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Monitoring of wheat crops using the backscattering coefficient and the interferometric coherence derived from Sentinel-1 in semi-arid areas

Nadia Ouaadi^{a,b,*}, Lionel Jarlan^b, Jamal Ezzahar^{c,d}, Mehrez Zribi^b, Saïd Khabba^{a,d},
Elhoussaine Bouras^{e,b}, Safa Bousbih^f, Pierre-Louis Frison^g

*corresponding author

^aLMFE, Department of Physics, Faculty of Sciences Semlalia, Cadi Ayyad University, Marrakech, Morocco.

^bCESBIO, University of Toulouse, IRD/CNRS/UPS/CNES, Toulouse, France.

^c MISCOS, National School of Applied Sciences, Cadi Ayyad University, Safi, Morocco.

^dCRSA, Mohammed VI Polytechnic University UM6P, Benguerir, Morocco.

^eProcEDE, Department of Applied Physique, Faculty of Sciences and Technologies, Cadi Ayyad University, Marrakech, Morocco.

^fINAT, GREEN-TEAM, Tunis, Tunisia.

^gLaSTIG//MATWAS, IGN, University of Paris-Est, Champs sur Marne, Paris, France.

nadia.ouaadi@gmail.com

lionel.jarlan@ird.fr

j.ezzahar@uca.ma

mehrez.zribi@cesbio.cnes.fr

khabba@uca.ac.ma

bouras.elhoussaine@gmail.com

safabousbih1@outlook.fr

pierre-louis.frison@u-pem.fr

Keywords

Sentinel-1, Surface soil moisture, Backscattering coefficient, C-band, Interferometric coherence, Winter wheat, Semi-arid region.

32 **Abstract**

33 Radar data at C-band has shown great potential for the monitoring of soil and canopy hydric
34 conditions of wheat crops. In this study, the C-band Sentinel-1 time series including the
35 backscattering coefficients σ^0 at VV and VH polarization, the polarization ratio (PR) and the
36 interferometric coherence ρ are first analyzed with the support of experimental data
37 gathered on three plots of irrigated winter wheat located in the Haouz plain in the center of
38 Morocco covering five growing seasons. The results showed that ρ and PR are tightly related
39 to the canopy development. ρ is also sensitive to soil preparation. By contrast, σ^0 was found
40 to be widely linked to changes in surface soil moisture (SSM) during the first growth stages
41 when Leaf Area Index remains moderate ($<1.5 \text{ m}^2/\text{m}^2$). In addition, drastic changes in the
42 crop geometry associated to heading had a strong impact on the C-band σ^0 , in particular for
43 VH polarization. The coupled water cloud and Oh models (WCM) were then calibrated and
44 validated on the study sites. The comparison between the predicted and observed σ^0
45 yielded a root mean square error (RMSE) values ranging from 1.50 dB to 2.02 dB for VV and
46 between 1.74 dB to 2.52 dB for VH with significant differences occurring in the second part
47 of the season after heading. Finally, new approaches based on the inversion of the WCM for
48 SSM retrieval over wheat fields were proposed using Sentinel-1 radar data only. To this
49 objective, the dry above-ground biomass (AGB) and the vegetation water content (VWC)
50 were retrieved from the interferometric coherence and the PR. The relationships were then
51 used as the vegetation descriptor in the WCM. The best retrieval results were obtained using
52 the relationship between ρ_{VV} and the AGB (R and RMSE of 0.82, $0.05 \text{ m}^3/\text{m}^3$ respectively and
53 no bias). The new retrieval approaches were then applied to a large database covering a
54 rainfed field in Morocco and 18 plots of rainfed and irrigated wheat of the Kairouan plain
55 (Tunisia) and compared to other classical techniques of SSM retrieval including simple linear

56 relationships between SSM and σ^0 . The method based on the WCM and the ρ_{VV} -AGB
57 relationships also provided with slightly better results than the others on the validation
58 database ($r=0.75$, $RMSE=0.06 \text{ m}^3/\text{m}^3$ and $bias=0.01 \text{ m}^3/\text{m}^3$ over the 18 plots of Tunisia) but
59 the simple linear relationships performed also reasonably well ($r=0.62$, $RMSE=0.07$, $bias=-$
60 0.01 in Tunisia for instance). This study opens perspectives for high resolution soil moisture
61 mapping from Sentinel-1 data over south Mediterranean wheat crops and *in fine*, for
62 irrigation scheduling and retrieval through the assimilation of these new products in an
63 evapotranspiration model.

64

65 **Introduction**

66 In the semi-arid regions where the water resources are very limited and where up to 90% of
67 the available water is used for irrigation, surface soil moisture (SSM) is a key parameter for
68 crop water stress detection and for irrigation management. Wheat crop is of prime
69 importance as it represents the most cropped cereal in the world, and particularly in
70 Morocco where 75% of the useful agricultural area are dedicated to wheat ([Ministre de
71 l'agriculture et peche maritime du developement rurale et des eaux et forets, 2018](#)). Several
72 global soil moisture products exist nowadays. They are derived from microwave remote
73 sensing including active sensors such as: scatterometers ([Naeimi et al., 2009; Wagner et al.,
74 1999](#)) or radiometers like the Soil Moisture and Ocean Salinity mission -SMOS- ([Kerr et al.,
75 2001](#)) or the Advanced Microwave Scanning Radiometer -AMSR- ([Njoku, 2004](#)). The potential
76 of microwave data in this context originates from their high sensitivity to changes of surface
77 parameters including the SSM, the soil roughness, the above ground biomass (AGB) and the
78 canopy geometry. In addition, microwave signal at these wavelengths is not prone to
79 atmospheric perturbation which is a major advantage with regards to optical data. However,
80 soil moisture products derived from scatterometers or microwave radiometers suffers from
81 a coarse spatial resolution above 10 km² not suited for a fine monitoring of crops at the field
82 scale. By contrast, SAR (Synthetic Aperture Radar) observations are acquired with a pixel of
83 around 10 m but the use of such data to monitor operationally soil moisture was still limited
84 until the recent launch of the Sentinel-1 constellation that opened new perspectives for the
85 monitoring of crops at the field scale by providing high resolution (10 m) data with revisit
86 time of about 6 days at C-band ([Torres et al., 2012](#)).

87 The numerous theoretical and experimental studies carried out during the 80s and the 90s
88 demonstrated the richness of information contained in the C-band signal but also the

89 complexity of interpreting the time series. Indeed, for annual crops like wheat, contributions
90 to the signal from the soil and from the vegetation are merged and are changing quickly. The
91 co-polarized (HH and VV) backscatter coefficient are usually preferred for soil moisture
92 retrieval (Bai et al., 2017; Gherboudj et al., 2011; Zribi et al., 2011) while some studies
93 revealed that the cross-polarized (VH and HV) data was better suited for vegetation
94 monitoring including both classification and biomass retrieval (Hosseini and McNairn, 2017).
95 Indeed, over bare soils, the backscattering coefficient σ^0 is affected by the dielectric
96 properties of the superficial layer of the soil mainly governed by SSM, and, to a lesser extent,
97 soil texture (Dobson and Ulaby, 1981; Ulaby et al., 1986) and by the soil roughness
98 (Ferrazzoli et al., 1992; Ulaby et al., 1978; Zribi and Baghdadi, 2015). Considering the
99 sensitivity to SSM, several retrieval algorithms based on C-band data have been developed
100 on bare soils. They were empirically based taking advantage of the linear relationships
101 between σ^0 and SSM (Amazirh et al., 2018; Griffiths and Wooding, 1996; Moran et al., 1997;
102 Sano et al., 1998; Zribi et al., 2003; Zribi and Dechambre, 2002) or they relied on the
103 inversion of a soil backscattering model (Baghdadi et al., 2008; Bertuzzi et al., 1992; Bindlish
104 and Barros, 2000; Ezzahar et al., 2020; Walker et al., 2004). For vegetated surface, the signal
105 at C-band is a complex mix of a soil contribution attenuated by the canopy, of the volume
106 scattering within the canopy and of the interactions between soil and vegetation (Ulaby et
107 al., 1986). In order to separate soil and vegetation contributions, the retrieval of SSM over
108 vegetated terrain is thus usually carried out using a model predicting the interaction
109 between the electromagnetic wave and the different surface elements. Within this context,
110 several backscattering models were developed (Attema and Ulaby, 1978; Karam et al., 1995,
111 1993, 1992; Picard and Toan, 2002; Ulaby et al., 1990) with the aim to get a better
112 understanding of the response of vegetation and soils and to be used within an inversion

113 process (Balenzano et al., 2011; Brisco et al., 1990; Mattia et al., 2003; Picard et al., 2003).
114 Among backscattering models of various complexity, the semi-empirical water cloud model
115 (WCM) (Attema and Ulaby, 1978) based on the first order solution of the radiative transfer
116 equations has been extensively used as it represents a good trade-off between domain of
117 validity and model complexity as response of the vegetation canopy is parameterized thanks
118 to two parameters only. Coupled to a soil backscattering model, it has been widely used for
119 SSM and biophysical parameters retrieval especially for crops such as wheat (Baghdadi et al.,
120 2017; Bai et al., 2017; Bindlish and Barros, 2001; Bousbih et al., 2017; El Hajj et al., 2016;
121 Gherboudj et al., 2011; Hosseini and McNairn, 2017; Periasamy, 2018; Taconet et al., 1994;
122 Ulaby et al., 1984; Wang et al., 2018; Zribi et al., 2011). To describe vegetation development
123 within the water cloud model, several variables have been proposed. Most of published
124 studies used preferentially Vegetation Water Content (Attema and Ulaby, 1978; Bindlish and
125 Barros, 2001; Wang et al., 2018) but Prevot et al. (1993) argued that there is no general
126 theoretical framework to define the best set of canopy descriptors in the WCM because the
127 complexity of the vegetation's structure and of the relative simplicity of the model. Within
128 this context, a few authors proposed different descriptors: plant height (Kumar et al., 2015),
129 HV backscattering coefficient (Li and Wang, 2018), polarization ratio (Dabrowska-Zielinska et
130 al., 2018), Radar Vegetation Index (Li and Wang, 2018) or LAI (Leaf Area Index) (Bai et al.,
131 2017; El Hajj et al., 2016; Kumar et al., 2014; Prevot et al., 1993). With the recent launch of
132 Sentinel-2, a lot of recent studies used optical-derived descriptors such as NDVI (Normalized
133 difference vegetation index) (Baghdadi et al., 2017; Bousbih et al., 2017; El Hajj et al., 2016)
134 that is related to vegetation greenness. Nevertheless, a severe lack of observations may
135 occur in case of a persistent cloud cover which is very likely when wheat is cropped during
136 the rainy season such as in the South Mediterranean region.

137 The radar interferometric coherence is defined as the variance of the interferometric phase,
138 which is related to the path length between the satellite antenna and the ground target. It is
139 related to the amount of coherent and incoherent scattering. Beside the system noise, the
140 coherence decreases with increasing volume scattering, because of target changes between
141 two successive radar acquisitions or because of the natural motion of the scatterers (Zebker
142 and Villasenor, 1992). State differently, volume scattering and arbitrary dislocation of
143 scatterers in the vegetation canopy reduce the coherence. Even if dry fields exhibit lower
144 interferometric coherence than wet fields (Blaes and Defourny, 2003; Nesti et al., 1998), the
145 interferometric coherence is relatively insensitive to soil effects considering that surface
146 roughness of crops does not change significantly between seeding and harvest. Wegmuller
147 and Werner (1997) found a strong correlation between the interferometric coherence and
148 the cover fraction opening perspectives for crop height and biomass estimation. Strong
149 relationships have been established between interferometric coherence at C-band and crop
150 height for some agricultural crops (winter wheat, potato, sugar beet...) at the beginning of
151 the growing season (Blaes and Defourny, 2003; Engdahl et al., 2001). Likewise, the ratio
152 HH/VV was also shown to be related to aboveground biomass during the growing season,
153 especially at 40° of incidence (Mattia et al., 2003). Since this ratio was not available in the
154 Sentinel-1 IW acquisition mode, Veloso et al. (2017) used the VH/VV backscattering ratio as a
155 solution that can reduce the vegetation-ground interaction effect as well as the errors
156 associated to the acquisition. VH/VV appears more stable in time than VH or VV and more
157 sensitive to the wheat growth cycle. Furthermore, it was correlated to the fresh biomass and
158 able to discriminate cereals from non-cereals surface dominated crops (Mattia et al., 2015;
159 Veloso et al., 2017).

160 This study presents a new SSM retrieval approach based on Sentinel-1 data only to describe
161 the vegetation contribution in the WCM. The approach is developed on two monitored
162 irrigated wheat fields located in Morocco and evaluated on a large database covering 20
163 rainfed and irrigated plots in Morocco and Tunisia. The next section describes the satellite
164 and the *in situ* measurements, the backscattering models and the retrieval algorithm.
165 Results are presented in section 3 including the experimental analysis of Sentinel-1 time
166 series, the forward modeling of the backscattering coefficient and the SSM retrieval. In
167 section 4, the main conclusions and perspectives are drawn.

168

169 **1. Experimental data and Methodology**

170 **1.1. Experimental data**

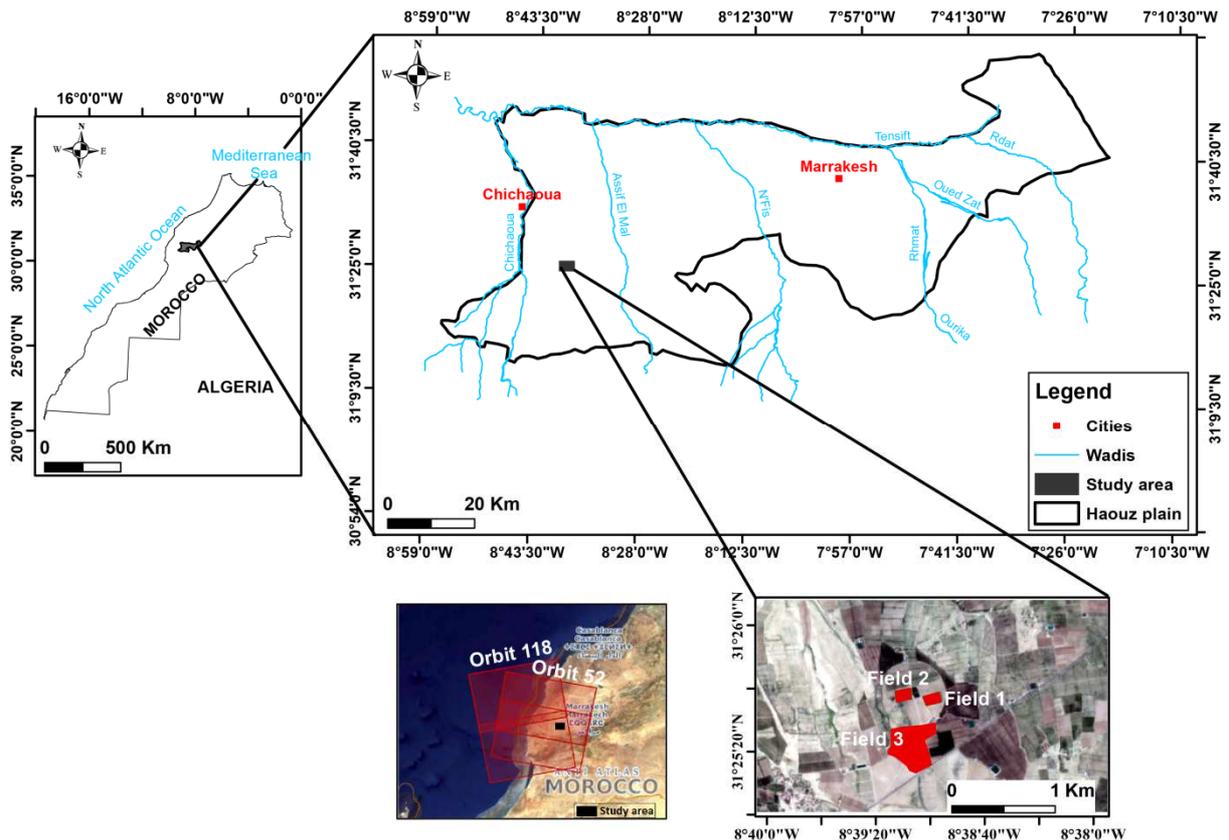
171 The SSM retrieval approaches were developed on three irrigated wheat plots located near
172 Chichaoua city that were intensively monitored during two crop seasons. A database of soil
173 moisture measurements on rainfed and irrigated wheat in Morocco and Tunisia described in
174 section 1.1.3 was gathered to validate the approach.

175 **1.1.1. Study area description**

176 The study site is located in the province of Chichaoua at 65 Km west of Marrakech city in the
177 Haouz plain center of Morocco (Fig. 1). The region is characterized by a semi-arid
178 Mediterranean climate. The annual average precipitation amount is about 250 mm (Ait
179 Hssaine et al., 2018; Rafi et al., 2019). The monthly average of rainfall distribution measured
180 at Chichaoua shows the existence of two characteristic periods: a wet season from October
181 to April (85-89% of the annual amount) and a dry season from May to September (11- 15%).
182 The average maximum temperature occurs in July-August (27.2°C) while the minimum
183 (10.8°C) is in January. The reference evapotranspiration ET_0 is about 1600 mm (Jarlan et al.,
184 2015).

185 Two fields, named Field 1 and Field 2 (Fig. 1), of about 1.5 ha each, were selected within a
186 private farm named "Domaine Rafi" and monitored during two crop seasons from November
187 2016 to July 2018. Soil texture is mainly clay (37.5%) and sand (32.5%). Field 1 and Field 2
188 were seeded with winter wheat on November, 27, 2016 and November, 25, 2017 for 2016-
189 2017 and 2017-2018 crop seasons, respectively. Harvest occurred on May, 16, 2017 and
190 June, 08, 2018. The irrigation method used is the drip technique with a flow rate of 7.14
191 mm/hour for each dripper. Field 2 was irrigated according to FAO recommendations while

192 Field 1 suffered from a triggered stress for the need of another research study ([Ait Hssaine](#)
193 [et al., 2018](#); [Rafi et al., 2019](#)). After harvest, the fields were used as cattle grazing up to mid-
194 July when the plowing works started. Please note that wheat growth on Field 2 during the
195 2017-2018 growing season was severely affected by very specific growing conditions: (1)
196 very invasive adventices with a strong horizontal development (cf picture S1 in the
197 supplementary material). The adventices species belong to the family of wild thistles that is
198 not very widespread on wheat fields in the South Mediterranean area ([Tanji, 2005](#)). Some
199 part of the field were almost completely covered around vegetation peak; (2) Field 2 during
200 the second year was more exposed to wind than Field 1 because the density of seeding was
201 much higher and because a mix of wheat and barley were seeded by mistake. Barley is
202 characterized by longer stems than wheat that grown up to 146 cm on April 2018 thanks to
203 irrigation. By contrast, the height of stems on Field 1 seeded with pure wheat, only reached
204 110 cm. Stems were almost completely laid down by the wind from April 12, 2018 (see
205 picture S2) on Field 2. Considering these very specific growing conditions of Field 2 during
206 the 2nd year, a third field named Field 3 (Fig. 1), was also instrumented during 2018-2019 to
207 extent the validation database under normal growing conditions. It was seeded on
208 November 4, 2018 and harvested on June 06, 2019. Field 3 has the same soil as Field 1 and 2
209 and is also watered by drip irrigation.



210

211 *Fig. 1. Location of the study sites: Field 1 (stressed), Field 2 (reference) and Field 3 drip-irrigated wheat crops near*
 212 *Chichaoua city in a private farm ("Domaine Rafi"), west of Marrakech, Haouz plain, center of Morocco.*

213 1.1.2. Field data description

214 Vegetation and soil measurements were collected according to the Sentinel-1 passage
 215 schedule. The days corresponding to precipitation events were discarded.

216 *Soil measurements*

217 Automatic measurements of SSM were acquired at a 30 min time step from Time Domain
 218 Reflectometry sensors (TDR Campbell Scientific CS616) buried at a depth of 5 cm. In order
 219 to get a measurement representative of the Sentinel-1 pixel, the soil moisture observations
 220 were taken as the average of two sensors data that were installed between and under the
 221 drippers. The gravimetric technique was used to calibrate the TDR measurements.
 222 Measurements were carried out, over Field 1 and Field 2, for five days in order to cover a

223 wide range of soil moisture values (0.08 to 0.33 m³/m³). Three samples were collected per
224 day and per field at the TDR installation depth using a 392.5 cm³ aluminum core. A linear
225 regression was established between the volumetric water content and the square root of
226 the TDR time response. The corresponding RMSEs (all the statistical metrics used in this
227 study are described in the supplementary material) over Field 1 and Field 2 are 0.023 m³/m³
228 and 0.010 m³/m³, respectively. The same relationship was applied to Field 3 data.

229 Soil roughness corresponds to micro-topographic variations of the soil surface. It was
230 measured once a week during the first stages of wheat development until the canopy
231 prevented from making the measurement (corresponding to a canopy fraction cover of
232 about 0.8). A pin profiler of 1 m length with 2 cm between two successive needles was used.
233 For Field 1 and Field 2, sixteen samples at different places were taken per field including
234 eight measurements made parallel to the row and eight perpendicular in order to take into
235 account the effect of the rows direction (Sieber et al., 1982). A picture of the pin profile was
236 taken for each sample and processed using an algorithm based on the normalization of the
237 needles height. For each roughness profile, two statistical parameters used as inputs of the
238 backscattering soil models were derived from the correlation functions of the heights of the
239 surface profiles: the root mean square surface height (h_{rms}) and the correlation length (L)
240 (Nolin et al., 2005). For each date and each field, an average of h_{rms} and L is computed from
241 the 16 sample estimates. h_{rms} and L values ranged from 0.7 to 1.5 cm and 4.8 to 7.3 cm,
242 respectively. A preliminary analysis of the time series of h_{rms} and L values show that the
243 values are quite similar for measurements parallel and perpendicular to the row apart from
244 the beginning of the season when rows are still clearly visible because of the sowing (not
245 shown). This anisotropy disappeared quickly with irrigation and plant growth. The average of
246 h_{rms} and L for all the measurements in each direction are reported in Table 1. The values are

247 of the same order of magnitude for Field 2 while a slight difference is observed for Field 1.

248 For reasons of simplicity, the surface roughness is considered isotropic in this study.

249 *Table 1*

250 *h_{rms} and L average values for measurements parallel and perpendicular to the row over Field 1 and Field 2.*

	Field 1				Field 2			
	Parallel		Perpendicular		Parallel		Perpendicular	
	h_{rms} (cm)	L (cm)						
Average	0.95	5.20	1.26	6.53	1.15	5.82	1.16	6.17

251

252 *Wheat measurements*

253 In the presence of vegetation canopy, the microwave backscattering is significantly related

254 to vegetation's parameters such as biomass, plant water content and geometry (Ferrazzoli et

255 al., 1992; Ulaby et al., 1986). Destructive above-ground biomass (AGB) measurements were

256 conducted about every 15 days. Plant sampling was conducted in eight quadrates

257 (0.25m*0.25m) selected randomly in each field. The AGB is weighted first in the field

258 (hereafter named fresh above ground biomass or FAGB). The samples were then dried in an

259 oven at 105°C for 48 h. The weighted samples after drying are used to compute the AGB

260 expressed in kg of dry matter by m². The difference between wet and dry samples is the

261 vegetation water content (VWC). The canopy fraction cover (Fc) and the leaf area index (LAI)

262 were calculated by processing eleven hemispherical digital images per field, taken every

263 week at various representative points and by computing the average of individual pictures.

264 The canopy height was also measured by averaging eleven measurements per field.

265 *Meteorological data*

266 A complete automatic weather station installed over an alfalfa field near the study site

267 provided continuous measurements of meteorological forcing, including air temperature and

268 rainfall. The data were collected half-hourly, the temperature values were averaged at a
269 daily time step and the precipitation measurements were summed up to obtain daily
270 amounts.

271 **1.1.3. Validation database**

272 SSM measurements using TDR and hand-held thetaprobe were carried out on different
273 wheat sites in Morocco and Tunisia, respectively. This database is used for the validation of
274 the retrieval approach presented in this study. Data were collected from: i) one rainfed
275 wheat located about 40 km east of Marrakech near the city of Sidi Rahal (hereafter named
276 “Sidi Rahal”) during two growing seasons (2016-2017 and 2017-2018; [Amazirh et al., 2018](#);
277 [Ezzahar et al., 2020](#)); ii) 18 plots located in the Kairouan plain in Tunisia during the 2016-
278 2017 growing season ([Bousbih et al., 2017](#)). General information about all plots is provided
279 in Table 2. Over the Moroccan field, measurements are taken every 30 min thanks to the
280 TDR probes while 20 thetaprobe samples are averaged per field for the Tunisian plots at the
281 time of the Sentinel-1 overpass (between 30 min before and 2h after for the ascending and
282 descending orbits, respectively). Please note that it is expected that the validation database
283 covers a large variability of wheat crop conditions representative of the south
284 Mediterranean area. Indeed, it covers rainfed and irrigated fields with different technique
285 (sprinkler); owners are different, in particular for the 18 fields in Tunisia. Consequently, the
286 agricultural practices differ depending on the experience of the farmer. “Domaine Rafi”
287 fields are well managed in terms of irrigation as the farmer follows the FAO-56
288 recommendation ([Allen et al., 1998](#)) while irrigated fields in Tunisia belong to different
289 smallholders farmers whose irrigation scheduling may be more empirical by lack of objective
290 scientific information. Likewise, nutrient inputs are used on irrigated fields of “Domaine

291 Rafi” while no inputs are applied to rainfed fields. The soil in Tunisia covered also a large
 292 variability of texture (Bousbih et al., 2019). For Morocco, the soil at “Domaine Rafi” is loamy-
 293 clay (37.5% clay, 32.5% sand) while it is mainly clay (47.5% clay, 18.5% sand) on the rainfed
 294 field “Sidi Rahal”. For the latter field, contrasted annual amount of rainfall are observed for
 295 the two crops season (204.2 mm from November to May in 2016-2017 versus 408.8 mm in
 296 2017-2018). Finally, the range of SSM for all data extended from 4 to 50%.

297 *Table 2*
 298 *General information about the validation sites over Morocco and Tunisia.*

	Crop's type	Number of plots	Irrigation system	h_{rms} (cm)	SSM (m ³ /m ³)
Sidi Rahal	Winter wheat	1	Rainfed	0.95	0.04-0.39
Kairouan		6	Rainfed	0.7-1.5	0.05-0.5
		12	Sprinkler		

299

300 **1.1.4. Satellite data description**

301 **1.1.4.1. Sentinel-1 radar data**

302 Sentinel-1 (S1) is an earth observation constellation with two satellites, S1A and S1B, that
 303 were launched by the European Space Agency (ESA) in April 2014 and 2016, respectively.
 304 The two satellites carry a synthetic aperture radar, operating at C-band and provide a revisit
 305 time of six days (Torres et al., 2012). The main operational imaging mode over land surfaces
 306 is the Interferometric Wide-swath mode (IW) realizing acquisitions in VV and VH
 307 polarizations with a 250 km wide swath, and high azimuth (20 m) and ground range (5 m)
 308 resolutions (Mission and Services, 2012). Across the swath, the incidence angle ranges
 309 between 31° and 46°. Level 1 products can be directly downloaded from the Sentinel-1 Data
 310 Hub website (<https://scihub.copernicus.eu/>). Two products types were used in this work:
 311 GRDH (Ground Range Detected High resolution) for backscattering coefficient and SLC

312 (Single Look Complex) for computing interferometric coherence. Table 3 summarizes all the
 313 images used within this study.

314 *Table 3*
 315 *Characteristics of the sentinel-1 data on the calibration and validation sites.*

Site	Season	Relative Orbit Number	Incidence angle	Relative Orbit	Overpass time	Product	Number of images
Field 1 & Field 2	October 2016 - July 2018	118 & 52	45,6° & 35,2°	Ascending & Descending	18:30 & 06:30	GRD SLC	207 219
Field 3	November 2018 - Mai 2019	118 & 52	45,6° & 35,2°	Ascending & Descending	18:30 & 06:30	GRD SLC	65 65
Sidi Rahal	November 2016-June 2017 & November 2017- June 2018	154	40°	Descending	06:28	GRD SLC	61 60
Kairouan	November 2016- April 2017	88 & 95	39,5°-40°	Ascending & Descending	17:20 & 05:21	GRD SLC	14 14

316

317 **GRD products processing: the backscattering coefficient**

318 GRD images product were processed using the Orfeo ToolBox (OTB) (CNES, 2018) at the
 319 original 10 m resolution to obtain the backscattering coefficients σ^0 . Three processing steps
 320 were applied: i) Thermal noise removal; ii) Calibration (Miranda et al., 2015); iii) Terrain
 321 correction (Small, 2011) using the DEM SRTM (Shuttle Radar Topography Mission) at 30 m
 322 resolution according to the method described in Small and Schubert (2008). In order to
 323 minimize speckle effects, a simple spatial average is performed at the field scale. For
 324 instance, the σ^0 of Field 1 and Field 2 are average values computed from 120 and 121 pixels,
 325 respectively. The standard deviation is also computed for each field and each acquisition
 326 time. Finally, the polarization ratio $\sigma_{VH}^0/\sigma_{VV}^0$ (PR) is computed.

327

328 **SLC products processing: the interferometric coherence**

329 Sentinel-1 Level 1 SLC products provide data in slant-range geometry and contain phase and
330 amplitude information. The interferometric coherence was calculated from two consecutive
331 acquisitions of the same orbit (*i.e.* 6 days with S1A and S1B) by cross multiplying pixel by
332 pixel the first SAR image with the complex conjugate of the second (Bamler and Hartl, 1998;
333 Touzi et al., 1999) for a given local neighborhood (in this study, 3*15 was used in order to
334 get a square pixel).

335 The amplitude $|\rho|$, named coherence, ranges between 0 (incoherence) and 1 (perfect
336 coherence). It characterizes the stability of the scatterers at the scale of the wavelength
337 within the same cell. The coherence decreases when changes of scatterers geometrical
338 properties (position, orientation, ...) occur. Consequently, it is expected to be low in the case
339 of dense vegetation and strong on bare rocky soils. Over vegetation, the random dislocation
340 of scatterers because of weather (wind and rain) or because of the plants growth is the main
341 cause of the temporal decorrelation.

342

343 The Sentinel application platform SNAP was used to calculate the coherence in 5 steps: (1)
344 The “Apply-Orbit-file” module for a better estimation of the position and speed of the
345 satellite; (2) the two images were co-registered (“Back-geocoding”) using the orbital data
346 and the DEM SRTM; (3) The “Coherence” module was applied (4) the bursts (black band in
347 the SLC products) were deleted by applying the “TOPSAR-Deburst” module; (5) finally,
348 “Terrain-Correction” was used to project the images on the earth surface using the SRTM
349 DEM.

350 **1.1.4.2. Sentinel-2 optical data**

351 ESA's optical Sentinel-2 satellites S2A and S2B were also launched on June 2015 and March
352 2017, respectively. Sentinel-2 provides images every 5 days for 13 spectral bands at a
353 resolution ranging from 10 to 60 m according to the spectral band. Level 2A images were
354 processed and provided by the National Centre for Space Studies (CNES) through the PEPS
355 platform free of charge within the frame of THEIA (<https://theia.cnes.fr/>). Data were
356 corrected from atmospheric effects using the MAJA processor designed at CESBIO (Hagolle
357 et al., 2015). 10 of the 17 images (S2A) were cloud-free for the first agricultural season
358 (November 2016 to May 2017) while 25 products were retained among 33 available for the
359 second season (November 2017 to June 2018) on the two fields (Field 1 and Field 2) of
360 “Domaine Rafi”. The NDVI was computed from individual bands 4 and 8 and averaged over
361 each field. Standard deviation of NDVI for each field and each date is also computed.

362 **1.2. Backscatter modeling**

363 In order to deepen our understanding of the signal, and for the SSM retrieval, a modeling
364 approach was implemented. Semi-empirical and empirical approaches were preferred here
365 to complex physically based models such as Karam et al. (Karam et al., 1992) or MIMICS
366 (Ulaby et al., 1990) as their use within an inversion scheme is still difficult because of their
367 complexity and their large number of input parameters. Within this study, the simple semi-
368 empirical water cloud model (Attema and Ulaby, 1978) representing the vegetation canopy
369 as a cloud of identical water droplets for vegetation backscattering coupled to the empirical
370 Oh et al. (1992) model for the underlying soil was chosen. A short description of the models
371 is provided in the appendix 1. The coupled models hereafter called WCM links the
372 backscattering coefficient to the two empirical parameters A_{pq} and B_{pq} (Equ. A8 and A9)

373 and a vegetation descriptor for the WCM and the standard deviation of the surface height
374 h_{rms} and the SSM for Oh et al.

375 **1.3. Surface soil moisture retrieval**

376 Several approaches based on the inversion of the water cloud model for SSM retrieval have
377 been already proposed using different vegetation descriptor: VWC (Attema and Ulaby, 1978;
378 Bindlish and Barros, 2001; Wang et al., 2018), AGB (Hosseini and McNairn, 2017), LAI (Bai et
379 al., 2017; Kumar et al., 2014; Prevot et al., 1993) or NDVI (Baghdadi et al., 2017; Bousbih et
380 al., 2017; El Hajj et al., 2016). In this study, a new approach is proposed based on the
381 interferometric coherence that has already been shown to be tightly related to vegetation
382 characteristic (Blaes and Defourny, 2003; Engdahl et al., 2001; Wegmuller and Werner,
383 1997).

384 As a preliminary step, a relation was first sought between Sentinel-1 variables and *in situ*
385 measurements of vegetation characteristics (VWC and AGB). The WCM was calibrated on
386 the two irrigated wheat fields (cf. section 2.2) of “Domaine Rafi” (Field 1 and Field 2) using
387 the measured vegetation characteristics, soil roughness and SSM. The calibration was
388 repeated twice using AGB and VWC. Then, for the retrieval of SSM, the relationships
389 between interferometric coherence and vegetation characteristics were used as input of the
390 calibrated WCM providing with two different inversion approaches called $WCM_{\rho-AGB}$ and
391 $WCM_{\rho-VWC}$. SSM time series were retrieved by minimizing the distance between observed
392 and predicted backscattering coefficient for each Sentinel-1 acquisition. VV and VH
393 polarizations were tested. The minimization was carried out using a simple “brute-force”
394 approach (Jarlan et al., 2002) consisting in exploring all SSM values from 0 to 0.5 m³/m³ with
395 a step of 0.0005 m³/m³. SSM time series retrieval is repeated for different soil roughness.

396 After sowing and until the next soil work occurring after harvest, it is assumed that the soil
397 roughness of wheat crops doesn't change. The measurements carried out on the two
398 irrigated wheat fields show that the variation of the h_{rms} parameter around its average
399 value reached 17% for Field 1 in 2016-2017 but remained below 10% for Field 2 and the
400 other seasons. In addition, it is also assumed that h_{rms} variability from one field to another is
401 small considering also the period from sowing to harvest. Within this context, a constant
402 h_{rms} is sought for the whole crop season with h_{rms} values varying from 0.7 cm to 1.5 cm
403 with a step of 0.05 cm. The range of h_{rms} has been determined from the *in situ* database and
404 from a literature review (Balenzano et al., 2011; Bousbih et al., 2017; Mattia et al., 2003;
405 Picard et al., 2003; Wang et al., 2018; Zribi et al., 2011). The average of all the retrieved SSM
406 time series is then kept as the solution to the inverse problem. Please note that a constant
407 value of 1 cm was first used. Keeping the average of SSM time series corresponding to
408 different values of soil roughness provided with slightly lower biases (not shown) than with
409 the unique h_{rms} value of 1 cm.

410 As a significant additional processing and storage are needed to derive Sentinel-1 coherence,
411 the added-value of using the interferometric coherence is evaluated by comparison to the
412 same approach but based on the PR as it is also well known to be related to vegetation
413 development (Greifeneder et al., 2018; Paloscia et al., 2013; Veloso et al., 2017). The two
414 approaches based on the relationships between PR and vegetation characteristics are
415 named WCM_{PR-AGB} and WCM_{PR-VWC} . In these configurations, SSM over wheat crops could
416 be retrieved based on Sentinel-1 data only: the backscattering coefficient and the
417 interferometric coherence or the PR. Finally, three more classical methods for SSM retrieval
418 composed of two empirical approaches and one based on WCM are also implemented for
419 comparison purposes :

- 420 - *Empirical approaches*: (1) A linear relationship between the backscattering
421 coefficient (at VV, σ_{VV}^0 , or VH, σ_{VH}^0 polarization) and SSM (Holah et al., 2005; Le
422 Hégarat-Masclé et al., 2002; Le Morvan et al., 2008; Ulaby et al., 1982); (2) A
423 linear relationship between the relative difference of backscattering coefficient
424 between two successive acquisitions ($\Delta\sigma^0$) of the same orbit and the
425 corresponding difference of SSM (ΔSSM) as proposed by Balenzano et al. (2011).
426 It has been proposed as an alternative method less sensitive to change of soil
427 roughness that may occurs during the season. Please note that for the latter
428 method, the SSM at the start of the crop season SSM_0 must be obtained as only
429 relative changes of SSM between successive acquisitions are retrieved. In this
430 study, as the method is only implemented for comparison purpose, SSM_0 is taken
431 from the *in situ* measurements. The retrieval of SSM_0 when no measurements
432 are available may increase the uncertainties of the SSM retrieval.
- 433 - *WCM based approach*: The NDVI is used directly as the vegetation descriptor as in
434 numerous previous works (Baghdadi et al., 2017; Bousbih et al., 2017; El Hajj et
435 al., 2016) and the method is named WCM_{NDVI} .

436 The inputs, outputs and the parameters to be calibrated prior to the inversion process for
437 each method are provided at Table 4. The number of algorithmic parameters to be
438 calibrated differs significantly and ranges from 2 (σ^0 , $\Delta\sigma^0$ and WCM_{NDVI}) to 5 (approaches
439 based on the WCM and radar observations). This means that the methods based on the PR
440 or the interferometric coherence require additional *in situ* measurements of the vegetation
441 characteristics by contrast with the other approaches relying on SSM data only.

442 For the seven methods , the data of the first season (2016-2017) over both Field 1 and Field
443 2 were used for calibration meaning that, for the empirical approaches, a linear relationship
444 between σ^0 (or $\Delta\sigma^0$) and SSM (or ΔSSM) is sought for the first year of data. For the WCM
445 based methods, the first year of data is used to calibrate: (1) the A_{pq} and B_{pq} coefficients of
446 the WCM model by minimizing the RMSE between the predicted and the observed
447 backscattering coefficient; (2) the empirical parameters of the relationships between
448 coherence or PR and the vegetation characteristics. A_{pq} and B_{pq} parameters were estimated
449 separately for each radar polarization following [Baghdadi et al. \(2017\)](#) and [Hosseini and
450 McNairn \(2017\)](#). The second year (2017-2018) on Field 1 and 2, field 3 data and the
451 validation database are used for validation. Please note that it was decided to keep the data
452 from the 2nd season of Field 2 for the method evaluation when wheat faces very adverse
453 growing conditions as already described.

454 *Table 4*
455 *Input, output and number of parameters to be calibrated for each methods.*

Method	Inputs	Outputs	Calibrated parameters
σ^0	σ^0	SSM	a and b / $\sigma^0=f(SSM)$
$\Delta\sigma^0$	σ^0	ΔSSM	a and b / $\Delta\sigma^0=f(\Delta SSM)$
WCM_{NDVI}	σ^0 , NDVI	SSM	A and B / WCM
WCM_{PR-AGB}	σ^0 , PR	SSM	A and B / WCM a, b and c / $AGB=f(PR)$
WCM_{PR-VWC}	σ^0 , PR	SSM	A and B / WCM a, b and c / $VWC=f(PR)$
$WCM_{\rho-AGB}$	σ^0 , ρ	SSM	A and B / WCM a, b and c / $AGB=f(\rho)$
$WCM_{\rho-VWC}$	σ^0 , ρ	SSM	A and B / WCM

456

457 **2. Results and discussions**

458 The first section is dedicated to the Sentinel-1 products interpretation based on the field
459 measurements and knowledge database. The second section is devoted to the WCM
460 calibration and to the direct predictions of the backscattering coefficient. Finally, the third
461 section deals with the SSM inversion.

462 **2.1. Analysis of experimental data**

463 **2.1.1. Time series interpretation**

464 Fig. 2 displays the time series of the radar responses for orbit 52 at 35.2° incidence angle, the
465 vegetation index from Sentinel-2 and *in situ* measurements for interpretation purposes
466 during crop seasons 2016-2017 and 2017-2018 on Field 1. The timing of the drastic drop of
467 VWC at the end of the season is superimposed on the time series of the interferometric
468 coherence and of the backscattering coefficients for interpretation purpose (vertical blue
469 line). The Fig. 3 displays the same information as Fig. 2 but for orbit 118 at 45.6° of incidence
470 angle for Field 2. The same figures but at 35.2° for Field 2 and at 45.6° for Field 1 are
471 provided as supplementary materials (Fig. S3 and S4).

472 *Vegetation descriptors*

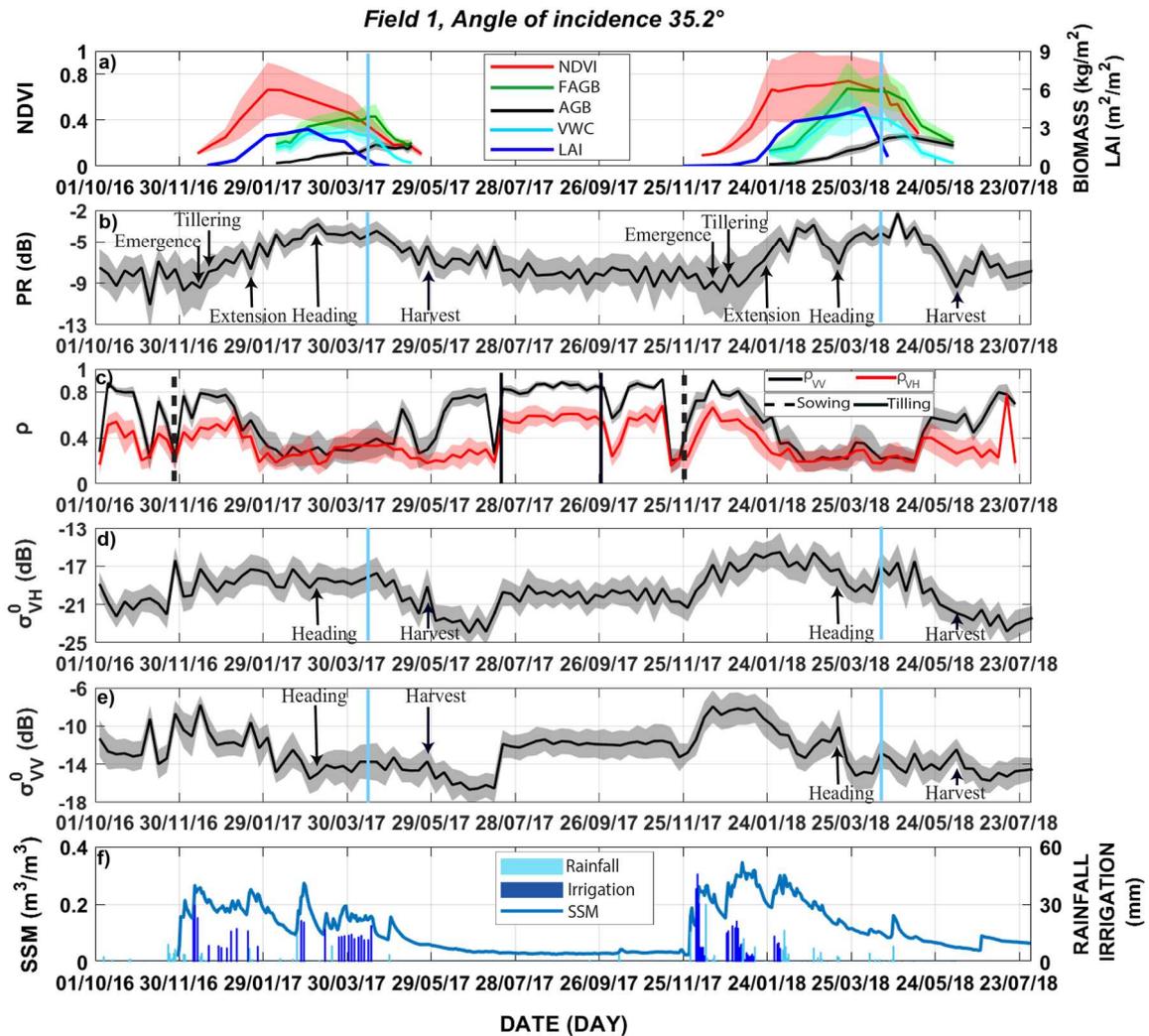
473 Cross correlations of AGB, FAGB and VWC before and after vegetation peak are provided at
474 Table T1 (supplementary material). NDVI and LAI exhibit a close seasonal course (Fig. 2 and
475 3) with almost similar peak timing. Likewise, FAGB and VWC are in-line (correlation
476 coefficients before or after peak are always above 0.97; Table T1) but with maximum values
477 reached around 50 days later than NDVI and LAI. By contrast, AGB (corresponding to green

478 and dead vegetation tissues expressed in kg dry matter/m²) is highly correlated with VWC
479 during the first part of the season (correlation coefficients of 0.73 and 0.81 for Field 1 and 2,
480 respectively) but the correlation coefficients drastically drop after the vegetation peak (Table
481 T1) when stems and leaves start to dry. Total VWC being dominated by stems and leaves, it
482 drops earlier than AGB. For Field 1 in 2016-2017, high air temperature values in March lead
483 plants to stop the leaves development early and to start the grain filling stage. Relatively low
484 LAI values were observed at the end of March while FAGB and AGB continue to increase
485 afterwards and until mid-April. In terms of AGB amount, systematic higher values for Field 2
486 are observed because of the triggered water stress on Field 1 through sub-optimal irrigation
487 planning. Finally, observed differences of biomass between the two seasons are related to
488 differences in the density of seeds and to more wetter conditions for season 2017-2018.

489 *Backscattering coefficients*

490 Backscattering coefficients exhibit a clear seasonal signal. An increase is observed on σ_{VV}^0
491 from beginning of October until January. At this time, the signal is dominated by the quick
492 change of soil moisture while wheat fraction cover is still low. Afterwards, the backscattering
493 coefficient decreases with the attenuation of the soil contribution by the canopy while
494 wheat develops. A minimum backscatter is attained around the heading stage and the signal
495 increases again afterwards. Although this second increase is almost nonexistent for Field 1
496 at 35.2° of incidence angle (Fig. 2), it is clear for the other plots (Fig. 3, S3 and S4) and it
497 appears stronger for σ_{VH}^0 than for σ_{VV}^0 and at 45.6° than at 35.2°. Please note that the long
498 plateau lasting until harvest during the second season on Field 2 is a typical behavior of a
499 crop developing a random canopy structure, which in turn produces a significant volume
500 scattering contribution. This is because of the specific growing conditions as already

501 highlighted. Under normal growing conditions, several authors have attributed the second
502 increase to the appearance of the heads creating a wet layer at the top of the canopy (Ulaby
503 and Bush, 1976; Mattia et al., 2003; Ulaby et al., 1986) specifically for incidence angle above
504 40° (Brown et al., 2003). Indeed, as most of the vegetation tissues are still wet at this time,
505 the increase of backscatter cannot be attributed to an increase of the soil contribution in
506 response to vegetation drying as the drastic drop of VWC occurred later in the season (see
507 blue vertical lines in figures 2, 3, S1 and S2). The second cycle from the heading stage
508 appeared also stronger on σ_{VH}^0 because volume diffusion process attributed to the head
509 layer triggers depolarization at this time (Picard et al., 2003; Balenzano et al., 2011). In
510 addition, maximum σ_{VH}^0 values are more related to AGB than σ_{VV}^0 showing the higher
511 sensitivity of cross polarization to vegetation elements. For instance, σ_{VH}^0 values at peak are
512 higher on Field 2 than on Field 1 because of the triggered water stress that limited crop
513 development on Field 1 (see σ_{VH}^0 time series at 45.6° on both fields during the first season as
514 Field 2 during the 2nd season faced very adverse growing conditions). The final decrease lasts
515 until harvest with the drying of all the vegetation elements and of the soil. The drastic
516 increase noticed in VV and VH responses after July 11 (2016-2017 season) was concomitant
517 with a tilling work (vertical black lines). Likewise, the signal decreased on November 22 in
518 relation to the drop of surface roughness associated to soil preparation for seeding.



519

520 *Fig. 2. Time series of PR, σ_{VV}^0 , σ_{VH}^0 , ρ_{VV} and ρ_{VH} at 35.2° of incidence angle over the Field 1 and during two*
 521 *agricultural seasons 2016-2017 and 2017-2018. Optical NDVI, measured LAI, measured VWC, FAGB and AGB*
 522 *are plotted in the first subplot. Mean values are represented by solid lines and standard deviations by the filled*
 523 *areas surrounding the curves. Rainfall, irrigation and SSM are displayed in the last subplot. Wheat phenological*
 524 *stages and ground working events are superimposed. The drop of VWC at the end of the season is reported as a*
 525 *blue vertical line on the time series of the polarization ratio and of the backscattering coefficients.*

526 Polarization ratio

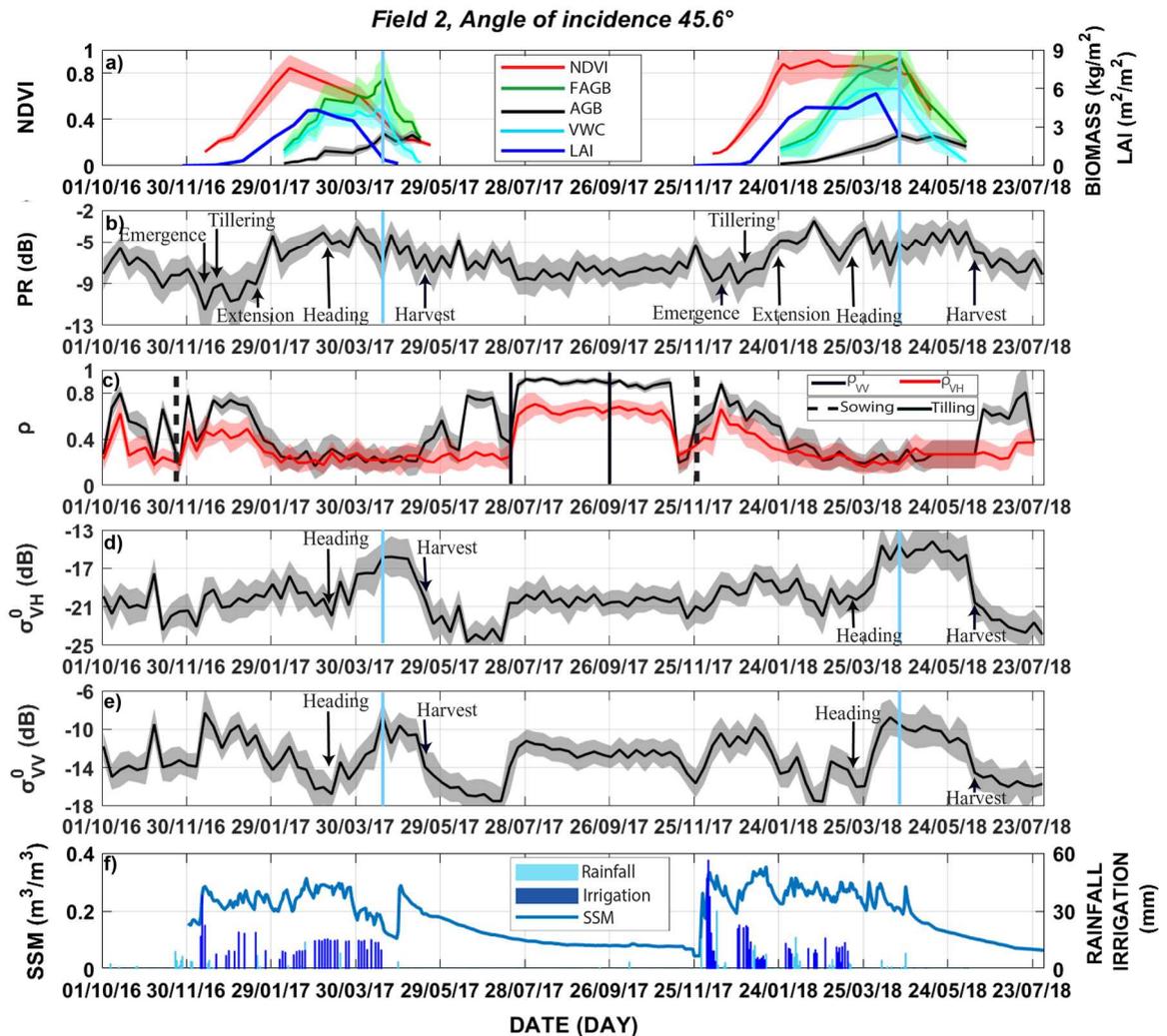
527 The PR appears to be more stable than the backscattering coefficient for both polarizations
 528 VV and VH. The ratio follows the evolution of FAGB. It begins to increase with the increasing
 529 of biomass from the emergence until the heading, and then, both of them start to decrease
 530 until harvest. For example, in Field 1 (first season), PR increases by about 9 dB from
 531 emergence to heading, and peaks at the same time as biomass around mid-April. This

532 behavior confirms the results of previous studies (Veloso et al., 2017) and foster the use of
533 this ratio for crop monitoring.

534 *Interferometric coherence*

535 VV and VH coherence exhibit similar seasonal cycle. High values of coherence (around 0.9 for
536 VV polarization) are observed during the summer month until sowing. These high values
537 express a dominance of coherent scattering from stable bare soils. Coherence drastically
538 drops to about 0.15 in autumn at the time of tilling work carried out before sowing. It then
539 gradually recovers high values (about 0.7) until emergence when it starts a slow decrease
540 until about the extension of the stems to become almost constant (corresponding to the
541 noise level) afterwards. As for the backscattering coefficient, this average seasonal course is
542 disturbed by agricultural actions. The observed peak between sowing and emergence may
543 be related to the installation of irrigation drippers that took place about two weeks after
544 sowing on both fields. Between the harvest and the first tilling on July 11th 2017, the plots
545 are used for cattles grazing which can explain the observed changes of coherence. The
546 abrupt decrease noted on July 11th 2017 is owing to deep ploughing. Soil works and farming
547 activities have already been found to induce a large decrease in coherence (Wegmuller and
548 Werner, 1997). After this date, the VV coherence ρ_{VV} reaches its highest value of about 0.9
549 until the sowing of the second season. Although some authors (De Zan et al., 2014; Morrison
550 et al., 2011; Scott et al., 2017) demonstrated a sensitivity of coherence to soil moisture, a
551 visual inspection of the time series of coherence and soil moisture (Fig. S5 in the
552 supplementary material) does not highlight any strong linkage between both variables. In
553 addition, the correlation coefficients r computed between the interferometric coherence
554 and either soil moisture or soil moisture change between the dates used to compute the

555 coherence remains below 0.20 at the seasonal scale (Table T2 in the supplementary
 556 material).



557

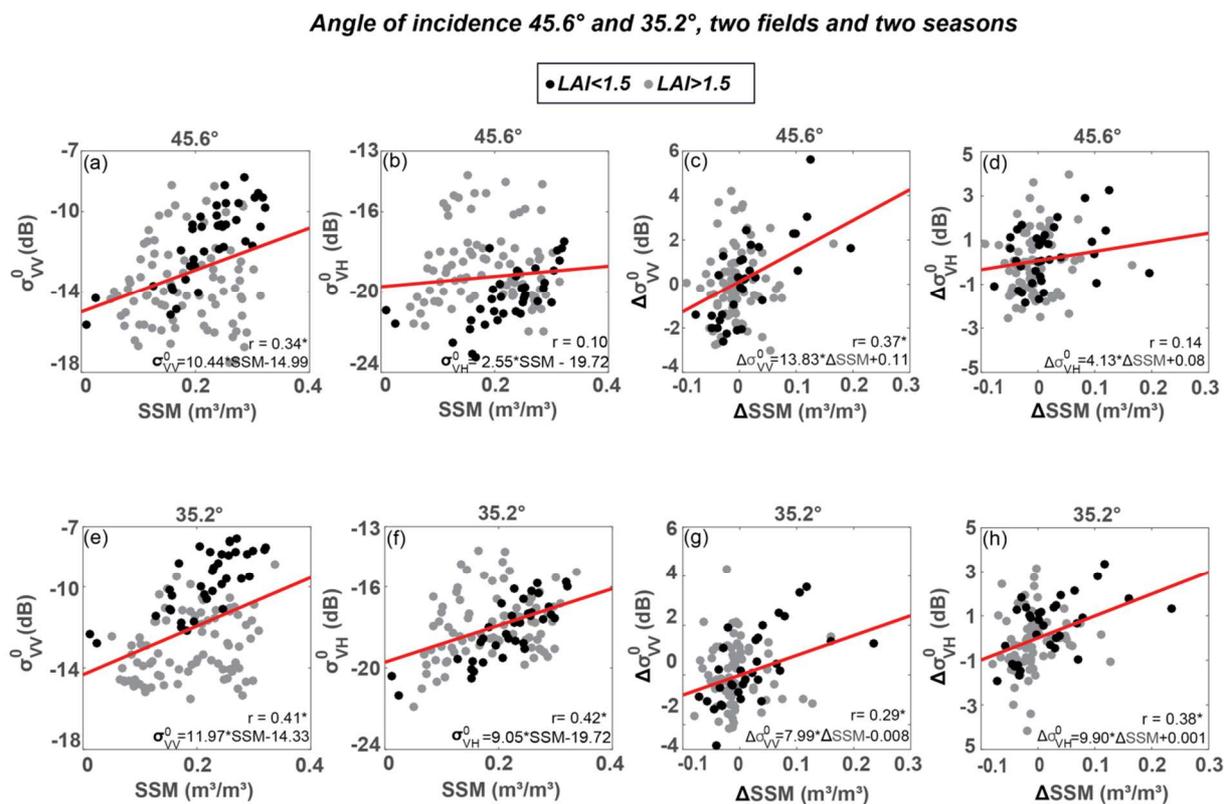
558 *Fig. 3. Time series of PR, σ_{VV}^0 , σ_{VH}^0 , ρ_{VV} and ρ_{VH} at 45.6° of incidence angle over the Field 2 and during two*
 559 *agricultural seasons 2016-2017 and 2017-2018. Optical NDVI, measured LAI, measured VWC, FAGB and AGB*
 560 *are plotted in the first subplot. Mean values are represented by solid lines and standard deviations by the filled*
 561 *areas surrounding the curves. Rainfall, irrigation and SSM are displayed in the last subplot. Wheat phenological*
 562 *stages and ground working events are superimposed. The drop of VWC at the end of the season is reported as a*
 563 *blue vertical line on the time series of the polarization ratio and of the backscattering coefficients.*

564

565

2.1.2. Backscattering coefficients and surface soil moisture

566 Fig. 4 displays the relationship between the backscattering coefficient and the SSM for VV
 567 and VH polarization at 45.6° (a and b) and 35.2° (e and f) of incidence angle, and between
 568 the difference of backscattering between two successive acquisitions and the corresponding
 569 difference of SSM (c, d, g and h). All data are represented (two fields and two seasons). Black
 570 points correspond to LAI up to 1.5 m²/m² while data corresponding to LAI value above this
 571 threshold are plotted in grey. The 1.5 m²/m² of LAI correspond on average to AGB≅0.14
 572 kg/m² and to VWC≅1.00 kg/m². The statistical metrics and the equation of the superimposed
 573 linear fit are given for the whole season. Statistical metrics for LAI<1.5 and for LAI>1.5 are
 574 also reported in Table T3 of the supplementary material.



575

576 Fig. 4. Relationship between: (a, b) and (e, f) σ_{VV}^0 and σ_{VH}^0 and SSM, (c, d) and (g, h) $\Delta\sigma_{VV}^0$ and $\Delta\sigma_{VH}^0$ and ΔSSM
 577 at 45.6° and 35.2°. Data are shown separately for LAI<1.5 (black points) and LAI>1.5 (grey points). Statistical
 578 metrics are provided for the whole season. Correlations significant at 99% level are marked with a star '*'.
 579 When data acquired over the entire season are considered, the relationships are obviously
 580 scattered (correlation coefficients r below 0.42; see Table T3). This is because the soil

581 contribution to the signal is progressively attenuated by the canopy when wheat grows. This
582 results in a progressive decrease of the slope of the relationship between the backscattering
583 coefficient (the backscattering difference between two acquisitions) and SSM (SSM
584 differences) to reach almost no sensitivity to SSM change. Backscattering coefficients are on
585 average better correlated with SSM at 35.2° than at 45.6° because of a stronger contribution
586 of the soil at lower incidence angle. As expected also, VV polarization is more tightly related
587 to SSM than VH at 45.6° as the contribution of the canopy is higher than at 35.2°. Slightly
588 lower statistical metrics are obtained for the $\Delta\sigma^0/\Delta SSM$ relationships than for the direct
589 relationships between σ^0 and SSM, in particular considering VV polarization at 35.2° (r=0.29
590 vs r=0.41) but the correlation coefficient is also significant at the 99% level at 45.6° (r=0.37)
591 for VV polarization. Please note that this analysis may be biased because of the very specific
592 growing conditions of Field 2 during the 2nd season including a strong horizontal extension of
593 the adventices that may alter the relationship.

594 When wheat is not fully covering the soil (LAI<1.5 m²/m²), much better statistics are
595 observed. In this case, significant correlations at the 99% level are obtained for all
596 configurations (Table T3). Quite similar relationships σ^0/SSM are observed at 35.2° for VV
597 and VH with r=0.76 and r=0.82, respectively while much significant differences in favor of VV
598 are obtained at 45.6° as the vegetation contribution increases with the incidence angle.
599 Likewise, at 35.2°, the slopes of the relations are similar ((17.4 and 16.7 dB/[m³/m³] for VH
600 and VV respectively), while at 45.6°, higher sensitivity is observed for VV (21.5 dB/[m³/m³]
601 compared to 12.7 dB/[m³/m³] for VH). For the $\Delta\sigma^0/\Delta SSM$, the best fitting is obtained for VV
602 with r=0.70 and r=0.63 at 35.2° and 45.6°, respectively while the difference of metrics
603 between VV and VH are more important with regards to σ^0/SSM . As expected, higher slopes

604 are observed at VV for both incidence angles with values of 14.1 dB/[m³/m³] and 24.4
605 dB/[m³/m³] at 35.2° and 45.6°, respectively.

606 These observations confirm the well known results: a higher sensitivity of the radar signal to
607 soil contribution (and consequently soil moisture) for low incidence angles and VV
608 polarization.

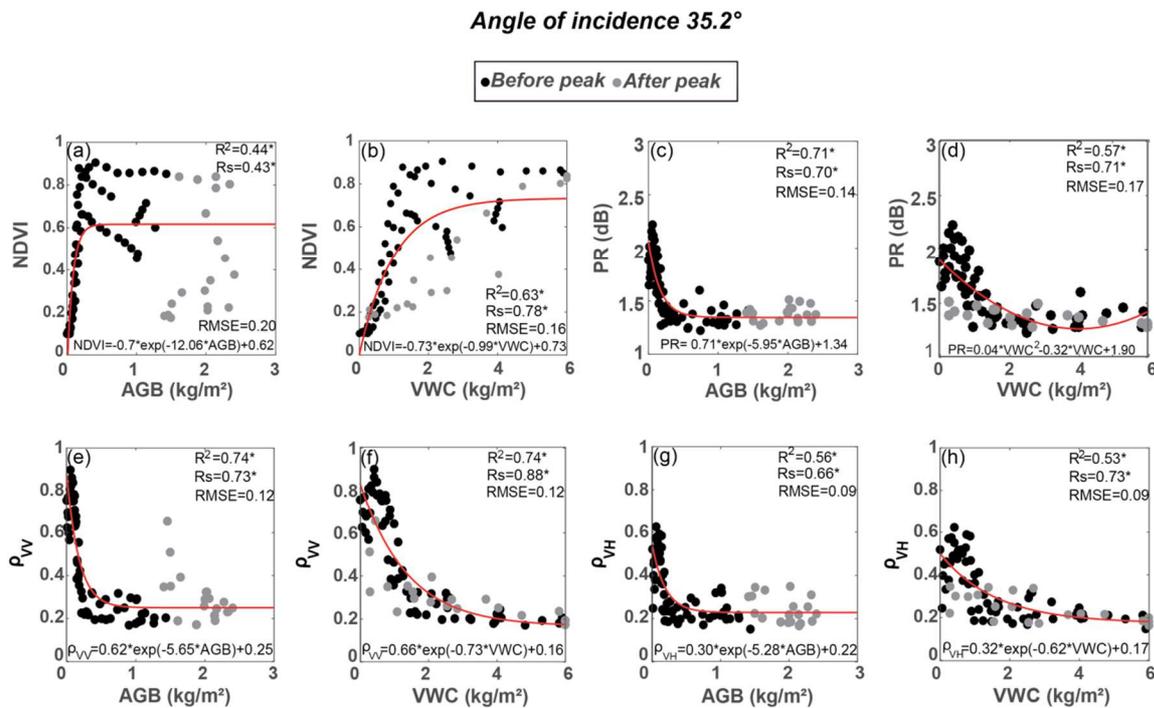
609 **2.1.3. Polarization ratio, interferometric coherence and vegetation**

610 **descriptors**

611 In this section, the relationships between the interferometric coherence and PR, that both
612 have been shown to be related to vegetation development, and AGB and VWC are analyzed.
613 As NDVI can be obtained with similar spatio-temporal resolutions from Sentinel-2, the same
614 relations are investigated with NDVI. Fig. 5 illustrates these relationships using the data of
615 both fields and seasons, at 35.2° incidence angle. The points in black corresponds to the data
616 acquired before AGB (or VWC) peak while data after the peak are plotted in grey. The same
617 figure but with data acquired at 45.6° is provided as supplementary material (Fig. S6). Please
618 note that an exponential fit is used for interferometric coherence while a polynomial fit is
619 chosen between PR and VWC because both exhibit a “bell” shape.

620 The relationships between NDVI and AGB (Fig. 5a) and VWC (Fig. 5b) exhibit a strong
621 dispersion and an hysteresis effect considering separately data acquired before and after the
622 peak. While NDVI is mainly sensitive to the green leaf area index (GLAI), the relation
623 between GLAI and VWC or AGB is not linear and depends on the plant structure. The
624 hysteresis effect observed for the relation with AGB is simply related to the leaf senescence
625 leading to a drastic drop of GLAI after the peak while AGB remain high. The relation
626 saturates for low values of AGB (~ 0.3 kg/m²). By contrast, the relationships are much better

627 when the polarization ratio and the interferometric coherence are considered. Considering
628 the spearman rank correlation, the best relationships are obtained with VWC for both
629 interferometric coherence and PR. For the PR, the relationships are good with both AGB and
630 VWC on the entire crop cycle at 35.2 with higher saturation values than with NDVI (AGB ~ 0.5
631 kg/m²). Unfortunately, the metrics seems not stable when the incidence angle is changing as
632 poorer results are obtained at 45.6° (Fig. S6). Finally, good relationships are also obtained
633 between interferometric coherence and AGB and VWC for both incidence angles with even
634 higher saturation value (around 0.9 kg /m² for the relationship between ρ_{VV} and AGB at
635 35.2°). Our assumption is that coherence is less sensitive to the geometry of the canopy than
636 the PR. Regarding the results above, the relationships between interferometric coherence at
637 VV polarization and the PR on one hand and, on the other hand, AGB and VWC are potential
638 candidates for the retrieval of SSM.



639
640 Fig. 5. Relationship between (a,b) NDVI and AGB and VWC; (c,d) PR and AGB and VWC; (e,f) ρ_{VV} and AGB and
641 VWC; (g,h) ρ_{VH} and AGB and VWC at 35.2°. Black point corresponds to data acquired before the AGB (or VWC)
642 peak while grey is for the peak after the peak. R^2 and R_s significant at the 99% are followed by a star (*).

643 **2.2. Simulation results**

644 Fig. 6 displays the time series of predicted and observed backscattering coefficients on both
645 fields at 35.2° together with contributions from the soil attenuated by the canopy and from
646 the canopy when using AGB as the vegetation descriptor. Fig. 7 is the same as Fig. 6 but at
647 45.6°. Table 5 summarizes the corresponding statistical metrics for calibration/ validation of
648 the WCM. Several vegetation descriptors were tested among which LAI, Fc, NDVI, AGB and
649 VWC. Fig. S7 and S8 in the supplementary material are the same as Fig.6 but using NDVI and
650 VWC. By considering AGB (Fig. 6), the seasonal course of the backscattering coefficient is
651 well reproduced for both incidences and both polarizations. The relative variations between
652 the configurations (higher σ_{VV}^0 than σ_{VH}^0 and higher σ^0 at 35.2° than σ^0 at 45.6° for both
653 polarizations) are also well reproduced demonstrating the proper calibration of the model.
654 Obviously, the soil contribution that dominates the scattering mechanism during the first
655 half of the season is progressively attenuated with the canopy development. As expected,
656 (Fontanelli et al., 2013; Macelloni et al., 2001; Paloscia et al., 2014; Picard et al., 2003), soil
657 attenuation is stronger for VV than for VH in response to the vertical stem extension. In
658 March, when both soil and vegetation contributes, the agreement between observations
659 and prediction deteriorates with regards to the rest of the cycle (RMSE=2.62 dB in March
660 2018 and 1.66 dB for the whole season for Field 1 at VV polarization and 35.2°).

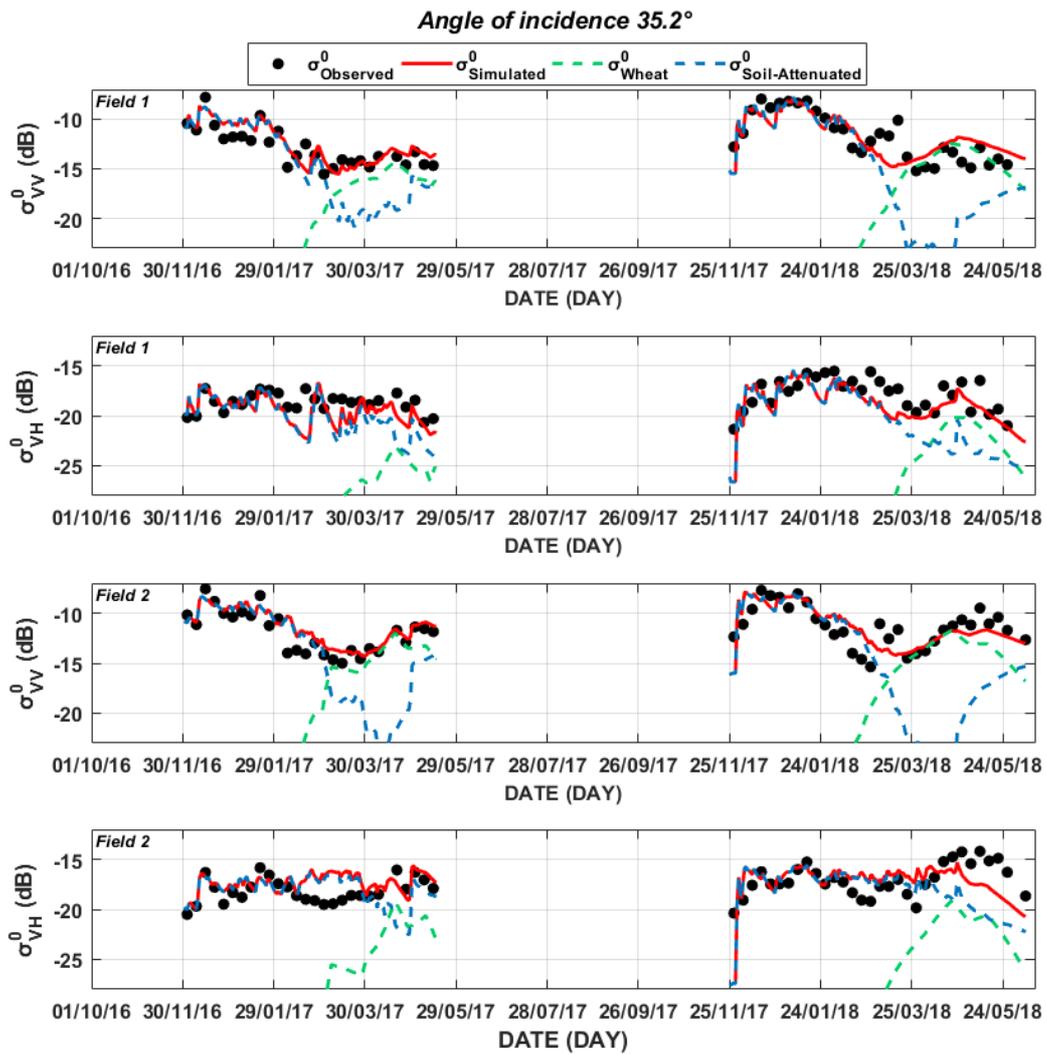
661 During the second cycle, the agreement is also good even if a bias can be observed (up to
662 2.84 dB for Field 1 at VV polarization and 35.2°). For Field 2 during 2017-2018, the bias is to
663 be attributed to the adverse growing conditions already highlighted. By contrast, the use of
664 VWC and, to a lesser extent NDVI as vegetation descriptor (Fig. S7 and S8), suffer from
665 several limitations during the second part of the season: (1) the observed decrease of the

666 backscattering coefficient from seeding to heading is poorly reproduced; (2) there is no
667 second cycle and (3) the drop of backscattering coefficient at the end of the season occurred
668 around 18 days earlier than observations. This is particularly prominent for VH polarization.
669 As demonstrated by [Picard et al. \(2003\)](#) and [Mattia et al. \(2003\)](#), the backscattering
670 mechanisms after heading is dominated by the volume scattering within the head layer
671 partially shielding the stem and leaves below. [Ulaby et al. \(1986\)](#) suggested that an
672 additional term needs to be added to the traditional three terms model (volume scattering
673 from vegetation, soil attenuated and interaction soil-vegetation) to properly represent
674 wheat backscattering after heading. This may explain why, for a simple model like the water
675 cloud unable to separate between the contribution from the leaves, stems and heads, the
676 use of AGB provided with the best predictions of the seasonal course of the backscattering,
677 including the second increase occurring from the heading stage and the drop of σ^0 at the
678 end of the season. Nevertheless, further investigations are needed to support this
679 assumption by using a multi-layer radiative transfer model.

680 *Table 5*
681 *Statistical metrics of the WCM calibration and validation (see text) at 45.6° and 35.2° of incidence angle and for*
682 *VV and VH polarizations when using AGB as vegetation descriptor.*

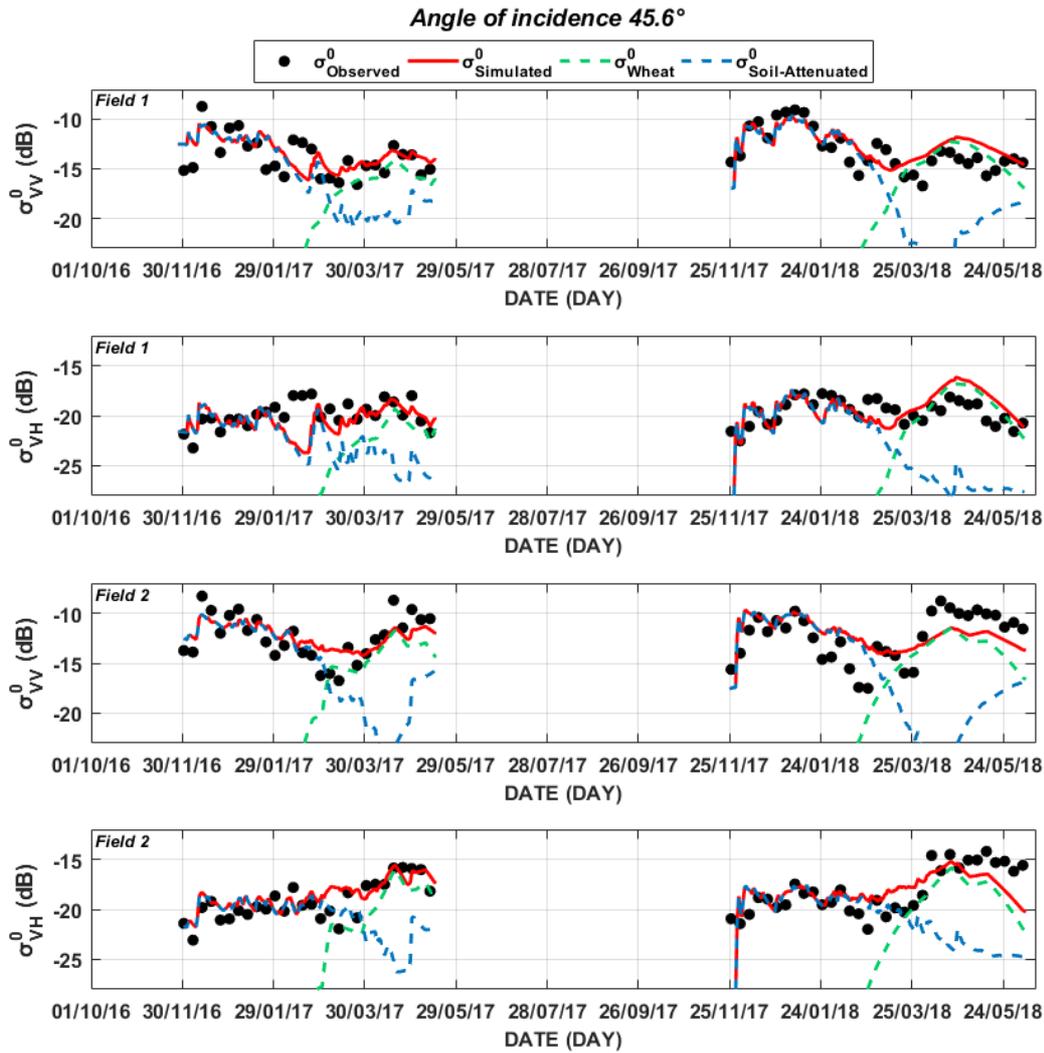
	Calibration				Validation							
	Field 1 & 2				Field 1				Field 2			
	45,6°		35,2°		45,6°		35,2°		45,6°		35,2°	
	VV	VH	VV	VH	VV	VH	VV	VH	VV	VH	VV	VH
r	0.73	0.47	0.76	0.24	0.72	0.46	0.73	0.61	0.56	0.52	0.68	0.43
RMSE	1.54	1.66	1.44	1.92	1.5	1.89	1.66	1.74	2.02	2.52	1.58	1.98
Bias	-0.17	0.25	-0.31	0.27	-0.39	0.02	-0.03	0.76	-0.03	0.54	0.08	0.32

683



684

685 *Fig. 6. Time series of the different contributions simulated using the WCM and AGB as vegetation descriptor*
 686 *fitting the observations at VV and VH polarizations over Field 1 and Field 2 and for both seasons (2016-2017 and*
 687 *2017-2018) at 35.2° of incidence angle.*



689 *Fig. 7. Time series of the different contributions simulated using the WCM and AGB as vegetation descriptor*
 690 *fitting the observations at VV and VH polarizations over Field 1 and Field 2 and for both seasons (2016-2017 and*
 691 *2017-2018) at 45.6° of incidence angle.*

692 **2.3. Surface soil moisture retrieval**

693 The focus of this section is on the retrieval of the SSM on wheat crops during the whole
 694 growing season using Sentinel-1 information only. The results of the two proposed
 695 approaches, based on the interferometric coherence and on the polarization ratio, are
 696 compared to three extensively used methods and discussed. The good relationship obtained
 697 between either the coherence ρ_{VV} or PR, and AGB or VWC, are used (Fig. 5e). Table 6
 698 summarizes the statistical metrics for the whole crop season.

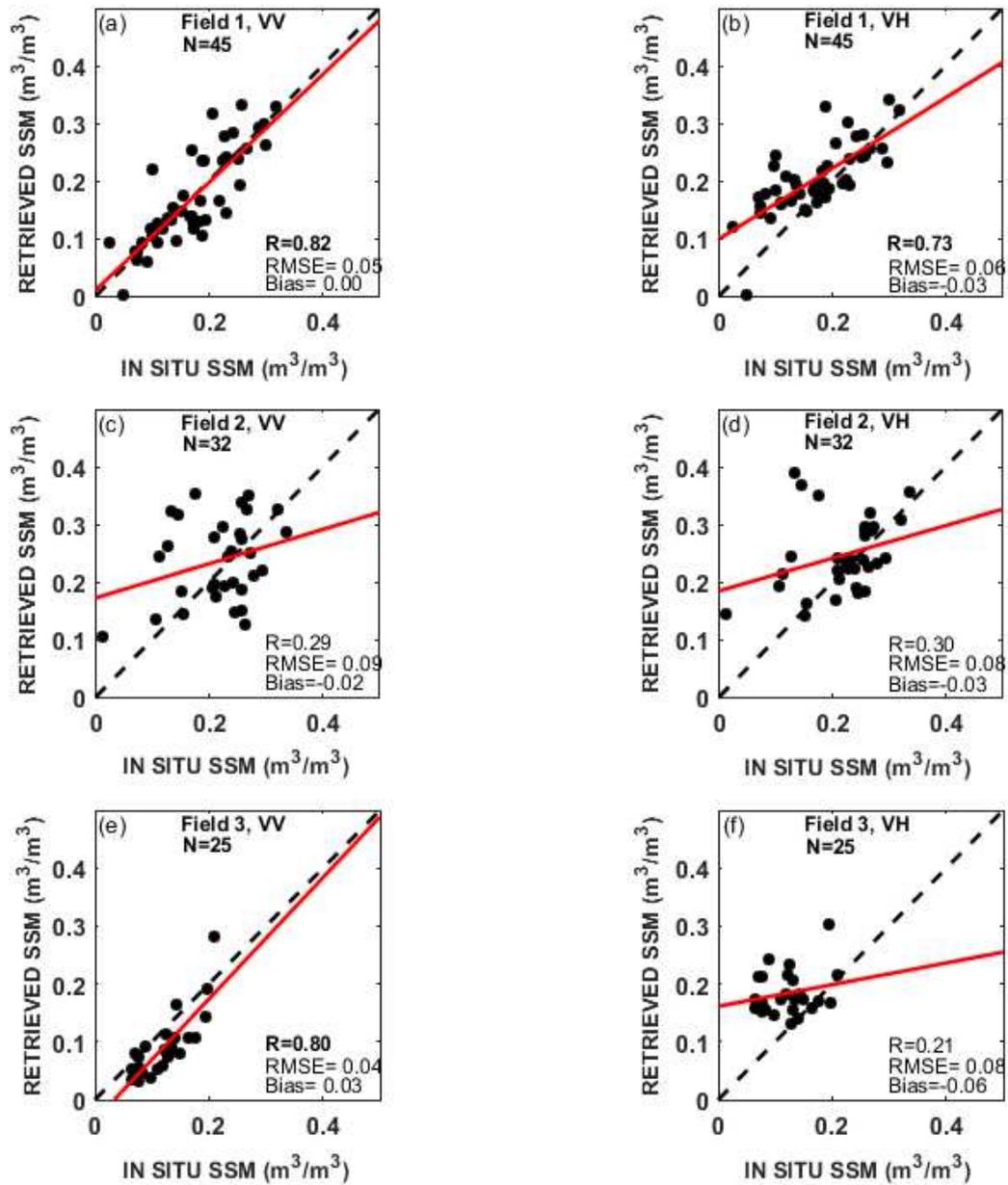
699 Table 6
700 Statistical metrics of the surface soil moisture estimation using the seven methods (see text) for the calibration
701 sites. Bold correlation coefficients are significant at the 99% level.

		Field 1				Field 2				Field 3			
		45.6°		35.2°		45.6°		35.2°		45.6°		35.2°	
		VV	VH	VV	VH	VV	VH	VV	VH	f	VH	VV	VH
$WCM_{\rho-AGB}$	r	0.6	0.34	0.82	0.73	0.01	0.13	0.29	0.3	0.71	0.4	0.8	0.21
	RMSE	0.08	0.09	0.05	0.06	0.13	0.11	0.09	0.08	0.04	0.09	0.04	0.08
	Bias	-0.03	-0.06	0	-0.03	0	-0.02	0.02	-0.03	0.03	-0.07	0.01	0.06
	slope	0.85	0.27	0.93	0.61	0.02	-0.17	0.3	0.28	0.69	0.59	1.05	0.19
$WCM_{\rho-VWC}$	r	0.62	0.4	0.59	0.58	0.18	0.31	0.1	-0.1	0.66	0.47	0.69	0.5
	RMSE	0.08	0.1	0.08	0.08	0.16	0.18	0.11	0.14	0.06	0.09	0.05	0.08
	Bias	0.02	-0.01	-0.02	-0.03	0.01	0.03	-0.01	0.03	0.05	-0.07	0.02	-0.07
	Slope	0.91	0.58	0.83	0.72	0.39	-0.61	0.16	-0.33	0.72	0.73	0.9	0.51
WCM_{PR-AGB}	r	0.26	0.39	0.61	0.61	0.04	-0.42	0.01	0.18	0.76	0.37	0.68	0.47
	RMSE	0.22	0.08	0.12	0.07	0.23	0.19	0.2	0.14	0.05	0.08	0.08	0.08
	Bias	-0.15	-0.04	0.02	-0.03	-0.16	-0.03	-0.01	0	0.04	0.05	0.05	-0.05
	Slope	0.57	0.35	1.3	0.71	0.13	-0.73	0.02	-0.23	0.8	0.57	1.09	0.57
WCM_{PR-VWC}	r	0.55	0.32	0.67	0.56	-0.19	-0.38	0.06	-0.15	0.61	0.47	0.68	0.59
	RMSE	0.09	0.12	0.06	0.1	0.17	0.21	0.11	0.18	0.08	0.08	0.06	0.09
	Bias	0.02	0.01	-0.01	0	0.01	-0.03	0	0	0.06	0	0.02	-0.02
	Slope	0.88	0.56	0.7	0.9	-0.46	-1.1	0.10	-0.39	0.76	1.04	0.95	1.18
WCM_{NDVI}	r	0.57	0.16	0.65	0.53	-0.2	-0.45	0.21	0.29	0.57	0.35	0.7	0.53
	RMSE	0.09	0.13	0.08	0.09	0.2	0.23	0.12	0.18	0.07	0.09	0.05	0.1
	Bias	0.01	-0.03	-0.01	-0.04	0.01	0	-0.01	0.02	0.06	0.05	0.03	-0.06
	slope	0.89	0.26	0.89	0.68	0.51	-1.15	0.37	-0.63	0.62	0.6	0.8	0.64
σ^0	r	0.63	0.28	0.67	0.66	-0.11	0.3	0	0.03	0.6	0.23	0.61	0.42
	RMSE	0.07	0.07	0.07	0.07	0.07	0.08	0.07	0.07	0.08	0.07	0.08	0.08
	Bias	-0.04	-0.02	-0.04	-0.04	0.02	0.05	0.02	0.01	-0.07	-0.06	-0.06	-0.06
	slope	0.11	-0.01	0.19	0.25	-0.02	0.01	0	0.01	0.12	-0.01	0.25	0.19
$\Delta\sigma^0$	r	0.29	0.21	0.38	0.35	0.43	0.09	0.21	0.42	0.71	0.62	0.65	0.15
	RMSE	0.04	0.04	0.04	0.04	0.05	0.05	0.05	0.05	0.07	0.07	0.07	0.06
	Bias	0	0.07	0	0	0	0	0	0	0.06	0.05	0.06	0.04
	Slope	0.08	0.02	0.13	0.17	0.11	0.01	0.06	0.17	0.31	0.24	0.15	0.02

702
703 All the methods are able to retrieve SSM reasonably well at 35.2° using VV backscattering
704 coefficients on Field 1 and Field 3 with r above 0.60 apart for the empirical approach based
705 on $\Delta\sigma^0$ in Field 1 (r=0.38 at 35°2 and VV polarization). By contrast, SSM for most of the
706 methods and, in particular for those based on the WCM, performed poorly on Field 2. For

707 information, for the WCM based approaches, the retrieval on Field 2 has also been tested by
708 calibrating the WCM on the second season or by using the calibrated coefficient of Field 1. In
709 both cases, poor results were obtained. This is attributed to very specific growing conditions
710 that severely affected the wheat development as already discussed (see pictures Fig. S1 and
711 Fig.S2 of the supplementary materials). Indeed, if data from the beginning of the season (LAI
712 $< 1.5 \text{ m}^2/\text{m}^2$) only are considered, results are similar to those obtained on Field 1 at both
713 45.6° and 35.2° meaning that the main issue is related to the development of the vegetation
714 in this field. This illustrates that the performance of the model based approaches could drop
715 drastically when growth conditions diverge significantly, in terms of vegetation structure in
716 particular, from the conditions on which the model was calibrated. Interestingly enough, the
717 empirical technique based on $\Delta\sigma^0$ performed very well on Field 3 ($r=0.71$) and to a lesser
718 extent on Field 2 ($r=0.43$). It is the best from all the evaluated methods on Field 2. In
719 addition, it provided with the lowest RMSE (RMSE $< 0.05 \text{ m}^3/\text{m}^3$) on Field 1 & 2 but 0.07
720 m^3/m^3 on Field 3. The best results are obtained on Field 1 by the new WCM based approach
721 using the relation between the interferometric coherence and AGB ($r=0.82$, RMSE= 0.05
722 m^3/m^3 and no bias for VV at 35.2°). For illustration purpose, Fig. 8 displays the scatter plots
723 between the observed and retrieved SSM using the latter method from sowing to harvest at
724 35.2° : (a) and (b) are for Field 1 at VV and VH, respectively; (c) and (d) are for Field 2 and (e)
725 and (f) for Field 3. Metrics are obviously worse at 45.6° because of a stronger contribution of
726 the canopy and for VH polarization for all considered methods.

Angle of incidence 35.2°



727

728 *Fig. 8. Retrieved SSM versus in situ measurements at VV and VH polarizations at 35.2° of incidence angle for the*
 729 *calibration sites: (a,b) Field 1, (c,d) Field 2 and (e,f) Field 3. Bold correlation coefficients are significant at the*
 730 *99% level.*

731

732 In order to evaluate the genericity of all methods, they have been implemented on the
 733 validation database using the calibration carried out on Field 1 and Field 2 during the first
 734 crop season. Table 7 displays the statistical metrics for the seven methods on the validation

735 database mixing rainfed and irrigated fields. All methods performed reasonably well at VV
736 polarization including the simplest approaches based on σ^0 and $\Delta\sigma^0$ with correlation
737 coefficients always significant at the 99% level apart from the $\Delta\sigma^0$ method on the “Sidi
738 Rahal” site (rainfed). Results are slightly worse but remain close to the ones obtained on the
739 site where the methods were calibrated for the three other approaches (WCM_{NDVI} , σ^0 and
740 $\Delta\sigma^0$). In addition, the lower correlation on “Sidi Rahal” and on the Tunisian plots could also
741 be due to the slightly higher incidence angle of the Sentinel-1 data acquired on these two
742 last site (40° versus 35.2° for the sites where the method has been calibrated). By contrast,
743 overall performances are worse for the empirical approaches but they appear more stable
744 from one site to another, in particular for the σ^0 based method as demonstrated by the small
745 changes of correlation coefficient ranging from 0.60 to 0.62 and of RMSE (0.07 m³/m³).
746 Despite the moderate loss of performance from the fields of “Domaine Rafi” to the
747 validation sites, the method based on the $\rho - AGB$ relationships provided with the best
748 results on the validation database with systematically higher correlation coefficients, lower
749 RMSE and biases remaining low with a maximum value of 0.03 m³/m³ for VV polarization
750 and an average bias of 0.01 m³/m³ on the entire database. For illustration purpose, Fig. 9
751 displays the scatter plot in the rainfed field, Morocco (a and b) and in the Kairouan plain,
752 Tunisia (c and d) for the latter approach. Fig. 9e and f shows the scatterplots for the whole
753 database including Field 1 and Field 3.

754

755 *Table 7*
756 *Statistical metrics of the surface soil moisture estimation using the seven methods (see text) on the validation*
757 *database. Bold correlation coefficients are significant at the 99% level.*

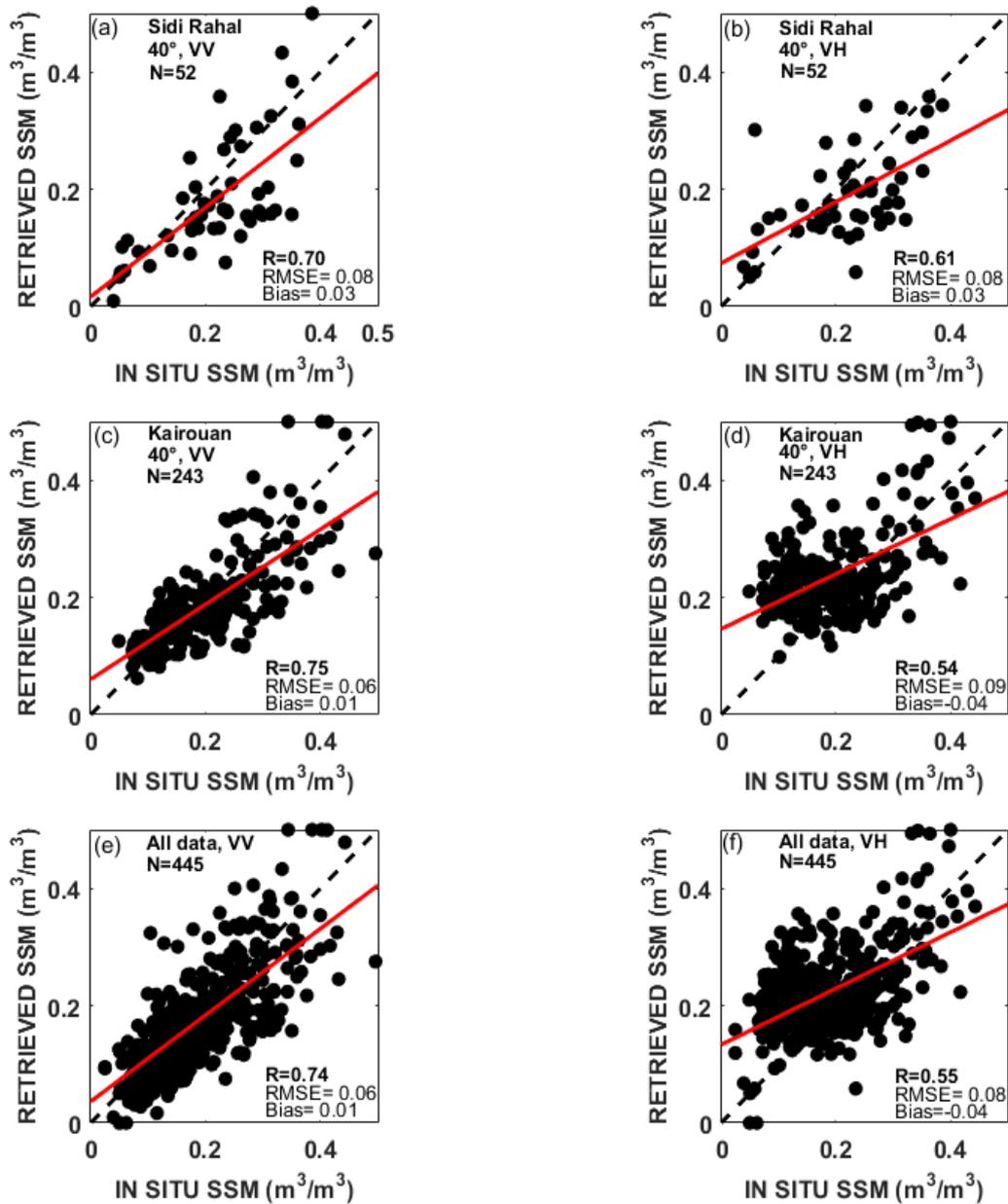
Sidi Rahal	Kairouan
40°	40°

		VV	VH	VV	VH
<i>WCM_{ρ-AGB}</i>	r	0.7	0.61	0.75	0.54
	RMSE	0.08	0.08	0.06	0.06
	Bias	0.03	0.03	0.01	0.04
	Slope	0.76	0.52	0.64	0.47
<i>WCM_{ρ-VWC}</i>	r	0.68	0.63	0.65	0.42
	RMSE	0.11	0.08	0.07	0.1
	Bias	0.08	0.02	0.01	-0.05
	Slope	0.7	0.58	0.62	0.38
<i>WCM_{PR-AGB}</i>	r	0.59	0.52	0.61	0.39
	RMSE	0.13	0.11	0.08	0.09
	Bias	0.09	0.05	0.02	-0.03
	Slope	0.71	0.54	0.7	0.39
<i>WCM_{PR-VWC}</i>	r	0,69	0,5	0,64	0,37
	RMSE	0,1	0,11	0,07	0,1
	Bias	0,07	0,04	0,01	-0,04
	Slope	0,73	0,56	0,56	0,35
<i>WCM_{NDVI}</i>	r	0.69	0.56	0.61	0.39
	RMSE	0.1	0.1	0.07	0.1
	Bias	0.07	0.03	0.02	-0.04
	Slope	0.71	0.62	0.62	0.39
σ^0	r	0.6	0.59	0.62	0.42
	RMSE	0.07	0.07	0.07	0.07
	Bias	0.02	0.02	-0.01	0
	slope	0.5	0.4	0.12	0.15
$\Delta\sigma^0$	r	0.24	-0.36	0.24	0.24
	RMSE	0.18	0.24	0.11	0.11
	Bias	0.11	0.15	-0.05	-0.06
	Slope	-0.24	-0.51	0.28	0.25

758

759

760



761

762 *Fig. 9. Retrieved SSM versus in situ measurements at VV and VH polarizations over the validation sites for the*
 763 *coherence based approach:(a,b) Sidi Rahal; (c,d) 18 plots of Kairouan plain (~40°); (e,f) All data (all fields and all*
 764 *orbits). Bold correlation coefficients are significant at the 99% level.*

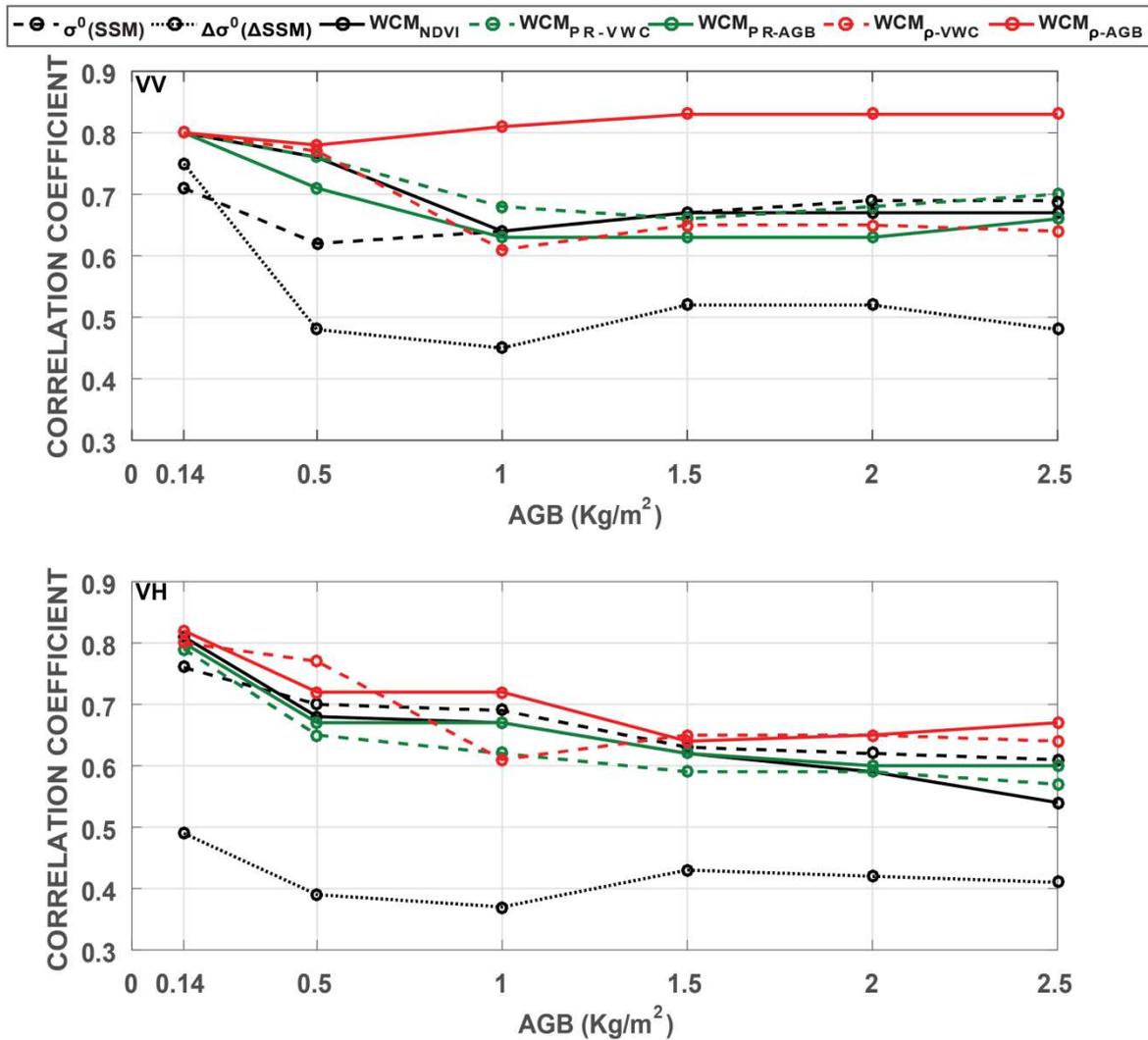
765

766 In order to evaluate the potential loss of performance associated to vegetation growth, the
 767 correlation coefficients of the seven methods are plotted as a function of AGB in Fig. 10
 768 using data of Field 1 and Field 3 because *in situ* measurements of AGB were available on
 769 these fields. Field 2 was discarded because of the specific growing conditions already

770 discussed. The number of points ranges from 26 at the start of the crop season ($AGB \leq 0.14$
771 kg/m^2 corresponding to $LAI \leq 1.5 m^2/m^2$) to 70 when all vegetation conditions are
772 considered ($AGB \leq 2.50 kg/m^2$). When soil contribution is dominating the signal at the
773 beginning of the season, performances of the seven retrieval methods are of the same order
774 with correlation coefficients above 0.70 for VV polarization. When soil is progressively
775 shielded by the canopy as vegetation grows, a drop of r is observed for most of the
776 methods as expected and r increases again afterwards or remains almost constant. This is
777 because most of the observations corresponding to AGB values above $1.5 kg/m^2$ are
778 acquired during the senescence period when wheat dries out and the soil contribution to the
779 backscattering become significant again (cf simulation results). The lower drop is observed
780 for the $WCM_{\rho-AGB}$ as r goes from 0.80 to 0.78 (about 2.5%). By contrast, r decreases of
781 more than 18% for all the others WCM based approaches (WCM_{NDVI} ,
782 WCM_{PR-AGB} , WCM_{PR-VWC} and $WCM_{\rho-VWC}$). Interestingly enough, despite the empirical
783 approach based on σ^0 provides with slightly lower performances than the WCM based
784 techniques at the start of the season, it shows a good stability as the drop of r associated to
785 vegetation development is low (around 13%). The lower performances of the $\Delta\sigma^0(\Delta SSM)$
786 approach are in close agreement with the paper of [El Hajj et al. \(2019\)](#) who show that it
787 offered poor performance at C-Band for $NDVI$ greater than 0.7.

788

Angle of incidence 35.2°

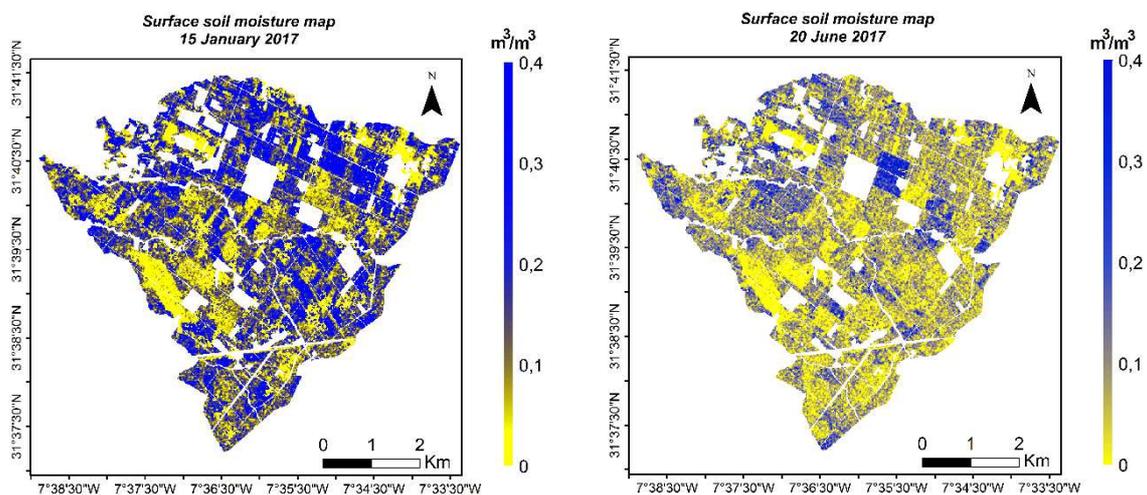


789

790 Fig. 10. Correlation coefficient between the observed and the retrieved SSM as a function of AGB using data of
 791 Field 1 and Field 3 at 35.2° and VV and VH polarizations for the seven methods: σ^0 (SSM), $\Delta\sigma^0$ (Δ SSM), WCM_{NDVI} ,
 792 WCM_{PR-VWC} , WCM_{PR-AGB} , $WCM_{\rho-VWC}$, $WCM_{\rho-AGB}$. All the correlations are significant at the 99% level.

793 Finally, the $WCM_{\rho-AGB}$ was implemented to map SSM over an irrigated perimeter located 40
 794 km east of Marrakech name R3 (Duchemin et al., 2006) for illustration purpose. The
 795 perimeter is dominated by wheat even if some vegetables and trees are also cropped. Fig. 11
 796 displays maps of SSM for two contrasted dates: (1) 15/01/2017 during the crop season when
 797 wheat is irrigated, and (2) 20/06/2017 when all wheat fields have been harvested. Tree fields
 798 are masked thanks to a land use map from the 2012-2013 crop season (Diarra et al., 2017)
 799 and an aerial picture acquired in 2019 from Google map. In January, most of the fields are

800 wet with soil moisture values reaching $0.4 \text{ m}^3/\text{m}^3$ while drier conditions are encountered in
801 June. An interesting feature is the high variability of hydric conditions from one field to
802 another during January in relation to irrigation distribution and sowing date. A complete
803 water turn takes about 15 days to irrigate all the fields introducing also a large diversity in
804 terms of hydric condition. The SSM map of January depicts well this variability. The large
805 oblique patch located west of the images exhibiting dry conditions on both date corresponds
806 to bare soil that are never cropped.



807
808 *Fig. 11. Surface soil moisture maps over an irrigated perimeter located 40 km east of Marrakech named R3 for*
809 *two different SSM conditions : wet condition (15 January 2017) and dry condition (20 June 2017).*

810

811 **Summary and conclusion**

812 The objective of this work was to develop and evaluate a new approach for surface soil
813 moisture (SSM) retrieval over wheat crops based on Sentinel-1 data. The goal was to rely on
814 Sentinel-1 only, without any additional ancillary data. This work is based on a large *in situ*
815 database from several irrigated and rainfed wheat in Morocco and Tunisia. A comprehensive
816 study of wheat C-band radar response was conducted. The time series of the backscattering
817 coefficient and the interferometric coherence derived from C-band Sentinel-1 are analyzed
818 and physically interpreted. The analysis showed that the backscattering coefficient is
819 obviously sensitive to the surface soil moisture changes, at least during the first stage of
820 wheat growth, while the interferometric coherence and PR are more affected by the wheat
821 crop growth. The good relationships obtained between PR/interferometric coherence, on
822 one hand and, on the other hand, AGB/VWC were selected as potential candidates for the
823 retrieval of SSM. The WCM coupled to Oh model was calibrated at VV and VH polarization
824 and for two angles of incidence (45.6° and 35.2°). Several parameters were tested as
825 descriptors of wheat development but observed backscattering coefficients after the
826 heading stage was better reproduced using the AGB. The model showed to reasonably
827 reproduce the observed seasonal course of the backscattering coefficient if the empirical
828 coefficients of the WCM were calibrated separately for VV and VH. The calibrated model was
829 used in an inversion process for the SSM. The four methods are named
830 WCM_{PR-VWC} , WCM_{PR-AGB} , $WCM_{\rho-VWC}$ and $WCM_{\rho-AGB}$. They are compared to three more
831 classical methods for SSM retrieval composed of two empirical approaches (linear
832 relationships $\sigma^0 - SSM$ and $\Delta\sigma^0 - \Delta SSM$) and one based on the water-cloud model but
833 with NDVI as the vegetation descriptor (WCM_{NDVI}). Please note that the new WCM based

834 approaches require additional measurements of the vegetation characteristics to develop
835 the relationships between PR/ ρ - AGB/VWC adding three parameters to be fitted with
836 regards to WCM_{NDVI} , $\sigma^0(SSM)$ and $\Delta\sigma^0(\Delta SSM)$ methods. The main results can be
837 summarized as follows:

- 838 - All methods performed reasonably well at VV polarization with better results for the
839 WCM-based when compared to the empirical ones (σ^0 and $\Delta\sigma^0$).
- 840 - Despite a moderate variability of the statistical metrics when going from one site to
841 another, the new method based on the relationship between the interferometric
842 coherence and the AGB provided with the best results with a correlation coefficient r
843 of 0.74 and a small bias of 0.01 m³/m³.
- 844 - By contrast, overall performances were worse for the empirical approaches but they
845 were more stable from one site to another, in particular for the σ^0 based method.

846 The proposed new approaches taking advantage of two complementary and relatively
847 independent information derived from Sentinel-1 data made it possible to get away from
848 dependence on optical data that are restricted by weather and illumination conditions. They
849 are valid for wheat crops (as the relationships between the interferometric coherence/PR
850 and vegetation characteristics were established for wheat) during the period from seeding
851 after all soil tillering action to harvest only meaning three conditions must be satisfied: (1)
852 soil roughness parameter h_{rms} remains within the range from 0.7 to 1.5 cm; (2) there is no
853 drastic change of soil roughness during the crop season. Stated differently, no soil tillering is
854 done from seeding to harvest; ; (3) the sensitivity of interferometric coherence to soil
855 moisture change is of a 2nd order with regards to AGB and VWC changes; (4) they reflect the
856 sensitivity of the radar signal to the vegetation geometrical structure, which can induce

857 significant errors if it is not well taken into account (explaining low results over the second
858 test field).

859 The limited loss of performances on the validation database of the coherence based
860 technique points out that it could be applied with a reasonable accuracy on sites outside of
861 the area where it has been developed. This question of the genericity of the retrieval
862 approach is fundamental. Very similar wheat varieties are sown in the south Mediterranean
863 region meaning that the canopy structure are similar. Likewise, the fact that the
864 phenological stages are very close as all the fields in our database are located in the South
865 Mediterranean region lead to similar development of the plants. A strong change of
866 structure would probably impact negatively the results. This means that the method would
867 not be valid for different crop and in particular row crops such as sunflower. Even for wheat
868 field, specific conditions such as the development of adventices with a different structure of
869 wheat or stems laid down by the wind degrade the performance of the approach as
870 demonstrated by the poor results obtained on Field 2. Further validation is thus required.

871 Further investigations will focused on the combination of C and L-band data within the frame
872 of the numerous L-band mission in preparation (ROSE-L, NISAR) or already into orbit (ALOS-
873 2, SAOCOM) for the joint retrieval of SSM and vegetation biomass, potentially separating its
874 stems and heads components. Another aspect of our work in progress deals also with
875 irrigated area mapping from which high spatio-temporal resolution SSM images could
876 benefit ([Malbêteau et al., 2018](#)) together with irrigation retrieval at the plot scale.

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888

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1169 two different SSM conditions : wet condition (15 January 2017) and dry condition (20 June 2017). 47

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1172 **Appendix 1: Backscattering model description**

1173 The canopy-backscattering coefficient is given as the incoherent sum of three contributions:
1174 the attenuated surface scattering from the underlying soil, the volume scattering from the
1175 canopy and the soil-vegetation multiple scattering interaction as follows:

$$1176 \quad \sigma_{pq, canopy}^0 = \sigma_{pq, vegetation}^0 + \sigma_{pq, soil-vegetation}^0 + L^2 \sigma_{pq, soil}^0 \quad (A1)$$

1177 Where pq is the polarization mode (V or H). $\sigma_{pq, vegetation}^0$, $\sigma_{pq, soil-vegetation}^0$ and $\sigma_{pq, soil}^0$
1178 denote the contributions of vegetation, interactions soil-vegetation and bare soil,
1179 respectively. L^2 is the two-way transmissivity factor of the canopy.

1180 **1. Oh Model**

1181 The contribution of the soil component was calculated using the Oh et al. model (1992). This
1182 model has been shown to be applicable to a large range of soil roughness conditions and a
1183 large range of incidence angle in various context (Frison et al., 1998; Jarlan et al., 2002). The
1184 soil backscattering coefficient is expressed as a function of one parameter related to the soil
1185 roughness (h_{rms}) only when compared to other models including IEM (Fung et al., 1992).
1186 Other input parameters are the angle of incidence (θ), the wave number (k) and the
1187 dielectric constant of the soil surface (ϵ_r). This latter was computed from soil moisture and
1188 soil texture using the empirical model proposed in Hallikainen et al. (1985). The Oh model
1189 expresses the co-polarized and cross-polarized ratio to compute the backscattering
1190 coefficient of three linear polarizations (HH, VV and HV/ VH) as follows:

$$1191 \quad \sigma_{VV, soil}^0 = g * (\cos \theta)^3 * (\Gamma_V + \Gamma_H) / \sqrt{p} \quad (A2)$$

$$1192 \quad \sigma_{VH, soil}^0 = q * g * (\cos \theta)^3 * (\Gamma_V + \Gamma_H) / \sqrt{p} \quad (A3)$$

1193 Where

$$1194 \quad q = 0.23 * (1 - e^{(-k * h_{rms})}) * \sqrt{\Gamma_0} \quad (A4)$$

$$1195 \quad \sqrt{p} = 1 - e^{(-k * h_{rms})} * \left(\frac{2\theta}{\pi}\right)^{\frac{1}{3} * \Gamma_0} \quad (A5)$$

$$1196 \quad g = 0.7 * (1 - e^{(-0.65 * (k * h_{rms})^{1.8})}) \quad (A6)$$

1197 Γ_V , Γ_H , and Γ_0 are the Fresnel coefficients given by the following expressions:

$$1198 \quad \Gamma_V = \frac{\varepsilon_r \cos \theta - \sqrt{\varepsilon_r - \sin^2 \theta}}{(\varepsilon_r \cos \theta + \sqrt{\varepsilon_r - \sin^2 \theta})^2}, \Gamma_H = \frac{\cos \theta - \sqrt{\varepsilon_r - \sin^2 \theta}}{(\cos \theta + \sqrt{\varepsilon_r - \sin^2 \theta})^2} \text{ and } \Gamma_0 = \left| \frac{1 - \sqrt{\varepsilon_r}}{1 + \sqrt{\varepsilon_r}} \right|^2 \quad (A7)$$

1199 **2. Water Cloud Model**

1200 The semi-empirical water cloud model (Attema and Ulaby, 1978) aims to predict the radar
1201 backscatter over vegetation canopies. It represents the vegetation canopy as a cloud of
1202 identical water droplets. Indeed, the dielectric constants of dry matter and dry air are much
1203 smaller than the dielectric constant of water and the vegetation cover is composed of more
1204 than 99% of air by volume. The main assumptions of the water cloud model are: (1) that the
1205 multiple scattering within the canopy volume can be neglected, and (2) that cloud height
1206 and density are proportional to the VWC. The model domain of validity covers a large range
1207 of frequencies (8-18 GHz) and of incidence angles (0-70°). It has been shown to perform well
1208 in a large range of vegetation conditions and frequencies for the direct prediction of the
1209 backscattering coefficient as well as for the retrieval of soil moisture content and AGB (Bai et
1210 al., 2017; Bindlish and Barros, 2001; Bousbih et al., 2017; El Hajj et al., 2016; Hosseini and
1211 McNairn, 2017).

1212 In the Water Cloud Model, the $\sigma_{soil-vegetation}^0$ term (cf. Eq. A1) is neglected (Frison et al.,
1213 1998; L. Jarlan et al., 2002; Kumar et al., 2014). The problem is then equivalent to the first
1214 order solution of the radiative transfer equation through a weak medium. $\sigma_{vegetation}^0$ and L^2
1215 are expressed as follows:

$$1216 \quad \sigma_{pq, vegetation}^0 = A_{pq} V_1 \cos\theta (1 - L^2) \quad (A8)$$

$$1217 \quad L_{pq}^2 = e^{-2B_{pq} V_1 \sec\theta} \quad (A9)$$

1218 Where θ is the incidence angle and A_{pq} and B_{pq} are the model's coefficients that depend on
1219 the canopy type, sensor's frequency and polarization and on the incidence angle. The first
1220 coefficient is related to the contribution of the direct scattering from the vegetation while
1221 the second represents the attenuation of the underlying soil backscattering by the canopy.
1222 V_1 is a parameter describing the vegetation canopy dynamics.

1223