0.712	0.010	56
Urgons	0.69	0.195	0.085	0.175	0.296	0.040	54
Villevielle	0.83	0.071	0.059	0.040	0.653	0.021	50
VAS							
Melbex1	0.87	0.043	0.037	0.021	1.068	-0.025	32
Melbex2	0.76	0.106	0.053	0.092	0.908	-0.085	28

Table 3. Summary of the statistical metrics (R, RMSD, cRMSD, bias, slope a and intercept b of the linear regression, and number of observations N) for the individual comparisons between the SMOS L4 instant and concurrent *in situ* observations at each network. Stations with not-significant correlation at 0.05/0.01 confidence level are indicated by */** respectively. Gains of the downscaling procedure (G_EFFI, G_PREC, G_ACCU) at the 3 km scale with respect to the SMOS L3 product are also shown. Bold indicates positive gain.

REMEDHUS	R	RMSD	cRMSD	bias	a	b	N	G_EFFI	G_PREC	G_ACC
E10	0.75	0.106	0.050	-0.093	2.51	0.068	48	-0.096	-0.121	-0.195
F6	0.47	0.069	0.061	0.031	0.76	-0.019	59	0.363	0.161	0.302
H7	0.51	0.090	0.061	-0.066	3.98	-0.026	56	-0.083	-0.054	-0.239
H9	0.77	0.210	0.121	0.171	0.28	0.011	63	0.069	0.205	0.067
H13	0.79	0.043	0.040	0.017	0.89	-0.007	64	0.601	0.126	0.404
I6	0.75	0.088	0.049	-0.072	3.38	0.034	80	0.083	-0.056	-0.126
J3	0.83	0.081	0.042	-0.070	2.43	0.046	78	-0.058	0.220	-0.141
J12	0.82	0.173	0.037	0.169	0.74	-0.107	64	0.261	0.144	0.057
K4	0.74	0.072	0.044	-0.057	2.19	0.019	80	0.063	-0.077	-0.173
K9 *	0.18	0.066	0.062	0.024	0.17	0.057	60	-0.060	-0.047	0.306
K10	0.62	0.073	0.047	-0.056	1.63	0.035	63	-0.355	0.036	-0.200
K13	0.75	0.113	0.046	0.103	0.69	-0.048	66	0.282	0.162	0.096
L3	0.59	0.045	0.045	-0.005	0.91	-0.001	80	-0.010	0.022	0.423
L7	0.82	0.081	0.043	0.069	0.62	-0.009	67	0.147	0.103	0.155
M5 **	0.60	0.044	0.043	-0.010	0.99	0.012	26	0.936	0.118	0.413
M9	0.78	0.083	0.036	0.075	0.69	-0.030	60	0.245	0.035	0.137
M13	0.70	0.135	0.092	0.099	0.36	0.028	47	0.145	0.276	0.157
N9	0.65	0.071	0.047	0.054	0.60	-0.001	65	0.185	0.042	0.202
O7	0.75	0.038	0.035	-0.014	0.81	0.024	62	0.129	-0.095	-0.197
SMOSMANIA										
Barnas	0.91	0.059	0.022	0.054	1.13	-0.081	8	0.665	0.748	0.396
Berzeme	0.88	0.084	0.025	0.080	0.90	-0.067	12	0.104	0.122	0.129
Condom	0.67	0.191	0.037	0.187	0.57	-0.066	47	0.021	0.126	-0.024
Creond	0.58	0.045	0.039	0.022	0.52	0.033	43	-0.324	-0.109	0.072
Lahas	0.62	0.166	0.075	0.148	0.36	0.017	53	0.046	0.186	-0.114
Lezignan	0.75	0.039	0.027	-0.028	0.72	0.049	46	0.027	-0.153	0.434
Mazan	0.82	0.158	0.061	0.146	0.41	0.025	6	0.208	0.618	0.188
Mejannes	0.65	0.111	0.078	0.080	0.28	0.054	43	-0.039	-0.027	-0.008
Montaut	0.50	0.186	0.077	0.169	0.23	0.037	43	-0.076	-0.338	0.001
Mouthoumet	0.65	0.094	0.042	0.085	0.80	-0.048	51	-0.138	-0.017	-0.204
Narbonne	0.79	0.074	0.039	0.063	0.55	0.023	59	-0.297	0.339	-0.951
Peyrusse	0.66	0.136	0.046	0.128	0.55	-0.021	57	0.069	0.141	-0.074
Pezenas	0.85	0.045	0.034	0.031	0.59	0.031	60	-0.209	0.121	-0.123
Prades	0.63	0.092	0.046	0.080	0.52	0.013	34	-0.611	0.031	-0.273
Sabres **	-0.30	0.118	0.092	-0.074	-	0.254	3	-0.095	0.061	-0.080
SaintFelix *	-0.39	0.132	0.060	0.117	-	0.263	19	-0.751	-0.403	-0.067
Savenes	0.55	0.070	0.048	0.050	0.39	0.040	56	-0.356	-0.164	-0.188
Urgons	0.69	0.219	0.090	0.200	0.22	0.035	54	-0.050	0.005	-0.066
Villevielle	0.77	0.104	0.082	0.063	0.26	0.068	50	-0.356	-0.163	-0.225
VAS										
Melbex1	0.89	0.037	0.031	0.021	0.79	0.005	32	-0.502	0.080	0.000
Melbex2	0.84	0.099	0.036	0.092	0.65	-0.039	28	-0.581	0.201	-0.001

Table 4. Summary of the statistical metrics (R, RMSD, cRMSD, bias, slope a and intercept b of the linear regression, and number of observations N) for the individual comparisons between the SMOS L4 instant (aggregated into 25 km) against concurrent *in situ* observations at each network. Stations with not-significant correlation at 0.05/0.01 confidence level are indicated by */** respectively. Gains of the downscaling procedure (G_EFFI, G_PREC, G_ACCU) at the 25 km scale with respect to the SMOS L3 are also shown. Bold indicates positive gain.

REMEDHUS	R	RMSD	cRMSD	bias	a	b	N	G_EFFI	G_PREC	G_ACCU
E10	0.73	0.104	0.049	-0.092	2.398	0.068	48	-0.056	-0.150	-0.189
F6	0.44	0.070	0.062	0.033	0.749	-0.019	59	0.339	0.139	0.274
H7	0.53	0.088	0.060	-0.065	4.024	-0.027	56	-0.089	-0.037	-0.229
H9	0.78	0.209	0.120	0.171	0.290	0.011	63	0.073	0.220	0.069
H13	0.80	0.042	0.039	0.016	0.884	-0.006	64	0.558	0.143	0.421
I6	0.76	0.090	0.051	-0.074	3.703	0.034	80	0.021	-0.046	-0.136
J3	0.83	0.083	0.044	-0.070	2.560	0.045	78	-0.099	0.221	-0.145
J12	0.82	0.172	0.037	0.168	0.745	-0.105	64	0.259	0.131	0.062
K4	0.74	0.075	0.047	-0.058	2.318	0.017	80	0.013	-0.087	-0.181
K9	0.21	0.065	0.061	0.023	0.229	0.054	60	-0.029	-0.029	0.319
K10	0.63	0.075	0.047	-0.059	1.680	0.035	63	-0.387	0.049	-0.221
K13	0.75	0.110	0.045	0.100	0.723	-0.049	66	0.323	0.171	0.109
L3	0.58	0.049	0.048	-0.006	0.920	-0.002	80	-0.002	0.007	0.342
L7	0.84	0.083	0.041	0.072	0.604	-0.011	67	0.116	0.146	0.136
M5 **	0.62	0.046	0.045	-0.012	1.023	0.009	26	0.745	0.139	0.337
M9	0.78	0.084	0.035	0.076	0.684	-0.029	60	0.234	0.037	0.133
M13	0.68	0.137	0.093	0.100	0.353	0.031	47	0.132	0.256	0.151
N9	0.66	0.071	0.046	0.054	0.626	-0.004	65	0.207	0.059	0.198
O7	0.76	0.038	0.035	-0.014	0.832	0.023	62	0.170	-0.075	-0.183
SMOSMANIA										
Barnas	0.89	0.058	0.024	0.053	1.079	-0.071	8	0.781	0.718	0.408
Berzeme	0.87	0.084	0.025	0.080	0.775	-0.044	12	-0.334	0.090	0.129
Condom	0.67	0.189	0.037	0.185	0.584	-0.066	47	0.033	0.131	-0.017
Creond	0.57	0.044	0.039	0.021	0.508	0.037	43	-0.341	-0.121	0.096
Lahas	0.62	0.167	0.075	0.149	0.332	0.023	53	0.023	0.181	-0.119
Lezignan	0.73	0.039	0.028	-0.027	0.685	0.051	46	-0.047	-0.181	0.452
Mazan	0.77	0.159	0.063	0.146	0.429	0.021	6	0.216	0.535	0.190
Mejannes	0.66	0.111	0.078	0.080	0.269	0.057	43	-0.047	-0.010	-0.008
Montaut	0.53	0.183	0.076	0.166	0.235	0.039	43	-0.077	-0.311	0.010
Mouthoumet	0.63	0.098	0.041	0.089	0.705	-0.034	51	-0.340	-0.045	-0.228
Narbonne	0.80	0.077	0.039	0.066	0.572	0.016	59	-0.281	0.343	-0.953
Peyrusse	0.66	0.138	0.046	0.130	0.530	-0.018	57	0.048	0.137	-0.080
Pezenas	0.86	0.034	0.032	0.012	0.645	0.042	60	-0.144	0.173	0.337
Prades	0.69	0.073	0.042	0.060	0.571	0.026	34	-0.579	0.117	-0.132
Sabres *	-0.35	0.125	0.100	-0.075	-0.680	0.273	3	-0.141	0.042	-0.091
SaintFelix *	-0.37	0.132	0.059	0.118	-0.368	0.248	19	-0.742	-0.399	-0.071
Savenes	0.56	0.070	0.048	0.051	0.398	0.040	56	-0.352	-0.158	-0.194
Urgons	0.67	0.221	0.091	0.201	0.213	0.037	54	-0.056	-0.020	-0.070
Villevielle	0.75	0.106	0.082	0.068	0.267	0.064	50	-0.358	-0.207	-0.255
VAS										
Melbex1	0.91	0.035	0.029	0.019	0.783	0.007	32	-0.524	0.175	0.051
Melbex2	0.86	0.097	0.033	0.091	0.696	-0.042	28	-0.536	0.270	0.004

Table 5. Summary of the statistical metrics (R, RMSD, cRMSD, bias, slope a and intercept b of the linear regression, and number of observations N) for the individual comparisons between the SMOS L4 daytime concurrent *in situ* observations at each network. Stations with not-significant correlation at 0.05/0.01 confidence level are indicated by */** respectively.

REMEDHUS	R	RMSD	cRMSD	bias	a	b	N
E10	0,66	0,121	0,072	-0,098	2,153	0,062	103
F6	0,39	0,088	0,080	0,035	0,714	-0,016	131
H7	0,43	0,109	0,077	-0,077	3,198	0,000	120
H9	0,66	0,246	0,146	0,198	0,236	0,022	125
H13	0,67	0,063	0,060	0,020	0,882	-0,010	124
I6	0,63	0,107	0,072	-0,079	3,914	0,005	129
J3	0,67	0,095	0,057	-0,076	2,276	0,039	134
J12	0,69	0,182	0,059	0,173	0,767	-0,115	124
K4	0,68	0,086	0,056	-0,065	2,407	0,013	132
K9 **	0,23	0,085	0,084	0,011	0,252	0,061	123
K10	0,55	0,096	0,069	-0,067	1,523	0,039	127
K13	0,63	0,120	0,063	0,101	0,709	-0,049	128
L3	0,45	0,062	0,060	-0,015	1,008	0,003	132
L7	0,68	0,094	0,062	0,071	0,547	-0,005	123
M5	0,45	0,077	0,076	-0,011	0,655	0,044	68
M9	0,66	0,089	0,062	0,064	0,775	-0,038	117
M13	0,66	0,145	0,103	0,102	0,387	0,016	123
N9	0,58	0,084	0,068	0,049	0,738	-0,019	121
O7	0,64	0,064	0,062	-0,019	0,746	0,025	119
SMOSMANIA							
Barnas	0,50	0,080	0,044	0,066	0,537	0,010	76
Berzeme *	0,19	0,100	0,082	0,057	0,155	0,084	38
Condom *	0,15	0,206	0,094	0,184	0,522	-0,057	110
Creond **	0,22	0,075	0,070	0,025	0,495	0,033	107
Lahas	0,40	0,186	0,081	0,167	0,329	0,014	115
Lezignan	0,55	0,053	0,052	-0,012	0,619	0,048	103
Mazan	0,47	0,132	0,101	0,086	0,218	0,058	80
Mejannes	0,49	0,121	0,082	0,089	0,344	0,033	106
Montaut	0,48	0,198	0,073	0,184	0,354	0,000	104
Mouthoumet	0,48	0,106	0,055	0,091	0,721	-0,040	109
Narbonne	0,43	0,102	0,064	0,080	0,476	0,029	123
Peyrusse	0,45	0,151	0,065	0,136	0,481	-0,015	119
Pezenas	0,43	0,089	0,080	0,040	0,541	0,027	117
Prades	0,54	0,096	0,058	0,076	0,499	0,018	113
Sabres *	-0,32	0,109	0,103	-0,037	-0,583	0,238	12
SaintFelix *	-0,08	0,130	0,063	0,113	0,019	0,135	37
Savenes	0,32	0,090	0,067	0,060	0,372	0,041	116
Urgons	0,36	0,234	0,105	0,209	0,226	0,027	118
Villevielle	0,45	0,112	0,091	0,066	0,267	0,062	108
VAS							
Melbex1	0,67	0,055	0,049	0,025	0,750	-0,004	118
Melbex2	0,57	0,099	0,061	0,079	0,704	-0,041	113

Table 6. Summary of the statistical metrics (R, RMSD, cRMSD, bias, slope a and intercept b of the linear regression, and number of observations N) of the comparisons for the averaged soil moisture at each network and product. All correlations are significant at 0.01 confidence level.

L3	R	RMSD	cRMSD	bias	a	b	N
REMEDIHUS	0.78	0.056	0.036	0.044	0.933	-0.038	102
SMOSMANIA	0.77	0.079	0.041	0.067	0.690	-0.001	143
VAS	0.84	0.070	0.045	0.054	0.925	-0.050	36
L4 instant							
REMEDIHUS	0.82	0.043	0.040	0.017	1.156	-0.038	102
SMOSMANIA	0.64	0.100	0.051	0.086	0.537	0.008	143
VAS	0.89	0.065	0.031	0.057	0.738	-0.018	36
L4 daytime							
REMEDIHUS	0,67	0,063	0,060	0,020	0,957	-0,024	148
SMOSMANIA	0,51	0,109	0,062	0,090	0,565	-0,006	190
VAS	0,67	0,072	0,051	0,051	0,830	-0,032	131

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Fig.1. Location of the 40 International Soil Moisture Network (ISMN) validation sites used in the study. Top left: location of the sites within Europe (image acquired from Google Maps). Top right: location of the SMOSMANIA sites in southern France. Bottom left: location of the REMEDHUS sites in the Duero Basin in Spain. Bottom right: location of the Valencia Anchor Station (VAS) sites in southern Spain.

Fig.2. SSM distribution over the REMEDHUS network for the SMOS/SEVIRI L4 Instantaneous (left) and the SMOS/SEVIRI L4 Daytime Average (right) obtained for a dry day on July 31st 2011 (top) and a wet day on December 27th 2011 (bottom). Blue lines are rivers; black triangles denote REMEDHUS stations.

Fig. 3. Evolution of soil moisture trends (left column) and scatter plots (right column) for L4 instant, L3 and collocated in-situ measurements for year 2011 at representative stations: O7 (first row), Narbonne (second row) and Melbex1 (third row).

Fig. 4. Evolution of soil moisture trends (left column) and scatter plots (right column) for L4 daytime and collocated in-situ measurements for year 2011 at representative stations: O7 (first row), Narbonne (second row) and Melbex1 (third row).

Fig. 5. R and cRMSD of the L4 daytime product divided into thresholds dependent on the percentage of SEVIRI overpasses (0-24%, 25-49%, 50-74%, 75-100%) available for each day of analysis. Results are shown only for the stations that have significant correlation at a 95% in the four percentages coverage considered.

Fig. 6. Scatter plots of satellite vs. ground-based measurements of instantaneous (left column) and daytime (right column) soil moisture measurements. Results are shown for year 2011 for the average of each network: REMEDHUS (first row), SMOSMANIA (second row), and VAS (third row).