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1 **SMOS disaggregated soil moisture product at 1 km resolution:**
2 **processor overview and first validation results**

3 B. Molero^{1*}, O. Merlin^{1,2}, Y. Malbêteau¹, A. Al Bitar¹, F. Cabot¹,

4 V. Stefan¹, Y. Kerr¹, S. Bacon¹, M. H. Cosh³, R. Bindlish³, T. J. Jackson³

5 1 Centre d'Etudes Spatiales de la Biosphère, Toulouse, France

6 2 Université Cadi Ayyad, Marrakech, Morocco

7 3 USDA ARS Hydrology and Remote Sensing Laboratory, USA

8 * beatriz.molero@cesbio.cnes.fr; tel.: +33 5 61 55 74 87

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10
11 **Abstract:** The SMOS (Soil Moisture and Ocean Salinity) mission provides surface soil moisture (SM)
12 maps at a mean resolution of ~50 km. However, agricultural applications (irrigation, crop monitoring) and
13 some hydrological applications (floods and modeling of small basins) require higher resolution SM
14 information. In order to overcome this spatial mismatch, a disaggregation algorithm called Disaggregation
15 based on Physical And Theoretical scale Change (DISPATCH) combines higher-resolution data from
16 optical/thermal sensors with the SM retrieved from microwave sensors like SMOS, producing higher-
17 resolution SM as the output. A DISPATCH-based processor has been implemented for the whole globe
18 (emerged lands) in the Centre Aval de Traitement des Données SMOS (CATDS), the French data
19 processing center for SMOS Level 3 products. This new CATDS Level-4 Disaggregation processor
20 (C4DIS) generates SM maps at 1 km resolution. This paper provides an overview of the C4DIS
21 architecture, algorithms and output products. Differences with the original DISPATCH prototype are
22 explained and major processing parameters are presented. The C4DIS SM product is compared against L3
23 and *in situ* SM data during a one year period over the Murrumbidgee catchment and the Yanco area
24 (Australia), and during a four and a half year period over the Little Washita and the Walnut Gulch
25 watersheds (USA). The four validation areas represent highly contrasting climate regions with different
26 landscape properties. According to this analysis, the C4DIS SM product improves the spatio-temporal

27 correlation with *in situ* measurements in the semi-arid regions with substantial SM spatial variability
28 mainly driven by precipitation and irrigation. In sub-humid regions like the Little Washita watershed, the
29 performance of the algorithm is poor except for summer, as result of the weak moisture-evaporation
30 coupling. Disaggregated products do not succeed to have an additional benefit in the Walnut Gulch
31 watershed, which is also semi-arid but with well-drained soils that are likely to cancel the spatial contrast
32 needed by DISPATCH. Although further validation studies are still needed to better assess the
33 performance of DISPATCH in a range of surface and atmospheric conditions, the new C4DIS product is
34 expected to provide satisfying results over regions having medium to high SM spatial variability.

35 1. Introduction

36 Soil moisture (SM) is an essential component of the water cycle that impacts infiltration, runoff and
37 evaporation processes. In addition, it modulates the energy exchange as well as the carbon exchange at the
38 land surface (Daly & Porporato, 2005). SM has influence over a range of spatial scales: the climatic
39 (Douville, 2004; Laio et al., 2002), the meteorological (Dirmeyer, 2000; Drusch, 2007), the hydrological
40 (Chen et al., 2011; Draper et al., 2012), the parcel and the local scale (Guérif & Duke, 2000).

41 Current satellite missions provide surface SM observations at large scales on a global basis. Passive
42 microwave L-band observations are widely used for surface SM retrievals, but in practice they constrain
43 the resolution of the retrievals to 30-60 km (Kerr & Njoku, 1990; Njoku & Entekhabi, 1996; Schmugge,
44 1998) with current technology. The Soil Moisture Ocean Salinity (SMOS) mission, launched in November
45 2009, incorporates an interferometric radiometer at L-band (1.4 GHz) and provides SM with a resolution
46 of 30-55 km and a sensing depth of 3-5 cm (Kerr et al., 2001, 2010). SMOS Level 2 (L2) and Level 3 (L3)
47 SM products have been validated extensively on a regular basis since the beginning of the mission (Al
48 Bitar et al., 2012; Delwart et al., 2008) and they have been assessed as suitable for hydro-climate
49 applications (Lievens et al., 2015; Wanders et al., 2014). However, most hydro-agricultural applications
50 need SM measurements of sub-kilometer spatial resolution with a still representative temporal coverage
51 (Walker & Houser, 2004). We should strive to provide a high resolution (HR) SM product that would
52 enhance the knowledge of the hydrological processes at local scale.

53 Different satellite-based approaches have been proposed to retrieve SM. One of the most popular is the
54 use of active sensors like the synthetic aperture radars (SAR) (ERS, ALOS, Sentinel 1) or scatterometers
55 (ASCAT). These instruments provide observations with a variety of spatial and time resolutions but they
56 are influenced to a great extent by the scattering produced by vegetation structure and surface roughness,
57 among other factors. Unlike active sensors, passive instruments are much less sensitive to scattering but
58 provide surface SM estimations at coarse resolutions (>40 km). C- and X-band radiometers like AMSR-E
59 and WindSat have shown good results (Mladenova et al., 2011), but because of the frequency used, their
60 sensing depth is shallow (~1cm) and vegetation becomes rapidly opaque. In contrast, L-band radiometer

61 acquisitions from SMOS provide SM estimations for a much wider range of vegetation conditions, with a
62 sensing depth of around 5 cm and a revisit time of ~3 days. However, the spatial resolution provided is
63 also coarse (35-55 km) as mentioned previously. The main strategies to workaroud this issue while
64 maintaining the benefits of L-band consist of merging the L-band acquisitions with HR ancillary data,
65 namely radar and optical observations.

66 Over the past decade, various methods have been proposed to combine active and passive sensors to
67 produce HR SM (Das et al., 2011; Narayan et al., 2006; Zhan et al., 2006). The NASA Soil Moisture
68 Active Passive (SMAP) mission, launched in 2015, intended to combine L-band brightness temperatures
69 (TB) and HR L-band radar backscatter data (Entekhabi et al., 2010a). Despite the radar failure in July
70 2015, related previous studies showed that SM could have been delivered at 9 km and even 3 km
71 resolution (Das et al., 2014).

72 Optical sensors (visible/near-infrared/thermal-infrared) can achieve finer spatial resolutions. However, the
73 quality of their observations is critically compromised by the presence of clouds. Examples of optical
74 sensors include the Landsat instruments and the Advanced Spaceborne Thermal Emission and Reflection
75 radiometer (ASTER), with data at ~100 m resolution, and the MODerate resolution Imaging
76 Spectroradiometer (MODIS), with data at ~1 km resolution. Such data include soil temperature and
77 vegetation cover information, which are variables linked to soil water content (Fang et al., 2013). The
78 relationship between land surface temperature (LST) and normalized difference vegetation index (NDVI)
79 was first formalized in the 90s with the triangle (Carlson et al., 1994; Carlson, 2007) and the trapezoid
80 (Moran et al., 1994) approaches.

81 Most of the methods for deriving HR SM from the synergy between optical and microwave observations
82 are based on the triangle/trapezoid approaches. Chauhan et al. (2003) stated that the relationship between
83 LST, NDVI and SM can be formulated as a regression formula specific to the region and climatic
84 conditions. Later, Piles et al. (2011) included SMOS TBs in the equation, which reduced the bias but
85 slightly degraded the spatio-temporal correlation between the obtained HR SM and the *in situ*
86 measurements. These empirical methods need local calibration of the regression coefficients at low
87 resolution (LR) before applying them to the HR ancillary data. On the contrary, semi-physical methods

88 replace the polynomial function by physically-based models that use evaporation as a proxy variable for
89 SM variability. Merlin et al. (2008) linked the SM to the soil evaporative efficiency (SEE), defined as the
90 ratio of actual to potential soil evaporation. Kim & Hogue (2012) established a linear relationship
91 between the soil evaporative fraction of Jiang & Islam (2003) and SM. Both approaches improved the
92 satellite SM spatial variability and showed better correspondence with ground measurements in the area of
93 study (SMEX04).

94 The semi-physical methods have three important advantages with respect to the purely empirical methods:
95 (i) the mean SM is preserved across the merging process (which justifies calling it ‘disaggregation’ or
96 ‘downscaling’), (ii) a physical link is established for HR between SM and the
97 evaporation/evapotranspiration rate and (iii) no local calibration or fit is needed. These are key factors in
98 developing a robust and global operational algorithm for HR SM.

99 Recent studies by Merlin et al. (2012, 2013) have improved the evaporation rate calculation and the
100 evaporation-SM link of Merlin et al. (2008). The DISaggregation based on Physical And Theoretical scale
101 Change (DISPATCH) algorithm estimates SEE at high-resolution from soil temperature and vegetation
102 data for modeling the spatial variations inside the microwave SM observation. In Merlin et al. (2012),
103 DISPATCH included corrections for the microwave sensor weighting function and grid oversampling and
104 provided an estimate of the uncertainty in the output disaggregated data. Later, Merlin et al. (2013)
105 demonstrated that the linear approximation of the SEE-SM link model is suitable for kilometer scales and
106 included soil temperature corrections for elevation effects. Both studies were conducted under semi-arid
107 conditions, in a 500x100 km study area within the Murrumbidgee river catchment, in southeastern
108 Australia, and in a 60x60 km study area east of Lleida in Catalunya, Spain. They showed that DISPATCH
109 improves the spatio-temporal correlation with *in situ* measurements, but that the accuracy of disaggregated
110 products is highly dependant on the SM-evaporation coupling. The downscaled resolution of 1 km
111 (Merlin et al., 2009, 2013) and the combination of satellite data from different time stamps in DISPATCH
112 (Malbêteau et al., 2016b; Merlin et al., 2012) have been considered as a good trade-off between spatial
113 representativeness and overall accuracy, given the current status of the algorithm.

114 Recently, a new Level-4 (L4) processor (C4DIS) based on DISPATCH has been implemented in the
115 Centre Aval de Traitement des Données SMOS (CATDS), the French ground segment for SMOS Level-3
116 and Level-4 data. The aim is to disaggregate the SMOS CATDS Level-3 (L3) 1-day SM maps to produce
117 maps of SM at 1 km resolution for any part of the globe on an operational basis. The ancillary temperature
118 and vegetation data are retrieved from the MODIS mission.

119 This paper seeks (i) to provide an overview of the C4DIS architecture, processing algorithms, output
120 products, strengths and weaknesses and (ii) to derive the first conclusions on the performance of the
121 C4DIS product depending on the climatic and landscape conditions. To do so, we evaluate the C4DIS
122 product against *in situ* data from the Murrumbidgee catchment and two additional contrasting networks.
123 Former versions of DISPATCH have so far been evaluated mostly in semi-arid conditions (Merlin et al.,
124 2012, 2013, Malbêteau et al., 2015). The Murrumbidgee network belongs to these previous studies, and it
125 is included here to serve as a reference for the current version of DISPATCH and the C4DIS processor
126 and for the other validation areas. The two other *in situ* networks considered in this study are located in
127 the Little Washita watershed in Oklahoma, USA, which exhibits sub-humid conditions, and the Walnut
128 Gulch watershed in Arizona, USA, which exhibits semi-arid to arid conditions. Their relief, soil properties
129 and land use differ from the Murrumbidgee's. The L4 disaggregated SM product is evaluated using *in situ*
130 0–5 cm and *in situ* 0–8 cm measurements taken at the same time as SMOS overpasses (around 6 am, 6
131 pm) during the period 01/06/2010 to 31/05/2011 for the Australian network and 01/06/2010 to 31/12/2014
132 for the USA networks. These networks have been providing ground SM data in a continuous basis and
133 have contributed to the validation of different satellite missions, SMOS among them (Cosh et al., 2004;
134 Jackson et al., 2010, 2012; Leroux et al., 2013; Peischl et al., 2012).

135 It is important to note that the DISPATCH algorithm will continue to evolve. Validation activities on the
136 Level-4 processor C4DIS will provide valuable information for the improvement of the algorithm and
137 processing chain. This current study is conducted on the products of the first version of the C4DIS
138 processor.

139 2. Input data collection

140 2.1 In situ measurements

141 Three validation networks were selected for this work, the Murrumbidgee Soil Moisture Monitoring
142 Network (MB) in Australia (Smith et al., 2012) and two different USDA (United States Department of
143 Agriculture) networks: Little Washita (LW) in Oklahoma (Cosh et al., 2006) and Walnut Gulch (WG) in
144 Arizona (Cosh et al., 2008). They exhibit contrasted types of climate, soil properties, land use and spatial
145 extension.

146 The MB network covers a large extension (82,000 km²) in southern New South Wales. Its climate ranges
147 from semi-arid in the west (average annual precipitation of 300 mm), to humid in the east (annual
148 precipitation of 1900 mm at the Snowy Mountains). The MB has been studied in previous DISPATCH
149 campaigns (Malbêteau et al., 2016b; Merlin et al., 2012). It is included here for different reasons: it
150 permits to confront results with previous versions of the algorithm, it contains within the Yanco area,
151 which gathers the nominal landscape and climatic conditions for DISPATCH (flat, semi-arid with low
152 vegetation), and it shows a variety of climate, soil and land use cases that can reveal the usefulness of
153 disaggregation.

154 The MB consists in 38 validation stations: 18 of them provide SM integrated over the first 8 cm of soil
155 (Campbell Scientific water content reflectometers) and the rest provide SM integrated over the first 5 cm
156 of soil (Stevens Hydra Probe). The stations are situated in four areas: 7 stations in the limits of the
157 catchment near to regional centers; 5 stations in Adelong Creek (145 km²), a grazing area with steep
158 slopes; 13 stations in Kyeamba creek (600 km²), a catchment with gentle slopes and grazing and dairy
159 land use; and finally, 13 stations in the Yanco region (3000 km²).

160 Yanco soils are mainly silty-loam. The climate is semi-arid with an average annual rainfall of about 400
161 mm, with most of the precipitation occurring in winter and spring. The land use is divided into irrigation
162 and dry land cropping and pastures. This area has been extensively monitored since 2001 (Smith et al.,

163 2012) and has been used in a variety of satellite validation campaigns (Mladenova et al., 2011; Panciera et
164 al., 2014; Peischl et al., 2012)

165 The USDA networks have been operating since 2002 and they have been used in the validation of
166 Advanced Microwave Scanning Radiometer-Earth Observing System (AMSR-E) products (Jackson et al.,
167 2010), Aquarius (Bindlish, 2015), ASCAT (Leroux et al., 2013) and SMOS products (Jackson et al.,
168 2012). The probes are installed at a depth of 5 cm, with an effective measurement depth between 3 and 7
169 cm (Stevens Hydra Probe).

170 LW is located in southwest Oklahoma and covers an area of about 610 km². The climate is sub-humid
171 with an average annual rainfall of 750 mm. Summers are hot and relatively dry while winters are short and
172 temperate. Autumn and spring are when most of the precipitation occurs (Allen & Naney, 1991). The land
173 use is mainly rangeland and crops that include winter wheat and some corn and grasses. Soils include a
174 wide range of textures, with large regions of sands, loams and clays. The topography is moderately rolling
175 with few hills.

176 WG occupies an area of 148 km² in southeastern Arizona. The climate is semi-arid, with an average
177 annual rainfall of 324 mm, lower than in the Yanco region. Most of the rains occur in the form of small
178 scale high-intensity thunderstorms during the summer months as part of the North American Monsoon
179 System (Cosh et al., 2008). Soils are mainly sands and gravel with good drainage. Desert shrubs and short
180 grasses dominate the landscape. The topography is considered as rolling with significant rock cover.
181 Although the climate class of WG is defined semi-arid as the Yanco area, the contrasting landscape
182 properties and precipitation conditions make WG an interesting validation area (Table 1).

183 It is important to outline that the area extent covered by the networks is different so it may have an impact
184 on the validation process: the MB comprises multiple SMOS pixels through sparse stations and more
185 dense localized sites, the Yanco region covers approximately one SMOS pixel, and the LW and WG cover
186 around 1/4 and 1/16 of the surface of one SMOS pixel. This does not affect the C4DIS processor, which
187 handles input larger surfaces, but it may affect the validation process since the smaller networks may not
188 be representative of the ~40 km surface.

Table 1- Main characteristics of validation areas

	Murrumbidgee	Yanco	LW	WG
<i>Extension</i>	82,000 km ²	3000 km ²	610 km ²	148 km ²
<i>Climate</i>	Semi-arid (west) to humid (east)	Semi-arid	Sub-humid	Semi-arid to arid
<i>Annual precipitation</i>	300 – 1900 mm	400 mm	750 mm	324 mm
<i>Main precipitation periods</i>	Relatively constant at the basin scale	Winter, spring	Autumn, spring	Summer (intense, localized)
<i>Soils</i>	Clayey (west) to sandy (east)	Silty-loam	Sands, loams and clays	Sands and gravel
<i>Topography</i>	Diverse, mountains in the east	Flat	Moderate rolling	Rolling

189 2.2 SMOS soil moisture data

190 The SMOS satellite was launched in November 2009. SMOS has global coverage with a revisit period of
 191 3 days at the equator, with ascending (A) overpass at 6:00 am and descending (D) overpass 6:00 pm local
 192 solar time. The SMOS instrument is a passive 2D interferometer operating at L band (1.4 GHz) (Kerr et
 193 al., 2001, 2010). The spatial resolution ranges from 35 to 55 km, depending on the incident angle. The
 194 goal is to retrieve SM (first 5 cm) with a target accuracy of 0.04 m³/m³ (Kerr et al., 2012).

195 The C4DIS processor disaggregates the SM provided by the SMOS Level-3 1-day global SM product
 196 (MIR CLF31A/D). In this paper, the version 2.72 (in 220 reprocessing mode RE02) product is used.
 197 Level-3 (L3) products are presented in NetCDF format on the EASE (Equal Area Scalable Earth) grid,
 198 with a grid spacing of ~25x25 km.

199 The L3 SM products are directly computed from the SMOS Level-1 products at the CATDS. The core of
 200 the algorithm for retrieving SM from brightness temperatures is derived from the L2 retrieval algorithm
 201 (Kerr et al., 2012; Wigneron et al., 2007). In both processing chains, SM is derived from the combination
 202 of multiangular observations. While the L2 chain considers only the multiangular observations of the same
 203 day and orbit (ascending/descending), the L3 chain uses several overpasses (3 at most) over a 7-day
 204 window. This results in more coverage and robustness for the L3 products (Al-Yaari et al., 2014). Details

205 on the L3 processing algorithm can be found in the Algorithm Theoretical Baseline Document (Kerr et al.,
206 2013) and in the L3 data product description (Kerr et al., 2014).

207 **2.3 MODIS temperature and vegetation data**

208 The C4DIS processor uses three ancillary products at 1 km resolution. Two of them are derived from
209 MODIS acquisitions: LST and NDVI. These are necessary elements for the SEE calculation inside
210 DISPATCH.

211 The LST datasets are extracted from version-5 MODIS/Terra LST and emissivity daily L3 global 1-km
212 grid products (MOD11A1) and version-5 MODIS/Aqua LST and emissivity daily L3 global 1-km grid
213 products (MYD11A1). The NDVI dataset is extracted from the version-5 MODIS/Terra vegetation
214 indices 16-day Level-3 global 1-km grid product (MOD13A2).

215 The MODIS products are retrieved from the NASA Land Processes Distributed Active Archive Center
216 (LP DAAC). They are presented in sinusoidal projection at 1 km resolution (Solano et al., 2010; Wan,
217 1999, 2006). The disaggregation approach requires the NDVI dataset acquired within the last 15 days and
218 the LST datasets of the day before, the same day and the day after. The MODIS products are available
219 between 1 and 9 days after the acquisition day.

220 **2.4 Digital Elevation Model**

221 The C4DIS processor requires elevation information, which is extracted from the GTOPO30 Digital
222 Elevation Model (DEM) product available in the WGS84 sphere at 30-arc second resolution. The
223 GTOPO30 product is distributed by the U.S. Geological Survey's EROS Data Center (USGS,
224 <https://lta.cr.usgs.gov/GTOPO30>).

225 3. The CATDS Level-4 Disaggregation (C4DIS) processor

226 The CATDS Level-4 (L4) Disaggregation (C4DIS) processor is the first operational version of the
 227 DISPATCH algorithm. The C4DIS processor selects the best algorithm and parameter configuration
 228 according to past DISPATCH studies and the latest research (Merlin et al., 2006, 2009, 2010a, 2010c,
 229 2012, 2013). It also makes possible to obtain disaggregated SM on a global and daily basis (under the
 230 assumption of no cloud-covered scenes and availability of input data). The C4DIS products have been
 231 marked as ‘scientific’ products because the algorithm is still evolving: their access will be granted on
 232 demand for specific areas of the world. In this and the following sections, we describe both the
 233 DISPATCH prototype and the C4DIS processor.

234 3.1 DISPATCH algorithm

235 DISPATCH relies on a SEE term to model the spatial variability over the low-resolution (LR) SMOS
 236 pixel. The first step is to account for the SEE term at HR, described as a linear function of soil
 237 temperature:

$$238 \text{SEE}_{\text{HR}} = (T_{\text{s,max}} - T_{\text{s,HR}}) / (T_{\text{s,max}} - T_{\text{s,min}}) \quad (1)$$

238 Soil ($T_{\text{s,HR}}$) and vegetation ($T_{\text{v,HR}}$) temperatures are derived from LST and NDVI datasets as in Merlin et
 239 al., (2012), where the surface temperature is partitioned into its soil and vegetation components according
 240 to the trapezoid method of Moran et al. (1994). Soil temperature is calculated as follows:

$$241 T_{\text{s,HR}} = (T_{\text{MODIS}} - f_{\text{v,HR}}T_{\text{v,HR}}) / (1 - f_{\text{v,HR}}) \quad (2)$$

242 with T_{MODIS} being the MODIS LST and f_{v} the MODIS-derived fractional vegetation cover. Here, the
 243 fractional vegetation cover is calculated as:

$$244 f_{\text{v,HR}} = (\text{NDVI}_{\text{MODIS}} - \text{NDVI}_{\text{s}}) / (\text{NDVI}_{\text{v}} - \text{NDVI}_{\text{s}}) \quad (3)$$

245 with $\text{NDVI}_{\text{MODIS}}$ being the MODIS NDVI, NDVI_{s} the NDVI for bare soil (set to 0.15), and NDVI_{v} the
 246 NDVI for full-cover vegetation (set to 0.90).

247 The vegetation temperature $T_{v,HR}$ is calculated according to the “hourglass” approach (Moran et al., 1994,
 248 Merlin et al., 2012):

$$249 \quad T_{v,HR} = (T_{v,min} + T_{v,max}) / 2 \quad (4)$$

250 At this point, vegetation ($T_{v,min}$, $T_{v,max}$) and soil ($T_{s,min}$, $T_{s,max}$) temperature end-members are estimated
 251 depending on the amount of vegetation. Given the minimum and maximum LST values of the scene
 252 $T_{MODIS,min}$ and $T_{MODIS,max}$, and the f_v values associated to the same pixels, $f_{v,Tmin}$ and $f_{v,Tmax}$, the following
 253 approximations hold (Merlin et al., 2013):

- 254 I) When the vegetation portion is low at $T_{MODIS,min}$ ($f_{v,Tmin} < 0.5$), then $T_{s,min} = T_{v,min} = T_{MODIS,min}$
- 255 II) When the vegetation portion is considerable at $T_{MODIS,min}$ ($f_{v,Tmin} \geq 0.5$), then $T_{v,min} =$
 256 $T_{MODIS,min}$ and $T_{s,min}$ is derived from Eq. 2, with $T_v = T_{v,min}$
- 257 III) When the vegetation portion is low at $T_{MODIS,max}$ ($f_{v,Tmax} < 0.5$), then $T_{s,max} = T_{MODIS,max}$ and
 258 $T_{v,max}$ is derived from Eq. 2, with $T_s = T_{s,max}$
- 259 IV) When the vegetation portion is considerable at $T_{MODIS,max}$ ($f_{v,Tmin} \geq 0.5$), then $T_{v,max} =$
 260 $T_{MODIS,max}$ and $T_{s,max}$ is derived from Eq. 2, with $T_v = T_{v,max}$

261 Note that LST has been preliminary corrected for elevation effects (decrease of air temperature with
 262 altitude) by using the DEM information at HR (Merlin et al., 2013):

$$263 \quad T_{MODIS} = T_{MODIS-ori} + \gamma(H_{HR} - H_{LR}) \quad (5)$$

264 with T_{MODIS} being the topography-corrected LST used in the previous equations, $T_{MODIS-ori}$ the original
 265 MODIS LST, γ ($^{\circ}\text{C m}^{-1}$) the mean lapse rate (set to 0.006 $^{\circ}\text{C m}^{-1}$), H_{HR} the altitude of the MODIS pixel
 266 and H_{LR} the mean altitude within the LR pixel.

267 In a second step, the semi-empirical linear model of Budyko (1956) and Manabe (1969) is used to link the
 268 surface SM (0-5 cm) and the SEE terms. According to Merlin et al. (2013), the linear model is a good
 269 approximation for kilometer scales so the SEE for each HR pixel can be written as:

270
$$SEE_{HR} = SM_{HR} / SM_p \quad (6)$$

271 where SM_p is a parameter estimated at LR at each execution from daily SM and SEE observations as
272 follows:

273
$$SM_p = SM_{LR} / SEE_{LR} \quad (7)$$

274 with SM_{LR} the radiometer-sensed SM and SEE_{LR} the average of the SEE_{HR} values inside the LR pixel.

275 The disaggregation is finished by applying a first order Taylor series to the SM-SEE model at each HR
276 pixel (downscaling relationship). The corresponding disaggregated SM is:

277
$$SM_{HR} = SM_{LR} + SM'(SEE_{LR}) \times (SEE_{HR} - SEE_{LR}) \quad (8)$$

278 with $SM'(SEE_{LR})$ the partial derivative of SM relative to SEE at LR (SM_p).

279 **3.2 DISPATCH operational implementation**

280 Following the methodology introduced in Merlin et al. (2012), C4DIS executes DISPATCH on a set of
281 possible combinations of input datasets, producing multiple HR outputs that are averaged together into a
282 single final disaggregated SM field (SM_{HR}). The rationale behind this is to account for the uncertainty
283 of the approach and to reduce independent random errors (Malbêteau et al., 2016b; Merlin et al., 2012).
284 The input ensemble is formed by 4 downsampled instances of the original L3 SM dataset and up to 6 LST
285 datasets corresponding to 3 consecutive days of MODIS acquisitions (Aqua and Terra overpasses). This
286 means that each SM_{HR} output comes from the composition of up to 24 DISPATCH outputs (up to 24
287 input SM-LST possible pairs).

288 SMOS original datasets are downsampled in order to work at the radiometer resolution. SMOS L3
289 products are provided on a 25 km grid, which can be up to half of the original SMOS resolution (35-50
290 km). The four SM datasets are derived from the original SM map by sampling the data at 50 km and are
291 assumed to be independent. This is not totally true, since grid cells depend on the surrounding cells from a
292 radiometric perspective, but helps to potentially reduce (and provide an estimate of) random errors in the
293 SM_{HR} data. Regarding the selection of 6 MODIS LST datasets from 3 consecutive days, it is assumed
294 that SM fields are spatially stable for periods of at least 1 day around the SMOS overpass time. This 3-day

295 derived product with daily estimated SM_p is referred as the ‘sm1k3d’ product in Malbêteau et al. (2015)
 296 and is the one built by the C4DIS processor. The 3-day product has much better temporal coverage than its
 297 1-day counterpart (‘sm1k1d’), but the uncertainty associated to the methodology is expected to be higher
 298 since the temporal stability assumption can be often violated by precipitation and irrigation events.

299 There is no dedicated dataset in the C4DIS product that specifies explicitly whether the 3-days stability
 300 condition is respected or not. In the future, this will be achievable with the use of ancillary precipitation
 301 information, for example. Meanwhile, in addition to the SM_HR dataset, two more datasets are produced
 302 as indicators of the aggregation of the DISPATCH ensemble: the STD dataset, which is the standard
 303 deviation of the up to 24 disaggregated SM fields, and the COUNT dataset, which is the size of the
 304 ensemble. The aggregation is conducted if at least 3 SM fields are generated, so the COUNT values range
 305 from 3 to 24. In this paper, we study the STD and the COUNT datasets as potential sources of information
 306 for a future quality control flag (section 5.5).

307 Finally, the current version of DISPATCH filters out any LST pixel values that have associated QC flags
 308 different from 0 and 17, which correspond to maximum LST quality (error <1K) and maximum emissivity
 309 error of 0.01 and 0.02 respectively (Solano et al., 2010; Wan, 2006). Areas with more than 1/3 of their
 310 surface covered by clouds are also discarded. Differences between the operational and the prototype
 311 versions of DISPATCH are summarized in Table 2.

Table 2 - Main differences between the DISPATCH operational implementation in the C4DIS processor and the previous prototype versions

	C4DIS processor	(Merlin et al., 2013)	(Merlin et al., 2012)
SEE model	Linear (Budyko, 1956; Manabe, 1969)	Linear (Budyko, 1956; Manabe, 1969)	Non-linear (Noilhan & Planton, 1989)
Calculation of T_v	“Hourglass” approach (Moran et al., 1994)	“Hourglass” approach (Moran et al., 1994)	“Hourglass” approach (Moran et al., 1994)
Calculation of temperature end-members ($T_{s,min}$, $T_{s,max}$, $T_{v,min}$, $T_{v,max}$)	Estimated by a simpler approach based on the combination of LST and f_v	Estimated by a simpler approach based on the combination of LST and f_v	Estimated by plotting MODIS LST against MODIS albedo and NDVI within the LR pixel (Merlin et al., 2010b)
Input SM data	SMOS L3 SM	SMOS L2 SM	SMOS L2 SM

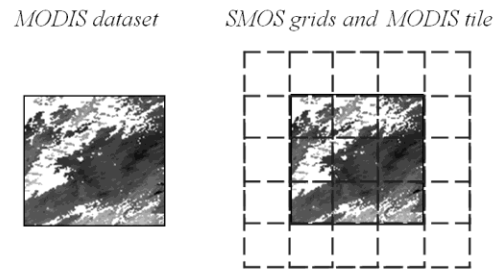
Input LST data	“sm1k3d” mode (3x2 input LST datasets)	“sm1k1d” mode (1x2 input LST datasets)	“sm1k3d” mode (3x2 input LST datasets)
Input DEM data	GTOPO30	GTOPO30	Not implemented
LST filtering	Yes, QC flags 0 and 17	Yes, QC flags 0 and 17	No
Cloud-free threshold	0.67	0.90	0.90
Sea-free threshold	0.90	0.90	Not implemented

312 3.3 Pre-processor

313 The C4DIS pre-processor prepares the input ensemble that is required by DISPATCH. The pre-processor
314 uses the MODIS sinusoidal tiling system as the execution reference, meaning that the processor is
315 executed for the SMOS and ancillary data contained within each MODIS tile bounds. More information
316 about the grid can be found in http://modis-land.gsfc.nasa.gov/MODLAND_grid.html. The SMOS and
317 ancillary data inside the tile bounds are selected and re-projected to an equal-spaced lat-lon WGS84 grid.
318 Considering that ancillary products are presented in different datums and grids, the choice of the WGS84
319 projection minimizes the total number of resampling operations.

320 The pre-processor is divided into modules for file format transformation, dataset extraction, re-projection
321 and re-gridding. As explained in the previous section, DISPATCH requires 4 subsampled instances of
322 SMOS data and up to 6 LST datasets. As a consequence, the re-projection and re-gridding are sensible
323 operations that deserve being explained in detail.

324 The pre-processor outputs are re-projected to the same WGS84 projection, but resampled to different
325 resolutions: SMOS subsampled rasters are provided on 0.4° grids while ancillary raster data are provided
326 on a 0.01° grid. The SMOS 0.4° grids are derived from an original global grid at 0.2° by sliding a 0.4°
327 window over it, so that the pixel centers are coincident. Based on this, the SM values become
328 representative of the double of the original grid resolution 0.2°, which approximately matches the average
329 SMOS resolution. The disaggregation is only performed in the intersection area between the 4 SMOS
330 grids and the ancillary data grid (Figure 1).



331

Figure 1 – Simplistic representation of the relation between the SMOS subsampled grids (at 0.4°) and the re-projected ancillary data at 0.01° . The extent of the re-projected ancillary image (LST, NDVI, etc.) matches the intersection of the four SMOS grids. The disaggregation is only applied in this overlapping zone.

332 **3.4 Post-processor**

333 The C4DIS post-processor transforms the DISPATCH outputs into the CATDS format. It includes two
 334 significant transformations that impact the disaggregated data. First, in the case that DISPATCH generates
 335 negative SM values (which is mathematically possible), the post-processor clips them to 0 to respect
 336 physical meaning. Second, since the outputs of DISPATCH are presented in local time and day, the post-
 337 processor assigns to them the corresponding UTC time and day to keep consistency with other SMOS
 338 products.

339 **3.5 Assumptions and applicability domains of the algorithm**

340 The application requirements of the C4DIS processor are directly inherited from DISPATCH. The
 341 following considerations must be taken into account:

342 - *Cloud free conditions*: soil temperature can only be retrieved from optical sensors if clouds are not
 343 present. C4DIS products show data gaps associated with clouds.

344 - *Low vegetation cover*: The LST-NDVI trapezoid describes a zone of values where no useful
 345 disaggregated data can be produced since LST is mainly controlled by vegetation transpiration, with
 346 no sensitivity to surface SM (Merlin et al., 2013). Sites with partial fractional vegetation cover at the 1
 347 km resolution are desired.

- 348 - *Moisture-driven evapotranspiration*: the disaggregation relies on the dependence established between
349 LST, evapotranspiration and SM. Some climates exhibit low dependency between those variables.
350 Typically, climates characterized as energy-limited, like humid climates, exhibit a weaker moisture-
351 evaporation coupling.
- 352 - *Medium to high spatial variability*: the MODIS-derived SEE is computed with a polygon method that
353 relies on LST and reflectance end-members (Moran et al., 1994). In the current version, DISPATCH
354 is contextual and thus heterogeneous scenes with meaningful dry-wet contrast are needed in order to
355 ensure good end-members accuracy (Merlin et al., 2010a). Note that LST end-members could be
356 estimated using available meteorological data (Moran et al. 1994) independently from the surface
357 (wet/dry) conditions observed at the 1 km resolution within the LR pixel (Stefan et al., 2015).
- 358 - *Accuracy of the SM_p parameter*: the SM_p parameter is calculated at LR scale by using a linear
359 relationship that has been studied as suitable for kilometer scales (Merlin et al., 2013). It is based on
360 the assumption that the sub-pixel variability of SM_p at HR is negligible. Soil characteristics (texture,
361 porosity, etc.) may impact the relationship between SEE and SM and thus SM_p . Hence, the current
362 versions of C4DIS and DISPATCH should perform better in areas with homogeneous soil
363 characteristics where the intra-pixel spatial SM variability is mainly due to forcing agents, namely
364 precipitation and irrigation.
- 365 - *Mismatch of overpass times*: the C4DIS processor uses MODIS LST datasets at 6 different
366 timestamps. This is based on the assumption that the SM pattern is maintained over a period of 3 days,
367 with no rain events occurring in between.
- 368 - *Mismatch of sensing depths*: SMOS L-band SM estimations are representative of the soil first 5 cm
369 content, while MODIS temperature acquisitions are representative of the soil skin layer. DISPATCH
370 assumes that the soil skin temperature is correlated with the soil evaporation process occurring in the
371 0-5 cm of soil (Merlin et al., 2010a).

372 3.6 Global product description

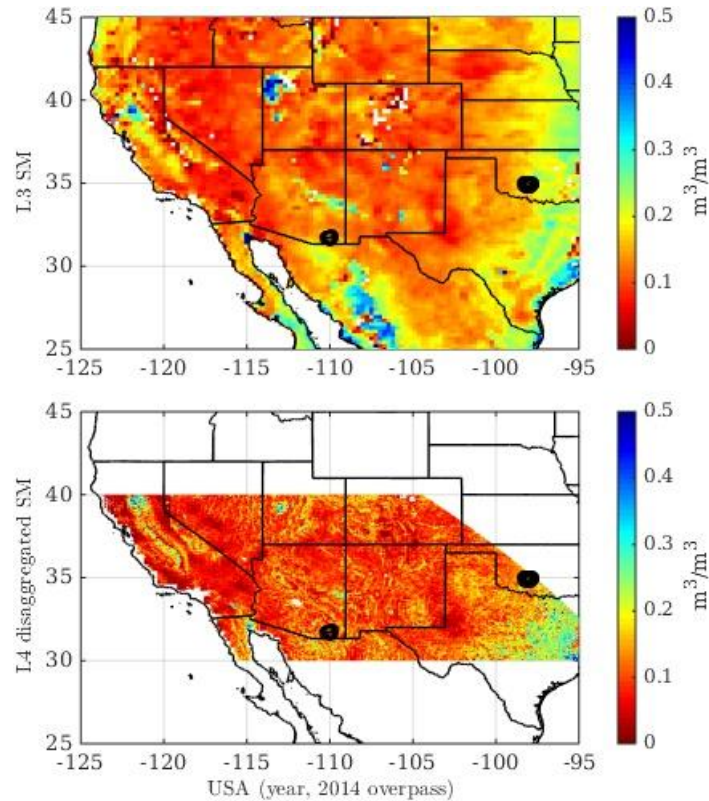
373 - *Coverage, grid and resolution.* C4DIS products are presented in a regular lat-lon grid at 0.01°
374 resolution. The projection is divided in a tiled grid that follows the MODIS sinusoidal tiling system,
375 meaning that the C4DIS tiles are centered at MODIS tiles and follow the same name convention in
376 (h,v) coordinates. Due to reprojection, the tiles present different size. C4DIS products can be
377 generated for all emerged lands (tiles with more than 50 % of land), but since they are tagged as
378 ‘scientific’ products, the tiles of interest have to be delivered on demand. For this study, the following
379 tiles have been produced: (29,12) and (30,12) for the validation over the MB, (09,05) for LW and
380 (08,05) for WG. Figure 2 shows annual averages of C4DIS products for the selected tiles. The
381 extension and border of the tiles are easily distinguishable.

382 - *Availability and timeliness.* The delivering of C4DIS products is determined by the availability and
383 timeliness of the input datasets. The limiting dataset is the MODIS MOD13A2 product (NDVI),
384 which is valid for a period of 15 days starting at its date of acquisition (DoA) but can be delivered
385 some days later. In consequence, C4DIS products for dates DoA to DoA+15 are produced at date
386 DoA+25. In other words, each 16 days the C4DIS products for acquisition dates between 25 to 10
387 days before are delivered.

388 - *Datasets and quality control.* We cannot provide a full-proof quality flag given the current status of
389 the processor and the algorithm. Nevertheless, the output COUNT and STD datasets can help to assess
390 the quality of the SM_HR dataset. Combining these datasets with additional ancillary data like
391 precipitation or MODIS/SMOS quality flags, may help to build a quality control dataset in the future.

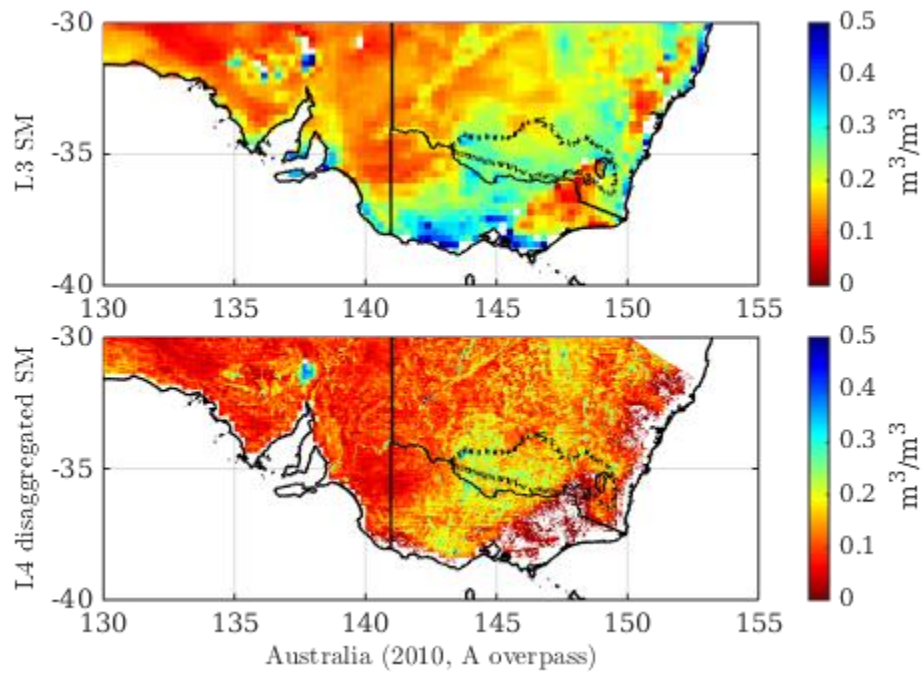
392 As introduced in Section 3.2, the COUNT field determines the number of SM-LST combinations used by
393 DISPATCH to produce one output. Low COUNT values indicate missing input data as result of diverse
394 reasons: SMOS RFI contamination, MODIS cloudy scenes, failures in the SMOS/MODIS acquisitions
395 delivering, etc. SM_HR fields generated when low COUNT values are present do not profit from the
396 reduction in independent random errors as result of averaging. The STD field contains the per-pixel
397 standard deviation of the up to 24 disaggregated datasets with respect to the averaged output SM_HR.

398 Low values of STD are desirable since they reveal temporal persistency of both temperature and moisture
 399 variables. High values may indicate external forcing agents (precipitation and irrigation) within the 3-days
 400 window.



401

Figure 2 - Year averages of SMOS L3 and L4 disaggregated products (ascending orbit) for part of the USA and for the year 2014. The L4 figure includes only the tiles (08,05) and (09,05), joined together. The black circles correspond, from left to right, to the location of Walnut Gulch and Little Washita validation networks.



402

Figure 3 - Year averages of SMOS L3 and L4 disaggregated products (ascending orbit) for part of Australia and for the year 2010. The L4 figure includes part of the tiles (29, 12) and (30, 12), joined together. The dotted line depicts the boundary of the Murrumbidgee catchment.

403 **4. Analysis Methodology**

404 Our analysis involves two main approaches: qualitative assessment of disaggregated SM maps and
405 statistical evaluation. The statistical evaluation consists on comparing the L3 SMOS product (LR) and the
406 L4 product (HR) against the *in situ* SM by using standard statistical metrics (e.g. correlation, bias, etc.).
407 This can be accomplished in the spatial or in the time domain. We base the statistical evaluation on the
408 assumption that the 1 km pixel is more representative of the *in situ* measurement than the whole LR pixel.

409 In order to assess the relative spatial performance of both L3 and L4 products at HR, we directly compare
410 the station measurements to the satellite retrievals, without aggregating them at LR. In the subsequent
411 sections, MB refers to the whole Murrumbidgee network, including Yanco area. Yanco only refers to the
412 12 stations contained in this region.

413 **4.1 Data preparation**

414 We filter L3 and L4 SM time series for radio frequency interference (RFI) by removing pixels having
415 more than 10 % RFI probability. The RFI information is extracted from the same CLF31A/D product and
416 accounts for the percentage of brightness temperatures acquisitions affected by RFI presence (Kerr et al.,
417 2013; Oliva et al., 2012). In addition, regarding the *in situ* data, we only keep the SM values at the SMOS
418 overpass times. Finally, we filter the three SM time series (in situ, L3 and L4) for common dates with
419 valid SM values ($>0.0 \text{ m}^3/\text{m}^3$).

420 **4.2 Analysis of the temporal and spatial variability of the *in situ* SM**

421 As expected for any data disaggregation approach, the application of DISPATCH is relevant when the SM
422 spatial variability at the downscaled resolution is larger than the output uncertainty. Since the current
423 version of DISPATCH relies on the spatial contrast of LST and SM of the scene, a preliminary study on
424 the spatial SM variability of the validation areas is desired. In homogeneous SM landscapes, the output
425 uncertainty is likely to be greater than the spatial gain provided at HR by disaggregation.

426 Similarly, it is desirable that the evaluation include *in situ* time series spanning the full range of SM
427 conditions and seasonal changes. In other words, the temporal standard deviation (σ) should be large
428 enough so that all the states of the SM variable are represented and no selection bias is present.
429 Additionally, stations exhibiting very different temporal σ may suggest landscape spatial heterogeneity:
430 soil characteristics like texture, vegetation and topography affect the dry-down process, generating
431 different extreme values in time.

432 Based upon the considerations discussed above, the evaluation of the performance of the C4DIS products
433 should include a preliminary assessment of the spatial and temporal SM variability of the validation
434 networks. The performance of DISPATCH outputs over MB and Yanco has been identified as rather
435 satisfactory in recent studies (Malbêteau et al., 2016b; Merlin et al., 2012), which makes them good
436 references for spatial and temporal σ .

437 **4.3 Classical metrics**

438 Given the spatial mismatch between *in situ* and satellite estimations and the spatial scarcity of ground
439 stations, most classical satellite validation campaigns only evaluate the temporal dimension, by means of
440 metrics like correlation (R), root mean square error (RMSE) and bias (B) (Albergel et al., 2012; Albergel,
441 et al., 2013; Entekhabi, et al., 2010b; Bitar et al., 2012). In this study, we use similar temporal analysis but
442 we also include an evaluation in the spatial domain since disaggregation techniques aim at producing
443 better spatial representation. The spatial statistical analysis consists of computing the metrics between the
444 satellite and *in situ* values for each day, then, deriving the average of each metric for the whole period. We
445 deliberately establish a minimum of 5 points per day to compute the metrics.

446 Herein, instead of the RMSE, we use as error metric the standard deviation of the error (Eq. 9) (Mood et
447 al., 1974; Salkind, 2010), which is a non-biased estimation of the error and so it is not compromised by the
448 bias in the mean and amplitude of the time series that affects the RMSE. The relationship between both
449 metrics is written in Eq. 10 and 11. Since we already use multiple terms to refer to different standard
450 deviation measures and datasets in this paper (σ , STD), we will refer to this metric as unbiased-RMSE or
451 ubRMSE (Entekhabi et al., 2010b). Given that the 1 km pixels are in general heterogeneous and that the

452 ground data also present measurement uncertainties, the term ‘error’ has been replaced by ‘difference’ in
 453 these metrics, i.e. RMSD and ubRMSD.

$$\text{ubRMSD} = \sqrt{E\{[(SM_{\text{satellite}} - E\{SM_{\text{satellite}}\}) - (SM_{\text{insitu}} - E\{SM_{\text{insitu}}\})]^2\}} \quad (9)$$

$$\text{RMSD} = \sqrt{E\{(SM_{\text{satellite}} - SM_{\text{insitu}})^2\}} \quad (10)$$

$$\text{ubRMSD} = \sqrt{(\text{RMSD}^2 - B^2)} \quad (11)$$

454 where $E\{\cdot\}$ is the expectation operator, $SM_{\text{satellite}}$ and SM_{insitu} the satellite and the *in situ* SM time series.

455 We include one additional metric to assess the efficiency gained in spatial representativeness: the slope (S)
 456 of the regression line between *in situ* and satellite estimates:

$$457 \quad S = R \cdot \sigma_{\text{satellite}} / \sigma_{\text{insitu}} \quad (12)$$

458 with $\sigma_{\text{satellite}}$ and σ_{insitu} being the standard deviations of satellite and *in situ* SM, respectively. The S metric
 459 can help to understand how much better the SM redistribution is represented after the disaggregation
 460 process. Whereas aggregation systematically decreases the $\sigma_{\text{satellite}}$, disaggregation specifically aims to
 461 improve the spatial representation of satellite SM by increasing the $\sigma_{\text{satellite}}$ at the level of σ_{insitu} , while
 462 keeping a significant R. Mathematically speaking, R is the slope of the standardized regression line, and S
 463 is scaled by the σ values of both data ensembles (Rodgers & Nicewander, 1988). Since the σ_{insitu} is fixed, S
 464 is more sensitive than R to changes in $\sigma_{\text{satellite}}$. In summary, an increase in random uncertainties (larger
 465 ubRMSD, smaller R) in disaggregated SM might be acceptable if S is closer to 1. Note that the random
 466 uncertainties in satellite SM can be significantly reduced via the techniques of data assimilation in land
 467 surface models, but the systematic errors associated with the mismatch between data resolution and model
 468 application scale are more difficult to take into account at HR (Merlin et al., 2006).

469 Finally, the metrics here (S, R, ubRMSD, B) assume that a linear relationship exists between the two
 470 datasets compared. This means that they cannot replace the visual assessment of the data. In the general
 471 case, both SMOS L3 and disaggregated SM may exhibit non-linear behavior with respect to *in situ* SM.

472 **4.4 Relative performance metrics**

473 Comparing the improvement/degradation in statistics for different cases of study (networks, filtering, time
 474 period, etc.) may be difficult: we propose as solution to calculate their relative gains as introduced in
 475 Merlin et al. (2015). Briefly, the gain is a measure of the improvement in the statistics obtained for the L4-
 476 *in situ* pair with respect to the L3-*in situ* pair. The gain can range from -1 to 1, where positive values
 477 indicate disaggregated data having better correspondence with *in situ* than LR data. In this study, we keep
 478 the nomenclature of Merlin et al. (2015) and we add a new gain term for the ubRMSD (see Table 3). The
 479 gains are calculated as in Eq. 13 for in S and R metrics, and as in Eq. 14 for B and ubRMSD.

$$G_X = - (|1-X_{L4}|-|1-X_{L3}|) / (|1-X_{L4}|+|1-X_{L3}|) \quad (13)$$

$$G_X = - (|X_{L4}|-|X_{L3}|) / (|X_{L4}|+|X_{L3}|) \quad (14)$$

480 where X designates the metric (S, R, B, ubRMSD), X_{L4} the value of the metric when disaggregated SM is
 481 compared against *in situ*, and X_{L3} the value of the metric when L3 SM is compared against *in situ*.

Table 3 - List of performance metrics used in this study, from (Merlin et al., 2015)

482

Gain(S)	G_{EFFI}
Gain(R)	G_{ACCU}
Gain(B)	G_{ROBU}
Gain(ubRMSD)	G_{ubRMSD}

483 5. Results and discussion

484 This study seeks to provide a first assessment on the applicability of the DISPATCH-based processor
485 under different climatic and landscape conditions. It also attempts to provide statistical guidelines on the *a*
486 *priori* suitability of a geographical area for the production of meaningful C4DIS fields. The analyses span
487 the 01/06/2010 to 31/12/2014 period for the MB network and Yanco area and the 01/06/2010 to
488 31/12/2014 period for the LW and WG networks. The SMOS data collected during the commissioning
489 phase (until 31/05/2010) is discarded.

490 5.1 Preliminary analysis

491 In order to predict the performance of the processor, we conduct a statistical analysis on the in situ SM
492 data. We derive conclusions about their temporal and spatial variabilities by looking at their distribution of
493 SM values and their distribution of ‘spatial σ ’ and ‘temporal σ ’. The ‘spatial σ ’ (upper row in Figure 4) is
494 the standard deviation of the SM distribution on each day. The ‘temporal σ ’ (middle row) is the standard
495 deviation of the SM series of each station.

496 As stated in section 4.2, we consider the in situ SM distribution characteristics of MB and Yanco networks
497 as reference in the present study. The spatial σ plot shows narrower distributions for LW and WG, and the
498 mean value is much lower for the latter ($0.03 \text{ m}^3/\text{m}^3$). This means that the spatial variability at LW and
499 WG seen at the satellite overpass times is lower than in the reference cases, so we expect poorer
500 performances in the spatial domain.

501 In the temporal domain (middle row of Figure 4), the mean variability of LW and WG networks is lower
502 than that of the Australian cases. The SM distribution of WG (4th column) shows a very strong peak near
503 zero that accounts for almost the half of the samples. Under these conditions, we expect WG to be the
504 network with worst temporal performance of C4DIS products, while LW should behave similarly to MB
505 and Yanco. It is important to mention that LW and WG only represent a portion of a SMOS pixel and the
506 *in situ* samples only concern some HR pixels in space, so the distributions depicted here serve only as
507 approximation.

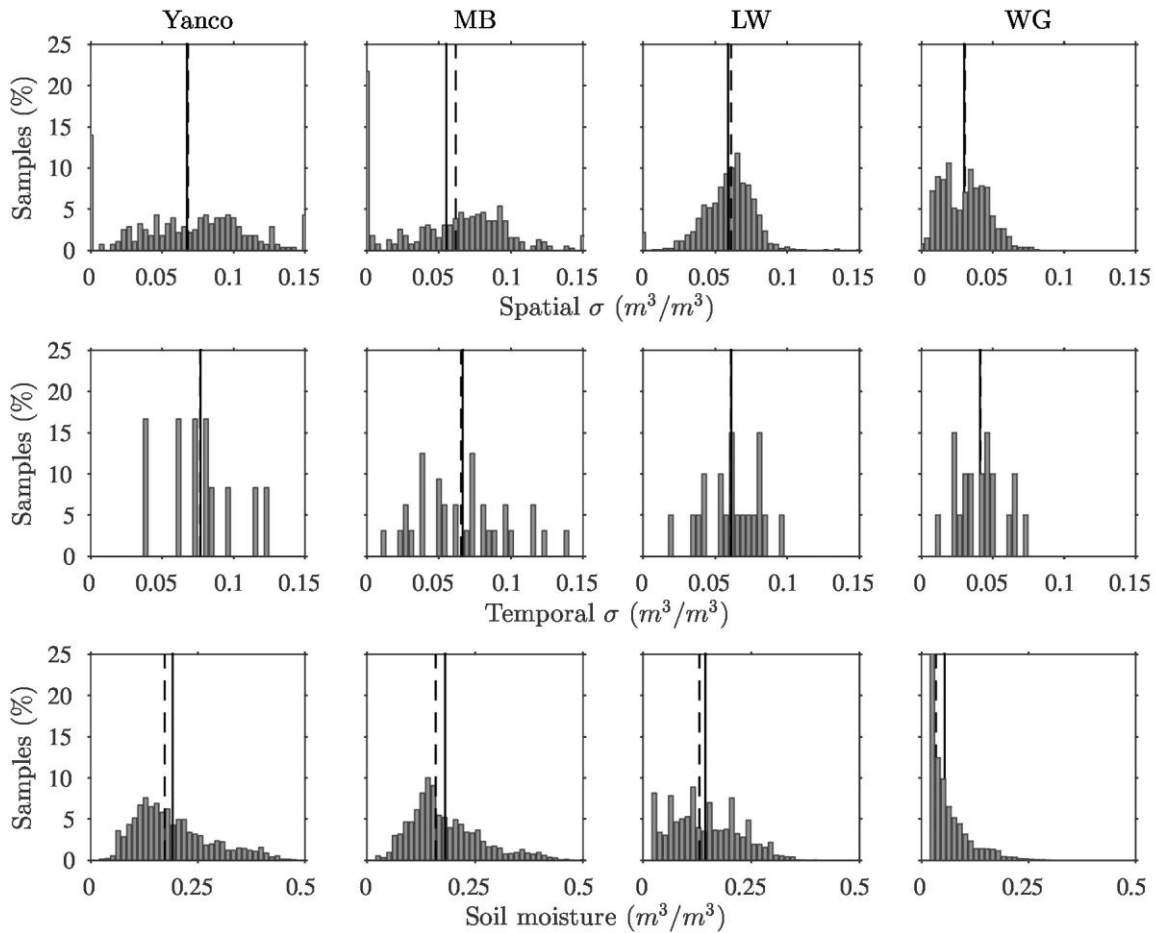


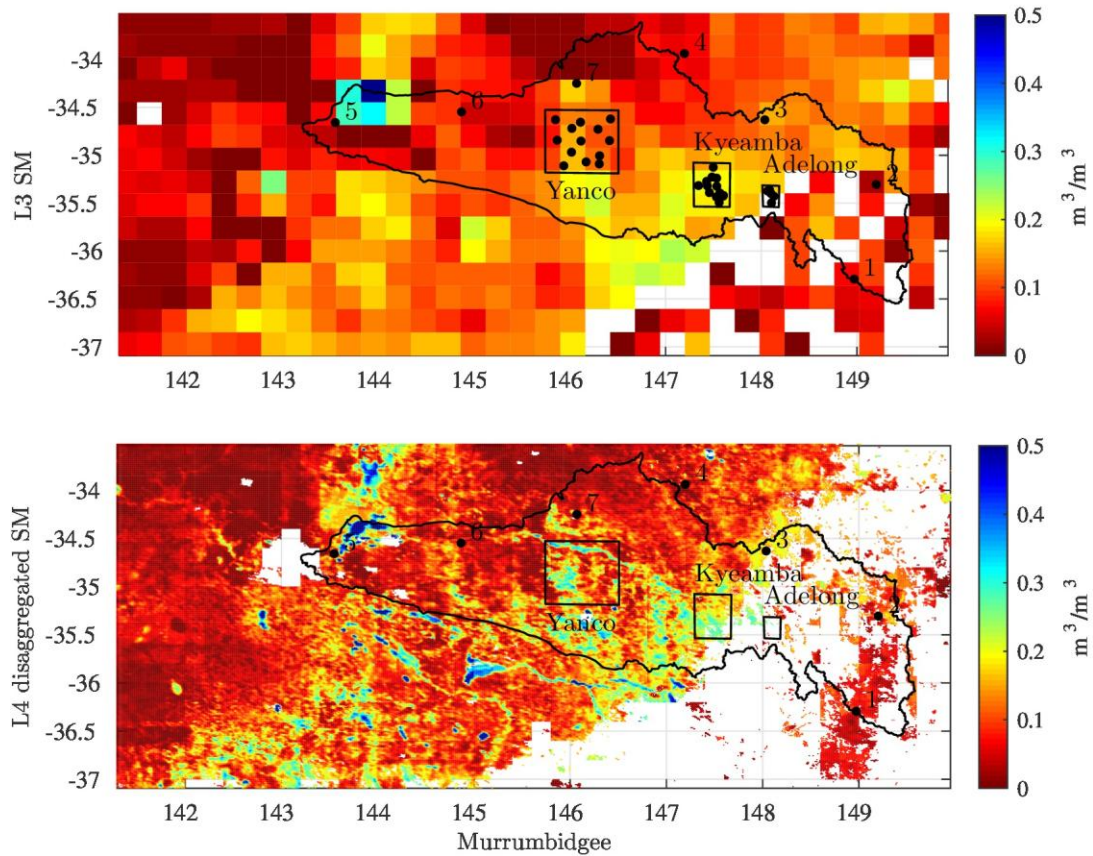
Figure 4- Distribution of spatial and temporal standard deviations and SM values for the in situ samples of Yanco, MB, LW and WG (1st to 4th columns respectively) at the SMOS overpass times. Number of bins of the histograms is 40. The median of the distributions is depicted in dashed line and the mean in solid line. The WG soil moisture maximum percentage is not shown (right-down graph) for readability and it reaches 47 % of the samples.

508 5.2 Qualitative examples

509 The qualitative inspection of disaggregated SM maps for MB, Yanco, LW and WG, shows that the L4
 510 product is able to reveal spatial entities like small and sparse water bodies.

511 Figures 5 and 6 contain sample outputs of the C4DIS processor on cloud-free days for the four areas. In
 512 the MB picture (Figure 5), the Murrumbidgee river is revealed thanks to disaggregation, while the south-
 513 eastern region is empty due to clouds and the SMOS non-retrieved pixels over the mountains. In Figure 6,
 514 disaggregation does not help reveal the Little Washita river course but it does with the surrounding lakes.

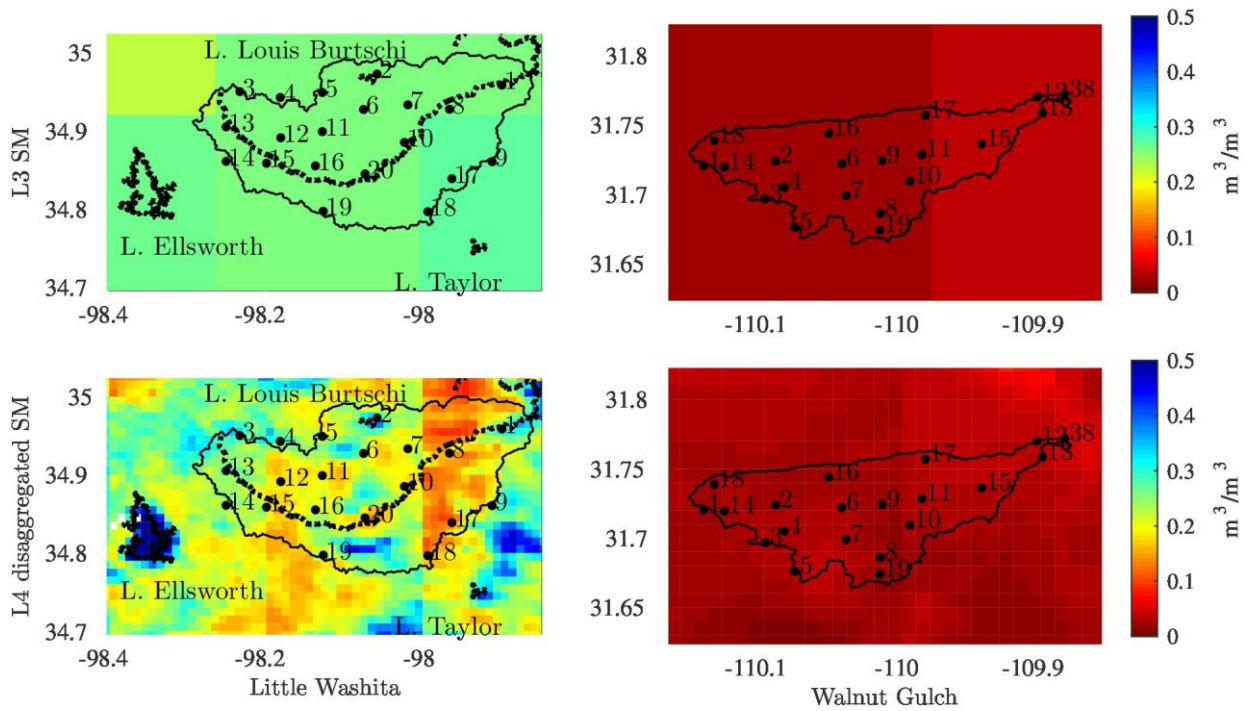
515 The processor fails to display any spatial pattern inside the WG watershed. These maps are in agreement
 516 with the evaluation in the previous section.



517

Figure 5 - Maps of L3 SM (CLF31D) and L4 disaggregated SM for MB watershed on 22/11/2010 for the SMOS descending overpass.

518 Yanco maps are a good example of the usefulness and relevance of the C4DIS products when the
 519 algorithm assumptions are met. Figure 7 shows the Yanco area with the limits of the Coleambally
 520 Irrigation Area (CIA) units superimposed. At a first glance, the L4 SM map reveals the farms that are
 521 actually irrigated, while original SM map do not.



522

Figure 6 – Maps of L3 SM (CLF31A) and L4 disaggregated SM for LW (left column) and WG (right column) watersheds on 02/05/2011 and 01/05/2011 respectively. Solid black contours correspond to watershed boundaries. In the left column, the bold dotted line in the middle of the watershed correspond to the Little Washita river and the bold dotted contours to surrounding lakes.

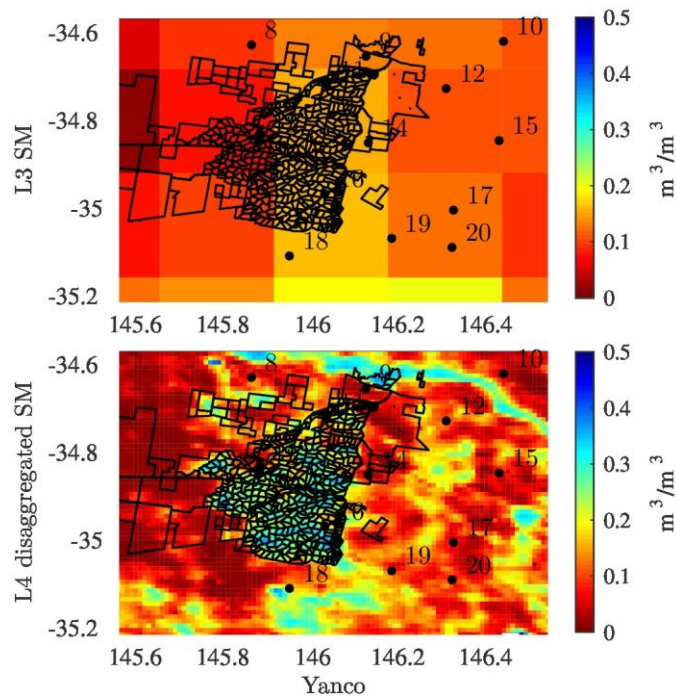
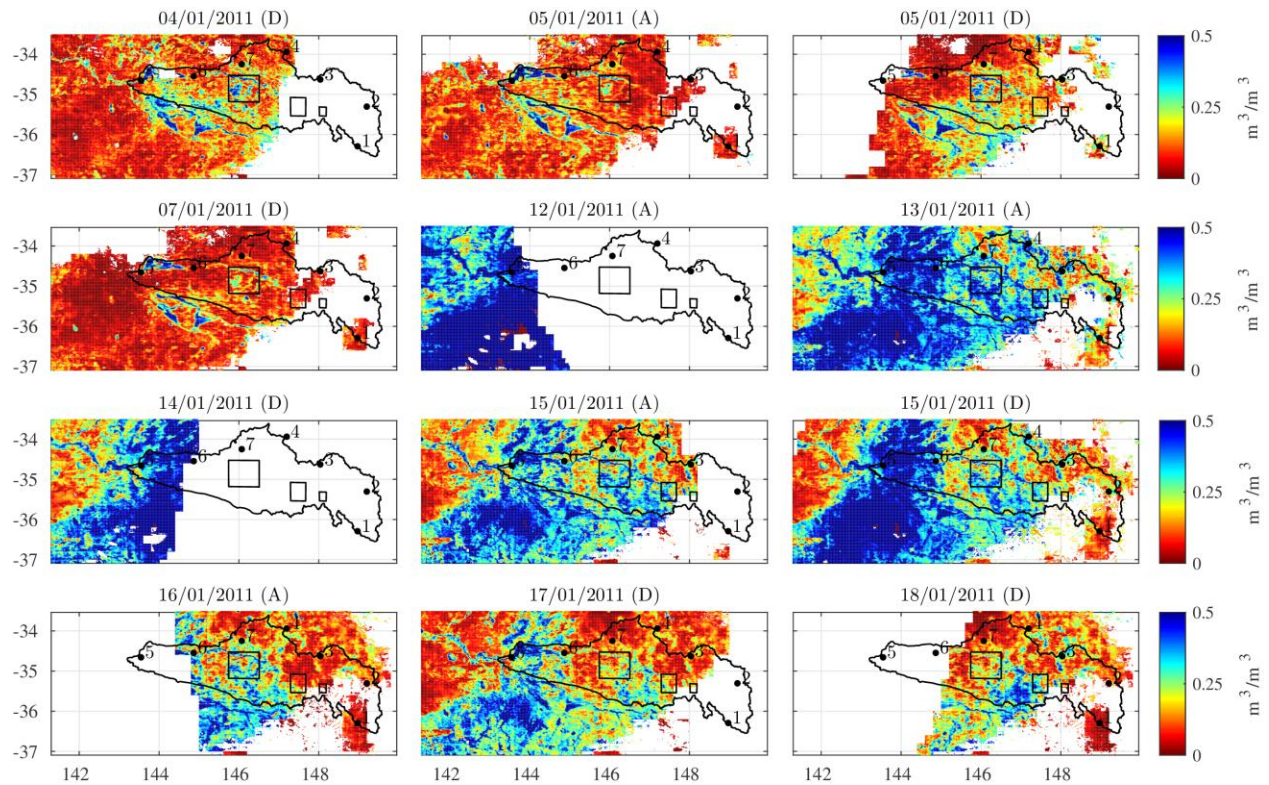


Figure 7- Maps of L3 SM (CLF31D) and L4 disaggregated SM for Yanco area on 22/11/2010. Black lines represent the contours of Coleambally irrigated farms.

523 Finally, we show in Figure 8 a series of C4DIS disaggregated outputs between the 4th and the 18th day of
 524 2011. We can identify in detail the areas affected by the floods that touched the states of New South
 525 Wales and Victoria on those days. Likewise, we see how the dry-down process is faster in some small
 526 areas than in others (west of Yanco).



527
 Figure 8 - Maps of L4 disaggregated SM for MB on the first days of January 2011, showing the progression of floods that affected New South Wales and Victoria states. The title of each image contains the date and the SMOS overpass ('A' for ascending, 'D' for descending).

528 5.3 Spatial evaluation

529 In this section, the L4 and L3 SM products are compared at HR on a daily basis against the *in situ*
 530 measurements.

531 Table 4 shows daily statistics averaged over the periods of analysis. When comparing the statistics
 532 obtained for L3 and L4 products in MB and Yanco networks, it is noted an important enhancement of the
 533 S and the R values, ranging between 0.24-0.32 and 0.09-0.17, respectively. Results are consistent with the
 534 conditions of the area, especially those of Yanco (semi-arid climate with SM spatial heterogeneity

535 dominated by irrigation). Spatial B is maintained while ubRMSD increases (around $0.02 \text{ m}^3/\text{m}^3$) which
536 can be explained by the added uncertainty when combining data from different sources.

537 LW and WG statistics are much poorer than MB ones: R and S never exceed 0.11. The reasons for that
538 can be found in both the algorithm and the conditions of the validation area. First, the L3 statistics (R and
539 S) are much worse in the American than in the Australian networks, which may entail uncertainty present
540 in the LR product that is propagated to the L4 product. Second, according to the preliminary statistical
541 analysis (section 5.1), the spatial σ distribution of WG is narrower and span over lower values than those
542 of the Australian networks. The spatial variability cannot explain however the poor statistics of LW, since
543 here the mean spatial σ is similar to the Australian ones ($0.07 \text{ m}^3/\text{m}^3$ for Yanco, $0.06 \text{ m}^3/\text{m}^3$ for MB and
544 LW). Another important aspect to take into consideration is the mismatch between the validation extent
545 and the SMOS resolution. LW and WG cover only part of the surface of one SMOS pixel ($\sim 1/4$ and $\sim 1/12$
546 of its equivalent surface, respectively), so the distribution of spatial σ may not be representative of the
547 surface perceived by DISPATCH. All this suggests that a qualitative analysis of the area is strongly
548 recommended.

549 The LW watershed has rolling relief and a variety of soil textures and vegetation types, which are not
550 considered in the soil temperature equations of DISPATCH. Moreover, its extension is around 4 times
551 smaller than the Yanco area: we can think that a higher heterogeneity within the 1 km pixel would hamper
552 R and S statistics as well. Most importantly, LW climate is defined as sub-humid, so we can expect the
553 link moisture-evaporation to be weak. Concerning WG, the soils are of fast infiltration (sands and
554 gravels), which reduces the apparent SM spatial contrast at the satellite overpass times, a necessary
555 condition for an accurate computation of the DISPATCH SMp parameter.

556 The comparison of the results here with previous versions of the algorithm can shed light on the
557 pertinence of the choices made in the algorithm since Merlin et al., 2012. Regarding the most recent study,
558 similar spatial statistics for MB and Yanco can be found in Malbêteau et al., 2015, which proves that the
559 performance of the processor is coherent with that of the prototype algorithm. The remaining differences
560 are originated by two factors. First, in our aim to assess the qualities of the entire C4DIS processor, we use

561 as LR SM reference the original SMOS CLF31A/D product, while Malbêteau et al., 2015 employed a
 562 reprojected form of the same product used by DISPATCH, which was a reasonable choice from the
 563 algorithm point of view. Second, the C4DIS post-processor clips to zero the negative values produced by
 564 DISPATCH, a module that was not still implemented at the time of Malbêteau et al., 2015.

565 Another two former validation campaigns of DISPATCH showed better correspondence with *in situ*
 566 measurements, but they were accomplished for specific areas with known high-evaporative demand and
 567 for no more than a dozen of dates. For the Murrumbidgee catchment and AACES-I campaign (Merlin et
 568 al., 2012), and the Catalunya campaign (Merlin et al., 2013), summer 2010 and 2011 respectively, the
 569 correlation values were close to the double of those obtained for MB in this study. However, the AACES-
 570 based study also reported negative values for those dates with very dry homogeneous SM scenes. This
 571 confirms our hypothesis for WG, were the large number of ‘flat’ SM scenes is probably behind the
 572 unsatisfactory statistics. In the same article of 2012, the AACES-II results (winter), allowed to presume that
 573 the weak evaporation-SM coupling was behind negative R values. Our statistics for LW seem to confirm
 574 this point, but since the mean R is higher, it suggests that the algorithm might be useful for some periods
 575 of the year.

Table 4 - Spatial statistics of Yanco and MB for the period 01/06/2010 to 31/05/2011 and of LW and WG for the period 01/06/2010 to 31/12/2014. ‘L3’ refers to the comparison between L3 SM and in situ SM and ‘L4’ refers to the comparison of L4 disaggregated SM and in situ SM. ‘A’ stands for ascending orbit and ‘D’ for descending orbit. All the values are expressed in m^3/m^3 , except for R and Number of days, which are unitless.

		Yanco		MB		LW		WG	
		L3	L4	L3	L4	L3	L4	L3	L4
S	A	0.064	0.309	0.086	0.403	0.003	0.047	0.004	0.110
	D	0.080	0.378	0.195	0.430	0.031	0.046	0.017	0.111
R	A	0.201	0.316	0.156	0.288	0.030	0.064	0.015	0.102
	D	0.194	0.363	0.251	0.335	0.115	0.057	0.042	0.111
B	A	0.018	0.021	0.031	0.035	0.023	0.016	0.031	0.026
	D	0.006	0.011	0.016	0.020	0.023	0.012	0.029	0.026
ubRMSD	A	0.072	0.094	0.082	0.103	0.063	0.076	0.030	0.037
	D	0.077	0.091	0.080	0.100	0.062	0.076	0.033	0.040
Nb days	A	74		100		573		552	
	D	66		95		557		545	

576 **5.4 Temporal evaluation**

577 For the temporal analysis, we consider the same period and datasets as in section 5.3. We compute
 578 statistics on the concatenation of all the SM series within a network. Table 5 displays temporal statistics
 579 for the four validation networks. Regarding Yanco and MB, the S metric is better for the HR SM product
 580 (between 0.12 and 0.18 higher), which is consistent with the spatial evaluation results. R is slightly
 581 degraded in Yanco while maintained in MB. This, and the increase in ubRMSD, can be explained by the
 582 temporal uncertainty induced by the processor when considering as inputs observations acquired in
 583 different days and times. These results are consistent with previous validation studies of DISPATCH:
 584 Merlin et al., 2013 showed that the temporal S could increase between 0.15 to 0.25 after disaggregation,
 585 while R being maintained or increased and ubRMSE increased.

586 In the case of LW , the disaggregated SM (L4) has a slightly better S when compared to *in situ* SM than
 587 does L3 SM for both orbits (improvement of +0.06 for A orbit and of +0.03 for D orbit). The same
 588 evaluation holds for WG (improvement of +0.05 and of +0.08 for A and D orbits respectively). Like in the
 589 Yanco case, disaggregation slightly degrades R and ubRMSD for both SMOS orbits, showing again the
 590 increase of random uncertainties attributed to the models and data used by DISPATCH.

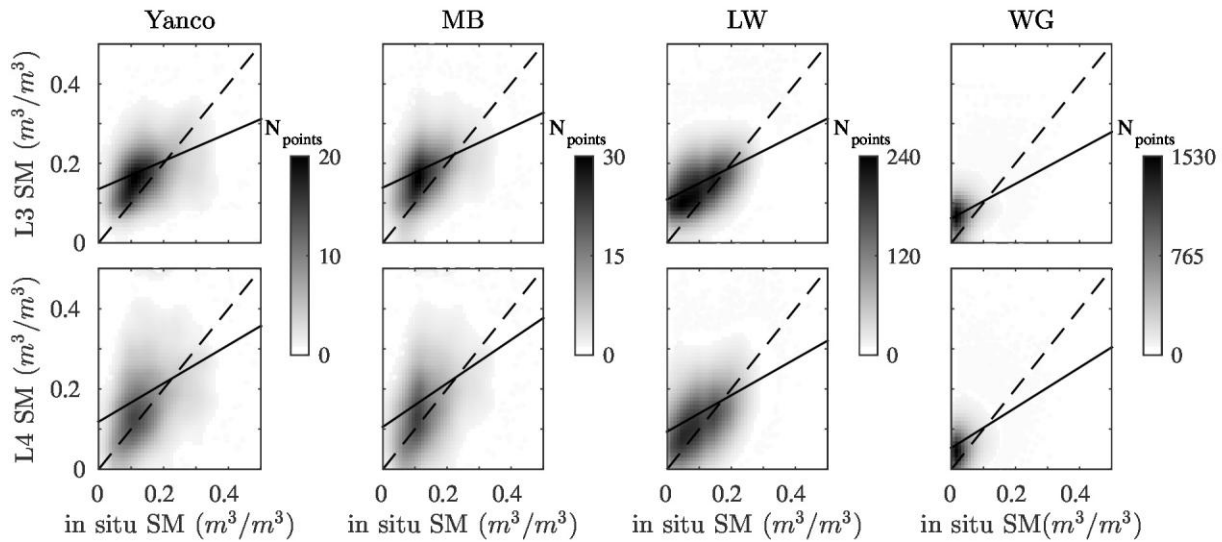
Table 5 - Temporal statistics of Yanco and for the period 01/06/2010 to 31/05/2011, and of LW and WG for the period 01/ 06/2010 to 31/12/2014. 'L3' refers to the comparison between L3 SM and in situ SM and 'L4' refers to the comparison of L4 disaggregated SM and in situ SM. In the second column, 'A' stands for ascending orbit and 'D' for descending orbit. All the values are expressed in m^3/m^3 , except for R and Number of points, which are unitless, and RFI percentage, which is in %.

		Yanco		MB		LW		WG	
		L3	L4	L3	L4	L3	L4	L3	L4
S	A	0.368	0.489	0.363	0.538	0.406	0.463	0.490	0.544
	D	0.333	0.465	0.383	0.542	0.415	0.441	0.381	0.458
R	A	0.432	0.370	0.321	0.377	0.468	0.434	0.468	0.436
	D	0.369	0.356	0.361	0.368	0.460	0.410	0.352	0.366
B	A	0.019	0.023	0.033	0.027	0.023	0.017	0.031	0.026
	D	0.004	0.014	0.020	0.019	0.025	0.014	0.030	0.026
ubRMSD	A	0.090	0.120	0.105	0.118	0.078	0.088	0.044	0.051
	D	0.095	0.118	0.095	0.118	0.077	0.088	0.052	0.056
RFI perc.	A	0.000	-	0.248	-	1.893	-	1.958	-
	D	0.000	-	0.000	-	1.893	-	1.562	-

Nb points	A	754	754	1429	9027
	D	723	723	1409	9337

591 According to our preliminary analysis on in situ temporal σ and SM samples, WG should at least behave
592 differently with respect to the other networks (much narrower distribution of SM values, skewed to the dry
593 section of the range and lower σ variability). However, no significant differences are found in the
594 temporal statistics.

595 Differences can be appreciated more easily through qualitative inspection of scatter plots (Figure 9). In
596 Yanco and MB plots, the increase in ubRMSD is observed in the more dispersed cloud of points, although
597 the distribution appears slightly closer and more symmetric around the 1:1 line. In the case of LW, we can
598 see that for drier SM conditions ($< 0.15 \text{ m}^3/\text{m}^3$), disaggregated values are closer to *in situ* values and
599 become equally distributed around the 1:1 line. Since LW climate is sub-humid, evapotranspiration
600 processes are mainly energy-driven; however, we can expect them to be moisture-driven during periods
601 with lower water availability and higher temperatures like summer. This is confirmed in Figure 10, which
602 shows the scatter plot for LW summers. Regarding WG, the scatter plots show no major differences
603 between L3 and L4 data. This is consistent with the very low spatial and temporal *in situ* σ : DISPATCH is
604 operating at the limit of its nominal range at 1 km resolution and the amount of information obtained is not
605 more important than the uncertainty introduced. It outlines also the importance of qualitative assessments:
606 although LW and WG show similar global spatial and temporal statistics, C4DIS disaggregated fields,
607 which are not of interest in WG, are valuable in the case of LW summers.



608

Figure 9 - Scatterplots of original L3 SM (1st row) and L4 disaggregated SM (2nd row) versus in situ measurements for both A and D orbits. The samples here correspond to the periods 06/2010 to 05/2011 for MB and Yanco, and 06/2010 to 12/2014 for LW and WG. Dashed line represents the 1:1 slope and the solid line corresponds to the linear regression line (S statistic).

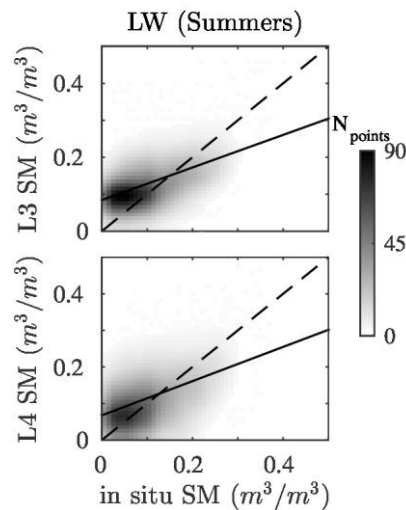


Figure 10 - Scatterplot of L3 SM (1st row) and L4 disaggregated SM (2nd row) against in situ SM samples for LW network for summer periods (June, July and August months of years 2010 to 2014). Dashed line represents the 1:1 slope and the solid line corresponds to the linear regression line (S statistic).

609 5.5 Analysis of the STD and COUNT datasets

610 As introduced in section 3.6, the STD and COUNT datasets can help derive conclusions on the quality of
 611 the SM_{HR} values. In this section, we evaluate spatial and temporal statistics on SM samples with
 612 different corresponding STD and COUNT values. We first select the samples with values falling inside a

613 given STD or COUNT range of values; then, we compute statistics on the *in situ*, L3 and L4 values for
 614 those samples. This analysis is conducted on MB and Yanco networks as USDA networks still show low
 615 statistics after filtering for STD and COUNT values. Herein, we use the gain metrics introduced in section
 616 4.4, which will simplify the task of comparison between bins of STD and COUNT.

617 Table 6 shows spatial statistics for MB and Yanco divided in 3 ranges of STD ($<0.03 \text{ m}^3/\text{m}^3$, $0.03\text{-}0.07$
 618 m^3/m^3 , $>0.07 \text{ m}^3/\text{m}^3$). Note that the total number of days analyzed drops drastically when STD or
 619 COUNT filtering is applied to spatial metrics. This is as expected since for a given time stamp, the
 620 samples have STD and COUNT values that belong to different bins and we need at least 5 samples in the
 621 same bin to compute statistics.. C4DIS SM dataset exhibits the lowest correlation (S and R) and the
 622 highest error (ubRMSD) with *in situ* when most of the pixels have high STD ($>0.07 \text{ m}^3/\text{m}^3$). This seems
 623 plausible since large ubRMSD values can be produced by forcing events (rain, irrigation) in the 3-days
 624 window of DISPATCH, so the final SM_HR values would contain high uncertainty. We cannot generalize
 625 any behavior in performances for the medium and lower STD ranges ($<0.07 \text{ m}^3/\text{m}^3$) since MB and Yanco
 626 show different trends. If we consider only Yanco, which is a much more homogeneous area in terms of
 627 climate and landscape properties, we can conclude that, regardless of the bias, the rest of spatial metrics
 628 are better as STD gets lower. Whether this is applicable to other homogeneous areas or not need to be the
 629 subject of additional studies.

630 Spatial statistics are also filtered for COUNT values (Table 7). In this respect, statistics are better for large
 631 values of COUNT (17-24 datasets). However, the number of days used in this computation is low (below
 632 15) so the results may not be accurate.

Table 6- Spatial statistics as a function of the values of the STD dataset for MB and Yanco areas from 01/06/2010 to 31/05/2011. Best statistics are outlined and in italics. Last line of Yanco table has been crossed out because it refers to only one day of statistics.

STD	Yanco					MB				
	G _{EFFI}	G _{ACCU}	G _{ROBU}	G _{ubRMSD}	N _{days}	G _{EFFI}	G _{ACCU}	G _{ROBU}	G _{ubRMSD}	N _{days}
< 0.03	<u>0.27</u>	<u>0.24</u>	-0.22	<u>0.05</u>	11	0.15	<u>0.11</u>	-0.12	<u>-0.04</u>	45
0.03 - 0.07	0.13	0.06	<u>-0.11</u>	-0.10	39	<u>0.17</u>	0.05	-0.03	-0.07	108
> 0.7	-0.47	-0.12	-0.42	-0.57	1	-0.02	-0.09	<u>0.05</u>	-0.28	16

Table 7 - Spatial statistics as a function of the COUNT dataset for MB and Yanco areas from 01/06/2010 to 31/05/2011. Best statistics are outlined and in italics.

COUNT	Yanco					MB				
	G _{EFFI}	G _{ACCU}	G _{ROBU}	G _{ubRMSD}	N _{days}	G _{EFFI}	G _{ACCU}	G _{ROBU}	G _{ubRMSD}	N _{days}
1-8	0.16	0.08	-0.16	-0.16	69	0.16	0.07	<u>-0.05</u>	-0.11	143
9-16	0.12	0.16	-0.15	-0.07	22	0.14	-0.01	-0.12	-0.15	51
17-24	<u>0.44</u>	<u>0.29</u>	<u>-0.08</u>	<u>0.06</u>	11	<u>0.35</u>	<u>0.15</u>	-0.24	<u>-0.04</u>	13

633 Regarding the temporal domain, Yanco shows a deterioration of the metrics as STD increases (Table 8),
 634 which is consistent with the preliminary *in situ* spatial analysis and would be mainly due to the uncertainty
 635 added when precipitation or irrigation take place in the 3-days window of DISPATCH. Such trend is not
 636 revealed in the MB data (same table), and conclusions are difficult to be derived given the high
 637 heterogeneity within the network.

638 Concerning the COUNT dataset, Table 9 clearly shows that temporal statistics improve as COUNT
 639 increases. This seems to confirm that the methodology of averaging of the disaggregated ensemble helps
 640 to reduce random uncertainties in the temporal domain.

Table 8 - Temporal statistics as a function of the STD dataset for MB and Yanco areas from 01/06/2010 to 31/05/2011. Best statistics are outlined and in italics.

STD	Yanco					MB				
	G _{EFFI}	G _{ACCU}	G _{ROBU}	G _{ubRMSD}	N _{samples}	G _{EFFI}	G _{ACCU}	G _{ROBU}	G _{ubRMSD}	N _{samples}
< 0.025	<u>0.18</u>	<u>0.04</u>	-0.30	<u>-0.06</u>	472	<u>0.16</u>	0.03	-0.81	-0.06	904
0.025 - 0.040	0.04	-0.06	<u>-0.14</u>	-0.11	813	0.11	0.01	<u>0.03</u>	<u>-0.10</u>	1459
0.040 - 0.055	0.03	-0.04	-0.41	-0.18	192	0.13	<u>0.06</u>	-0.12	-0.03	475

Table 9 - Temporal statistics as a function of the COUNT dataset for MB and Yanco areas from 01/06/2010 to 31/05/2011. Best statistics are outlined and in italics.

COUNT	Yanco					MB				
	G _{EFFI}	G _{ACCU}	G _{ROBU}	G _{ubRMSD}	N _{samples}	G _{EFFI}	G _{ACCU}	G _{ROBU}	G _{ubRMSD}	N _{samples}
1-8	0.08	-0.06	-0.21	-0.15	965	0.14	0.02	0.08	-0.08	1910
9-16	0.17	-0.02	-0.18	-0.12	386	0.19	0.02	0.04	-0.09	737
17-24	<u>0.22</u>	<u>0.19</u>	<u>0.35</u>	<u>0.01</u>	126	<u>0.21</u>	<u>0.15</u>	<u>0.44</u>	<u>-0.03</u>	191

642 6. Conclusions

643 The C4DIS processor is the new SMOS L4 processor of the French ground segment CATDS, which
644 provides global maps of disaggregated SM at 1 km resolution. The C4DIS processor is the operational
645 version of the DISPATCH prototype (Merlin et al., 2012, 2013). DISPATCH disaggregates LR SM
646 observations using HR soil temperature data. It models the physical link between soil temperature,
647 evaporation and moisture with a semi-empirical SEE model and a first-order Taylor series expansion
648 around the SM observation. The soil temperature is derived from the combination of LST, NDVI and
649 elevation information. The C4DIS processor uses the SM dataset of the SMOS 1-day L3 CLF31A/D
650 product from CATDS, the LST dataset of the MODIS MOD11A1 and MYD11A1 products from LP
651 DAAC services, the NDVI dataset from the MOD13A2 product from LP DAAC services, and the
652 elevation dataset from the GTOPO30 product from the USGS Eros Data Center.

653 In this study, the C4DIS products were evaluated for four different geographical areas: the Murrumbidgee
654 validation network and the Yanco area for the period 06/2010 to 05/2011, and the Little Washita and
655 Walnut Gulch networks for the period 01/2010 to 12/2014. The objective was to provide a first assessment
656 of the processor under different climatic and land conditions. The performance was assessed by
657 comparing the disaggregated (L4) and non-disaggregated (L3) SM datasets against the *in situ*
658 measurements in both the spatial and temporal domains.. The *in situ* SM data was statistically analyzed
659 beforehand in order to predict the suitability of the C4DIS processor for each area. We also evaluated the
660 output COUNT and STD datasets as potential sources of information for quality assessment.

661 The evaluation of the disaggregated SM dataset in Murrumbidgee and Yanco brought results in coherence
662 with previous versions of DISPATCH (Malbêteau et al., 2016b; Merlin et al., 2012), and presented
663 improvements on the spatial correlation in the range 0.09-0.17. Similar enhancements were present in the
664 temporal domain. Additionally, C4DIS SM maps succeeded to reveal spatial heterogeneities (rivers,
665 irrigation areas, floods).

666 Little Washita and Walnut Gulch showed very low spatial metric values for both non-disaggregated and
667 disaggregated SM fields, though disaggregation slightly improved the statistics. For the Little Washita, the
668 scatter plots revealed that the performances were better in the dry section of the SM range ($<0.15 \text{ m}^3/\text{m}^3$)
669 and during summers, meaning that the improvement in spatial representation was possible under moisture-
670 driven evaporation periods. Visual assessment of C4DIS SM maps showed that the disaggregated product
671 was capable of revealing the presence of water bodies in the surrounding areas namely lakes.

672 For the Walnut Gulch network, the poor spatial correspondence with *in situ* was easily explained by the
673 preliminary statistical analysis that we conducted on *in situ* SM data: this revealed very low spatial
674 variability (mean spatial σ was equal to $0.03 \text{ m}^3/\text{m}^3$), which is one of the essential conditions for a good
675 performance of the algorithm. The evaluation of this network brought to view that the algorithm needs to
676 be improved to adapt to all types of soil. Although Walnut Gulch watershed also has a moisture-controlled
677 evaporative profile (semi-arid to arid climate) like the Australian areas, the soil is mainly sandy with high
678 infiltration rates, which obstructs the detection of surface SM variations by the algorithm.

679 When evaluating the temporal behavior of the (non-disaggregated and C4DIS) satellite SM series, we
680 found an improvement of the slope of the regression line between C4DIS and the *in situ* data. The
681 correlation was slightly hampered, especially in LW and WG, and the standard deviation of the
682 differences also increased. This was likely to be caused by the increase in uncertainty associated with the
683 use of multi-satellite data.

684 With the aim of making the C4DIS products useful in a global perspective, we evaluated how the other
685 two output datasets, COUNT and STD, could help in the future definition of a quality flag. We showed
686 that for a homogeneous area like Yanco, spatial and temporal metrics were better as STD decreased.
687 Consistently, large COUNT values helped to decrease the random uncertainties and they improved
688 temporal statistics. In this area, heterogeneity is mainly driven by precipitation and irrigation, and STD
689 was directly linked to such events. On the contrary, STD and COUNT could not give sufficient
690 information for quality control in more heterogeneous areas (like the entire Murrumbidgee), so we
691 concluded that output C4DIS datasets must be combined with ancillary information like precipitation or
692 other heterogeneity-related data sources to implement a good quality flag field.

693 In conclusion, the C4DIS processor performs well in regions with SM spatial variability mainly produced
694 by external forcing agents (precipitation or irrigation). Additionally, the degree of variability must be
695 enough so the application of a disaggregation technique is advisable. These two characteristics are mainly
696 conditioned by the climate (semi-arid), soil properties (with moderate drainage), and land properties (low
697 topography, quasi-homogeneous land cover). The proper performance of the processor can be predicted by
698 looking at the *in situ* SM variability and assessing qualitatively the enounced characteristics. The C4DIS
699 SM products can be evaluated by applying ordinary spatial and temporal statistics, visual inspection of
700 maps as well as using the STD and COUNT datasets on homogeneous areas. In the future, including
701 meteorological forcing (solar radiation, air temperature, wind speed and air humidity at 2 m; Stefan et al.,
702 2015), precipitation (Djamai et al., 2015), soil texture (Merlin et al., 2016) and solar exposure (Malbêteau
703 et al., 2016a) as ancillary data will help improve DISPATCH and elaborate a quality control dataset that
704 will enlarge the applicability areas of the processor.

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715 **Bibliography**

- 716 Al Bitar, A., Leroux, D. J., Kerr, Y. H., Merlin, O., Richaume, P., Sahoo, A., & Wood, E. F. (2012).
 717 Evaluation of SMOS Soil Moisture Products Over Continental U.S. Using the SCAN / SNOTEL
 718 Network. *IEEE Transactions on Geoscience and Remote Sensing*, 50(5), 1572–1586.
- 719 Albergel, C., Brocca, L., Wagner, W., de Rosnay, P., & Calvet, J. C. (2013). Selection of Performance
 720 Metrics for Global Soil Moisture Products: The Case of ASCAT Soil Moisture Product. In *Remote*
 721 *Sensing of Energy Fluxes and Soil Moisture Content* (pp. 431–448).
- 722 Albergel, C., de Rosnay, P., Gruhier, C., Muñoz-Sabater, J., Hasenauer, S., Isaksen, L., Kerr, Y. H., &
 723 Wagner, W. (2012). Evaluation of remotely sensed and modelled soil moisture products using global
 724 ground-based in situ observations. *Remote Sensing of Environment*, 118, 215–226.
 725 doi:10.1016/j.rse.2011.11.017
- 726 Allen, P. B., & Naney, J. W. (1991). *Hydrology of the Little Washita River Watershed, Oklahoma: Data*
 727 *and Analyses*. United States Department of Agriculture, Agricultural Research Service, ARS-90.
- 728 Al-Yaari, A., Wigneron, J.-P., Ducharne, A., Kerr, Y. H., de Rosnay, P., de Jeu, R., Govind, A., Al Bitar,
 729 A., Albergel, C., Richaume, P., & Mialon, A. (2014). Global-scale evaluation of two satellite-based
 730 passive microwave soil moisture datasets (SMOS and AMSR-E) with respect to Land Data
 731 Assimilation System estimates. *Remote Sensing of Environment*, 149, 181–195.
 732 doi:10.1016/j.rse.2014.04.006
- 733 Bindlish, R. (2015). Global Soil Moisture From the Aquarius/SAC-D Satellite: Description and Initial
 734 Assessment. *IEEE Geoscience and Remote Sensing Letters*, 12(5), 923–927.
 735 doi:10.1109/LGRS.2014.2364151
- 736 Budyko, M. I. (1956). *Heat balance of the Earth's surface*. Leningrad.
- 737 Carlson, T. N. (2007). An Overview of the “Triangle Method” for Estimating Surface Evapotranspiration
 738 and Soil Moisture from Satellite Imagery. *Sensors*, 7(8), 1612–1629. doi:10.3390/s7081612
- 739 Carlson, T. N., Gillies, R. R., & Perry, E. M. (1994). A method to make use of thermal infrared
 740 temperature and NDVI measurements to infer surface soil water content and fractional vegetation
 741 cover. *Remote Sensing Reviews*. doi:10.1080/02757259409532220
- 742 Chauhan, N. S., Miller, S., & Ardanuy, P. (2003). Spaceborne soil moisture estimation at high resolution:
 743 a microwave-optical/IR synergistic approach. *International Journal of Remote Sensing*, 24(22),
 744 4599–4622. doi:10.1080/0143116031000156837
- 745 Chen, F., Crow, W. T., Starks, P. J., & Moriasi, D. N. (2011). Improving hydrologic predictions of a
 746 catchment model via assimilation of surface soil moisture. *Advances in Water Resources*, 34(4),
 747 526–536. doi:10.1016/j.advwatres.2011.01.011
- 748 Cosh, M. H., Jackson, T. J., Bindlish, R., & Prueger, J. H. (2004). Watershed scale temporal and spatial
 749 stability of soil moisture and its role in validating satellite estimates. *Remote Sensing of*
 750 *Environment*, 92, 427–435. doi:10.1016/j.rse.2004.02.016

- 751 Cosh, M. H., Jackson, T. J., Moran, S., & Bindlish, R. (2008). Temporal persistence and stability of
752 surface soil moisture in a semi-arid watershed. *Remote Sensing of Environment*, 112(2), 304–313.
753 doi:10.1016/j.rse.2007.07.001
- 754 Cosh, M. H., Jackson, T. J., Starks, P. J., & Heathman, G. (2006). Temporal stability of surface soil
755 moisture in the Little Washita River watershed and its applications in satellite soil moisture product
756 validation. *Journal of Hydrology*, 323(1-4), 168–177. doi:10.1016/j.jhydrol.2005.08.020
- 757 Daly, E., & Porporato, A. (2005). A Review of Soil Moisture Dynamics: From Rainfall Infiltration to
758 Ecosystem Response. *Environmental Engineering Science*. doi:10.1089/ees.2005.22.9
- 759 Das, N. N., Entekhabi, D., & Njoku, E. G. (2011). An algorithm for merging SMAP radiometer and radar
760 data for high-resolution soil-moisture retrieval. *IEEE Transactions on Geoscience and Remote
761 Sensing*, 49(5), 1504–1512. doi:10.1109/TGRS.2010.2089526
- 762 Das, N. N., Entekhabi, D., Njoku, E. G., Shi, J. J. C., Johnson, J. T., & Colliander, A. (2014). Tests of the
763 SMAP combined radar and radiometer algorithm using airborne field campaign observations and
764 simulated data. *IEEE Transactions on Geoscience and Remote Sensing*, 52(4), 2018–2028.
765 doi:10.1109/TGRS.2013.2257605
- 766 Delwart, S., Bouzinac, C., Wursteisen, P., Berger, M., Drinkwater, M., Martín-Neira, M., & Kerr, Y. H.
767 (2008). SMOS validation and the COSMOS campaigns. *IEEE Transactions on Geoscience and
768 Remote Sensing*, 46(3), 695–703. doi:10.1109/TGRS.2007.914811
- 769 Dirmeyer, P. A. (2000). Using a global soil wetness dataset to improve seasonal climate simulation. *J.
770 Climate*, (13), 2900–2922.
- 771 Djamai, N., Magagi, R., Goïta, K., Merlin, O., Kerr, Y. H., & Roy, A. (2015). Downscaling satellite-based
772 soil moisture for cloudy days using the DISPATCH algorithm and CLASS land surface scheme.
773 *Submitted Remote Sensing of Environment*.
- 774 Douville, H. (2004). Relevance of soil moisture for seasonal atmospheric predictions: Is it an initial value
775 problem? *Climate Dynamics*, 22(4), 429–446. doi:10.1007/s00382-003-0386-5
- 776 Draper, C., Reichle, R. H., De Lannoy, G. J. M., & Liu, Q. (2012). Assimilation of passive and active
777 microwave soil moisture retrievals. *Geophysical Research Letters*, 39(4).
778 doi:10.1029/2011GL050655
- 779 Drusch, M. (2007). Initializing numerical weather prediction models with satellite-derived surface soil
780 moisture: Data assimilation experiments with ECMWF's integrated forecast system and the TMI soil
781 moisture data set. *Journal of Geophysical Research: Atmospheres*, 112(3).
782 doi:10.1029/2006JD007478
- 783 Entekhabi, D., Njoku, E. G., O'Neill, P. E., Kellogg, K. H., Crow, W. T., Edelstein, W. N., ... Van Zyl, J.
784 (2010a). The soil moisture active passive (SMAP) mission. *Proceedings of the IEEE*, 98(5), 704–
785 716. doi:10.1109/JPROC.2010.2043918
- 786 Entekhabi, D., Reichle, R. H., Koster, R. D., & Crow, W. T. (2010b). Performance Metrics for Soil
787 Moisture Retrievals and Application Requirements. *Journal of Hydrometeorology*, 11, 832–840.
788 doi:10.1175/2010JHM1223.1

- 789 Fang, B., Lakshmi, V., Bindlish, R., Jackson, T. J., Cosh, M. H., & Basara, J. (2013). Passive Microwave
790 Soil Moisture Downscaling Using Vegetation Index and Skin Surface Temperature. *Vadose Zone*
791 *Journal*, 12(3), 0. doi:10.2136/vzj2013.05.0089
- 792 Guérif, M., & Duke, C. . (2000). Adjustment procedures of a crop model to the site specific characteristics
793 of soil and crop using remote sensing data assimilation. *Agriculture, Ecosystems & Environment*.
794 doi:10.1016/S0167-8809(00)00168-7
- 795 Jackson, T. J., Bindlish, R., Cosh, M. H., Zhao, T., Starks, P. J., Bosch, D. D., Seyfried, M., Moran, M. S.,
796 Goodrich, D. C., Kerr, Y. H., & Leroux, D. J. (2012). Validation of soil moisture and Ocean Salinity
797 (SMOS) soil moisture over watershed networks in the U.S. *IEEE Transactions on Geoscience and*
798 *Remote Sensing*, 50(5), 1530–1543. doi:10.1109/TGRS.2011.2168533
- 799 Jackson, T. J., Cosh, M. H., Bindlish, R., Starks, P. J., Bosch, D. D., Seyfried, M., Goodrich, D. C.,
800 Moran, M. S., & Du, J. (2010). Validation of advanced microwave scanning radiometer soil moisture
801 products. *IEEE Transactions on Geoscience and Remote Sensing*, 48(12), 4256–4272.
802 doi:10.1109/TGRS.2010.2051035
- 803 Jiang, L., & Islam, S. (2003). An intercomparison of regional latent heat flux estimation using remote
804 sensing data. *International Journal of Remote Sensing*. doi:10.1080/01431160210154821
- 805 Kerr, Y. H., Berthon, L., Mialon, A., Cabot, F., Al Bitar, A., Richaume, P., Leroux, D. J., Bircher, S.,
806 Lawrence, H., Quesney, A., & Jacqueline, E. (2014). *CATDS LEVEL 3 - Data product description -*
807 *Soil Moisture and Brightness Temperature*.
- 808 Kerr, Y. H., Jacqueline, E., Al Bitar, A., Cabot, F., Mialon, A., & Richaume, P. (2013). *CATDS SMOS L3*
809 *soil moisture retrieval processor, Algorithm Theoretical Baseline Document (ATBD)*.
- 810 Kerr, Y. H., & Njoku, E. G. (1990). Semiempirical model for interpreting microwave emission from
811 semiarid land surfaces as seen from space. *IEEE Transactions on Geoscience and Remote Sensing*,
812 28(3), 384–393. doi:10.1109/36.54364
- 813 Kerr, Y. H., Waldteufel, P., Richaume, P., Wigneron, J.-P., Ferrazzoli, P., Mahmoodi, A., Al Bitar, A.,
814 Cabot, F., Gruhier, C., Juglea, S. E., Leroux, D. J., Mialon, A., & Delwart, S. (2012). The SMOS
815 Soil Moisture Retrieval Algorithm. *Geoscience and Remote Sensing*, 50(5), 1384–1403.
- 816 Kerr, Y. H., Waldteufel, P., Wigneron, J.-P., Delwart, S., Cabot, F., Boutin, J., Escorihuela, M.-J., Font, J.,
817 Reul, N., Gruhier, C., Juglea, S. E., Drinkwater, M., Hahne, A., Martin-Neira, M., & Mecklenburg,
818 S. (2010). The SMOS Mission: New Tool for Monitoring Key Elements of the Global Water Cycle.
819 *Proceedings of the IEEE*, 98(5), 666–687. doi:10.1109/JPROC.2010.2043032
- 820 Kerr, Y. H., Waldteufel, P., Wigneron, J.-P., Martinuzzi, J. M., Font, J., & Berger, M. (2001). Soil
821 moisture retrieval from space: The Soil Moisture and Ocean Salinity (SMOS) mission. *IEEE*
822 *Transactions on Geoscience and Remote Sensing*, 39(8), 1729–1735. doi:10.1109/36.942551
- 823 Kim, J., & Hogue, T. S. (2012). Improving spatial soil moisture representation through integration of
824 AMSR-E and MODIS products. *IEEE Transactions on Geoscience and Remote Sensing*, 50(2), 446–
825 460. doi:10.1109/TGRS.2011.2161318
- 826 Laio, F., Porporato, A., Ridolfi, L., & Rodríguez-Fernández, N. J. (2002). On the seasonal dynamics of
827 mean soil moisture. *Journal of Geophysical Research: Atmospheres*. doi:10.1029/2001JD001252

- 828 Leroux, D. J., Kerr, Y. H., Al Bitar, A., Bindlish, R., Jackson, T. J., Berthelot, B., & Portet, G. (2013).
829 Comparison Between SMOS, VUA, ASCAT, and ECMWF Soil Moisture Products Over Four
830 Watersheds in U.S. *IEEE Transactions on Geoscience and Remote Sensing*, 52(3), 1–10.
- 831 Lievens, H., Tomer, S. K., Al Bitar, A., De Lannoy, G. J. M., Drusch, M., Dumedah, G., Hendricks
832 Franssen, H.-J., Kerr, Y. H., Martens, B., Pan, M., Roundy, J. K., Vereecken, H., Walker, J. P.,
833 Wood, E. F., Verhoest, N. E. C., & Pauwels, V. R. N. (2015). SMOS soil moisture assimilation for
834 improved hydrologic simulation in the Murray Darling Basin, Australia. *Remote Sensing of
835 Environment*, 168, 146–162. doi:10.1016/j.rse.2015.06.025
- 836 Malbêteau, Y., Merlin, O., Gascoin, S., Gastellu, J. P., Olivera, L., Mattar, C., & Khabba, S. (2016a).
837 Correcting land surface temperature data for elevation and illumination effects in mountainous areas:
838 a case study using ASTER data over the Imlil valley, Morocco. *Submitted to Remote Sensing of
839 Environment*.
- 840 Malbêteau, Y., Merlin, O., Molero, B., Rüdiger, C., & Bacon, S. (2016b). DisPATCH as a tool to evaluate
841 coarse-scale remotely sensed soil moisture using localized in situ measurements: Application to
842 {SMOS} and AMSR-E data in Southeastern Australia. *International Journal of Applied Earth
843 Observation and Geoinformation*, 45, Part B, 221–234.
844 doi:http://dx.doi.org/10.1016/j.jag.2015.10.002
- 845 Manabe, S. (1969). Climate and the ocean circulation. I. The atmospheric circulation and the hydrology of
846 the Earth's surface. *Monthly Weather Review*, 97(11), 739–774.
- 847 Merlin, O., Al Bitar, A., Walker, J. P., & Kerr, Y. H. (2009). A sequential model for disaggregating near-
848 surface soil moisture observations using multi-resolution thermal sensors. *Remote Sensing of
849 Environment*, 113(10), 2275–2284. doi:10.1016/j.rse.2009.06.012
- 850 Merlin, O., Al Bitar, A., Walker, J. P., & Kerr, Y. H. (2010a). An improved algorithm for disaggregating
851 microwave-derived soil moisture based on red, near-infrared and thermal-infrared data. *Remote
852 Sensing of Environment*, 114(10), 2305–2316. doi:10.1016/j.rse.2010.05.007
- 853 Merlin, O., Chehbouni, A., Boulet, G., & Kerr, Y. H. (2006). Assimilation of Disaggregated Microwave
854 Soil Moisture into a Hydrologic Model Using Coarse-Scale Meteorological Data. *Journal of
855 Hydrometeorology*. doi:10.1175/JHM552.1
- 856 Merlin, O., Duchemin, B., Hagolle, O., Jacob, F., Coudert, B., Chehbouni, G., Dedieu, G., Garatuza, J., &
857 Kerr, Y. H. (2010b). Disaggregation of MODIS surface temperature over an agricultural area using a
858 time series of Formosat-2 images. *Remote Sensing of Environment*, 114(11), 2500–2512.
859 doi:10.1016/j.rse.2010.05.025
- 860 Merlin, O., Escorihuela, M.-J., Mayoral, M. A., Hagolle, O., Al Bitar, A., & Kerr, Y. H. (2013). Self-
861 calibrated evaporation-based disaggregation of SMOS soil moisture: An evaluation study at 3 km
862 and 100 m resolution in Catalunya, Spain. *Remote Sensing of Environment*, 130(2013), 25–38.
- 863 Merlin, O., Malbêteau, Y., Notfi, Y., Bacon, S., Er-raki, S., Khabba, S., & Jarlan, L. (2015). Performance
864 metrics for soil moisture downscaling methods: Application to DISPATCH data in central Morocco.
865 *Remote Sensing*, 7(4), 3783–3807. doi:10.3390/rs70403783
- 866 Merlin, O., Rüdiger, C., Al Bitar, A., Richaume, P., Walker, J. P., & Kerr, Y. H. (2012). Disaggregation of
867 SMOS Soil Moisture in Southeastern Australia. *IEEE Transactions on Geoscience and Remote
868 Sensing*, 50(5), 1556–1571. doi:10.1109/TGRS.2011.2175000

- 869 Merlin, O., Rüdiger, C., Richaume, P., Al Bitar, A., Mialon, A., Walker, J. P., & Kerr, Y. H. (2010c).
870 Disaggregation as a top-down approach for evaluating 40 km resolution SMOS data using point-
871 scale measurements: application to AACES-1. *Remote Sensing for Agriculture, Ecosystems, and*
872 *Hydrology Xii*, 7824, -r666. doi:Artn 78240i\rDoi 10.1117/12.865751
- 873 Merlin, O., Stefan, V. G., Amazirh, A., Chanzy, A., Ceschia, E., Tallec, T., Beringer, J., Gentine, P., Er-
874 Raki, S., Bircher, S., & Khabba, S. (2016). Modeling soil evaporation efficiency in a range of soil
875 and atmospheric conditions: A downward approach based on multi-site data. *Submitted to Water*
876 *Resources Research*.
- 877 Merlin, O., Walker, J. P., Chehbouni, A., & Kerr, Y. H. (2008). Towards deterministic downscaling of
878 SMOS soil moisture using MODIS derived soil evaporative efficiency. *Remote Sensing of*
879 *Environment*, 112(10), 3935–3946. doi:10.1016/j.rse.2008.06.012
- 880 Mladenova, I., Lakshmi, V., Jackson, T. J., Walker, J. P., Merlin, O., & de Jeu, R. A. M. (2011).
881 Validation of AMSR-E soil moisture using L-band airborne radiometer data from National Airborne
882 Field Experiment 2006. *Remote Sensing of Environment*, 115(8), 2096–2103.
883 doi:10.1016/j.rse.2011.04.011
- 884 Mood, A. M., Graybill, F. A., & Boes, D. C. (1974). *Introduction to the Theory of Statistics*. McGrawHill
885 *series in probability and statistics* (Vol. 3). Retrieved from
886 <http://www.librarything.com/work/1154157/book/32217714>
- 887 Moran, M. S., Clarke, T. R., Inoue, Y., & Vidal, A. (1994). Estimating crop water deficit using the
888 relation between surface-air temperature and spectral vegetation index. *Remote Sensing of*
889 *Environment*. doi:10.1016/0034-4257(94)90020-5
- 890 Narayan, U., Lakshmi, V., & Jackson, T. J. (2006). High-resolution change estimation of soil moisture
891 using L-band radiometer and radar observations made during the SMEX02 experiments. *IEEE*
892 *Transactions on Geoscience and Remote Sensing*, 44(6), 1545–1554.
893 doi:10.1109/TGRS.2006.871199
- 894 Njoku, E. G., & Entekhabi, D. (1996). Passive microwave remote sensing of soil moisture. *Journal of*
895 *Hydrology*. doi:10.1016/0022-1694(95)02970-2
- 896 Noilhan, J., & Planton, S. (1989). A simple parameterization of land surface processes for meteorological
897 models. *Monthly Weather Review*, 117(3), 536–549.
- 898 Oliva, R., Daganzo-Eusebio, E., Kerr, Y. H., Mecklenburg, S., Nieto, S., Richaume, P., & Gruhier, C.
899 (2012). SMOS radio frequency interference scenario: Status and actions taken to improve the RFI
900 environment in the 1400-1427-MHZ passive band. *IEEE Transactions on Geoscience and Remote*
901 *Sensing*, 50(5 PART 1), 1427–1439. doi:10.1109/TGRS.2012.2182775
- 902 Panciera, R., Walker, J. P., Jackson, T. J., Gray, D. a., Tanase, M. a., Ryu, D., Moneris, A., Yardley, H.,
903 Rüdiger, C., Wu, X., Gao, Y., & Hacker, J. M. (2014). The soil moisture active passive experiments
904 (SMAPEX): Toward soil moisture retrieval from the SMAP mission. *IEEE Transactions on*
905 *Geoscience and Remote Sensing*, 52(1), 490–507. doi:10.1109/TGRS.2013.2241774
- 906 Peischl, S., Walker, J. P., Rüdiger, C., Ye, N., Kerr, Y. H., Kim, E., Bandara, R., & Allahmoradi, M.
907 (2012). The AACES field experiments: SMOS calibration and validation across the Murrumbidgee
908 River catchment. *Hydrology and Earth System Sciences*, 16(6), 1697–1708. doi:10.5194/hess-16-
909 1697-2012

- 910 Piles, M., Camps, A., Vall-Llossera, M., Corbella, I., Panciera, R., Rüdiger, C., Kerr, Y. H., & Walker, J.
 911 P. (2011). Downscaling SMOS-derived soil moisture using MODIS visible/infrared data. *IEEE*
 912 *Transactions on Geoscience and Remote Sensing*, 49(9), 3156–3166.
 913 doi:10.1109/TGRS.2011.2120615
- 914 Rodgers, J. L., & Nicewander, W. A. (1988). Thirteen ways to look at the correlation coefficient. *The*
 915 *American Statistician*, 42(1), 59–66.
- 916 Salkind, N. J. (2010). Standard error of the estimate. In SAGE (Ed.), *Encyclopedia of research design*.
 917 *Volume 3* (pp. 1426–1430). London.
- 918 Schmugge, T. J. (1998). Applications of passive microwave observations of surface soil moisture. *Journal*
 919 *of Hydrology*, 212-213(1-4), 188–197. doi:10.1016/S0022-1694(98)00209-1
- 920 Smith, A. B., Walker, J. P., Western, A. W., Young, R. I., Ellett, K. M., Pipunic, R. C., Grayson, R. B.,
 921 Siriwardena, L., Chiew, F. H. S., & Richter, H. (2012). The Murrumbidgee soil moisture monitoring
 922 network data set. *Water Resour. Res.*, 48(7), W07701. doi:10.1029/2012WR011976
- 923 Solano, R., Didan, K., Jacobson, A., & Huete, A. (2010). *MODIS Vegetation Index User's Guide (MOD13*
 924 *Series)* (Vol. v2.0).
- 925 Stefan, V. G., Merlin, O., Er-Raki, S., Escorihuela, M.-J., & Khabba, S. (2015). Consistency between in
 926 situ, model-derived and image-based soil temperature endmembers: towards a robust data-based
 927 model for multi-resolution monitoring of crop evapotranspiration. *Remote Sensing*, 7(8), 10444–
 928 10479.
- 929 Walker, J. P., & Houser, P. R. (2004). Requirements of a global near-surface soil moisture satellite
 930 mission: Accuracy, repeat time, and spatial resolution. *Advances in Water Resources*, 27(8), 785–
 931 801. doi:10.1016/j.advwatres.2004.05.006
- 932 Wan, Z. (1999). *MODIS Land-Surface Temperature Algorithm Theoretical Basis Document (LST ATBD)*.
- 933 Wan, Z. (2006). *MODIS Land Surface Temperature Products Users' Guide - Collection 5*. Sioux Falls,
 934 South Dakota,. Retrieved from
 935 http://www.ices.ucsb.edu/modis/LstUsrGuide/MODIS_LST_products_Users_guide_C5.pdf
- 936 Wanders, N., Bierkens, M., de Jong, S. M., de Roo, A., & Karssenber, D. (2014). The benefits of using
 937 remotely sensed soil moisture in parameter identification of large-scale hydrological models. *Water*
 938 *Resources Research*, 50(8), 6874–6891. doi:10.1002/2013WR014639
- 939 Wigneron, J.-P., Kerr, Y. H., Waldteufel, P., Saleh, K., Escorihuela, M.-J., Richaume, P., Ferrazzoli, P., de
 940 Rosnay, P., Gurney, R., Calvet, J.-C., Grant, J. P., Guglielmetti, M., Hornbuckle, B., Mätzler, C.,
 941 Pellarin, T., & Schwank, M. (2007). L-band Microwave Emission of the Biosphere (L-MEB) Model:
 942 Description and calibration against experimental data sets over crop fields. *Remote Sensing of*
 943 *Environment*, 107, 639–655. doi:10.1016/j.rse.2006.10.014
- 944 Zhan, X., Houser, P. R., Walker, J. P., & Crow, W. T. (2006). A method for retrieving high-resolution
 945 surface soil moisture from hydros L-band radiometer and radar observations. *IEEE Transactions on*
 946 *Geoscience and Remote Sensing*, 44(6), 1534–1544. doi:10.1109/TGRS.2005.863319

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