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1 **Towards a surface soil moisture product at high spatio-temporal resolution:**
2 **temporally-interpolated spatially-disaggregated SMOS data**

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ABSTRACT

20 High spatial and temporal resolution surface soil moisture is required for
21 most hydrological and agricultural applications. The recently developed Dis-
22 PATCH (DISaggregation based on Physical And Theoretical scale Change) al-
23 gorithm provides 1-km resolution surface soil moisture by downscaling the
24 40-km SMOS (Soil moisture Ocean Salinity) soil moisture using MODIS
25 (MODerate-resolution Imaging Spectroradiometer) data. However, the tem-
26 poral resolution of DisPATCH data is constrained by the temporal resolution
27 of SMOS (a global coverage every 3 days) and further limited by gaps in
28 MODIS images due to cloud cover. This paper proposes an approach to over-
29 come these limitations based on the assimilation of the 1-km resolution Dis-
30 PATCH data into a simple dynamic soil model forced by (inaccurate) precip-
31 itation data. The performance of the approach was assessed using ground
32 measurements of surface soil moisture in the Yanco area in Australia and the
33 Tensift-Haouz region in Morocco during 2014. It was found that the analyzed
34 daily 1-km resolution surface soil moisture compared slightly better to *in situ*
35 data for all sites than the original disaggregated soil moisture products. Over
36 the entire year, assimilation increased the correlation coefficient between es-
37 timated soil moisture and ground measurement from 0.53 to 0.70, whereas
38 the mean ubRMSE slightly decreased from $0.07 \text{ m}^3 \text{ m}^{-3}$ to $0.06 \text{ m}^3 \text{ m}^{-3}$
39 compared to the open-loop force-restore model. The proposed assimilation
40 scheme has significant potential for large scale applications over semi arid ar-
41 eas, since the method is based on data available at global scale together with
42 a parsimonious land surface model.

43 **1. Introduction**

44 Soil moisture is an important variable of the terrestrial hydrosphere. Whereas precipitation
45 provides the amount of available water at the surface, soil moisture impacts the partitioning of
46 rainfall into runoff, evaporation and infiltration. Moreover, soil moisture is highly variable in
47 space and time, as a result of (1) the alternation between wetting and drying events, and (2)
48 the heterogeneity in land cover, topography and soil properties. An accurate and continuous
49 description of soil moisture in space and time is therefore critical for understanding the continental
50 water cycle and for achieving efficient and sustainable water management (Entekhabi 1995; Gao
51 et al. 2014; Rodriguez-Iturbe 2000).

52
53 Satellite remote sensing is often the most practical and effective method to observe the land
54 surface soil moisture over large geographical areas. The recent Soil Moisture and Ocean Salinity
55 (SMOS) mission, launched in 2009, operates at L-band (the optimal microwave band to estimate
56 soil moisture (Kerr 2007; Njoku and Entekhabi 1996)) and provides near-surface soil moisture
57 (SSM) with a resolution of about 40 km (Kerr et al. 2012). This mission has been complemented
58 by the SMAP (Soil Moisture Active Passive) satellite mission launched in 2015; ensuring the
59 continuity of L-band passive microwave data for global SSM monitoring (Entekhabi et al. 2010b).
60 Recent studies, based on the temporal stability of soil moisture (Vachaud et al. 1985), have shown
61 that even coarse scale satellite soil moisture can add a benefit in hydrological modeling (Pauwels
62 et al. 2001; Draper et al. 2011; Brocca et al. 2012; Alvarez-Garreton et al. 2015; Chen et al.
63 2014; Massari et al. 2015; Lievens et al. 2015b). Nevertheless, the current spatial resolution
64 of microwave radiometers is too coarse for most hydrological and agricultural applications.
65 Therefore, downscaling methodologies have been developed to improve the spatial resolution of

66 passive microwave-derived SSM data (Das et al. 2014; Fang et al. 2013; Kim and Hogue 2012;
67 Merlin et al. 2008a; Piles et al. 2011; Sánchez-Ruiz et al. 2014; Srivastava et al. 2013). For
68 example, DisPATCh (DISaggregation based on Physical And Theoretical scale Change) estimates
69 the SSM variability within a 40 km resolution SMOS pixel at 1 km resolution using MODIS
70 (MODerate-resolution Imaging Spectroradiometer) data (Merlin et al. 2012, 2013). However, the
71 temporal resolution of DisPATCh data based on SMOS and MODIS data is limited by 1) gaps
72 in MODIS images due to cloud cover, and 2) the 2-3 day temporal resolution of global SMOS
73 coverage (Djamai et al. 2016).

74
75 A land surface model (LSM) forced by uncertain meteorological inputs and constrained with
76 discontinuous disaggregated soil moisture through data assimilation could both address the
77 issue of discontinuity in the soil moisture products and as well as improve the SSM estimate.
78 Several studies have been undertaken to assimilate the observed satellite brightness temperature
79 directly (Crow and Wood 2003; Dumedah et al. 2011; Margulis et al. 2002; Reichle et al. 2007;
80 Lievens et al. 2015a, 2017) and/or the satellite SSM retrieval (Reichle et al. 2008; Draper et al.
81 2011; Brocca et al. 2012; Dumedah and Walker 2014; Ridler et al. 2014; Kumar et al. 2014;
82 Wanders et al. 2014; Lievens et al. 2015b; Leroux et al. 2016) into LSMs. Others studies have
83 assimilated coarse scale SSM into a fine land surface models to produce fine model predictions
84 and consistently improve soil moisture and other land surface variables (Reichle et al. 2001b,
85 2010; Parada and Liang 2004; Pan et al. 2009a,b; De Lannoy et al. 2010, 2012; De Lannoy and
86 Reichle 2016; Sahoo et al. 2013; Lievens et al. 2016, 2017). These approaches are based on spatial
87 error correlations that are modeled within the assimilation system. Moreover, Djamai et al. (2016)
88 estimated SSM at 1 km resolution during cloudy days by combining DisPATCh data and the
89 Canadian Land Surface Scheme (CLASS), forced by a 30 km atmospheric re-analysis. However,

90 the SSM DisPATCh estimates were not improved by the combination of DisPATCh and CLASS
91 when compared to *in situ* measurements of the SMAP Validation Experiments data set in 2012
92 over Winnipeg in Canada. In a similar context, Dumedah et al. (2015) assimilated DisPATCh data
93 into the Joint UK Land and Environment Simulator (JULES) to estimate root zone soil moisture
94 over the Yanco area in Australia. The assimilation of DisPATCh data into the JULES model had
95 a limited positive impact on the SSM estimation accuracy compared to DisPATCh and open-loop
96 JULES simulation.

97

98 These results demonstrate that data assimilation remains one of the most promising approaches
99 to link satellite based SSM with LSMs, while accounting for uncertainties in the observation data
100 and the simulated output from the model (Calvet et al. 1998; Entekhabi et al. 1994; Jackson et al.
101 1981; Reichle et al. 2001a; Sabater et al. 2007). However, assimilation strategies still need to be
102 improved. Two aspects should be addressed when assimilating downscaled SSM data into a LSM:
103 1) the number of state variables in the LSM should be consistent with the available observations
104 in order to eliminate equifinality (Beven 1989; Franks et al. 1997), and 2) the accuracy in forcing
105 data at the application scale. Most of surface models developed since the 80s (Sellers et al. 1986;
106 Noilhan and Planton 1989) have a large number of variables which cannot be directly measured
107 at the model application scale (Demaria et al. 2007; Franks et al. 1997). As over-parameterization
108 is the main limitation for implementation of such complex models in an operational context,
109 there is a need to develop simplified modeling approaches that are forced by available remote
110 sensing and meteorological data (Allen et al. 1998). A number of studies have shown the potential
111 of this approach (Albergel et al. 2008; Ceballos et al. 2005; Pellarin et al. 2006; Wagner et al.
112 1999) for representing components of the surface water budget. One of the main issues is that
113 large-scale data sets of meteorological variables are currently unavailable at 1 km (or higher)

114 spatial resolution. Nevertheless, a disaggregation/assimilation coupling scheme is potentially
115 capable of compensating errors in atmospheric (mainly precipitation) forcing data available at a
116 coarse scale only (Merlin et al. 2006).

117

118 Within this context, the objective of this study was to develop a new methodology based on
119 an assimilation scheme for interpolating DisPATCh SSM in a sub-optimal manner using global
120 (meteorological and soil map) datasets. Since DisPATCh is a physically-based method to provide
121 natively SSM at 1 km resolution using 1 km resolution MODIS data, the native resolution of the
122 DisPATCh SSM products developed is 1 km resolution. The approach was tested using ground
123 measurements of soil moisture and precipitation over two semi arid sites: 1) the Yanco area in
124 the Murrumbidgee river catchment, Australia and 2) the Tensift-Haouz basin located in central
125 Morocco.

126 **2. Sites description**

127 *a. Yanco: Murrumbidgee catchment (Australia)*

128 The Murrumbidgee catchment, located in southeastern of Australia, covers about 82,000 km²
129 (34°S to 37°S, 143°E to 150°E) and is a part of the Murray Darling basin. The Yanco study site
130 is a 55 km x 55 km area located in the center of the Murrumbidgee western plains where the
131 topography is flat, with very few geological outcropping. The soil texture is predominantly sandy
132 loam. The climate is semi-arid, with an average annual precipitation of about 300 mm while
133 evaporative demand is about 1,200 mm per year, according to the reference evapotranspiration
134 (ET₀), derived from the Food and Agriculture Organization (FAO) Penman Monteith equation
135 (Allen et al. 1998). The land use in the west of the site comprises irrigation, while elsewhere land

136 use is composed of rain-fed crops and native pasture with scattered trees.

137

138 The Yanco region has been intensively monitored for remote sensing studies since 2001 (Smith
139 et al. 2012). This area has been selected as a core site for the calibration/validation of the SMOS
140 (Peischl et al. 2012), SMAP (Panciera et al. 2014), and GCOM-W1 (Mladenova et al. 2011) mis-
141 sions, and has also been the focus of field experiments dedicated to algorithm development studies
142 for the SMOS and SMAP missions: National Airborne Field Experiment 2006 (NAFE06; Merlin
143 et al. (2008b)); Australian Airborne Cal/Val Experiments for SMOS (AACES-1, -2; Peischl et al.
144 (2012)) and Soil Moisture Active Passive Experiments (SMAPex-1, -2, -3; Panciera et al. (2014)).
145 To assess the ERA-interim precipitation product, OzNet ground based precipitation measurements
146 using tipping bucket rain gauges were used (Smith et al. 2012). These data are available on the
147 World Wide Web at <http://www.oznet.org.au/>. Seven sites presenting the best data quality and
148 continuity were selected for this study (Yanco 1, 2, 8, 9, 10, 12 and 13). Table 1 displays the site
149 characteristics, and their locations are shown in Fig. 1. These sites are representative of the 3 main
150 land uses of the region (Fig. 1): irrigated crops (Yanco 9), rain-fed crops (Yanco 1 and 11; typi-
151 cally wheat and fallow), and grazing (Yanco 2, 8, 10, 13; typically perennial grass type vegetation).

152

153 Fig. 1

154 *b. Tensift-Haouz basin (Morocco)*

155 The Tensift-Haouz basin covers about 24,000 km² (30.75°N 32.40°N and 7.05°E to 9.9°W)
156 around the city of Marrakech, in central Morocco (Fig. 2). The climate is semi-arid, typically
157 Mediterranean, with an average annual precipitation of about 250 mm (Chehbouni et al. 2008)
158 concentrated between November and April over the Haouz plain, where the study site is located.

159 Evaporative demand is about 1,600 mm per year.

160

161 In the Tensift-Haouz basin, the Sidi Rahal monitoring station was installed on a rain-fed wheat
162 field (Fig. 2) in December 2013, in the framework of the Joint International Laboratory TREMA
163 (a French acronym for Remote Sensing and Water Resources in the Semi-arid Mediterranean;
164 <http://trema.ucam.ac.ma>; Jarlan et al. (2015)). It is equipped with micro-meteorological instru-
165 ments to estimate latent and sensible heat fluxes at the soil-vegetation-atmosphere interface,
166 and probes for the measurements of soil water content at different depths. The automatic
167 meteorological station installed in the vicinity was equipped with sensors for the measurement
168 of rainfall, global radiation, temperature, relative humidity, and wind speed at a half-hourly time
169 step. The soil texture is predominantly loams. Information about the monitoring stations is
170 provided in Table 1 and Fig. 2.

171

172 Fig. 2 and Table 1

173 **3. Materials and method**

174 *a. Globally available data*

175 1) SMOS SOIL MOISTURE DATA

176 The SMOS level 3 one day global SSM (MIR_CLF31A\D, version 7.72 in reprocessing mode
177 RE04) product is used in this study as input to DisPATCH algorithm and assimilation scheme.
178 These products are presented in NetCDF format on the EASE grid, with a grid spacing of ~ 25
179 x 25 km in cylindrical projection. Note that L3 data is a 25 km grid representation of the 40 km
180 data. Details on the processing algorithms can be found in the Algorithm Theoretical Baseline

181 Document (Jacquette et al. 2013) and in the Level 3 data product description (Kerr et al. 2014).
182 For comparison purpose, the assimilation scheme was applied at 1 km resolution using the non-
183 disaggregated (25 km) SMOS L3 data by oversampling the 25-km product.

184 2) DISPATCH SOIL MOISTURE DATA

185 DisPATCh provided 1 km resolution SSM data from 40 km SMOS SSM and 1 km MODIS
186 LST (Land Surface Temperature), MODIS NDVI (Normalized Difference Vegetation Index) and
187 GTOPO30 DEM (Digital Elevation Model) data. MODIS-derived soil temperature was used
188 to estimate Soil Evaporative Efficiency (SEE), which is known to be relatively constant during
189 the day on clear sky conditions (Merlin et al. 2012). MODIS-derived 1 km resolution SEE was
190 finally used as a proxy for SSM variability within the low-resolution pixel using a first-order
191 series expansion around the SMOS observation. The disaggregated SSM products are expressed
192 in $\text{m}^3 \text{m}^{-3}$. The current version of the DisPATCh methodology is fully described in Molero et al.
193 (2016). Note that only ascending SMOS overpass (6 am) was used in this paper.

194
195 The DisPATCh product was derived from the average of an output ensemble for each SMOS
196 overpass time. This output ensemble was obtained by applying DisPATCh to 1) four SMOS
197 re-sampling grids by taking advantage of the Level 3 SMOS data oversampling, 2) three MODIS
198 overpass dates by taking into account the MODIS data collected within plus or minus one day
199 around the SMOS overpass, and 3) two daily MODIS observations aboard Terra and Aqua.
200 The number of elements used to compute this average (a maximum of 24 elements per SMOS
201 overpass) is called the DisPATCh count. Note that the DisPATCh count is often smaller than 24
202 due to gaps in MODIS data associated with cloud cover and/or limited overlap with the SMOS
203 swath. The error of the DisPATCh product is taken as the standard deviation from the output

204 ensemble computing. This error accounts for the downscaling and retrieval errors (more details in
205 Merlin et al. (2012); Malbêteau et al. (2016)).

206

207 DisPATCh outputs have been validated mostly in semi-arid conditions where SEE is well con-
208 strained by the SSM: the Murrumbidgee catchment in Australia (Bandara et al. 2015; Malbêteau
209 et al. 2016; Molero et al. 2016), the Little Washita watershed in Oklahoma, Walnut Gulch in Ari-
210 zona over USA (Molero et al. 2016), the Tensift-Haouz basin in central Morocco (Merlin et al.
211 2015) and the Lleida area in Spain (Escorihuela and Quintana-Seguí 2016; Merlin et al. 2013).

212 3) VEGETATION INDEX

213 In order to estimate evapotranspiration, the vegetation cover (f_v) was derived from the 1 km
214 resolution MODIS NDVI data. The NDVI dataset was extracted from the version-5 MODIS/
215 Terra vegetation indices 16-day Level-3 global 1-km grid product (MOD13A2). Fractional f_v was
216 computed using the linear relationship between NDVI of the fully-covered vegetation and NDVI
217 of the bare soil proposed by Gutman and Ignatov (1998).

218 4) METEOROLOGICAL DATASET

219 The ECMWFs (European Centre for Medium-Range Weather Forecasts) Interim re-analysis
220 product (ERA-interim; Dee et al. (2011)) was used for meteorological (relative humidity, air
221 temperature, wind speed, pressure, shortwave and longwave radiations and precipitation) forc-
222 ing. ERA-Interim is produced at the highest resolution of about 0.125° with a 3-hourly time
223 step covering the period from January 1979 to present, with product updates at approximately
224 1 month behind real-time. This study used the ERA-interim datasets provided daily at 0.125°
225 spatial resolution. Note that the product is generated at a much coarser resolution (a spectral

226 T255 horizontal resolution, which corresponds to approximately 79 km spacing grid) and then
227 mapped to 0.125°. The ERA-Interim atmospheric re-analysis is built upon a consistent assimila-
228 tion of an extensive set of observations distributed worldwide from satellite remote sensing, *in situ*
229 measurements, and radio-sounding. ERA-Interim data sets are free of charge and available via:
230 www.ecmwf.int/en/research/climate-reanalysis/era-interim. The environmental parameters simu-
231 lated by ERA-Interim have been widely validated by *in situ* and remote sensing observations at
232 different spatio-temporal scales (Balsamo et al. 2015; Bao and Zhang 2013; Boisvert et al. 2015;
233 Mooney et al. 2011; Su et al. 2013; Szczypta et al. 2011; Wang and Zeng 2012). Several stud-
234 ies (Belo-Pereira et al. 2011; Pfeifroth et al. 2013; Szczypta et al. 2011; Zhang et al. 2013) have
235 reported an overestimation of ECMWF precipitation data, but Balsamo et al. (2010) have shown
236 that the original ERA-Interim products have reasonable skill for land applications at time scales
237 from daily to annual over the conterminous US. The total annual amount and daily distribution of
238 ECMWF precipitation is compared to meteorological stations in this study for the two test sites.

239 5) GLOBAL SOIL TEXTURE

240 The relative amounts of bound and free water are influenced by the soil texture (sand, clay and
241 silt fractions) and bulk density. The map used for this study was a 0.01° resolution combination of
242 the soil maps (Kim 2013) from 1) FAO (Food and Agriculture Organization) and 2) HWSD (Har-
243 monized World Soil Database), and the regional datasets 1) STATSGO (State Soil GeographicUS),
244 2) NSDC (National Soil Database Canada), and 3) ASRIS (Australian Soil Resources Information
245 System). Note that this soil texture map is used by both SMOS (Kerr et al. 2012) and SMAP
246 (Entekhabi et al. 2010b) level 2 SSM retrieval algorithms.

247 *b. Land surface model (LSM)*

248 In an effort to reduce as much as possible the number of model parameters, while attempting
249 to preserve the representation of the physics which controls the SSM dynamics, the LSM used in
250 this study was based on the force-restore method developed by Deardorff (1977). This scheme is
251 used in many LSMs including ISBA (Interactions between Soil Biosphere Atmosphere; Noilhan
252 and Planton (1989)). The force-restore method appears to be a good tradeoff between realism
253 (physics) and complexity (number of parameters) for calibration over large areas. In this semi-
254 physical model, the dynamics of soil moisture is described within two layers: the SSM (noted Θ_1)
255 and the root zone soil moisture (noted Θ_2). In this study, only the SSM dynamics were simulated
256 with the root-zone soil moisture taken as a buffer variable to minimize possible biases between
257 DisPATCH SSM and the force restore prediction for compensating errors in meteorological (mainly
258 precipitation and irrigation) forcing data. The equation for SSM is:

$$\frac{\partial \Theta_1}{\partial t} = \frac{C_1}{\rho_w d_1} (P - E_g) - \frac{C_2}{\tau} (\Theta_1 - \Theta_{eq}), \quad (1)$$

259 with Θ_{eq} the equilibrium soil moisture, P the ERA-interim precipitation reaching the soil surface,
260 E_g the evaporation at the soil surface, ρ_w the density of liquid water, τ the time constant taken as
261 one day and d_1 an arbitrary normalization depth of 10 cm. C_1 and C_2 are empirical parameters
262 named force and restore coefficients, respectively representing the process of mass exchange be-
263 tween the soil and the atmosphere, and the surface and the root-zone layer, respectively. The force
264 and restore coefficients C_1 and C_2 are dimensionless and highly dependent upon both the soil mois-
265 ture content and the soil texture. Note that coefficients C_1 and C_2 are spatially distributed based on
266 Noilhan and Mahfouf (1996) and vary over time. They were calibrated against a multi-layer soil
267 moisture model (Noilhan and Mahfouf 1996) such that

$$C_1 = C_{1sat} \left(\frac{\Theta_{sat}}{\Theta_1} \right)^{\left(\frac{\beta}{2}+1\right)}, \quad (2)$$

$$C_2 = C_{2ref} \left(\frac{\Theta_2}{\Theta_{sat} - \Theta_2 + \Theta_l} \right), \quad (3)$$

268 with Θ_{sat} being the saturated soil moisture for a given texture, β the slope of the retention curve,
 269 C_{1sat} and C_{1ref} hydraulic parameters and Θ_l a small numerical value equal to 0.001. Each pa-
 270 rameter was estimated from clay/sand fractions and default empirical parameters (equations are
 271 detailed in Noilhan and Mahfouf (1996)). E_g in equation 1 is expressed as in Allen (2000) and
 272 Allen et al. (2005) by

$$E_g = ET_0 \times K_e, \quad (4)$$

273 with ET_0 being the reference evapotranspiration estimated according to the FAO Penman-Monteith
 274 equation (Allen et al. 1998) and the ERA-interim meteorological forcing data (relative humidity,
 275 air temperature, wind speed, pressure, shortwave and longwave radiations). K_e the soil evaporation
 276 coefficient computed from

$$K_e = (1 - f_v) K_r, \quad (5)$$

277 with K_r the soil evaporation reduction coefficient derived from the SSM. Soil evaporation from
 278 the exposed soil was assumed to take place in two stages: an energy limiting stage and a falling
 279 rate stage. After rain, evaporation was only determined by the energy available for evaporation,
 280 thus K_r was set to 1; then when the soil surface dried out, K_r decreased linearly and evaporation
 281 was reduced. K_r was equal to zero when no significant water was left for evaporation, being when

282 SSM was smaller than $\frac{1}{2}\Theta_{wp}$ (where Θ_{wp} was the soil moisture at wilting point) as reported by
283 Allen et al. (1998).

284 *c. Assimilation scheme: A combined 2D variational and sequential approach*

285 The purpose of assimilating DisPATCH data into a LSM was to combine the downscaled snap-
286 shots of DisPATCH SSM with the continuous LSM predictions, in order to obtain the best estimate
287 of the SSM at 1 km every day. The simplified two-dimensional variational (2D VAR) method de-
288 veloped by Balsamo et al. (2004) to analyze the root-zone soil moisture (as a buffer variable) was
289 combined to a simplified Kalman filter approach to update the SSM state. The relation between
290 surface and root-zone soil moisture is not physically based with the force-restore scheme. For that
291 reason a linear variational algorithm may not be well suited for updating surface soil moisture by
292 contrast with the root-zone. Moreover, the sequential approach is able to update the potentially
293 rapid changes related to irrigation that are not represented by the LSM but are observed in Dis-
294 PATCH data. Thus, the two-scheme procedure has the advantage to consider the two temporal
295 dynamics, being (rapid) surface and (slow) root-zone soil moisture.

296 The 2D VAR method was initially designed to analyze the root zone soil moisture using 2 m
297 air temperature and humidity observations (Balsamo et al. 2004). It has been adapted by Sabater
298 et al. (2007) to analyze the root zone soil moisture from SSM observations, and to the analysis of
299 both above ground biomass and root zone soil moisture by Sabater et al. (2008). The simplified
300 2D VAR has also been applied to the analysis of above-ground biomass from satellite-derived leaf
301 area index products over West Africa (Jarlan et al. 2008). In the present study, Θ_2 was taken as
302 a buffer variable without any dynamic equation. Stated differently, this variable was left free to
303 adjust the model prediction to DisPATCH SSM through the simplified 2DVAR approach. This first

304 step of the assimilation algorithm was necessary to represent SSM dynamics with consistency to
 305 the restore parameter. The analyzed state is given by:

$$\Theta^a = \Theta^b + K(y - H\Theta^b), \quad (6)$$

306 where the superscripts a and b indicate the analysis and background, respectively; y is the Dis-
 307 PATCh SSM and \mathbf{H} is the observation operator that allows the projection of the state vector in
 308 the observation space. In the 2D VAR approach, \mathbf{H} is computed from a one side finite difference,
 309 while \mathbf{H} is equal to 1 in the sequential approach. The SSM update step is close to that of the
 310 Kalman filter, but the propagation of the background error matrix was avoided here for simplicity
 311 purpose. \mathbf{K} is called the gain and is calculated as:

$$\mathbf{K} = \mathbf{B}\mathbf{H}^T (\mathbf{H}\mathbf{B}\mathbf{H}^T + \mathbf{R})^{-1}, \quad (7)$$

312 where \mathbf{B} and \mathbf{R} are the covariance matrices of the background and SSM observations errors, re-
 313 spectively. \mathbf{R} is scalar values equal to σ_{obs} (DisPATCh error). \mathbf{B} is calculated as

$$\mathbf{B} = \begin{pmatrix} \sigma_{\Theta_2} & 0 \\ 0 & \sigma_{\Theta_1} \end{pmatrix} \quad (8)$$

314 with σ_{Θ_1} is Θ_1 background error and σ_{Θ_2} is Θ_2 background error.

315 Considering a 1-day assimilation window, \mathbf{H} equals to :

$$\mathbf{H} = \begin{pmatrix} \frac{\Delta\Theta_1(t)}{\Delta\Theta_2(t-1)} & 0 \\ 0 & 1 \end{pmatrix} \quad (9)$$

316 1) IMPLEMENTING AND EVALUATING THE DATA ASSIMILATION ALGORITHM

317 (i) Background error covariance matrix

318 The parameters \mathbf{B} , \mathbf{P} and \mathbf{R} determine the relative weight given to the background, forecast

319 and to the observations covariance, respectively, while σ_{obs} corresponds to the observation
320 (DisPATCh) error (see section *DisPATCh soil moisture data*). Observation errors are correlated
321 in space. An accurate estimation of the background error is likely to be the most difficult task
322 in the error prescription (Bouttier 1994; Reichle et al. 2002). Thus, a sensitivity analysis to
323 background error on SSM and root zone soil moisture was carried out; a set of σ_{Θ_1} and σ_{Θ_2} were
324 compared in order to estimate both background errors since there is no propagation equation of
325 the background error covariance matrix using variational assimilation. In practice, an ensemble of
326 10 perturbations from 0.02 to 0.1 $\text{m}^3 \text{m}^{-3}$ was built for both the background error terms and the
327 global statistics (correlation coefficient r , Root Mean Square Error RMSE, and mean bias) were
328 computed based on the analyzed and *in situ* SSM comparison. Results of the sensitivity study are
329 displayed in Fig. 3. The optimal choices obtained from this sensitivity study were about 0.04
330 $\text{m}^3 \text{m}^{-3}$ and 0.09 $\text{m}^3 \text{m}^{-3}$ for σ_{Θ_1} and σ_{Θ_2} , respectively. Note that the same sensitivity study
331 has been performed at 25 km, and the optimal choices obtained are 0.05 $\text{m}^3 \text{m}^{-3}$ and 0.06 m^3
332 m^{-3} for σ_{Θ_1} and σ_{Θ_2} , respectively. Nevertheless, the range of bias and RMSE were low (about
333 0.009 $\text{m}^3 \text{m}^{-3}$) for the whole range of potential values. This means that the sensitivity analysis
334 for both background errors presented limited choices. Interestingly, a Θ_1 background error lower
335 than that of Θ_2 seems also consistent with the objective of the study, since Θ_2 was considered as a
336 buffer variable to minimize biases on Θ_1 . Finally, this quite low value of background error on Θ_1
337 was also certainly to be attributed to the good quality of ERA-interim data, which were the main
338 forcing of the Θ_1 dynamics. Based on this analysis, the sub-optimal values of background error
339 were chosen for the implementation of the data assimilation algorithm.

340

341 Fig. 3

342 (ii) *Statistical metrics*

343 It was important to assess the performance of the method, not only in terms of linear dependency
344 and error, but also in terms of relative variability of the original and updated dataset. Therefore, r,
345 RMSE, ubRMSE (unbiased-RMSE) and the mean bias were used to fully assess the accuracy
346 of SSM (Entekhabi et al. 2010a). Moreover, a new metric called the Gain of DOWNscaling
347 (GDOWN), introduced by Merlin et al. (2015), was also used. The gain is a measure of the
348 statistical improvement dedicated to disaggregated SM products. The gain can range from -1 to
349 1, where positive values indicate better correspondence with *in situ* than low resolution products
350 such as SMOS data. One key advantage of GDOWN, with regards to other performance metrics,
351 is to provide an estimate of the overall improvement in soil moisture data with a single value.

352 **4. Results and discussion**

353 The DisPATCh/assimilation approach has been run over the entire year 2014 for both areas
354 (Yanco in Australia and Tensift-Haouz in Morocco). First, ERA-interim precipitation products
355 were assessed and validated using ground measurements. After, the analyzed SSM was evaluated
356 at the time of DisPATCh availability. Finally, the analyzed SSM was assessed for the entire year
357 datasets.

358 *a. ERA-interim precipitation assessment*

359 Although the assimilation scheme can compensate error on precipitation input data, a good
360 agreement of ERA-Interim with ground rainfall in term of frequency (instead of quantity)
361 is preferable to update the SSM state on a daily basis. A preliminary comparison between
362 ERA-interim precipitation and the station data showed that ERA-interim presented too frequent
363 low rainfall events (between 0.1 and 3 mm/day). This has already been observed by Ibrahim et al.

364 (2012) and Diaconescu et al. (2015) over another semi-arid region in the West African Sahel. The
365 general overestimation of wet days is due to the fact that precipitation in reanalyses is mainly
366 model generated, and therefore highly related to forecast-model physical parameterizations
367 (surface pressure, temperature and wind). In this study, the precipitation values during low rainfall
368 events (< 3 mm/day) were set to zero (Ibrahim et al. 2012; Diaconescu et al. 2015). After this
369 pre-processing, ERA-interim precipitation were in better agreement with local station data (not
370 shown). The daily ERA-interim precipitations were compared to the *in situ* data using 24-h
371 accumulation from the raw 30 minutes observations. Fig. 4 and Table 2 reported the annual
372 amounts and differences between the two precipitation data sets for each site. With an average
373 bias of 27 mm/year and a r of 0.48, ERA-interim annual amounts matched quite well the *in situ*
374 observations considering the large resolution of ERA-interim data and the high spatial variability
375 of precipitation in semi-arid regions. Apart from sites Yanco 10 and Sidi Rahal, biases remained
376 below 40 mm/year. Fig. 4 and Table 2 showed also that timing was well reproduced at ± 1 day,
377 based on the correlation coefficient value when using a 3-days accumulated precipitation. For
378 instance, daily ERA-interim precipitations at the Sidi Rahal site were really well correlated (r of
379 0.93) with the ground measurements. Regarding Yanco 10 site, the daily r was low; however it
380 increased greatly using the 3-days accumulated precipitation (from 0.18 to 0.51). These results
381 were similar to results found in Balsamo et al. (2010). In particular, none of the big storms events
382 recorded by the local stations were missed by ERA-interim. Both timing and event amount were
383 particularly well reproduced on Yanco 1 and 2. Two anomalies were noted at the Sidi Rahal site:
384 the ERA-interim precipitation was underestimated compared with *in situ* observations, whereas
385 the ERA-interim precipitation was overestimated at Yanco 10 station. For both sites, all events
386 were well detected but the amounts of water were under and overestimated for Sidi Rahal and
387 Yanco 10 sites, respectively. On average, ERA-interim precipitation data compared quite well

388 with *in situ* stations apart from moderated biases. The ERA-interim data set was thus used
389 in the data assimilation algorithm in order to evaluate the performance of the approach when
390 precipitation data are inaccurate, which is a very likely situation when no meteorological station
391 is available.

392

393 Fig. 4 and Table 2

394 *b. Assimilation results*

395 Herein, the performance of the approach was assessed by comparing SMOS, DisPATCh, open
396 loop and analyzed SSM with *in situ* measurements at the time of DisPATCh availability, in
397 order to check if the analyzed SSM shows an improvement with regards to disaggregated SSM.
398 All statistics were estimated on a yearly basis to evaluate the capability of a dynamical model
399 to interpolate and, potentially, to improve DisPATCh SSM data. Table 3 showed the yearly
400 statistics for each monitoring station and the number of comparison days. In this section, the
401 number of days used was strongly dependent on the number of SMOS overpasses and cloud
402 coverage. When comparing the statistics obtained over both areas, it was observed that the
403 disaggregation and the assimilation scheme reduced bias by approximately $0.02 \text{ m}^3 \text{ m}^{-3}$, while
404 r was systematically higher after data assimilation. The disaggregation at 1 km (DisPATCh)
405 has the advantage to produce SSM at a spatial resolution closer to the representativeness scale
406 of ground measurements; it has been shown that this reduces the bias (Malbêteau et al. 2016).
407 The mean r over the Yanco area rose from 0.62 to 0.77 after disaggregation and up to 0.80 after
408 application of the assimilation scheme. Regarding Yanco 2, r improved from 0.69 to 0.79; bias
409 reduced from 0.03 to $0.01 \text{ m}^3 \text{ m}^{-3}$ and ubRMSE decreased from 0.07 to $0.05 \text{ m}^3 \text{ m}^{-3}$. Similar
410 results were observed for Sidi Rahal as r increased from 0.82 to 0.87 after assimilation while

411 bias was closer to 0, and ubRMSE decreased slightly from 0.05 to 0.04 m³ m⁻³. Across all
412 sites, the assimilation scheme does not improve significantly SSM in terms of statistics when
413 using a limited (DiPATCh) time series for validation. Differences can be appreciated more easily
414 through qualitative inspection of scatter plots. Sidi Rahal (Fig. 5b), Yanco 9 (Fig. 6b) and
415 Yanco 10 (Fig. 7b) illustrate the Table 3 results. In these three plots, the analyzed distribu-
416 tion appears closer and more symmetric around the 1:1 line than for both DisPATCh and open loop.

417
418 As illustrated in Table 4, GDOWN was approximately equal for both the disaggregated and the
419 analyzed data. Moreover the only site with negative values (meaning that SMOS shows better
420 results) was Yanco 12, because DisPATCh and the analyzed SSM had a larger mean bias than
421 SMOS (Table 3). However, r was slightly improved after assimilation, which means that the SSM
422 dynamics were better represented. Yanco 2 was the site with the best enhanced GDOWN, with
423 values going from 0.35 to 0.53 before and after assimilation, respectively. This was mainly due
424 to a large improvement of r (from 0.47 to 0.79) and of the bias (from -0.03 m³ m⁻³ to -0.01 m³
425 m⁻³). The assimilation scheme was also compared to the open loop estimates using the same
426 statistics (Table 3). The assimilation clearly outperformed the open-loop prediction at the time of
427 DisPATCh availability.

428
429 As a summary, this new approach improved the r values and also reduced the ubRMSE with
430 regards to either the satellite observations or the model open loop, indicating that the assimilation
431 has the capability to improve the SSM estimates over the model results or DisPATCh alone.

432
433 Table 3, Table 4, Fig. 5, Fig. 6 and Fig. 7

434 *c. Soil moisture analysis*

435 In order to assess the potential of using the force-restore model and the assimilation scheme for
436 infilling disaggregated SSM, a conventional validation strategy was adopted, by comparing the
437 analyzed and *in situ* SSM datasets for the full time series. This strategy was useful to characterize
438 the overall quality of the analyzed SSM over both areas. The open loop estimate of SSM
439 estimates determined from the force restore-model forced by ERA-interim were also computed
440 for comparison purposes, along with the assimilation scheme applied to the original SMOS L3
441 product. This comparison evaluated the contribution of fine (instead of coarse) resolution soil
442 moisture data. Table 5 displays temporal statistics for open loop, analyzed 25 km and analyzed
443 1 km SSM estimates for all *in situ* stations. Overall results showed that r was about 0.7, while
444 mean bias was equal to $0.03 \text{ m}^3 \text{ m}^{-3}$ and ubRMSE was $0.06 \text{ m}^3 \text{ m}^{-3}$ for the analyzed SSM
445 estimates. The r values were found to be systematically higher after assimilation, whereas bias,
446 RMSE and ubRMSE were equivalent for both data sets. Regarding Sidi Rahal station (Fig. 5
447 and Table 5), r after data assimilation was about 0.83, while bias was close to $0.01 \text{ m}^3 \text{ m}^{-3}$ and
448 the ubRMSE was around $0.06 \text{ m}^3 \text{ m}^{-3}$. The time series exhibited the dominant seasonal cycle
449 very well and showed a similar dynamical response to precipitation events. Comparison between
450 analyzed 25 km and 1 km statistics showed that DisPATCH SSM improved results for all sites,
451 even though the original SMOS L3 data had a larger temporal repetition. In others words, the
452 spatial information provided by DisPATCH provide superior assimilation results despite the data
453 gaps associated with cloud coverage over the study sites. Figs. 6 and 7 illustrate time series for
454 two sites in the Yanco area. Regarding Yanco 10 (Fig. 7a), data assimilation enhanced r from
455 0.47 to 0.70, whereas the bias was larger by approximately $0.01 \text{ m}^3 \text{ m}^{-3}$. The open loop SSM
456 estimates showed a threshold for dry conditions at around $0.1 \text{ m}^3 \text{ m}^{-3}$ due to Θ_2 being forced

457 to $0.1 \text{ m}^3 \text{ m}^{-3}$ by lack of information. The analyzed SSM was not constrained any more by this
458 artificial threshold. This demonstrated the importance of the analysis of Θ_2 for a correct estimate
459 of Θ_1 . Interestingly, the best improvement was observed for the irrigated site Yanco 9 (Fig. 6a)
460 where precipitation was supplemented by irrigation inputs that were not taken into account in the
461 model run. Consequently, the assimilation of DisPATCh data improved r (from 0.42 to 0.74),
462 while bias, RMSE and ubRMSE were similarly compared to open loop results. The time series
463 in Fig. 6a showed water input events at day 140 and day 325 (for example) that were certainly
464 due to irrigation. Thus this approach could be used to detect and retrieve irrigation information
465 that is very difficult to obtain over large areas on a daily basis. This information is requested
466 by managers to monitor and control irrigation, especially for the monitoring of groundwater (Le
467 Page et al. 2012).

468
469 The coupled scheme has the advantage of combining the spatial (but static) information
470 provided by DisPATCh data with the temporal (but mono-dimensional) information provided by
471 the force-restore scheme, in order to get SSM estimates every day at 1 km (Merlin et al. 2006).
472 Fig. 8 and Fig. 9 showed the temporal average of SSM during one year over the Yanco area and
473 the Tensift-Haouz basin, respectively. The irrigated areas are indicated for comparison purposes.
474 Regarding the Australian case study, the Murrumbidgee river banks and irrigated areas appeared
475 wetter than the dry grassland. The wet area located in the south of the study area is the floodplain
476 of the Yanco Creek System, which is a tributary of the Murrumbidgee River downstream of
477 Narrandera, flowing south-west. Over the Tensift-Haouz basin, the wetter pixels were mainly
478 located in the irrigated areas. Nevertheless, it is important to keep in mind that the irrigated areas
479 indicated may be inaccurate since many boreholes have been dug since the beginning of the
480 2000s, and they are neither registered nor monitored. A wet zone was also shown in the south

481 east of the study area. This region corresponds to the Atlas Mountain and its piedmont. A large
482 amount of water in the piedmont is provided by the water from Atlas snowmelt (Boudhar et al.
483 2009). However, it is necessary to note that DisPATCh data may be unreliable in mountainous
484 areas as the illumination effect on LST can be significant in steep-sided valleys (Malbêteau et al.
485 2017), and no correction for such effects has been included in DisPATCh yet (Molero et al.
486 2016). Note that the disaggregation images (fig. 8 and 9) present a slight boxy artifact at low
487 (SMOS) resolution. Such an artifact is typical of downscaling methods like DisPATCh that apply
488 a conservation law at low resolution (meaning that the average of disaggregated SM at SMOS
489 resolution is set to SMOS observation).

490

491 Table 5, Fig. 8 and Fig. 9

492

493 As a summary, the proposed downscaling/assimilation scheme showed systematically higher
494 r values with regards to the open loop and with regards to DisPATCh alone, indicating that the
495 dynamic of the SSM at a daily time scale has been improved. The maps of yearly average SSM
496 were consistent with the main hydrological characteristics of both catchment (rivers, wetlands and
497 irrigated areas). This opens perspectives for the retrieval of irrigation water inputs.

498 **5. Conclusion**

499 The DisPATCh algorithm has been developed to improve the spatial resolution of readily
500 available passive microwave-derived SSM data that is too coarse for many hydrological and
501 agricultural applications. However, the temporal resolution of DisPATCh data based on SMOS
502 and MODIS data is limited by the data gaps in MODIS images due to cloud cover, and by the
503 temporal resolution of SMOS. This paper evaluated the potential of assimilating DisPATCh data

504 into the force-restore soil moisture model, forced by the ERA-interim precipitation data in order
505 to obtain daily SSM at 1 km resolution. A variational scheme was used for root-zone soil moisture
506 analysis taken as a buffer variable, together with a sequential approach for the update of SSM.
507 The approach was tested during a one year period (2014) over two semi arid regions: 1) the Yanco
508 zone in Australia and 2) the Tensift-Haouz basin in Morocco.

509

510 The performance of the data assimilation was first evaluated at the time of DisPATCh availabil-
511 ity in order to check if the analyzed SSM showed an improvement with regards to the original
512 products. Results showed that the analyzed SSM series were closer to the *in situ* measurement
513 than DisPATCh (1 km resolution), model open loop (12.5 km resolution) and L3 SMOS SSM
514 estimates (25 km resolution). The temporal statistics, when DisPATCh data were available,
515 indicate an increase of r from 0.61 to 0.77 for downscaled data and up to 0.81 after assimilation.
516 The bias was also reduced from 0.04 to 0.02 $\text{m}^3 \text{m}^{-3}$ after downscaling, and ubRMSE decreased
517 from 0.07 to 0.06 $\text{m}^3 \text{m}^{-3}$ after assimilation of DisPATCh. The second step consisted in evaluating
518 the analyzed SSM for the full time-series in order to assess the potential of interpolating SSM
519 when the DisPATCh data was not available. The assimilation of DisPATCh data into the simple
520 LSM improved quasi systematically the dynamic of the SSM with respect to the open-loop,
521 as evidenced by enhanced r (from 0.53 to 0.70) and ubRMSE (from 0.07 to 0.06 $\text{m}^3 \text{m}^{-3}$).
522 These results showed that the disaggregated SSM was able to improve the representation of the
523 surface processes occurring at both fine and coarse scales, even when coarse scale and inaccurate
524 meteorological data including rainfall were used. These results corroborate the study of Merlin
525 et al. (2006), based on synthetic data showing that assimilation of a SSM downscaled product
526 can compensate error on precipitation input data for the monitoring of SSM. Another interesting
527 result was that the maps of yearly average SSM were consistent with the main hydrological char-

528 acteristics of both catchment (rivers, wetlands and irrigated areas). As future work, this approach
529 will be applied and evaluated using the entire time series of SMOS/DisPATCh (6 years) to capture
530 the inter-annual variability, and on other validation sites covering different eco-climatic conditions.

531

532 This study opens perspectives for developing new remote sensing-based methods in order to
533 retrieve irrigation water inputs at 1 km resolution, and/or to improve precipitation estimates. In
534 particular, several studies have been undertaken to estimate and/or improve precipitation estimates
535 based on remotely sensed coarse-scale SSM (Brocca et al. 2013, 2014; Pellarin et al. 2008, 2013).
536 A continuous SSM data in space and time could allow the disaggregation of coarse-scale pre-
537 cipitation data from re-analysis data sets at 1 km resolution for hydrological and agronomical
538 applications. Likewise, 1 km daily irrigation input data set could help improve knowledge on how
539 water is used for irrigation purposes.

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904 to *in situ* measurement; *r* is the correlation coefficient, RMSE is the root mean
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906 son days. With a p-value <0.01 for all sites, statistics are significant. 48

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908 **Table 5.** Temporal statistics and their 95% confidence intervals of open loop and ana-
909 lyzed SSM at all stations with respect to *in situ* measurement; *r* is the correla-
910 tion coefficient, RMSE is the root mean square error, ubRMSE is the unbiased-
911 RMSE and *n* is the number of comparison days. With a p-value <0.01 for all
912 sites, statistics are significant. 50

TABLE 1. Main characteristics of validation sites.

Country	Station	Longitude WGS84 (°)	Latitude WGS84 (°)	Elevation (m)	Land use	SM 0-5 cm (% of obs)	Precipitation (mm)	Irrigation
Morocco	Sidi Rahal	-7.3535	31.7035	767	Dryland crop/grazing	91.5	398	
Australia	Yanco 1	145.8490	-34.6288	120	Dryland crop/grazing	67.7	294	X
	Yanco 2	146.1103	-34.6547	130	Grazing	100.0	323	
	Yanco 8	146.4140	-34.8470	149	Grazing	98.6	374	
	Yanco 9	146.0163	-34.9678	122	Crop	100.0	329	
	Yanco 10	146.3099	-35.0054	119	Grazing	95.3	368	
	Yanco 12	146.1689	-35.0696	120	Crop/grazing	79.2	345	
	Yanco 13	146.3065	-35.0903	121	Gazing	66.0	368	

913 TABLE 2. Comparison between *in situ* and ERA-interim precipitation: annual bias and correlation coefficient
 914 *r* for accumulating precipitation of 1, 3, 5 and 10 days; *n* is the number of comparison days.

Country	Station	n	Precipitation <i>in situ</i>	Precipitation ECMWF	bias (mm)	r	r 3days	r 5days	r 10days
Morocco	Sidi Rahal	334	393	265.3	127.7	0.93	0.94	0.95	0.96
Australia	Yanco 1	245	294.6	258.7	35.9	0.44	0.6	0.62	0.63
	Yanco 2	365	358.6	323.3	35.3	0.48	0.59	0.6	0.59
	Yanco 8	No data	No data	350.8	No data	No data	No data	No data	No data
	Yanco 9	365	299.2	329.2	-30	0.5	0.64	0.67	0.66
	Yanco 10	342	187.6	327.3	-139.7	0.18	0.51	0.62	0.69
	Yanco 12	256	260.2	242.9	17.3	0.66	0.76	0.79	0.8
	Yanco 13	249	249.4	282.9	-33.5	0.59	0.69	0.72	0.74
Average			274.9	302.2	-27.2	0.48	0.63	0.67	0.69

915 TABLE 3. Temporal statistics and their 95% confidence intervals are provided of all stations between SMOS
916 L3, DisPATCh, open loop and analyzed SSM with respect to *in situ* measurement; r is the correlation coefficient,
917 RMSE is the root mean square error, ubRMSE is the unbiased-RMSE and n is the number of comparison days.
918 With a p-value <0.01 for all sites, statistics are significant.

			r				bias (m ³ m ⁻³)				RMSE (m ³ m ⁻³)				ubRMSE (m ³ m ⁻³)			
Country	Stations	n	SMOS	DisPATCh	OL	Analysed	SMOS	DisPATCh	OL	Analysed	SMOS	DisPATCh	OL	Analysed	SMOS	DisPATCh	OL	Analysed
Morocco	Sidi Rahal	104	0.64(±0.12)	0.82(±0.06)	0.74(±0.06)	0.87(±0.05)	-0.01(±0.01)	-0.01(±0.01)	0.01(±0.01)	-0.01(±0.01)	0.06(±0.01)	0.05(±0.01)	0.06(±0.01)	0.04(±0.01)	0.06(±0.01)	0.05(±0.01)	0.06(±0.01)	0.04(±0.01)
Australia	Yanco 1	104	0.69(±0.10)	0.76(±0.08)	0.63(±0.12)	0.80(±0.07)	0.06(±0.01)	0.02(±0.01)	0.08(±0.01)	0.04(±0.01)	0.08(±0.01)	0.06(±0.01)	0.09(±0.01)	0.06(±0.01)	0.06(±0.01)	0.06(±0.01)	0.05(±0.01)	0.05(±0.01)
	Yanco 2	111	0.47(±0.14)	0.69(±0.09)	0.65(±0.11)	0.79(±0.07)	-0.03(±0.01)	-0.03(±0.01)	0.03(±0.01)	-0.01(±0.01)	0.08(±0.01)	0.08(±0.01)	0.07(±0.01)	0.06(±0.01)	0.07(±0.01)	0.07(±0.01)	0.06(±0.01)	0.05(±0.01)
	Yanco 8	100	0.62(±0.12)	0.84(±0.06)	0.46(±0.16)	0.85(±0.05)	0.06(±0.01)	0.02(±0.01)	0.04(±0.01)	0.02(±0.01)	0.08(±0.01)	0.04(±0.01)	0.07(±0.01)	0.04(±0.00)	0.06(±0.01)	0.04(±0.01)	0.06(±0.01)	0.03(±0.00)
	Yanco 9	122	0.66(±0.10)	0.82(±0.06)	0.50(±0.12)	0.84(±0.05)	-0.02(±0.01)	0.01(±0.01)	-0.01(±0.01)	0.01(±0.01)	0.07(±0.01)	0.06(±0.01)	0.06(±0.01)	0.05(±0.01)	0.06(±0.01)	0.06(±0.01)	0.05(±0.01)	0.05(±0.01)
	Yanco 10	114	0.68(±0.10)	0.84(±0.05)	0.69(±0.10)	0.88(±0.04)	0.04(±0.01)	0.02(±0.01)	0.04(±0.01)	0.03(±0.01)	0.08(±0.01)	0.05(±0.01)	0.06(±0.01)	0.04(±0.00)	0.07(±0.01)	0.04(±0.01)	0.04(±0.01)	0.03(±0.00)
	Yanco 12	79	0.65(±0.13)	0.66(±0.13)	0.62(±0.14)	0.70(±0.12)	-0.04(±0.01)	-0.08(±0.01)	-0.04(±0.01)	-0.06(±0.01)	0.07(±0.01)	0.10(±0.01)	0.07(±0.01)	0.08(±0.01)	0.06(±0.01)	0.06(±0.01)	0.06(±0.01)	0.05(±0.01)
	Yanco 13	69	0.52(±0.17)	0.74(±0.11)	0.52(±0.17)	0.78(±0.09)	0.04(±0.02)	0.01(±0.01)	0.02(±0.01)	0.0(±0.01)	0.09(±0.02)	0.05(±0.01)	0.06(±0.01)	0.04(±0.01)	0.08(±0.02)	0.04(±0.01)	0.05(±0.01)	0.04(±0.01)
average			0.62	0.77	0.60	0.81	0.04	0.02	0.04	0.02	0.08	0.06	0.07	0.05	0.07	0.05	0.05	0.04

TABLE 4. GDOWN results.

Country	Site	DisPATCH	Analyzed
Morocco	Sidi Rahal	0.232	0.330
Australia	Yanco 1	0.119	0.112
	Yanco 2	0.352	0.530
	Yanco 8	0.571	0.314
	Yanco 9	0.014	0.067
	Yanco 10	0.108	0.235
	Yanco 12	-0.111	-0.066
	Yanco 13	0.282	0.220
average		0.196	0.218

919 TABLE 5. Temporal statistics and their 95% confidence intervals of open loop and analyzed SSM at all
 920 stations with respect to *in situ* measurement; r is the correlation coefficient, RMSE is the root mean square error,
 921 ubRMSE is the unbiased-RMSE and n is the number of comparison days. With a p-value <0.01 for all sites,
 922 statistics are significant.

			r			bias (m ³ m ⁻³)			RMSE (m ³ m ⁻³)			ubRMSE (m ³ m ⁻³)		
Country	Station	n	OL	Analysed 25 km	Analysed 1 km	OL	Analysed 25 km	Analysed 1 km	OL	Analysed 25 km	Analysed 1 km	OL	Analysed 25 km	Analysed 1 km
Morocco	Sidi Rahal	334	0.73(±0.05)	0.66(±0.08)	0.83(±0.03)	0.00(±0.01)	0.01(±0.01)	0.01(±0.01)	0.07(±0.00)	0.06(±0.00)	0.06(±0.00)	0.07(±0.00)	0.06(±0.00)	0.06(±0.00)
Australia	Yanco 1	247	0.60(±0.08)	0.49(±0.10)	0.64(±0.07)	0.08(±0.01)	0.06(±0.01)	0.05(±0.01)	0.10(±0.01)	0.08(±0.01)	0.08(±0.01)	0.06(±0.01)	0.05(±0.01)	0.06(±0.01)
	Yanco 2	365	0.66(±0.05)	0.30(±0.12)	0.71(±0.05)	0.03(±0.01)	0.01(±0.01)	0.03(±0.01)	0.07(±0.01)	0.07(±0.01)	0.08(±0.01)	0.06(±0.01)	0.07(±0.01)	0.08(±0.01)
	Yanco 8	360	0.40(±0.08)	0.56(±0.09)	0.66(±0.06)	0.03(±0.01)	0.04(±0.01)	0.04(±0.01)	0.08(±0.00)	0.07(±0.01)	0.07(±0.00)	0.07(±0.00)	0.05(±0.00)	0.06(±0.00)
	Yanco 9	365	0.42(±0.08)	0.52(±0.09)	0.74(±0.05)	0.02(±0.01)	0.03(±0.01)	0.02(±0.01)	0.07(±0.00)	0.06(±0.00)	0.07(±0.00)	0.07(±0.00)	0.06(±0.00)	0.06(±0.00)
	Yanco 10	348	0.47(±0.07)	0.63(±0.08)	0.70(±0.04)	0.03(±0.01)	0.04(±0.01)	0.04(±0.01)	0.08(±0.00)	0.06(±0.00)	0.07(±0.00)	0.07(±0.00)	0.05(±0.00)	0.06(±0.00)
	Yanco 12	289	0.56(±0.07)	0.37(±0.13)	0.70(±0.06)	0.05(±0.01)	0.04(±0.01)	0.05(±0.01)	0.10(±0.01)	0.08(±0.01)	0.09(±0.01)	0.07(±0.01)	0.07(±0.01)	0.07(±0.01)
	Yanco 13	241	0.35(±0.10)	0.41(±0.14)	0.61(±0.07)	0.02(±0.01)	0.02(±0.01)	0.04(±0.01)	0.08(±0.01)	0.07(±0.01)	0.07(±0.01)	0.08(±0.01)	0.06(±0.01)	0.07(±0.01)
average			0.53	0.49	0.70	0.03	0.03	0.03	0.08	0.08	0.07	0.07	0.06	0.06

923 **LIST OF FIGURES**

924 **Fig. 1.** The experimental Yanco area located in southeastern Australia showing the SMOS L3 grid
 925 corner (red cross), DisPATCH grid (black cross), the selected OzNet stations, and the irri-
 926 gated area. 52

927 **Fig. 2.** The Tensift Haouz basin located in central Morocco showing the SMOS L3 grid corner (red
 928 cross), DisPATCH grid (black cross), Sidi Rahal station, and the irrigated area. 53

929 **Fig. 3.** Sensitivity analysis for background errors. An ensemble of 10 perturbations from 0.02 to
 930 $0.1 \text{ m}^3 \text{ m}^{-3}$ was built for both the background error terms (Θ_1 and Θ_2). The global statistics
 931 (correlation coefficient, Root Mean Square Error RMSE, and mean bias) were computed
 932 based on the analyzed and in situ SSM comparison. 54

933 **Fig. 4.** Cumulative daily precipitation (mm) for all sites. The blue lines are the ERA-interim pre-
 934 cipitation at 0.125° spatial resolution distributed by the ECMWF and the red lines are the *in*
 935 *situ* precipitation. Note that *in situ* data are not available for Yanco 8. 55

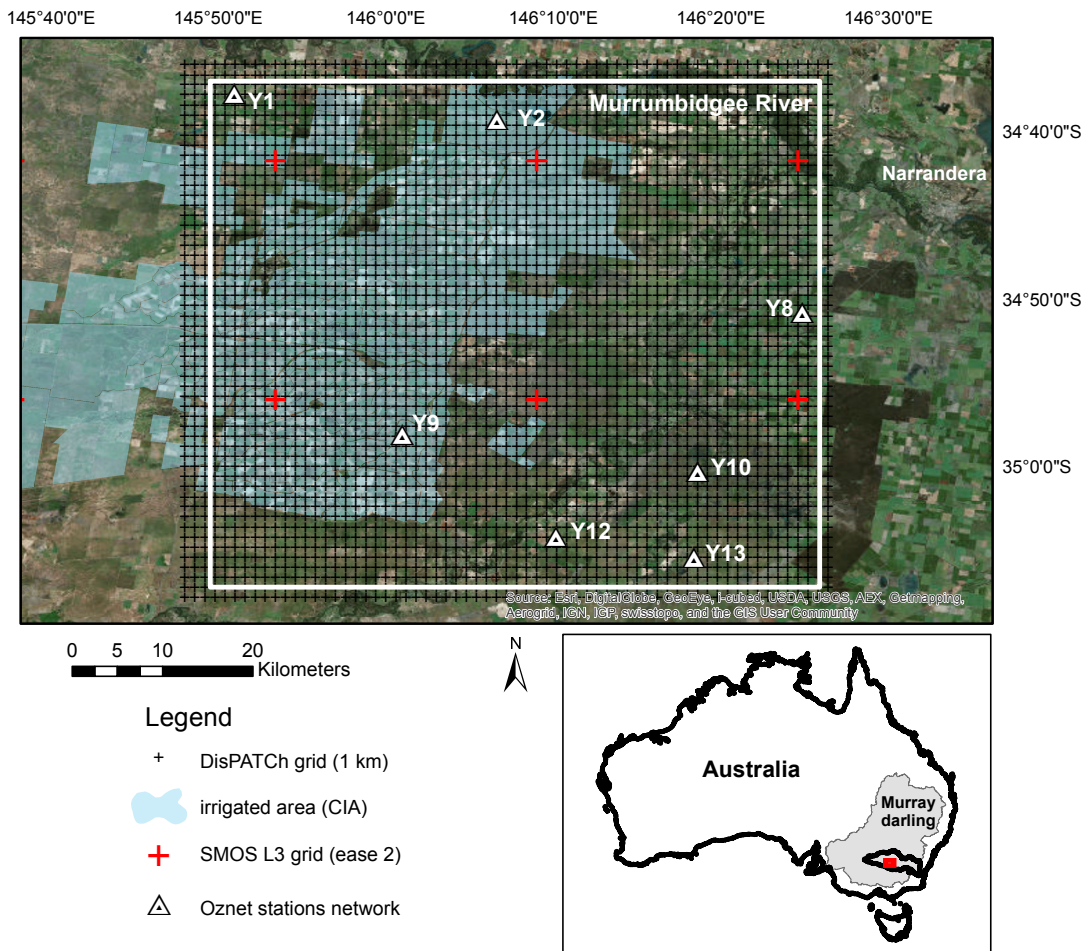
936 **Fig. 5.** (a) Time series evaluation of the DisPATCH (black circle) with the errors bars representing
 937 standard deviation of DisPATCH, open loop (blue dots), and the analyzed (red dots) SSM
 938 against *in situ* (black line) measurements and cumulative daily precipitation (blue bars) for
 939 Sidi Rahal station. (b) Scatterplot of DisPATCH (black dots), open loop (blue dots), analyzed
 940 (red dots) SSM versus *in situ* measurements. 56

941 **Fig. 6.** As for fig. 5 but for Yanco 9 station 57

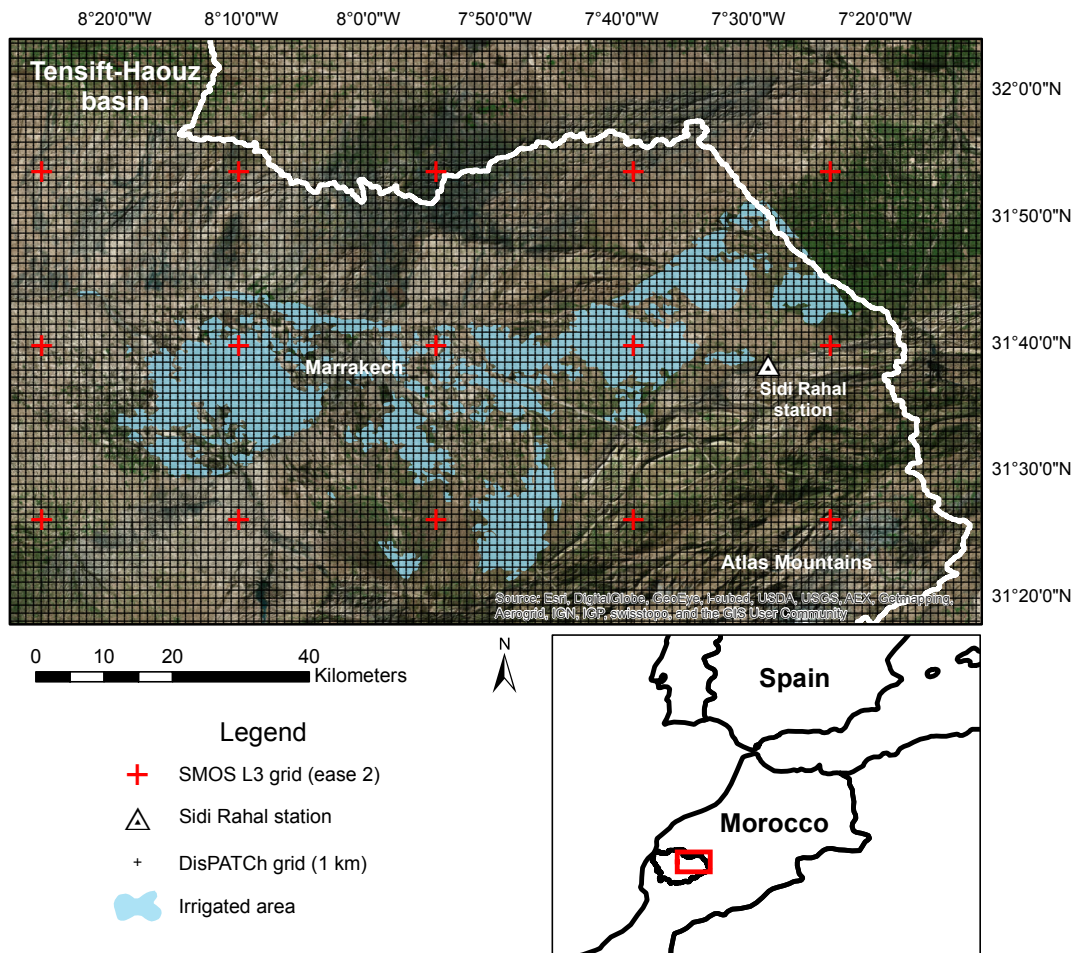
942 **Fig. 7.** As for fig. 5 but for Yanco 10 station 58

943 **Fig. 8.** Image of yearly (2014) average of analyzed SSM over Yanco area. Black lines represent the
 944 irrigated fields. 59

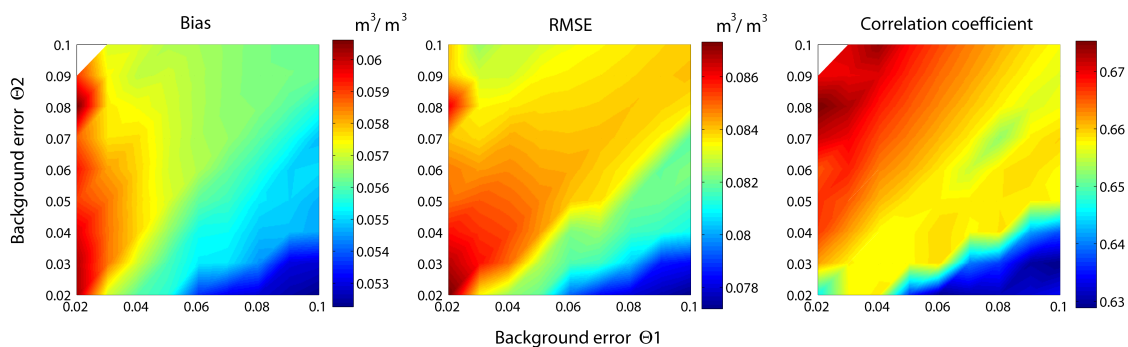
945 **Fig. 9.** Image of yearly (2014) average of analyzed SSM over Tensift Haouz region. Black lines
 946 represent the irrigated fields. 60



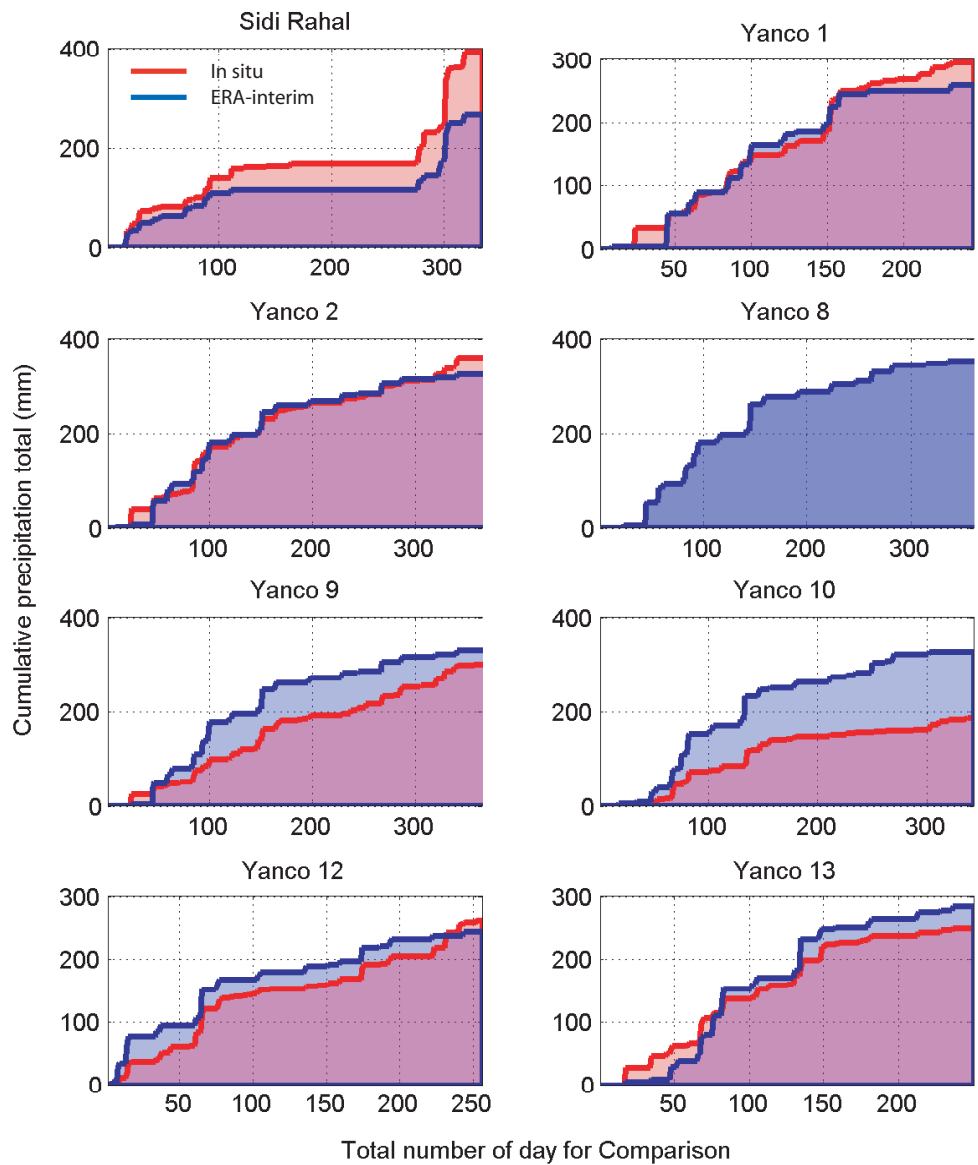
947 FIG. 1. The experimental Yanco area located in southeastern Australia showing the SMOS L3 grid corner
 948 (red cross), DisPATCH grid (black cross), the selected OzNet stations, and the irrigated area.



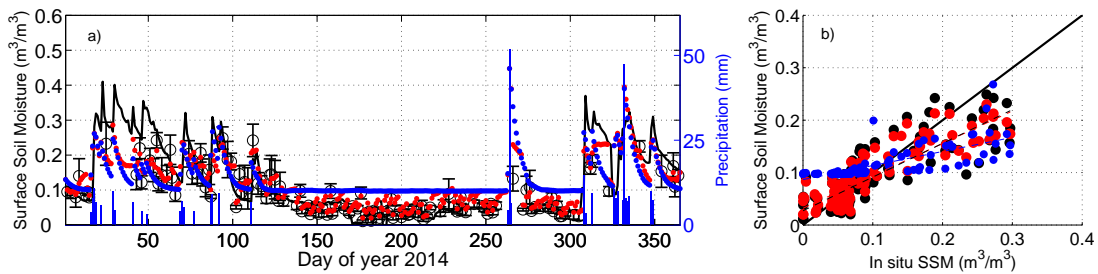
949 FIG. 2. The Tensift Haouz basin located in central Morocco showing the SMOS L3 grid corner (red cross),
 950 DisPATCh grid (black cross), Sidi Rahal station, and the irrigated area.



951 FIG. 3. Sensitivity analysis for background errors. An ensemble of 10 perturbations from 0.02 to 0.1 $\text{m}^3 \text{m}^{-3}$
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954 FIG. 4. Cumulative daily precipitation (mm) for all sites. The blue lines are the ERA-interim precipitation at
 955 0.125° spatial resolution distributed by the ECMWF and the red lines are the *in situ* precipitation. Note that *in*
 956 *situ* data are not available for Yanco 8.



957 FIG. 5. (a) Time series evaluation of the DisPATCH (black circle) with the errors bars representing standard
 958 deviation of DisPATCH, open loop (blue dots), and the analyzed (red dots) SSM against *in situ* (black line)
 959 measurements and cumulative daily precipitation (blue bars) for Sidi Rahal station. (b) Scatterplot of DisPATCH
 960 (black dots), open loop (blue dots), analyzed (red dots) SSM versus *in situ* measurements.

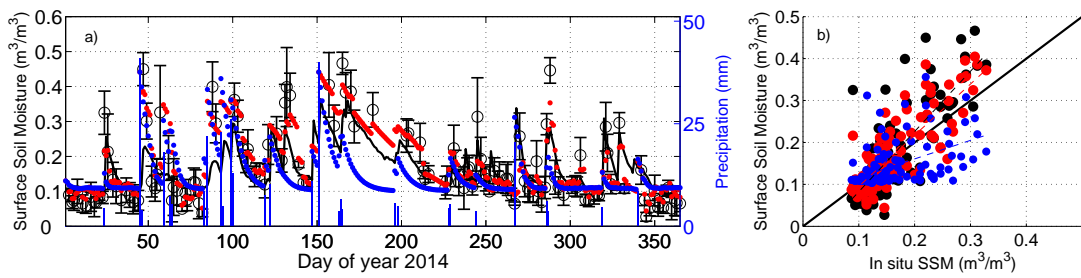


FIG. 6. As for fig. 5 but for Yanco 9 station

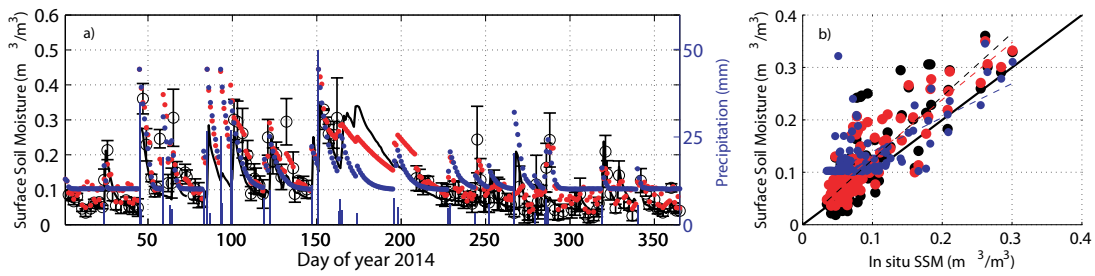
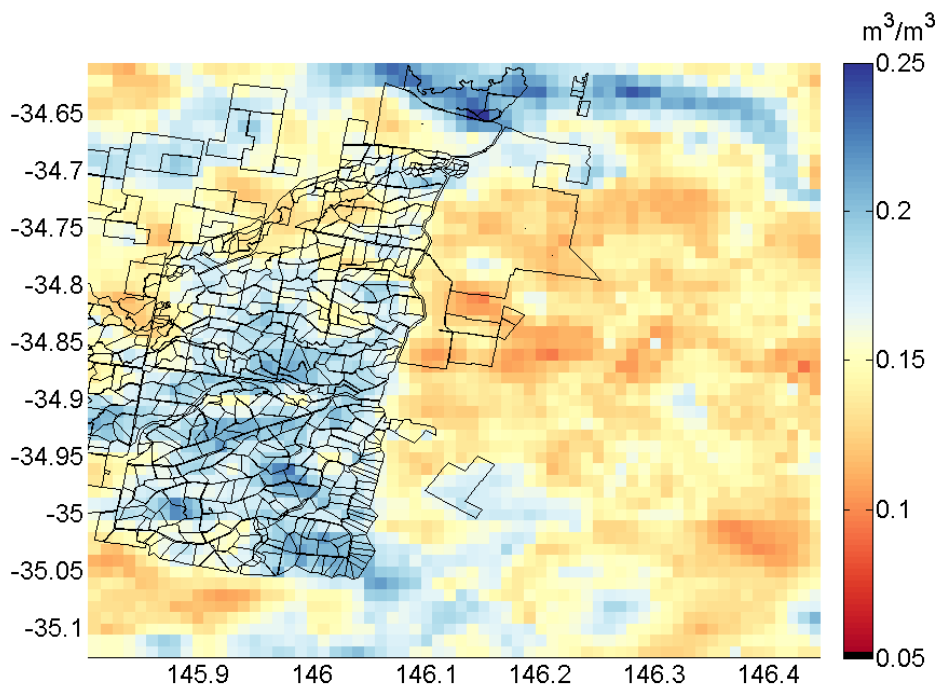
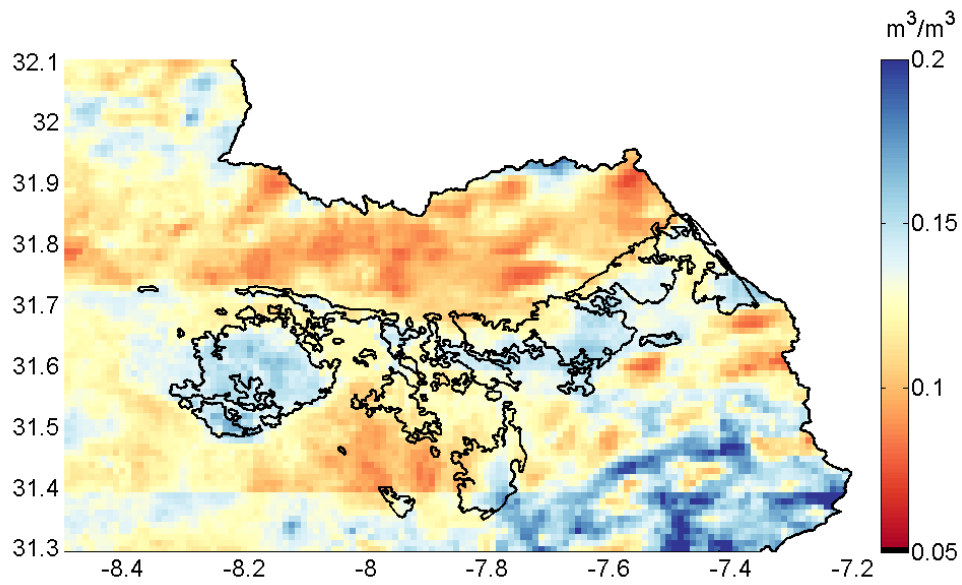


FIG. 7. As for fig. 5 but for Yanco 10 station



961 FIG. 8. Image of yearly (2014) average of analyzed SSM over Yanco area. Black lines represent the irrigated
962 fields.



963 FIG. 9. Image of yearly (2014) average of analyzed SSM over Tensift Haouz region. Black lines represent the
964 irrigated fields.